

### Metage2Metabo: metabolic complementarity applied to genomes of large-scale microbiotas for the identification of keystone species

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# Metage2Metabo metabolic complementarity applied to genomes of large-scale microbiotas for the identification of keystone species

Arnaud Belcour\*, **Clémence Frioux**\*, Méziane Aite, Anthony Bretaudeau, Falk Hildebrand, Anne Siegel

Source code: <u>https://github.com/AuReMe/metage2metabo</u> Documentation: <u>https://metage2metabo.readthedocs.io/</u> Preprint: <u>https://doi.org/10.1101/803056</u>



### Context

### **Metagenomics flooding:**

- Newly-discovered (uncultured) microbes/taxa in microbiota
- Assemblies of numerous new reference genomes
- Incoming golden era of Metagenome-Assembled Genomes (MAGs) and metagenomic species

### $\rightarrow$ Collections of thousands of genomes/MAGs

Rely on relevant modelling approaches to tackle:

- **incompleteness** of poorly-studied genomes
- **impossibility to manually curate** thousands of metabolic networks (GSMNs)
- The **high combinatorics** brought by the analysis of all possible communities in the initial collection

 $\rightarrow$  Network expansion algorithm to model producibility

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Almeida et al 2019, Nayfach et al 2019, Pasolli et al 2019, Parks et al 2017, Almeida et al 2019

### Going beyond « who is there? » in metagenomics

datasets and large collections of genomes

- What can microbes do?
- What does putative cooperation between microbes brings to the community?
- Which microbes matter most for specific functions?

<u>Handorf et al 2005,</u> <u>Van der Ark et al 2017,</u> <u>Bernstein et al 2019</u> <u>Edgar et al 2017,</u> <u>De Oliveira Martins et al 2020</u>, Sun et al 2020

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# Workflow



Metagenomics data: genomes, MAGs Annotated metabolic cooperation keystone potential genomes/MAGs networks species .fasta Large-scale microbiota Functional annotation e.g. Prokka, Eggnog-mapper recon Pathway Tools 🛞 PathoLogic newt 🔁 Identification of 2MI nutrients Automatic and .qbk community GSMN reconstruction multi-process added value: workflow iscope reconstruction community-MeneTools cscope of metabolic producible m2m Computation of networks metabolites nisCoTo Individual & Individual metabolic keystone (Mpwt) (MiSCoTo) potential Collectice metabolic capabilities collective species: screening of addedvalue essential and Minimal community Keystone species selection identification individual alternative Metabolic potential metabolism of cooperation symbionts mincom Essential Alternative (MeneTools) symbionts symbionts

Fig. 1: flexibility of m2m's global workflow. The metacom command can run the workflow using existing metabolic networks (SBML)

Frioux et al, Bioinformatics 2018
Aite et al, PIOS Comp. Biol 2018

M2M reconstructs metabolic networks for genomes/MAGs and screens the complementarity of metabolisms in a large community.

## Application to datasets

Keystone species (KS) = microbes occurring in at least one minimal community ensuring the producibility of a set of target metabolites from given nutrients. Efficient solving: no need to enumerate all communities to retrieve them.

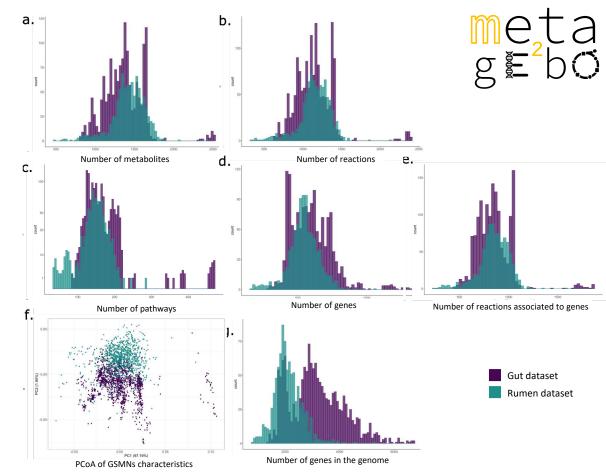
KS = essential symbionts (ES) + alternative symbionts (AS)

*ES are found in every minimal community AS are found in some minimal communities* 

913 cow rumen MAGs (<u>Stewart et al 2018</u>) 1520 draft bacterial reference genomes (<u>Zou et al 2019</u>) ↓ m2m workflow

Insights:

- Metabolic networks from reference genomes and MAGS display similar characteristics (Fig. 2)
- M2M metabolic screening and KS identification are robust to low genome degradations (Fig. 3)



#### Fig. 2: Comparison of GSMNs from both datasets

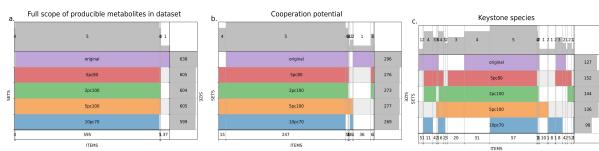


Fig. 3: Robustness analysis following MAGs degradation for the rumen dataset (upper row: original genomes, up to down: increasing genome degradation)

## Analysis of gut communities

Collection of genomes = 1520 draft bacterial reference genomes (Zou et al 2019)

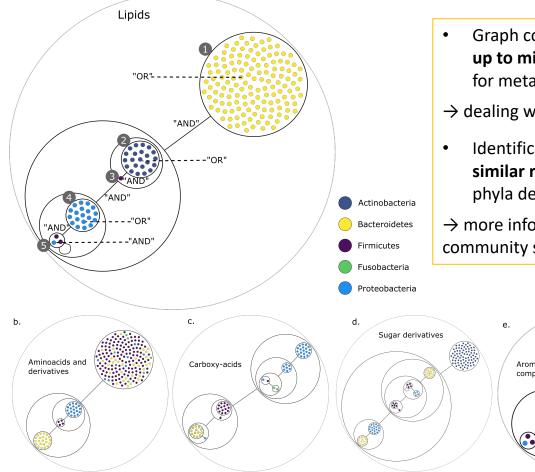
= typical EU diet (qualitative)

Nutrients Targets

= metabolites producible only through cooperation processes, grouped by categories

Enumeration  $\rightarrow$ of all minimal communities with m2m-analysis to study putative associations of microbial metabolisms

	1	Firm.	Bact.	Acti.	Prot.	Fuso.	total
all (156 targets)	KS	41	47	103	12	2	205
25 bact. per community	ES	8	0	1	2	0	11
not enumerated	AS	33	47	102	10	2	194
aminoacids and derivatives (5 targets)	KS	142	52	0	27	6	227
4 bact. per community	ES	0	0	0	0	0	0
120,329 communities	AS	142	52	0	27	6	227
aromatic compounds (11 targets)	KS	52	0	0	20	0	72
5 bact. per community	ES	2	0	0	1	0	3
950 communities	AS	50	0	0	19	0	69
carboxyacids (14 targets)	KS	16	13	0	28	2	59
9 bact. per community	ES	2	0	0	2	0	4
48,412 communities	AS	14	13	0	26	2	55
coA derivatives (10 targets)	KS	106	0	50	17	1	174
5 bact. per community	ES	0	0	0	0	1	1
95,256 communities	AS	106	0	50	17	0	173
lipids (28 targets)	KS	3	140	22	20	0	185
7 bact. per community	ES	3	0	0	1	0	4
58,520 communities	AS	0	140	22	19	0	181
sugar derivatives (58 targets)	KS	11	30	78	23	0	142
11 bact. per community	ES	5	0	0	0	0	5
7,860,528 communities	AS	6	30	78	23	0	137



Graph compression enables representing up to millions of minimal communities for metabolic groups of targets.

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 $\rightarrow$  dealing with high combinatorics

Identification of **microbial groups with** similar roles in communities, that follow phyla decomposition

 $\rightarrow$  more informative than providing a single community solution

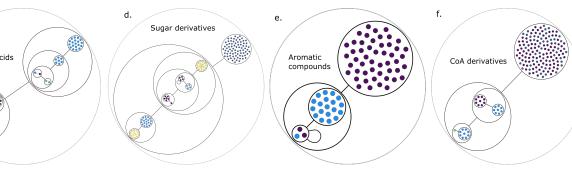


Table 1: Enumeration of minimal comunities and their phyla composition for groups of target metabolites. KS = keystone species, Fig. 4: Power graph analysis (graph compression) of the association of genomes in the predicted communities, coloured ES = essential symbionts, AS = alternative symbionts by phylum. In the non-compressed graphs, two nodes (microbes) were linked if they were found together in at least one minimal community.