Identification of Robust Biomarkers using the Biomarker Meta-Analysis Module

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The aim of this tutorial is to demonstrate how the Biomarker Meta-Analysis module of MetaboAnalyst can be used to identify robust and novel biomarkers of disease/other conditions through the integration of individual metabolomics studies. The example data used in this tutorial comes from a subset of GCTOFMS data deposited in the Metabolomics Workbench from Fiehn et al. 2016 (doi: 10.21228/M85P57) which has been slightly modified to demonstrate the full capabilities of this module. The primary objective of their study is to identify biomarkers of adenocarcinoma (lung cancer) in blood.

Introduction to Biomarker Meta-Analysis

Biomarker identification is an important area of research in metabolomics, and their validation is challenging due to inconsistencies in identified biomarkers amongst similar experiments. With the wide application of metabolomics and the establishment of several metabolomics data repositories, there is an ever-increasing interest to perform secondary analysis of published metabolomics datasets collected under similar study conditions in similar populations, a practice often referred to as "meta-analysis". When executed properly, meta-analysis can leverage the collective power of multiple studies to overcome study biases and small effect sizes to improve the precision in identifying true patterns and robust biomarkers within data. The primary goal of the Biomarker Meta-Analysis module is to provide a user-friendly tool for the integration of individual metabolomics studies to identify robust biomarkers. The main steps for Biomarker Meta-Analysis are as following and will be described in further detail:

- i. Upload individual datasets. Prior to uploading the data, clean the datasets to ensure consistency amongst feature names (compound IDs, spectral bins, or peaks) as well as consistency in the class labels across all included studies.
- ii. The module will perform differential enrichment analysis for each individual study to compute summary level-statistics for each metabolite feature (e.g. p-value).
- iii. The summary level-statistical results from all studies are combined, and meta-analysis is performed using one of several statistical options: combining of p-values, vote counting, or direct merging for very similar datasets.
- iv. The results can be visualized as a Venn diagram to view all possible combinations of shared features between the datasets.

Data Upload Preparation

Before uploading your data to the module, please make sure that the names of your features (compound names, spectral bins, peaks) are consistent between the individual studies. At least 25% of the features must match between the studies. Also make sure that the group labels are also

consistent between the studies, i.e. Cancer and Healthy. Finally, all uploaded sample identifiers must be unique. An example of what your dataset should look like is below:

| | A | В | C | D | E | F | G | Н | 1 |
|----|---------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| 1 | Samples | 140225dlvsa44_1 | 140226dlvsa30_1 | 140226dlvsa36_1 | 140227dlvsa36_1 | 140227dlvsa47_1 | 140228dlvsa08_1 | 140228dlvsa17_1 | 140228dlvsa30_1 |
| 2 | Class | Adenocarcinoma | Adenocarcinoma | Adenocarcinoma | Adenocarcinoma | Adenocarcinoma | Cancer | Cancer | Cancer |
| 3 | 1_5-anhydroglucitol | 6799 | 17473 | 38267 | 12027 | 19565 | 20174 | 8153 | 6878 |
| 4 | 1-monoolein | 165 | 411 | 525 | 726 | 386 | 339 | 197 | 3225 |
| 5 | 1-monopalmitin | 107 | 100 | 195 | 122 | 108 | 132 | 51 | 82 |
| 6 | 1-monostearin | 67 | 125 | 209 | 200 | 108 | 113 | 71 | 162 |
| 7 | 2_3_5-trihydroxypyrazine NIST | 34 | 54 | 45 | 107 | 55 | 46 | 41 | 61 |
| 8 | 2_3-dihydroxybutanoic acid NIST | 74 | 146 | 183 | 152 | 202 | 211 | 101 | 143 |
| 9 | 2-deoxyerythritol | 334 | 765 | 474 | 495 | 581 | 353 | 469 | 306 |
| 10 | 2-deoxytetronic acid NIST | 762 | 1830 | 1356 | 1128 | 1803 | 772 | 758 | 1173 |
| 11 | 2-hydroxybutanoic acid | 7786 | 15277 | 7794 | 9810 | 12725 | 18446 | 10663 | 13056 |
| 12 | 2-hydroxyglutaric acid | 233 | 1274 | 1021 | 1533 | 2124 | 1191 | 197 | 926 |
| 13 | 2-hydroxyhippuric acid | 84 | 82 | 107 | 109 | 103 | 78 | 322 | 74 |
| 14 | 2-hydroxyvaleric acid | 1392 | 1047 | 876 | 1170 | 1658 | 453 | 498 | 1073 |
| 15 | 2-ketoisocaproic acid | 2094 | 1229 | 1021 | 2840 | 1946 | 3155 | 2421 | 2535 |
| 16 | 3-aminoisobutyric acid | 891 | 473 | 362 | 387 | 621 | 276 | 278 | 779 |
| 17 | 3-hydroxybutanoic acid | 5015 | 2336 | 1509 | 4757 | 6757 | 13223 | 4428 | 2562 |
| 18 | 3-phosphoglycerate | 131 | 61 | 52 | 980 | 67 | 46 | 60 | 93 |
| 19 | 4-hydroxyproline | 1389 | 5112 | 4323 | 4082 | 3832 | 2080 | 1458 | 3146 |
| 20 | 5-hydroxynorvaline NIST | 197 | 142 | 264 | 178 | 427 | 116 | 64 | 200 |
| 21 | 5-methoxytryptamine | 314 | 304 | 246 | 83 | 744 | 725 | 124 | 127 |
| 22 | acetophenone NIST | 299 | 971 | 801 | 1732 | 1246 | 1353 | 497 | 584 |
| 23 | aconitic acid | 132 | 99 | 149 | 223 | 139 | 142 | 131 | 104 |
| 24 | adenosine-5-phosphate | 155 | 283 | 163 | 193 | 156 | 152 | 220 | 201 |
| 25 | adipic acid | 192 | 695 | 1045 | 931 | 740 | 849 | 241 | 418 |
| 26 | alanine | 94588 | 183357 | 189323 | 158568 | 109405 | 125119 | 46592 | 188992 |
| 27 | alpha ketoglutaric acid | 244 | 92 | 67 | 60 | 130 | 96 | 129 | 151 |
| 28 | aminomalonic acid | 613 | 622 | 1598 | 1332 | 1430 | 1508 | 986 | 879 |
| 29 | arabinose | 159 | 308 | 500 | 294 | 132 | 248 | 126 | 321 |
| 30 | arabitol | 56 | 195 | 137 | 130 | 125 | 95 | 75 | 386 |
| 31 | arachidic acid | 2291 | 1067 | 748 | 769 | 1032 | 1468 | 3078 | 1206 |
| 32 | arachidonic acid | 230 | 7348 | 9097 | 18245 | 7869 | 7071 | 2006 | 550 |
| 33 | asparagine | 2168 | 3462 | 4609 | 4160 | 5327 | 5130 | 1414 | 4466 |
| 34 | aspartic acid | 561 | 1238 | 2026 | 2327 | 4619 | 2614 | 465 | 1060 |
| 35 | azelaic acid | 54 | 574 | 532 | 597 | 513 | 412 | 68 | 102 |
| 36 | behenic acid | 163 | 185 | 212 | 225 | 230 | 92 | 156 | 128 |

Biomarker Meta-Analysis Step-By-Step

Step 1: On the MetaboAnalyst home page, press "click here to start" to enter the module overview.





Step 2: On the Module View page, click the "Biomarker Meta-Analysis" circle to begin.

Step 3: In the Biomarker Meta-Analysis upload page, press the "Upload" button to begin uploading your individual metabolomic datasets. Please specify the format of your data (samples in columns or in rows) and select your data. Click "Submit" to upload the data. A message will pop up in the top corner of your screen informing you if the data upload was successful.

| | Data Upload | Sanity Check | Visualization | Normalization | DE Analysis | Data Summary | Include | | |
|-----|---------------------------|--------------|---------------|---------------|-------------|--------------|---------|--|--|
| | Ŧ Upload | ≁ Process | E View | © Normalize | P Analyze | • Detail | * | | |
| | | | | | | | Add New | | |
| Adj | Adjust study batch effect | | | | | | | | |

Following uploading of your data, the remaining buttons are now clickable. Press "Process" to perform a sanity check on your uploaded data, such as verifying sample names are unique, identifying group labels, and checking the number of samples and features uploaded (see example in the screenshot below). Click "Done" to close the Sanity Check.



Next, click "View" to see boxplots of your data showing the distribution of the first 100 samples (screenshot below). As you can see from this example, the distributions are very uneven amongst the samples. Click "Done" to close the box.



Click "Normalize" to choose to perform Log2 transformation and auto-scaling (see screenshot below). As the data was unevenly distributed, both will be performed. Click "Submit" to perform the normalization.

| Data Normalization | |
|--|--|
| We suggest all datasets to be co across different datasets. You co data visualization plots) to help scale. | ompared at log scales with similar distribution an use boxplots (available in the previous step - you determine if the data is already on the log |
| Normalization procedure | Log2 transformation |
| | Submit |

Now, if you click the "View" button once again, we can see a visualization of the results of the data normalization. From the screenshot below, the data is much more evenly distributed.



Remember that the module will perform differential analysis (DE) on each individual dataset uploaded. Click "Analyze" to perform DE using linear models (limma) on your dataset. Please input the p-value (FDR) cut-off and the fold-change cut-off and then click "Submit".

| - DE Analysis | |
|--|--|
| You can perform differential anal this is for current exploratory and value cutoff as specified in the m Venn Diagram comparison. | lysis using linear models (limma). Note, alysis. It will be re-computed using the p- neta-analysis (next page) and for the |
| Set p value (FDR) cutoff | þ.1 |
| Set fold change (FC) cutoff | 0.0 |
| | Submit |

The number of significant and non-significant features will appear in a pie chart below the "Submit" button (see screenshot below). Click "Done" to close the pop-up box.

| - DE Analysis | |
|--|--|
| You can perform differential an this is for current exploratory a value cutoff as specified in the Venn Diagram comparison. | alysis using linear models (limma). Note, nalysis. It will be re-computed using the p- meta-analysis (next page) and for the |
| Set p value (FDR) cutoff | 0.1 |
| Set fold change (FC) cutoff | 0.0 |
| | Submit |
| Sig [3] Non-Sig [149] | |
| | Done |

To view an over-view of the data processing performed on your uploaded data, click "Detail". As you can see in the example below, the number of features and samples are shown, as are the group labels, which normalization procedures were applied, and how many features were significantly different between the two groups. Click "Done" to close the pop-up box.



Finally, click "Add new" to add a new data set and perform the same steps as above for each new dataset uploaded.

| Data Upload | Sanity Check | Visualization | Normalization | DE Analysis | Data Summary | Include | | |
|---------------------------|--------------|---------------|--------------------|-------------|--------------|---------|--|--|
| ✓ data4 | V Process | L View | ✓ Normalize | ✓ Analyze | Detail | ~ | | |
| Ŧ Upload | A Process | E View | o Normalize | P Analyze | Detail | * | | |
| | | | | | | Add New | | |
| Adjust study batch effect | | | | | | | | |

Please note that a maximum of 1000 samples are allowed. Also, after uploading all your datasets, you can check the boxes in the "Include" column of the data-upload page to include a study or not in the meta-analysis. As well, check the "Adjust study batch effect" if you would like batch-effect to be accounted for in the meta-analysis.

Use Case: Click the "Try Examples" button on the bottom of the page to use the example dataset detailed above (Adenocarcinoma vs. Control). A dialogue will appear, click "Yes", and then the four datasets will be automatically uploaded and processed.

| Datasets | Data Type | Description | Phenotype |
|----------------------------------|--|--|--|
| iata1 iata2 iata3 iata4 | Untargeted metabolomics data (GC- TOF-MS). | Four test datasets were created from a subset of data from a study investigating biomarkers of adenocarcinoma in blood (For more details: Fiehn et al.) | Groups: Adenocarcinoma and Control |

Following the uploading of your data/example data, click "Proceed" on the bottom of the page to move onto the next step.



Example Datasets

This will initiate a final data integrity check on all of your uploaded data that is included for metaanalysis. It will check if group labels are consistent, if at least 25% of features are common, the number of uploaded samples, etc. Click "Next" to continue.



Step 4: Following data uploading and processing, we can choose from 1 of 3 methods to perform meta-analysis. In this tutorial, we will go through the results of the "Combining p-values" method. The screenshot below highlights the 3 methods available, paired with a detailed description. Please note that on the right-hand side is the R Command history, which reveals the step-by-step of your analysis in real-time. This R Command History can be used to reproduce your analysis locally in R

with the MetaboAnalystR package. Also, on the left-hand side is the navigation panel, which can directly navigate you through different steps of the Biomarker Meta-Analysis module.

| seaboAnaga | MetaboAnalyst a comprehensive tool for metabolomics analysis and interpretation | |
|---|---|---|
| Upload Mota analysis Result table Venn diagram Download Exit | Combining P Values There are two widely used methods to combine p values from multiple studies for information integration - the Fisher's method (-2*{Log(p)}) and the Stouffer's method (based on inverse normal transformation). Stouffer's method incorporates weight (i.e. based on sample sizes) into the calculation; while Fisher's method is normat as a weight free method. They usually have very similar gredimance. However, in metabolonic meta-analysis, larger sample sizes do not warrant targer weights as the quality of each study can vary. Users should choose to apply Stouffer's method only when all studies are of similar qualities (i.e. same analytical platforms with similar levels of missing values). Select a method Faher's method 0.05 Vote Counting State significance level 0.05 This is the simplest method to perform meta-analysis. Differentially expressed metabolites are first selected based on a threshold to obtain a list of significant features from each study. The vote for each feature can then be calculated as the total number of times it appears as significant in all features lists. The final significance level Obtime 0.05 Stume Direct Merging This approach directly merges all datasets into a mega-dataset and then analyzes it as a single dataset. It should only be used when all datasets are very similar (i.e. collected by the same lab using the same analytical platforms) | R Command History Keep collapsed Save I Inithatabijetta ("come", "metadata", F addet", Badindbata [mdet, "datal.com", "colu"); addet".Badindbata [mdet, "datal.com", "colu"); addet".Badindbata [mdet, "datal.com", "datal.com", 10; addet".Badindbata [mdet, "datal.com", "colut"]; addet".Badindbata [mdet, "datal.com", "colut"]; addet.Severing [indet, "datal.com", "colut"]; addet.Severing [indet.Badata [indet, "datal.com", "colut"]; addet.Severing [indet.Badata [indet, "datal.com", "colut"]; addet.Severing [indet.Badata [indet.Badata]; addet.Severing [indet.Badata]; addet.Severing [indet.Badata]; addet.Severing [indet.B |
| | Privilous | |

Combining P Values: In the Combining P Values box, click the "Select a method" box to choose either the Fisher's method or the Stouffer's method for combining p-values. As the same GCTOFMS instrumentation was used, and all studies have no missing values, we will select the Stouffer's method. By default the significance level in "Set a significance level" is 0.05, which we will keep for the meta-analysis. Click "Submit" to perform p-value combination. A dialogue box will appear in the top-right corner of your screen, informing you of the total number of significant features identified in the meta-analysis (screenshow below). Click "Proceed" on the bottom right corner of your screen to continue to the detailed results of the meta-analysis.



Step 5: Remember that the goal of Biomarker Meta-Analysis is to identify robust metabolic biomarkers of disease/conditions. Using the example dataset, we aim to identify consistent markers of adenocarcinoma in blood across all four datasets. The results of the "Combining P Values" meta-analysis are listed in a table as in the screenshot below. In the table, the features are ranked by their combined p-value from lowest to highest. Here, we see that adenosine-5-phosphate, pyrophosphate, and pyruvic acid are the top 3 biomarkers identified, all with a combined p-value of 0.

| ł | The statistics from individual data an | alysis are given | in columns with | n the correspondir | g dataset names. | You can either adjust it | s content or sort the tabl | е. | R Command History Keep collapsed | |
|----------------------|--|---|-----------------|--------------------|------------------|--------------------------|----------------------------|---|---|--|
| Upload | Data summary: Log fold change | Data summary: Log fold change 🗘 Sort by: CombinedPval 🛊 Order: Ascending 🛊 Update | | | | | ± Download | <pre>vnload 1. InitDataObjects('conc', 'me ALSE) 2. mSet<-ReadIndData(mSet, 'dr </pre> | | |
| ta analysis | ID | data1 | data2 | data3 | data4 | CombinedTstat | CombinedPval | View | "colu"); 3. mSet<-SanityCheckIndData(mSe | |
| sult table | adenosine-5-phosphate | -1.7535 | -0.81954 | -0.89017 | -1.6839 | -187.97 | 0.0 | E View | nSet<-PerformIndNormalizatio detal arms" "larg" like | |
| in diagram vnload | pyrophosphate | -1.6539 | -0.68801 | -1.0106 | -1.6181 | -174.04 | 0.0 | View | <pre>data1.csv , log , l); 5. mSet<-PerformLimmaDE(mSet, " v", 0.05, 0.0);</pre> | |
| Exit | pyruvic acid | -1.7275 | -0.02462 | -1.154 | -0.18216 | -123.22 | 0.0 | E View | mSet<-ReadIndData(mSet, "dat "colu"); | |
| | maltotriose | -0.57042 | -0.78002 | -0.62125 | -0.34062 | -45.974 | 8.2354E-6 | E View | mSet<-SanityCheckIndData(mSe 2.csv") | |
| | glutamine | 0.25055 | 0.58333 | 0.9243 | 0.23142 | 42.535 | 2.9447E-5 | E View | <pre>data2.csv", "log", 1); . mSet<-PerformLimmaDE(mSet, "</pre> | |
| | lactamide | -0.16134 | -0.33998 | -0.99086 | -0.14049 | -37.845 | 1.8363E-4 | E View | v", 0.05, 0.0); 10.mSet<-ReadIndData(mSet, "dat | |
| | citrulline | 0.17019 | 0.70856 | 0.64683 | 0.23439 | 34.702 | 5.1871E-4 | E View | "colu"); 11. mSet<-SanityCheckIndData(mSe | |
| | lactic acid | -0.048584 | -0.13516 | -1.0411 | 0.010808 | -34.79 | 5.1871E-4 | E View | <pre>12. mSet<-PerformIndNormalizatio "data3.csv", "log", 1);</pre> | |
| | alpha ketoglutaric acid | -0.52005 | -0.28152 | -0.58456 | -0.40263 | -32.543 | 0.0011327 | L View | 13. mSet<-PerformLimmaDE(mSet, " v", 0.05, 0.0); | |
| | cystine | 0.21575 | 0.80808 | 0.38177 | 0.20646 | 31.319 | 0.0015355 | E View | <pre>14. mSet<-ReadIndData(mSet, "dat "colu"); 15. mSet<-SanityCheckIndData(mSet)</pre> | |
| | taurine | 0.0050866 | -0.21137 | -0.88704 | -0.27037 | -31.389 | 0.0015355 | E View | <pre>4.csv") 16.mSet<-PerformIndNormalizatio</pre> | |
| | maltose | -0.35858 | -0.69713 | -0.38259 | -0.22187 | -30.371 | 0.0020746 | View | "data4.csv", "log", 1); 17.mSet<-PerformLimmaDE(mSet, " | |
| | fructose | 0.54515 | 0.28723 | 0.60315 | 0.1174 | 29.697 | 0.0025194 | View | <pre>18. mSet<-CheckMetaDataConsisten F);</pre> | |
| | asparagine | 0.26279 | 0.37151 | 0.66667 | 0.28026 | 29.053 | 0.0030375 | E View | <pre>19. mSet<-PerformPvalCombination isher", 0.05)</pre> | |
| | oxalic acid | -0.24872 | -0.55199 | -0.44125 | -0.32291 | -27.222 | 0.0059119 | E View | 20. mSet<-GetNetaResultMatrix(mS | |
| | | | (1 of 3) | | 3 82 81 | 15 \$ | | | | |

Click "View" to view a box-plot of the expression pattern of the compounds per each uploaded dataset. In the screenshot below of adenosine-5-phosphate (A5P), we can clearly see that A5P is consistently higher in patients with adenocarcinoma than in healthy controls.



Step 6: We can then visualize the results of the meta-analysis in a Venn diagram (click "Venn Diagram"). A dialogue box will appear, listing all of the datasets and the results of the meta-analysis (as meta_dat), the number of differentially expressed features per each dataset, and a box for users to click on under the "Include" header to include or not to include datasets in the venn diagram. Note that a maximum of four datasets can be visualized using a Venn diagram. In this case, we will not include dataset 4 (screenshot below). Click "Submit" to continue.

| he max number of datasets th | at can be compa | ared is four. |
|----------------------------------|--------------------|---------------|
| atasets without significant hits | s will be excluded | d. |
| Name | DE # | Include |
| data1 | 3 | * |
| data2 | 12 | * |
| data3 | 21 | * |
| data4 | 2 | * |
| meta_dat | 34 | * |
| meta_dat | 34 | * |

Step 7: On this page, we can view the resulting Venn diagram. Each area of the Venn diagram is clickable. If we click directly in the center of the overlapping datasets, we can see that a total of 2 features (A5P and pyrophosphate) overlap between datasets 1, 2, 3, and the meta-analysis. Click on all possible areas to view all possible combinations of features.



Step 8: On the left-hand side navigation panel, click "Download" to view all images and tables generated throughout the Biomarker Meta-Analysis, as well as to download the Analysis Report, which contains all the details of each step of your analysis as well as all of the results. You can also directly download all the results in a zip file by clicking "Download.zip".

Result Download

Please download the PDF Analysis Report and results (tables and images) below. The "Download.zip" contains all the files in your home directory. The PDF report may not be generated sometimes. You can try to re-generate PDF using an alternative approach using the button below.

| Regenerate | Analysis Report |
|-------------------------------|---------------------------|
| Download.zip | SigFeatures data4.csv |
| Rhistory.R | data4.csv |
| venn diagram.png | data2.csv |
| MetaboAnalyst merged data.csv | adenosine-5-phosphate.png |
| data1.csv | SigFeatures_data2.csv |
| SigFeatures data3.csv | data3.csv |
| meta sig features metap.csv | SigFeatures_data1.csv |
| Logout | |

--End of tutorial --