

# <sup>1</sup> Metage2Metabo PostaViz: a Python package for exploring, visualising, and comparing the metabolic potential of microbial communities

<sup>4</sup> **Léonard Brindel**  <sup>1</sup> and **Clémence Frioux**  

<sup>5</sup> <sup>1</sup> Inria, Univ. Bordeaux, INRAE, F-33400 Talence, France ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

## Software

- [Review](#) 
- [Repository](#) 
- [Archive](#) 

Editor: 

Submitted: 25 August 2025

Published: unpublished

## License

Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](https://creativecommons.org/licenses/by/4.0/))<sup>16</sup>

## <sup>6</sup> Summary

<sup>7</sup> Microbial communities consist of up to thousands of distinct microbial populations, each <sup>8</sup> characterized by its genomic DNA sequences, and all sharing a habitat and environmental <sup>9</sup> conditions. The word *microbiome* describe the holistic concept associated all the previous <sup>10</sup> components (Berg et al., 2020). Characterising the populations in samples and understanding <sup>11</sup> both their roles of and interactions within the microbiome require a combination of <sup>12</sup> experimentation, high-throughput data acquisition and computational models (Klitgord & <sup>13</sup> Segrè, 2011). The role of microbial populations can be abstracted by the study of their <sup>14</sup> *metabolism*, encompassing all biochemical reactions that cells may perform. The genome <sup>15</sup> encodes the genetic information associated to the metabolism, and can therefore be queried to <sup>16</sup> estimate the metabolic capabilities of microorganisms, represented as *metabolic networks*. <sup>17</sup> Because such metabolism is highly redundant, depends on the environment, and because of <sup>18</sup> the size of microbial communities, computational models are needed and predict, from the <sup>19</sup> networks, the possible behaviours of and interactions within microbial populations in given <sup>20</sup> environmental conditions. Comparing the outcomes of such predictive models in multiple <sup>21</sup> samples further increases the difficulty of integrating results into actionable hypotheses. <sup>22</sup> Visualisation and integration of metadata can help perform such comparison. They need to be <sup>23</sup> as customisable as possible to facilitate exploration by end-users.

## <sup>24</sup> Statement of need

<sup>25</sup> Metage2Metabo-PostaViz (M2M-PostAViz) is a Python package that performs analyses on <sup>26</sup> the predictions generated by the metabolic-modelling tool Metage2Metabo (M2M) (Belcour et <sup>27</sup> al., 2020). M2M screens the metabolic potential of a microbial community represented as a <sup>28</sup> collection of genome-scale metabolic networks. When working with cohorts of hundreds or <sup>29</sup> thousands of samples, one has to run the tool as many times as there are samples, then analyse <sup>30</sup> the results of the model. The tool's outputs are, for each community, several data frames <sup>31</sup> describing the role of each microorganism with respect to the whole community's functions. <sup>32</sup> Properly comparing all samples requires combining all the outputs, and taking into account <sup>33</sup> sample metadata describing individuals lifestyle or clinical information for instance.

<sup>34</sup> M2M-PostaViz integrates all such data and provides a visualisation interface that permits <sup>35</sup> exploration through custom plot generation and statistical tests. The underlying data treatment <sup>36</sup> was optimised in order to deal with large numbers of samples without impeding user experience. <sup>37</sup> M2M-PostaViz notably permits a pre-treatment and storage of the data such that future <sup>38</sup> exploration can be launched in a computationally efficient manner. Exploration is performed <sup>39</sup> at several levels: molecules (metabolites) that may or may not be producible across samples, <sup>40</sup> microorganisms that may have different behaviours across samples depending on interactions

41 with other community members, or more general overviews of the community functions. The  
42 tool works as a local web-based application.  
43 Overall, M2M-PostaViz was designed to address three needs: (i) comparing large metagenomic  
44 datasets using a metabolic modelling approach; (ii) integrating additional data into the  
45 analysis, such as microbial community composition and associated metadata; and (iii) making  
46 these analyses accessible to non-specialists through a graphical user interface that supports  
47 customisable workflows.”

## 48 State of the field

49 Metabolic modelling is widely used to determine the roles of microorganisms in microbial  
50 communities (Cerk et al., 2024): what molecules they can produce, which interactions are  
51 likely to happen depending on the environmental conditions... Many models rely on integer  
52 linear programming optimisations (García-Jiménez et al., 2021) and some alternatives use  
53 Boolean abstractions (Frioux et al., 2018) (Belcour et al., 2020) or probabilistic approaches  
54 (Bernstein et al., 2019) to provide predictions on community behaviours. Key questions are  
55 scalability to large communities, and also integration of these predictions when analysing many  
56 samples or community compositions, which is more and more frequent as large metagenomic  
57 cohorts get published (Asnicar et al., 2025).

58 In practice, each microorganism is abstracted by a collection of biochemical reactions it may  
59 perform according to its genomic information, thus forming a network connecting transformed  
60 molecules (Cerk et al., 2024). A community of microorganisms is therefore represented as  
61 a collection of such networks, referred to as genome-scale metabolic networks. A metabolic  
62 model will provide predictions on the possible behaviour of microorganisms and communities in  
63 defined simulation conditions. Boolean abstractions, as used by M2M, ensure the scalability of  
64 predictions; although the model is qualitative and does not quantify interactions, such methods  
65 are considered a reasonable proxy for more quantitative models (Kruse & Ebenhöh, 2008).

## 66 Software design

### 67 Data integration and storage

68 Each sample has to be run in M2M prior analysis. Inputs to the application are a set of directories  
69 generated by M2M for each sample, composed of several tabulated and json files. Additional  
70 inputs to M2M-PostaViz include relative abundance of microbes in each sample, used to weigh  
71 the predictions, metadata associated to the samples and possibly metadata related to molecule  
72 descriptions and microbial taxonomy of the corresponding metabolic networks present in the  
73 communities.

74 Reading and integrating all data is computationally demanding when considering several  
75 hundreds or several thousands of samples (and M2M outputs directories). Taking into account  
76 that users are likely to explore the same data across several runs of the application, efforts  
77 were done to efficiently store the required and processed data such that only the first run takes  
78 time and the future ones directly load pre-processed data. The parquet format is used to store  
79 all this information as a database limiting the use of memory for accesses.

### 80 Application content

81 The application opens as a multi-tab browser page where the first one is an overview of the  
82 data that summarises it and enables several first analyses customisable by variables of metadata.  
83 Two tabs provide analyses centered of microbe roles and molecules respectively (see below)  
84 and a last one summarises the metadata and permits customising variable types to fine-tune  
85 analyses and plots.

**86 Exploration of microorganism roles**

87 The second tab of the application focuses on the role of microorganisms in the production  
88 of metabolites across samples. The same species, and thus the same metabolic network can  
89 appear in several samples, but behave differently because of interactions with other microbial  
90 populations. In addition, microbial species can be grouped according to their taxonomy,  
91 enabling to consider not only the role of a metabolic network but the role of all those falling  
92 in taxonomic groups of different levels (phylum, family, genera...). Again, sample metadata  
93 variables can refine the analysis, enabling users to compare groups or filter certain samples.

**94 Exploration of metabolite production across samples**

95 The third tab of the application is dedicated to the analysis the metabolites, that can also be  
96 groups of families if a proper ontology is provided. Focusing on metabolites enables a targeted  
97 analysis in order to compare samples or groups of samples on specific metabolic functions.

**98 Research impact statement**

99 M2M-PostaViz builds on the widely used M2M framework, which has been cited more than  
100 one hundred times and remains actively maintained, by addressing key barriers that currently  
101 limit the broader adoption of large-scale metabolic modelling. While M2M enables powerful  
102 predictions of metabolic complementarity and community-level functions, its complexity and  
103 the volume of generated outputs require substantial expertise, restricting its use to a limited  
104 and expert audience.

105 M2M-PostaViz overcomes these limitations by providing an interactive and user-friendly graphical  
106 interface that enables systematic exploration, comparison, and interpretation of M2M outputs  
107 across large metagenomic datasets consisting of up to thousands samples. The tool integrates  
108 metabolic modelling results with microbial community composition and associated metadata,  
109 facilitating multi-dimensional analyses at scales that were previously difficult to achieve.

110 By lowering technical barriers, M2M-PostaViz broadens access to metabolic modelling  
111 approaches and enables their application by non-specialists. To promote transparency,  
112 reproducibility, and adoption, M2M-PostaViz is accompanied by an extensive tutorial and  
113 curated test datasets, supporting users in applying metabolic modelling analyses to diverse  
114 microbial ecosystems.

**115 AI usage disclosure**

116 AI tools (GitHub Copilot and GPT-5) were used occasionally for code generation, particularly  
117 for debugging, and for grammar and language checks of the manuscript. All suggestions were  
118 reviewed and validated by the human authors.

**119 Acknowledgements**

120 CF is supported by the French National Research Agency (ANR) France 2030 PEPR  
121 Agroécologie et Numérique MISTIC ANR-22-PEAE-0011. Experiments and development  
122 were carried on the PlaFRIM experimental testbed, supported by Inria, CNRS (LABRI  
123 and IMB), Université de Bordeaux, Bordeaux INP and Conseil Régional d'Aquitaine (see  
124 <https://www.plafirim.fr>).

## 125 References

- 126 Asnicar, F., Manghi, P., Fackelmann, G., Baldanzi, G., Bakker, E., Ricci, L., Piccinno, G.,  
127 Piperni, E., Mladenovic, K., Amati, F., Arrè, A., Ganesh, S., Giordano, F., Davies, R.,  
128 Wolf, J., Bermingham, K. M., Berry, S. E., Spector, T. D., & Segata, N. (2025). Gut  
129 micro-organisms associated with health, nutrition and dietary interventions. *Nature*, 1–9.  
130 <https://doi.org/10.1038/s41586-025-09854-7>
- 131 Belcour, A., Frioux, C., Aite, M., Breteau, A., Hildebrand, F., & Siegel, A. (2020).  
132 Metage2Metabo, microbiota-scale metabolic complementarity for the identification of key  
133 species. *eLife*, 9, e61968. <https://doi.org/10.7554/elife.61968>
- 134 Berg, G., Rybakova, D., Fischer, D., Cernava, T., Vergès, M.-C. C., Charles, T., Chen, X.,  
135 Cocolin, L., Eversole, K., Corral, G. H., Kazou, M., Kinkel, L., Lange, L., Lima, N.,  
136 Loy, A., Macklin, J. A., Maguin, E., Mauchline, T., McClure, R., ... Schloter, M. (2020).  
137 Microbiome definition re-visited: old concepts and new challenges. *Microbiome*, 8(1), 103.  
138 <https://doi.org/10.1186/s40168-020-00875-0>
- 139 Bernstein, D. B., Dewhirst, F. E., & Segrè, D. (2019). Metabolic network percolation  
140 quantifies biosynthetic capabilities across the human oral microbiome. *eLife*, 8, e39733.  
141 <https://doi.org/10.7554/elife.39733>
- 142 Cerk, K., Ugalde-Salas, P., Nedjad, C. G., Lecomte, M., Muller, C., Sherman, D. J., Hildebrand,  
143 F., Labarthe, S., & Frioux, C. (2024). Community-scale models of microbiomes: Articulating  
144 metabolic modelling and metagenome sequencing. *Microbial Biotechnology*, 17(1), e14396.  
145 <https://doi.org/10.1111/1751-7915.14396>
- 146 Frioux, C., Fremy, E., Trottier, C., & Siegel, A. (2018). Scalable and exhaustive screening of  
147 metabolic functions carried out by microbial consortia. *Bioinformatics*, 34(17), i934–i943.  
148 <https://doi.org/10.1093/bioinformatics/bty588>
- 149 García-Jiménez, B., Torres-Bacete, J., & Nogales, J. (2021). Metabolic modelling approaches  
150 for describing and engineering microbial communities. *Computational and Structural  
151 Biotechnology Journal*, 19, 226–246. <https://doi.org/10.1016/j.csbj.2020.12.003>
- 152 Klitgord, N., & Segrè, D. (2011). Ecosystems biology of microbial metabolism. *Current  
153 Opinion in Biotechnology*, 22(4), 541–546. <https://doi.org/10.1016/j.copbio.2011.04.018>
- 154 Kruse, K., & Ebenhöh, O. (2008). Comparing flux balance analysis to network expansion:  
155 producibility, sustainability and the scope of compounds. *Genome Informatics. International  
156 Conference on Genome Informatics*, 20, 91–101.