

#### Characterizing microbial interactions in controlled and natural microbial communities

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### Characterizing microbial interactions in controlled and natural microbial communities

Maxime Lecomte, Simon Labarthe, David Sherman, Hélène Falentin, Clémence Frioux

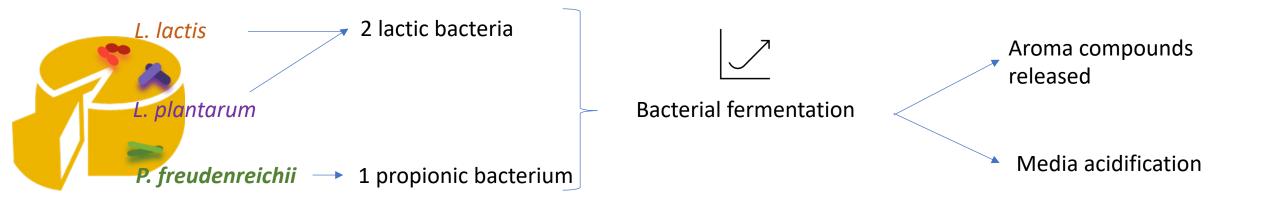
Workshop SymBioDiversity 2021-2022





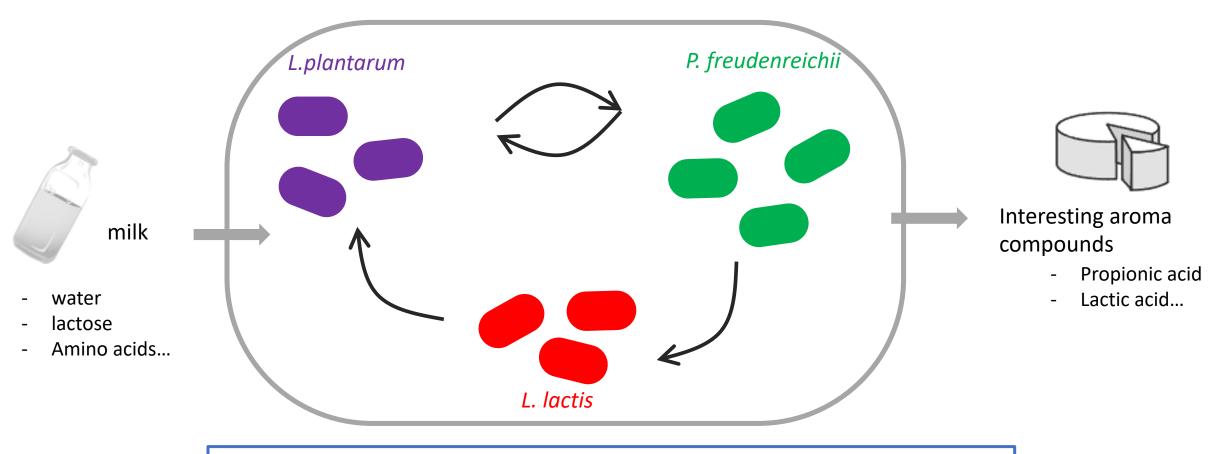


### Industrial cheese starter bacterial community as a controlled ecosystem



Which biological phenomena rules aroma compounds production?

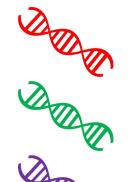
#### Bacterial fermentation process in cheese



Model the metabolism enable us to monitor compounds

#### Multi-omics strategy









Genes expression	
(metatranscriptomic	s)

Acétate-HPLC-F1	Acétate-HPLC-F3
0,01	0,01
0,04	0,05
0,44	0,36
0,92	0,81
1,05	0,97
2,00	1,77
2,59	2,52

Metabolomics data

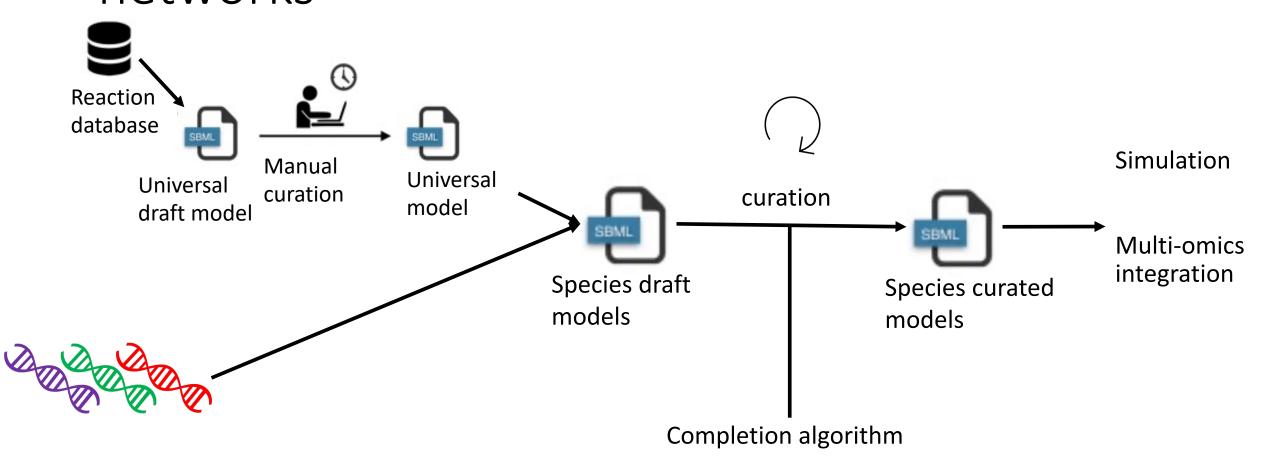




Growth and pH data in pure cultures

To integrate all this data, we first reconstruct the metabolism

### Inference of genome-scale metabolic networks



### FBA as a numerical model of metabolism

$$\text{Stoichiometric matrix} = \left( \begin{array}{cccc} & \text{metabolites} & r_1 & \dots & r_n \\ & \text{A} & \left( \begin{array}{cccc} -1 & \dots & 0 \\ 1 & \dots & -2 \\ 0 & \dots & 1 \end{array} \right) \\ \end{array} \right)$$

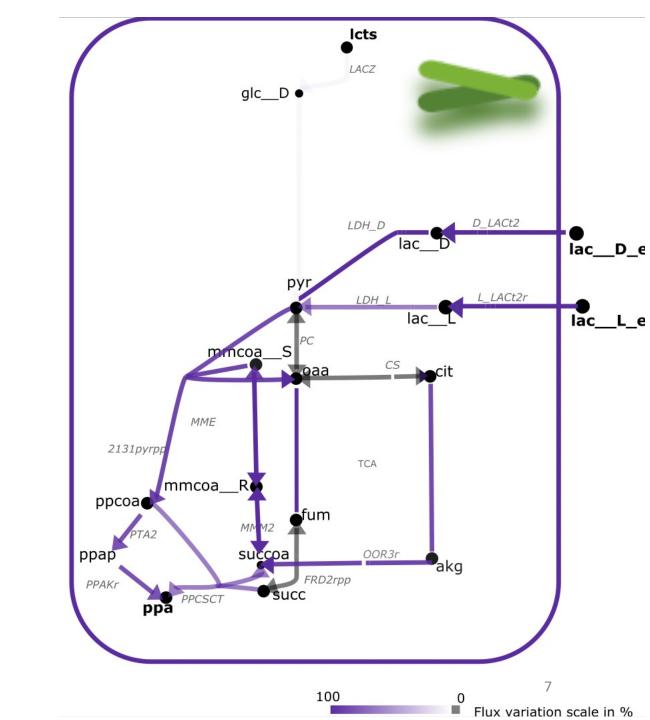
$$\max v_{growth}$$
 such that  $S.v = 0$  and  $v_{min} \leq v \leq v_{max}$ 

### FBA as a numerical model of metabolism

Stoichiometric matrix = 
$$\begin{array}{c} \text{metabolites} & r_1 & \dots & r_n \\ \text{A} & \begin{pmatrix} -1 & \dots & 0 \\ 1 & \dots & -2 \\ 0 & \dots & 1 \\ \end{pmatrix}$$

 $\max v_{growth}$  such that S.v = 0 and  $v_{min} \leq v \leq v_{max}$ 

Flux distribution that maximizes biomass production



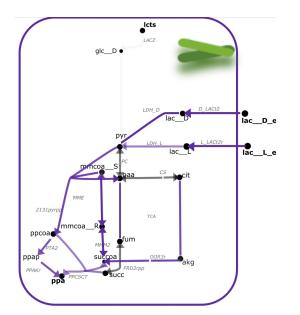
Orth, J. D. et al,2010, *Nature Biotechnology* King, Z. et al,2015. *PLoS Computational Biology* 

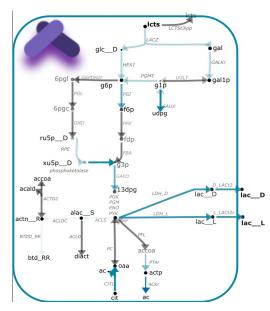
### FBA as a numerical model of metabolism

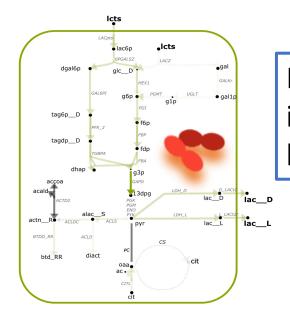
Stoichiometric matrix = 
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Flux distribution that maximizes biomass production







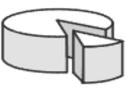
Individual models are in accordance with literature

Orth, J. D. et al,2010, *Nature Biotechnology* King, Z. et al,2015. *PLoS Computational Biology*  Thierry, A et al, 2011, International Journal of Food Microbiology Loux, V. et al, 2015, BMC Genomics

Liquid environment

solid environment



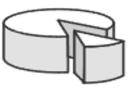


The consistency of the environment changes

Liquid environment

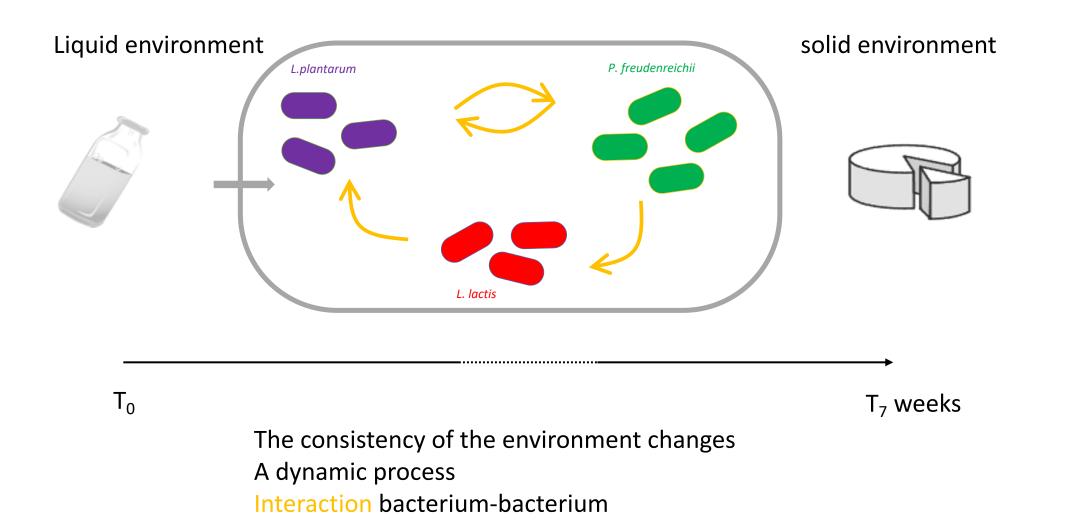
solid environment

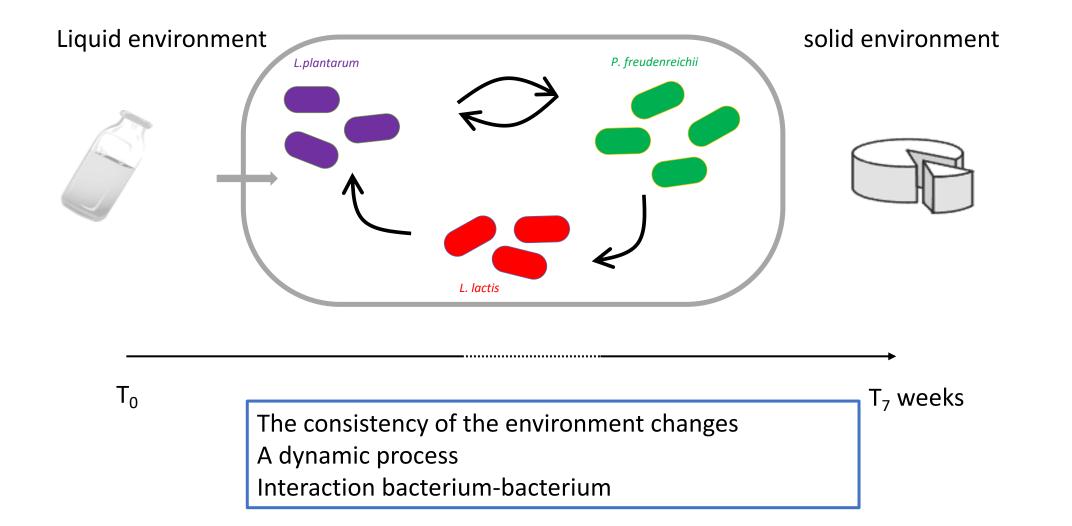




 $T_0$  T<sub>7</sub> weeks

The consistency of the environment changes A dynamic process





List of pre-defined interest compounds:

$$\partial_t m_j = \mu_{FBA_i}(c)_j b_i$$

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**Bacterial concentration:** 

$$\partial_t b_i = q_s(b_i) \mu_{FBA_i}(c)_i b_i$$

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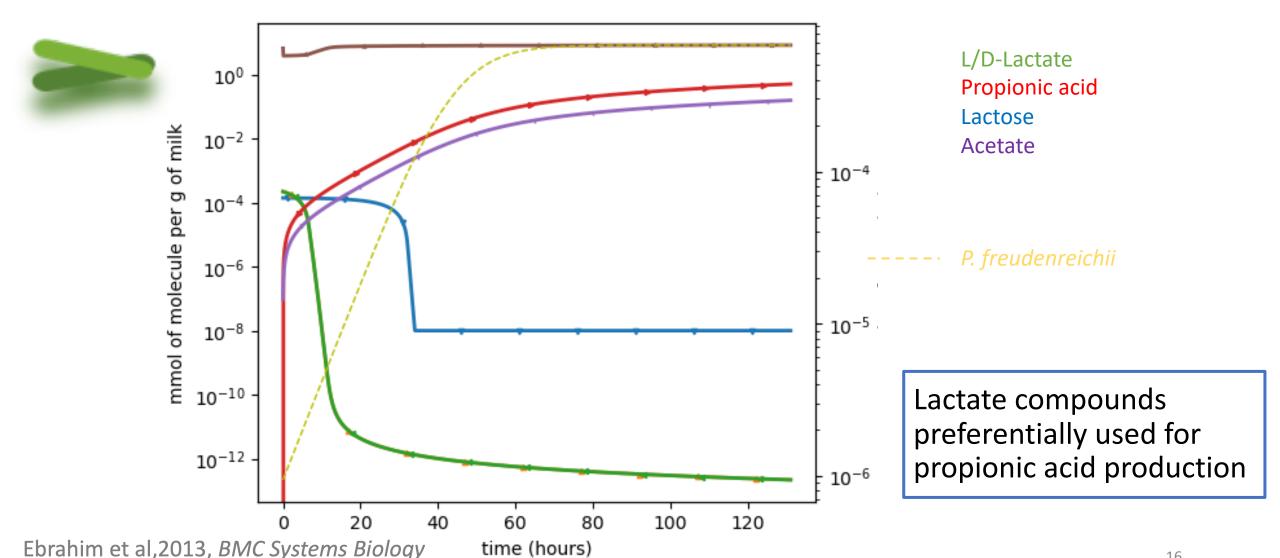
**Bacterial concentration:** 

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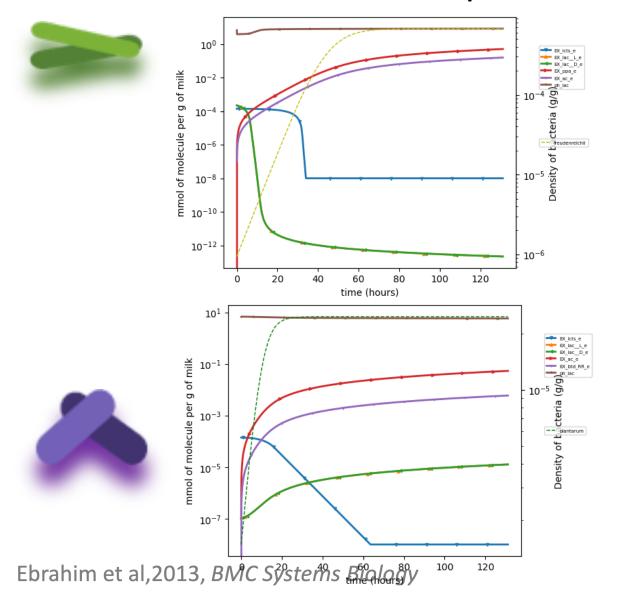
q<sub>s</sub> = Quorum sensing

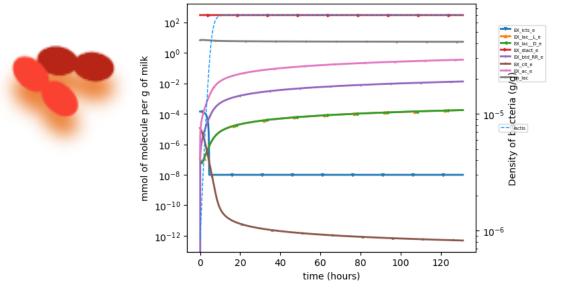
$$q_s(b_i) = 1 - \frac{b_i}{\beta_i}$$

#### dFBA results of pure cultures



#### dFBA results of pure cultures





Individual dFBA simulations are performed

Fit with experimental data ? → growth and pH curves and metabolomics data

#### Optimizing dynamic models on pure cultures

$$J(b, pH|b_{exp}, pH_{exp}) = ||b - b_{exp}||^2 + \alpha ||pH - pH_{exp}||^2$$

#### Optimizing dynamic models on pure cultures

$$J(b, pH|b_{exp}, pH_{exp}) = ||b - b_{exp}||^2 + \alpha ||pH - pH_{exp}||^2$$

- Lambda 🍃



- C1 & C2

- K lactate





- QS







- Vmin & Vmax lactose

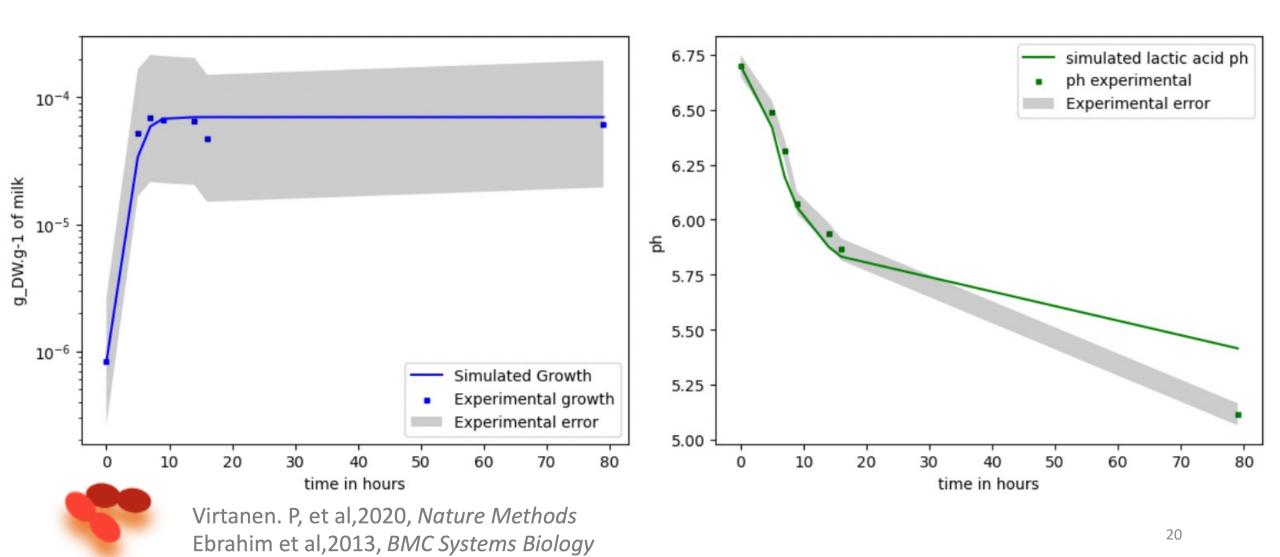


- Lactate\_upper

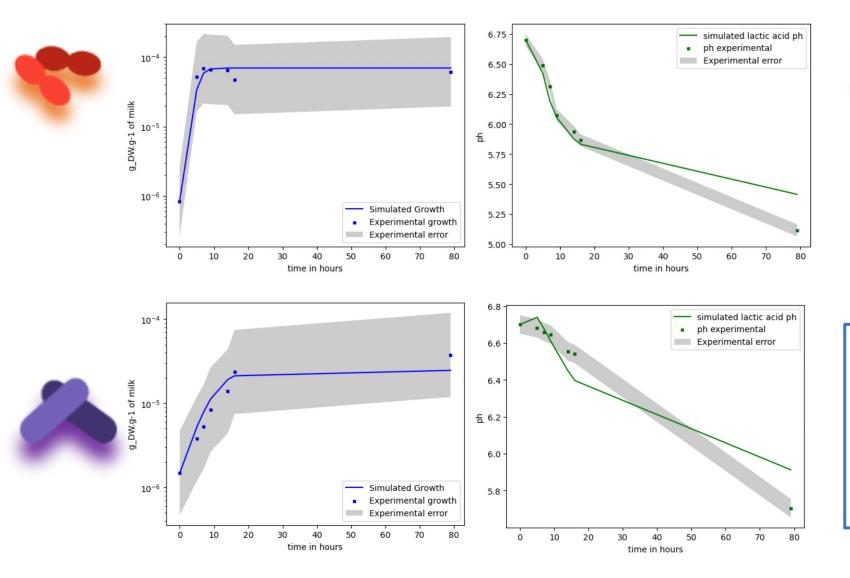


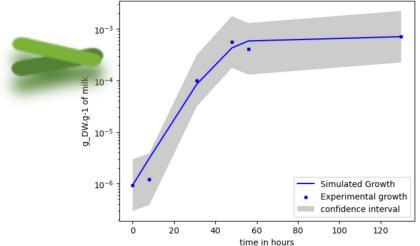
Identification of parameters to fit with experimental data

#### dFBA results after optimization



#### dFBA results after optimization

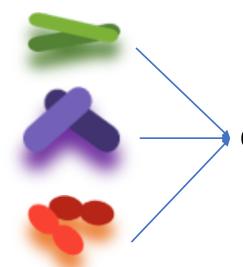




The small number of parameters is sufficient to explain the experimental data

What about metabolomics?

#### Community dFBA



Community dFBA model

Consider the change in medium volume

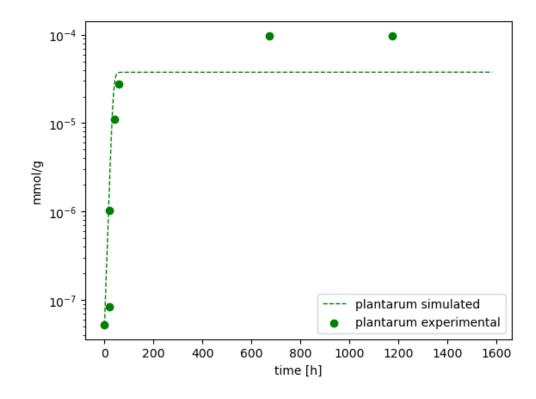
 Each bacterium optimizes its own biomass

Optimised dFBA models for each bacterium

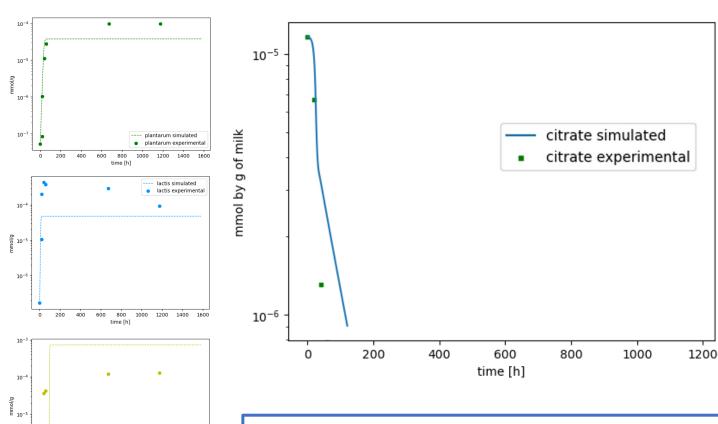
$$\partial_t b_i = q_s(b_i) \mu_{FBA_i}(c)_i b_i + \mathcal{V}(t) b_i$$

$$\mathcal{V}(t) = rac{\partial_t v(t)}{V(t)}$$
 where  $v(t) = egin{cases} V_M & ext{if} t \leq t_M \ V_M + rac{t - t_M}{t_D - t_M} V_D & ext{if} t_M \leq t \leq t_D \ V_D & ext{if} t \geq t_D \end{cases}$ 

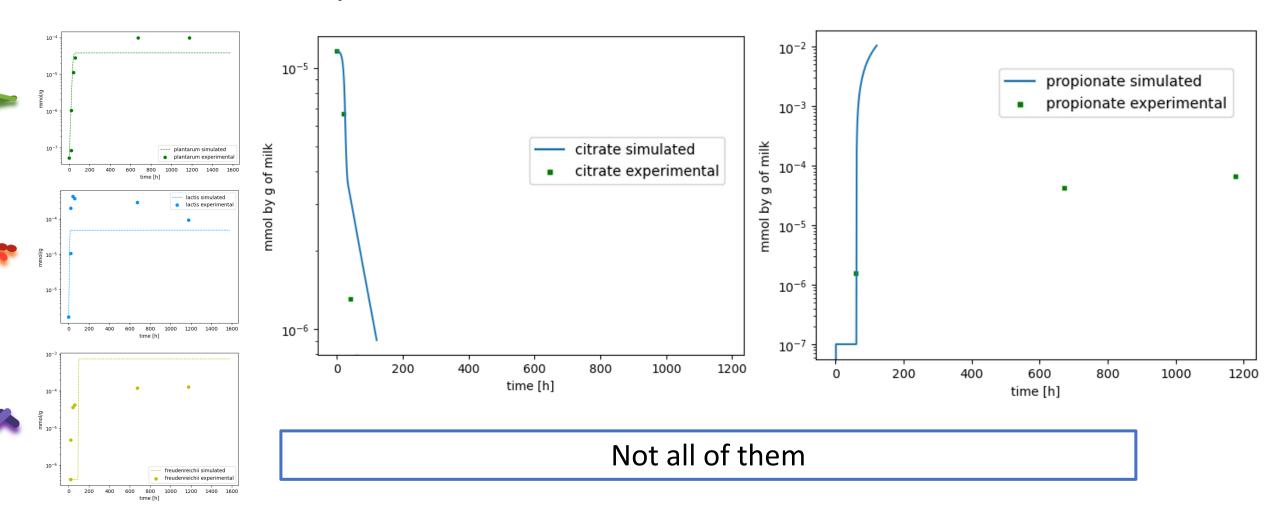


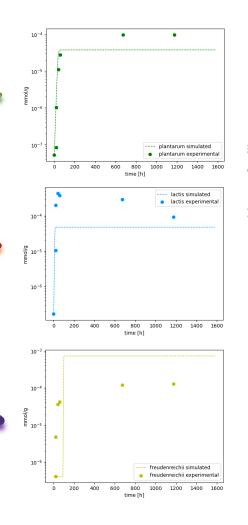


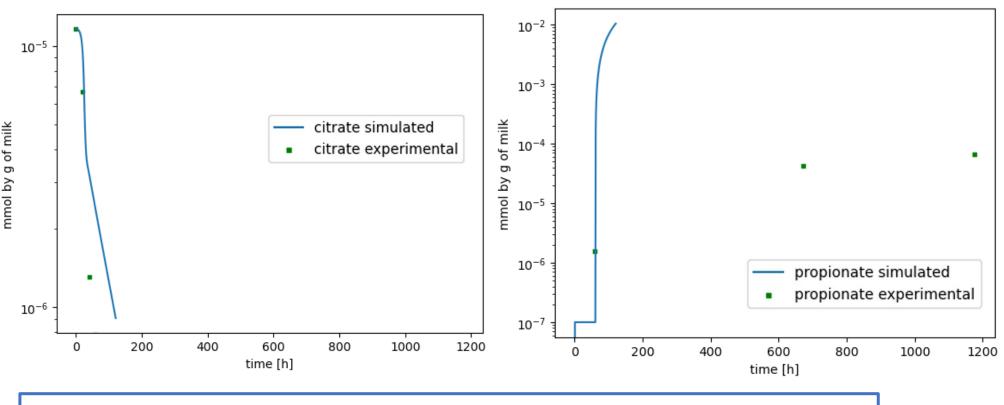
Bacterial growth computed with community dFBA fits with experimental data



Some metabolites fit with metabolomics data ...

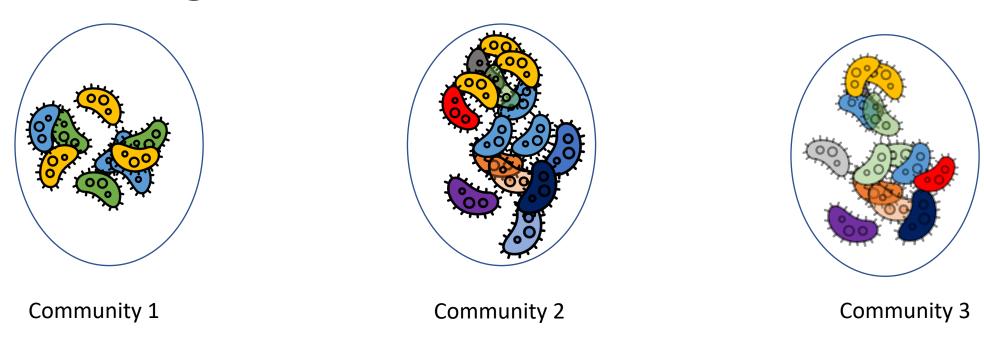






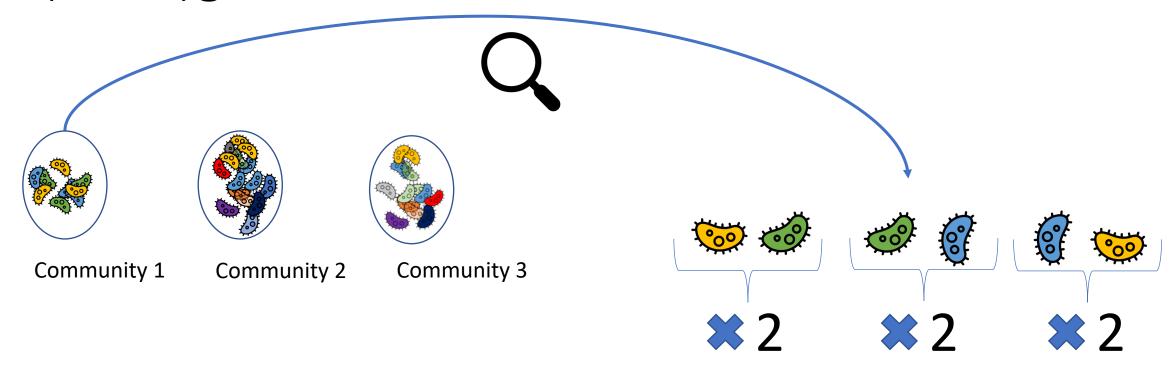
- The model do not capture all modifications brings by the community
- Integration of transcriptomic data is not significantly different
- Is qualitative result enough for characterizing communities?

## Characterizing natural communities (meta)genomics data



Calculating cooperation and competition potentials

## Characterizing natural communities with (meta)genomics data



Not easily scalable

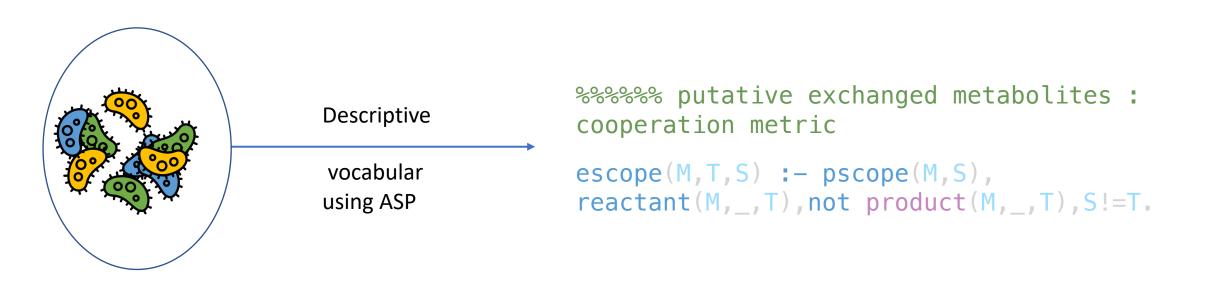
Freilich. S, et al,2011, *Nature Communications*Zelezniak, A et al,2015, *Proceedings of the National Academy of Sciences of the United States of America*.

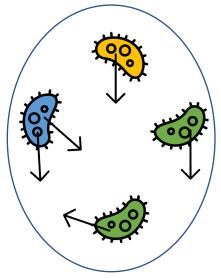
- Numerical methods

Discrete methods

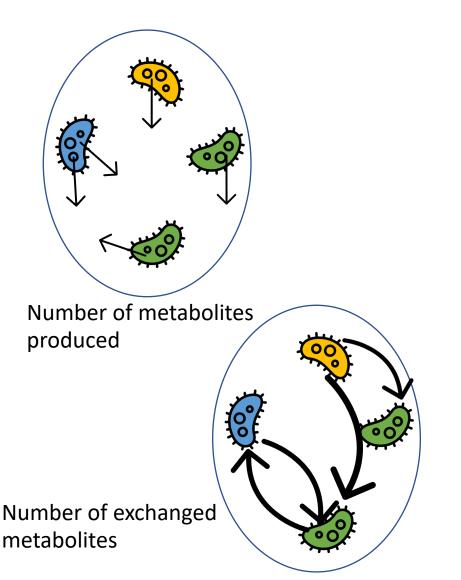
Levy et al, 2015., *BMC Bioinformatics*. Kreimer, A et al, 2012 *Bioinformatics*.

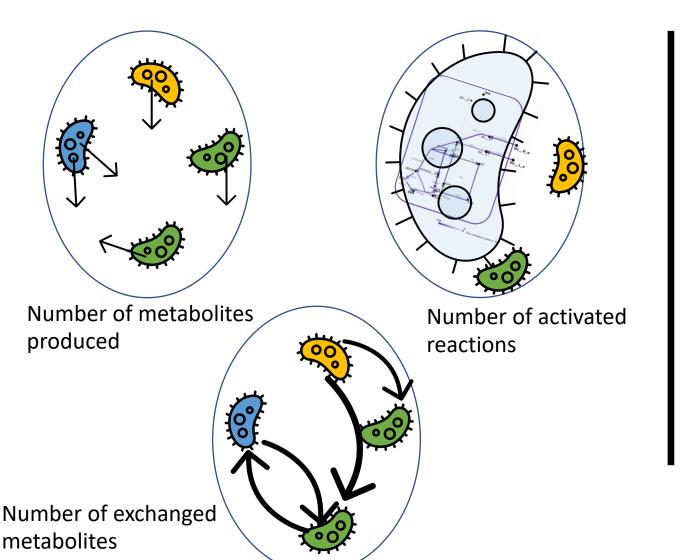
### Discrete modelling of metabolism using metabolic potentials (work in progress)

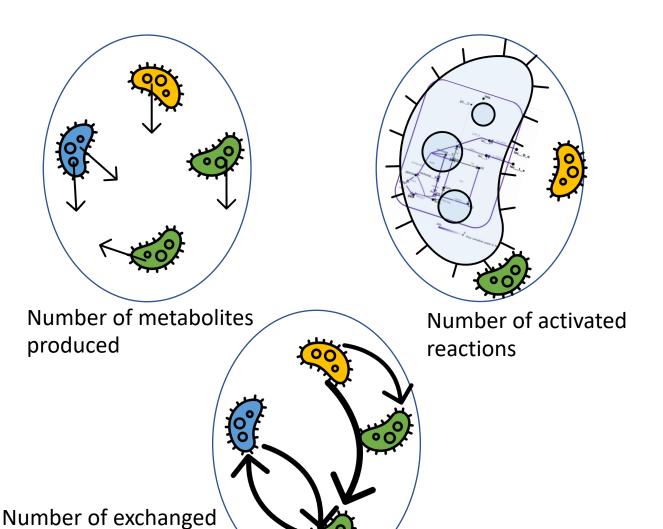




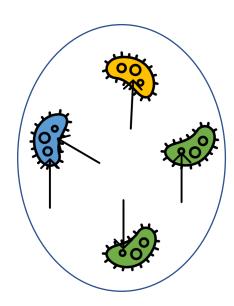
Number of metabolites produced



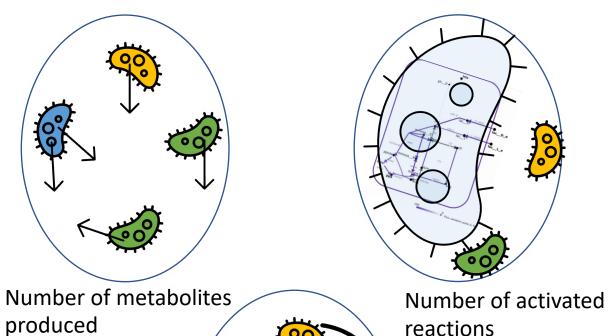




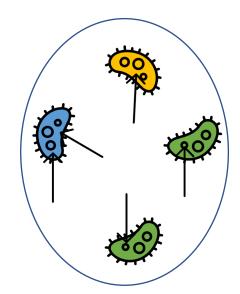
metabolites



Related to limiting substrates consumed



reactions

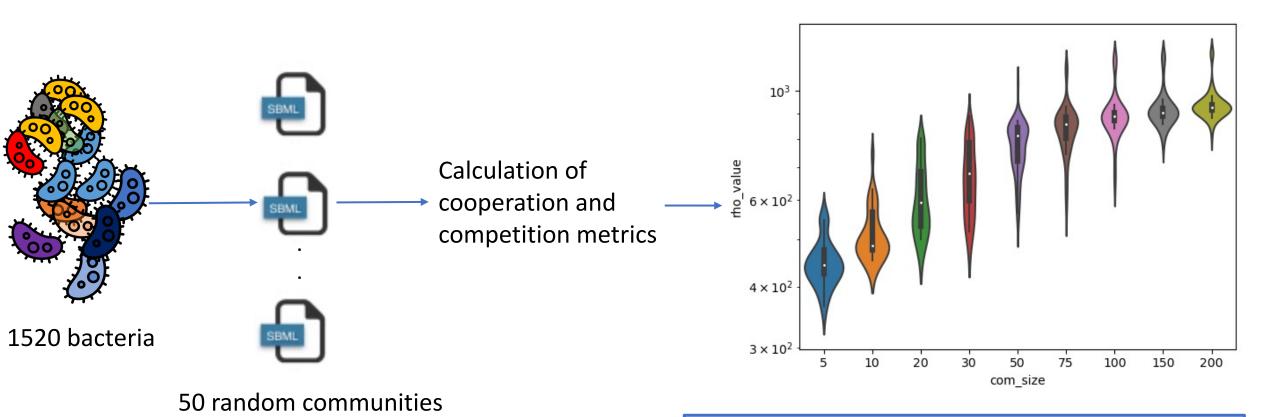


Related to limiting substrates consumed

Number of exchanged metabolites

Unify cooperation metrics to one unique score

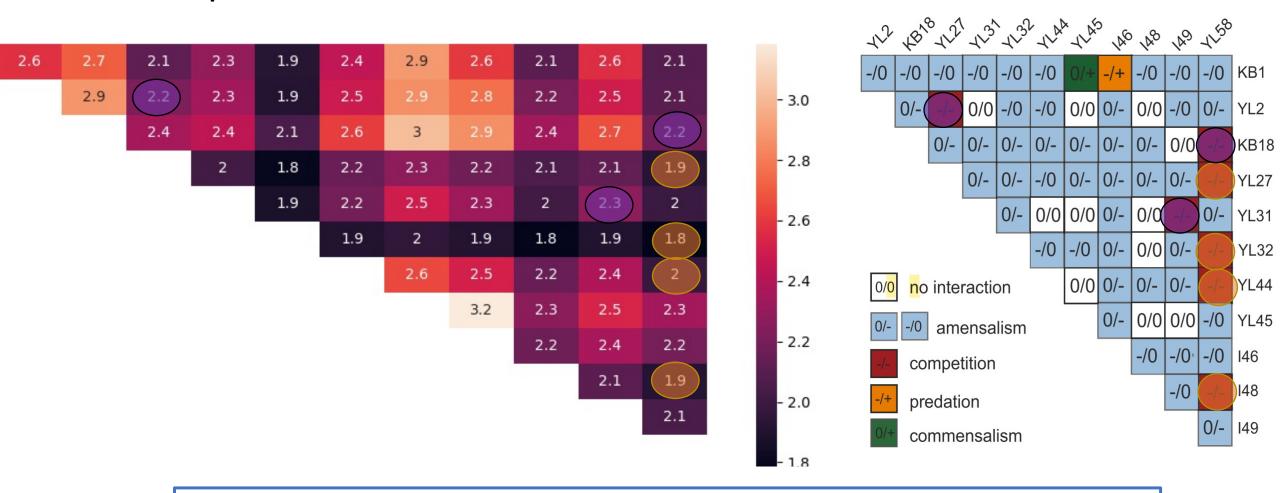
#### Model test on designed communities



Metrics are not linearly correlate with the community size

of size 5 to 200

#### Competition score test on real data



Identify some correlation between our score and the experimental data

#### Conclusion

Numerical accuracy not mandatory to characterize community

 Our method based on discrete modeling seems to characterize natural community → improve cooperation and competition scores

• Test on different communities  $\rightarrow$  Hiring data (genomic data)







- David Sherman
- Clémence Frioux
- Simon labarthe

- Hélène Falentin

#### Thanks for your attention

List of pre-defined interest compounds:

$$\partial_t m_j = \mu_{FBA_i}(c)_j b_i$$

$$c_k = \begin{cases} \lambda_i \max(-m_k/(\Delta_t \sum_{i \in \mathcal{B}} b_i, c_k) & \text{if } 1 \neq k \neq N_m \\ = e_k & \text{if } N_m + 1 \leq k \leq N_c \end{cases}$$

# Summary of the interactions in the cheese ecosystem

