

Correlated responses to selection for IMF on microbial genomes in rabbits (using compositional data analysis techniques)

Martínez-Álvaro M., Zubiri-Gaitán A., Hernández P. and Blasco A.
ICTA, Universitat Politècnica de València



70th Annual Meeting of EAAP
27th August 2019, Ghent

WHY INTRAMUSCULAR FAT?

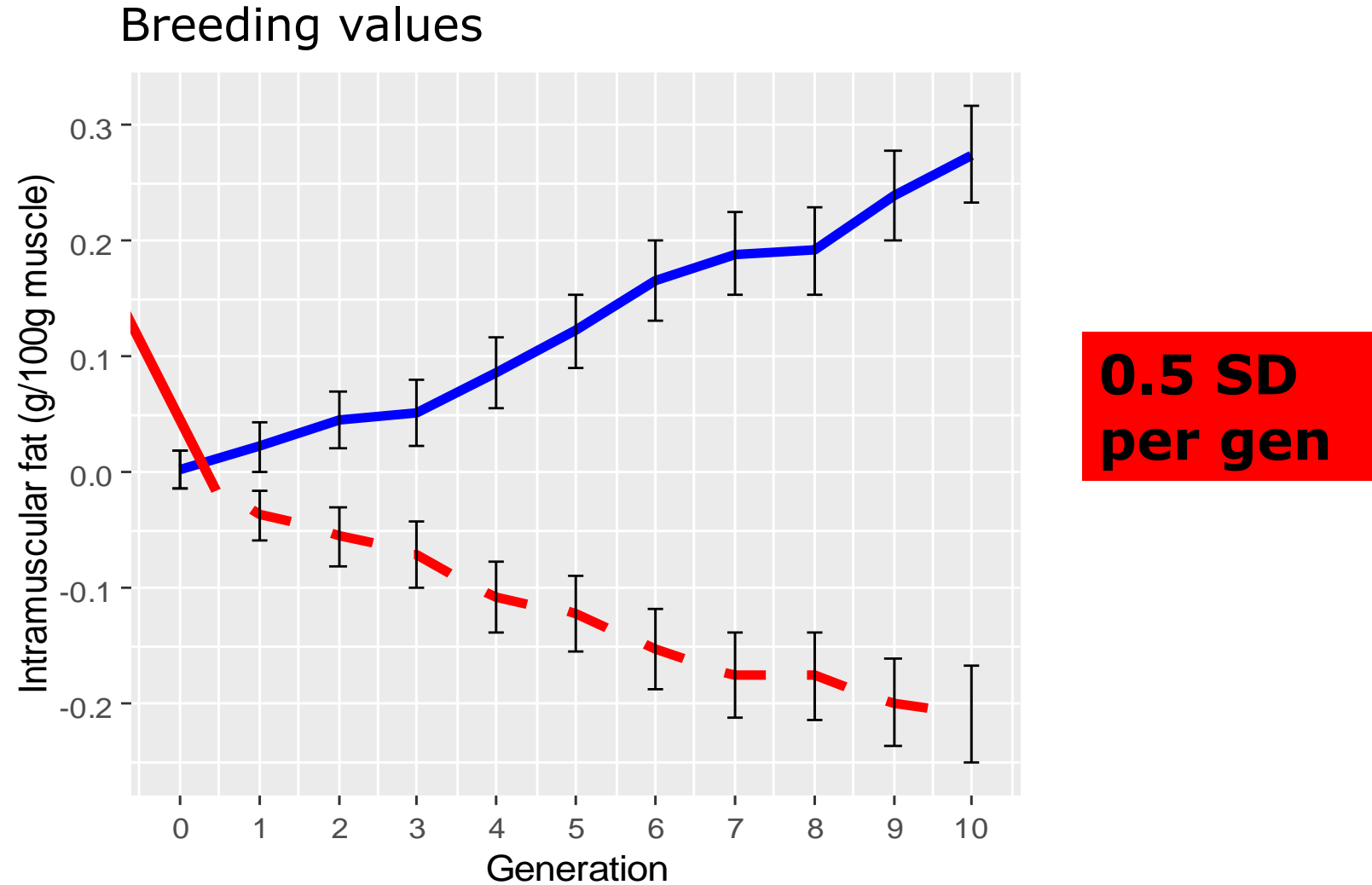


WHY IN RABBITS?



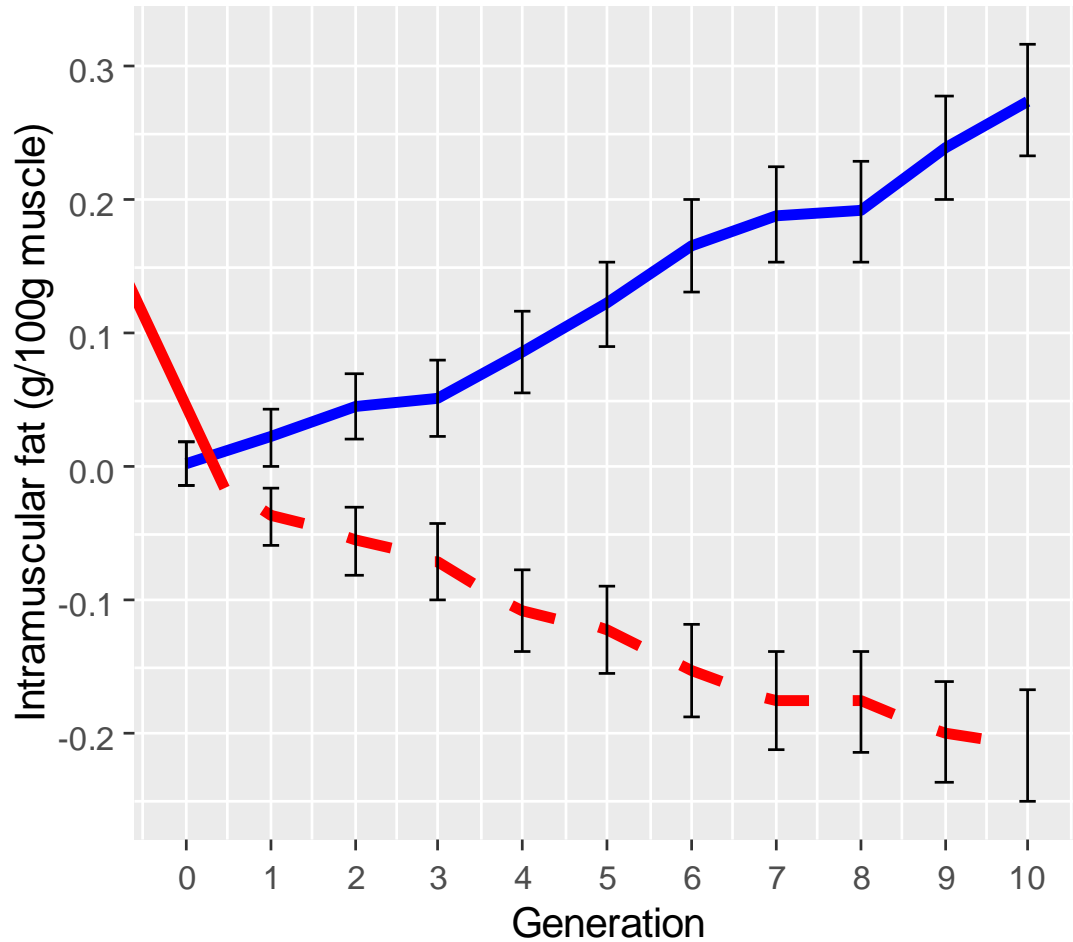
Divergent selection for IMF

Response to selection for IMF



Divergent selection for IMF

SAME ENVIRONMENT!!



**CORRELATED RESPONSES
TO SELECTION FOR IMF
IN OTHER TRAITS**

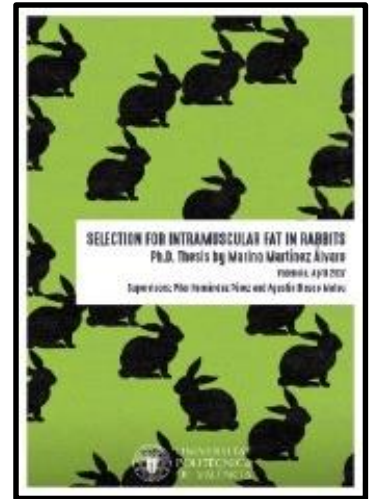


**PHENOTYPIC
DIFFERENCES
HIGH LINE - LOW LINE**

Divergent selection for IMF

CORRELATED RESPONSES IN MEAT QUALITY TRAITS

Carcass fat



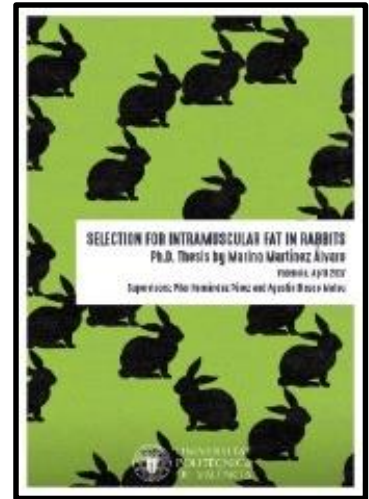
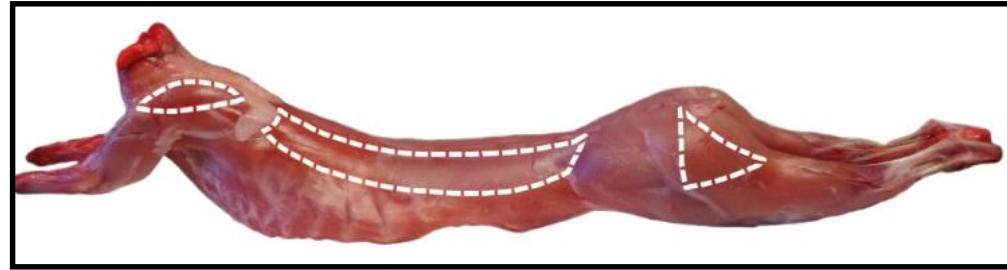
Divergent selection for IMF

CORRELATED RESPONSES IN MEAT QUALITY TRAITS

Carcass fat



IMF in other muscles



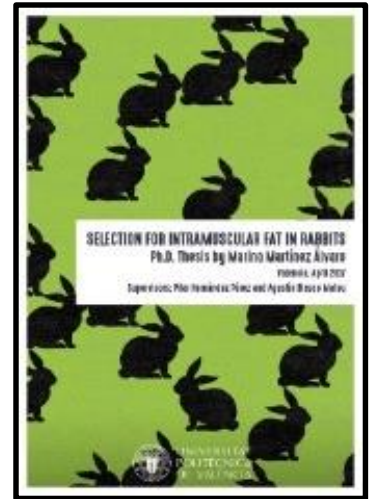
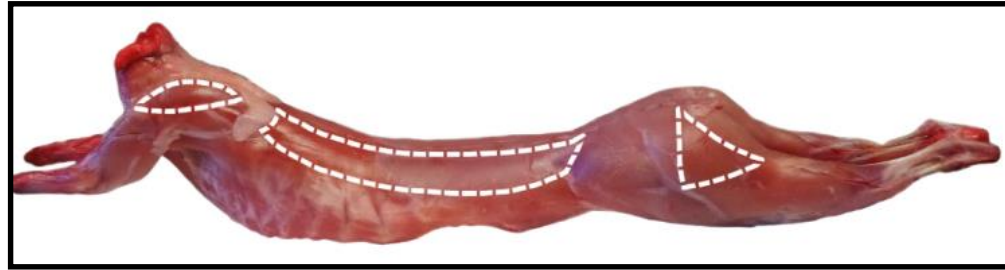
Divergent selection for IMF

CORRELATED RESPONSES IN MEAT QUALITY TRAITS

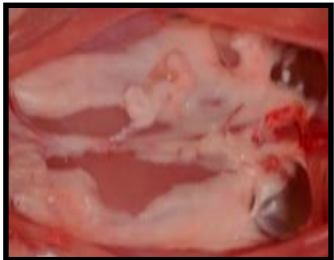
Carcass fat



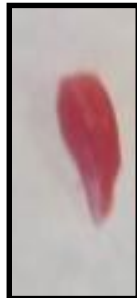
IMF in other muscles



Lipogenic activity



G6PDH



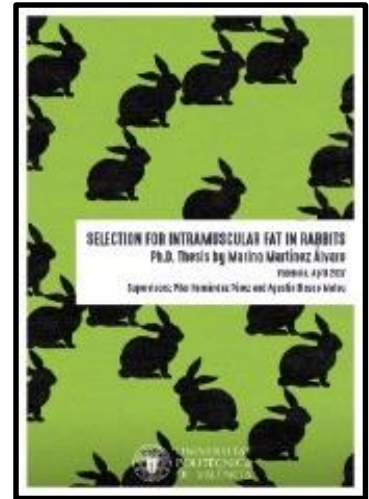
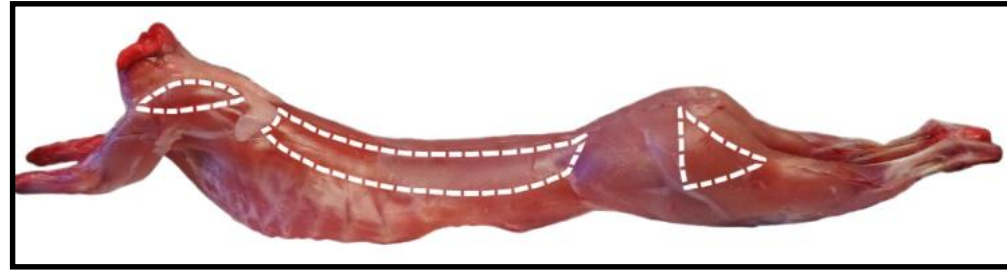
Divergent selection for IMF

CORRELATED RESPONSES IN MEAT QUALITY TRAITS

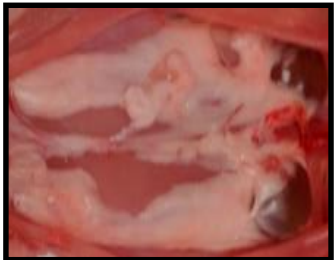
Carcass fat



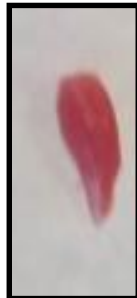
IMF in other muscles



Lipogenic activity



G6PDH



Adipocytes size



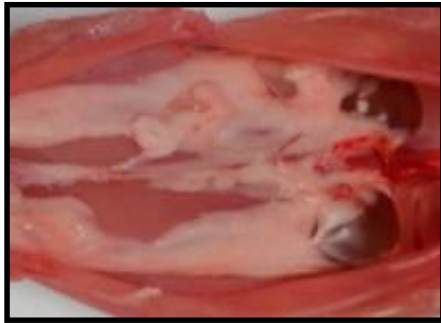
Liver size



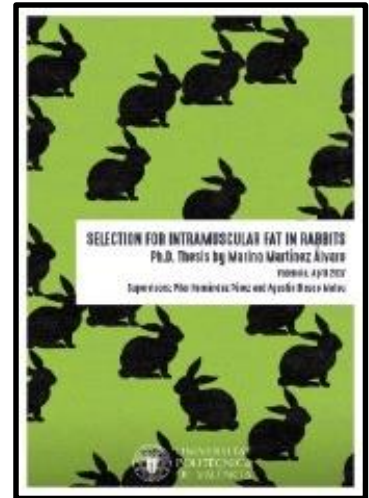
Divergent selection for IMF

CORRELATED RESPONSES IN MEAT QUALITY TRAITS

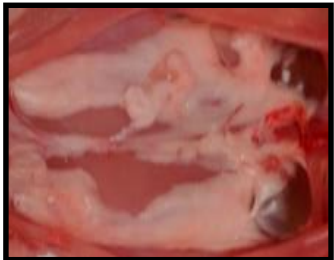
Carcass fat



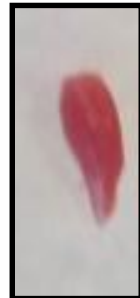
IMF in other muscles



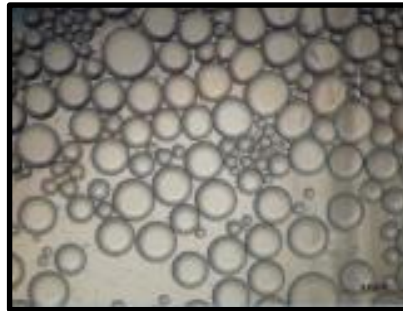
Lipogenic activity



G6PDH



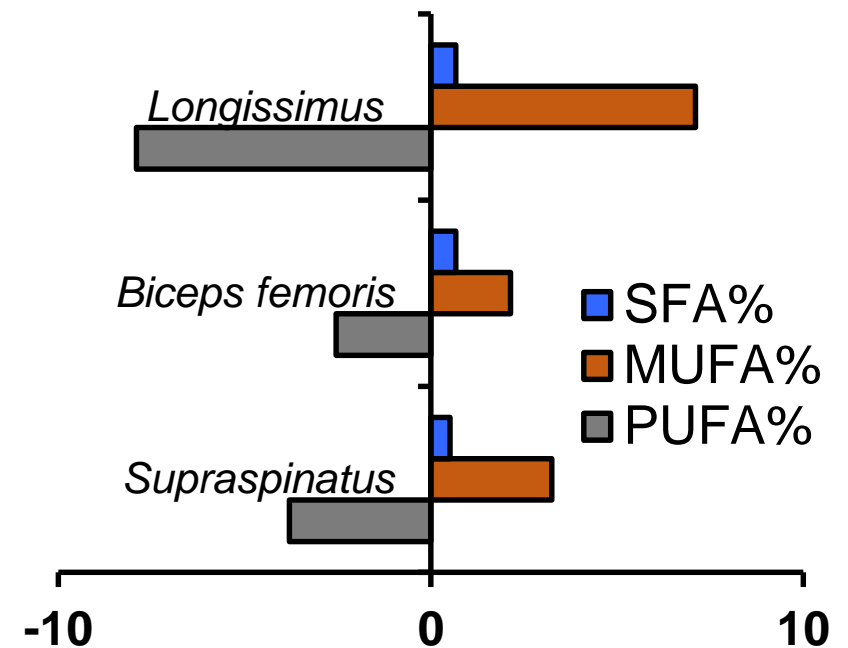
Adipocytes size



Liver size

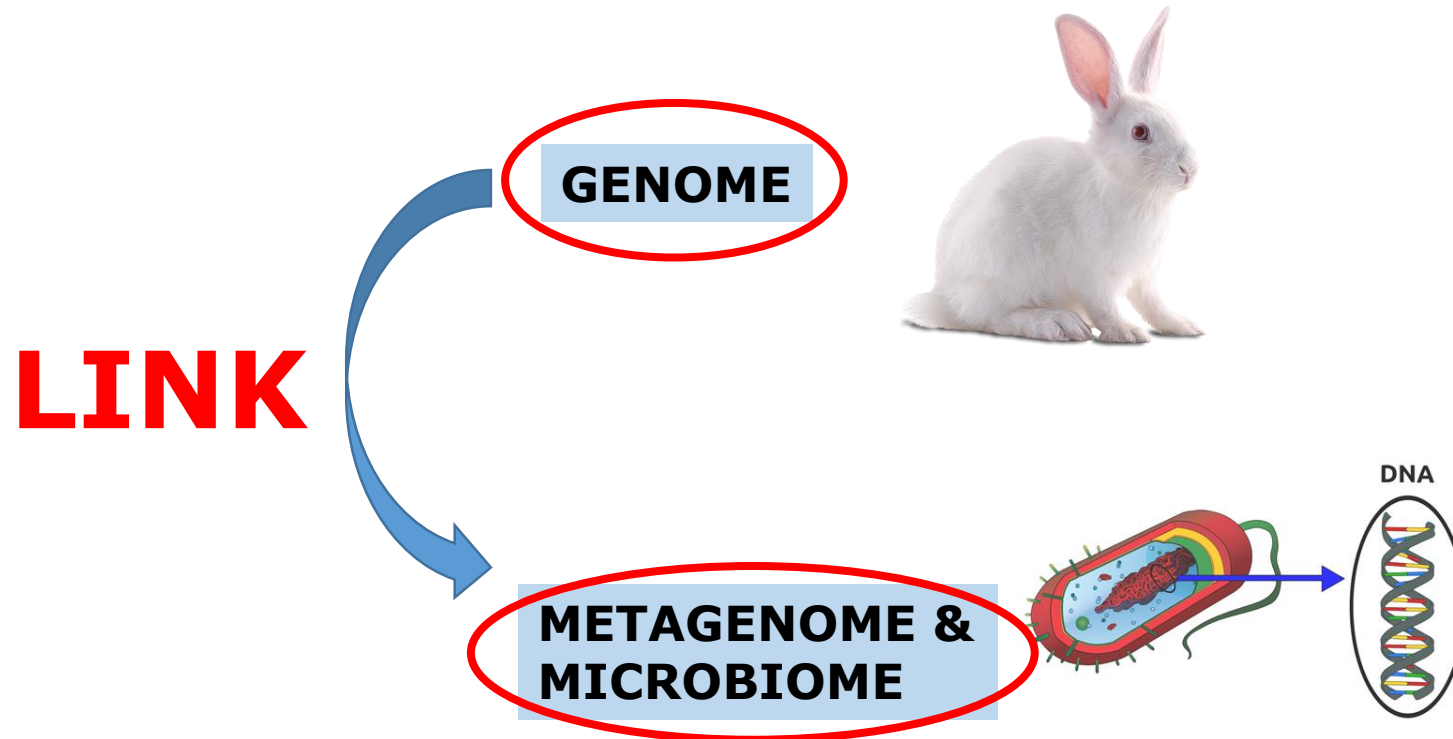


Meat Fatty Acid profile



OBJECTIVE

CORRELATED RESPONSES IN MICROBIALS GENOME



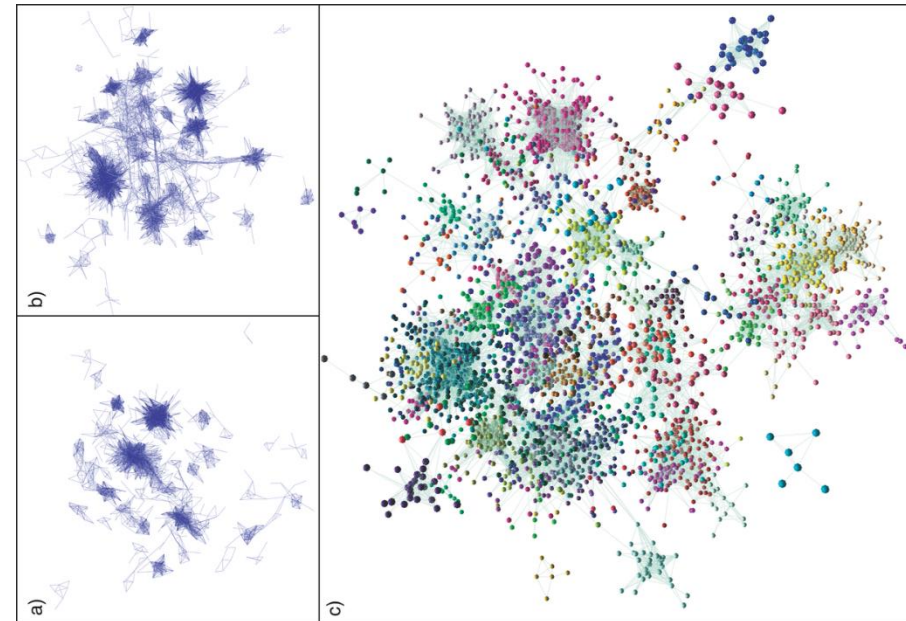
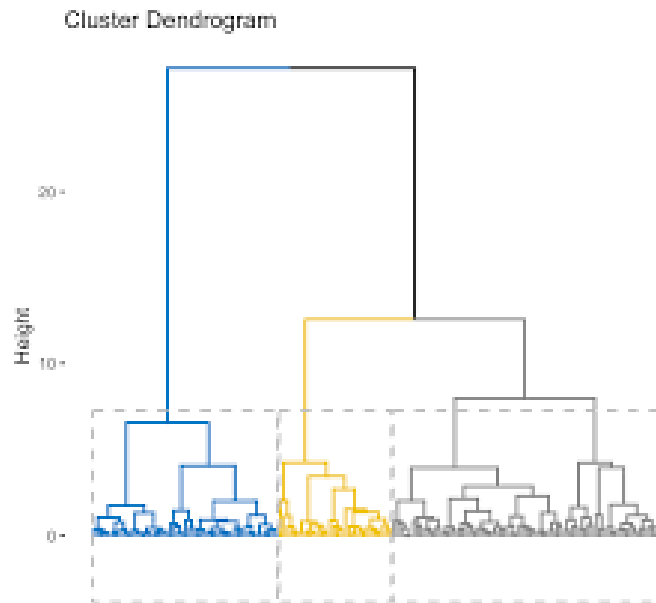
SOME IDEAS ABOUT COMPOSITIONAL DATA ANALYSIS...

STATISTICAL ANALYSIS OF METAGENOMIC DATA



MULTIVARIATE ANALYSIS DATA BASED ON COV OR CORRELATIONS

PLS, Clusters, Correlation networks, Multiple regression, etc



STATISTICAL ANALYSIS OF METAGENOMIC DATA



INTERPRETATION PROBLEM

ABSOLUTE VALUES

IMF (g/100 g)	1	2	5
Microbial gene A	1	10	40
Microbial gene B	4	6	8



IMF



Microbial Genes A & B

STATISTICAL ANALYSIS OF METAGENOMIC DATA



INTERPRETATION PROBLEM

ABSOLUTE VALUES

IMF (g/100 g)	1	2	5
Microbial gene A	1	10	40
Microbial gene B	4	6	8

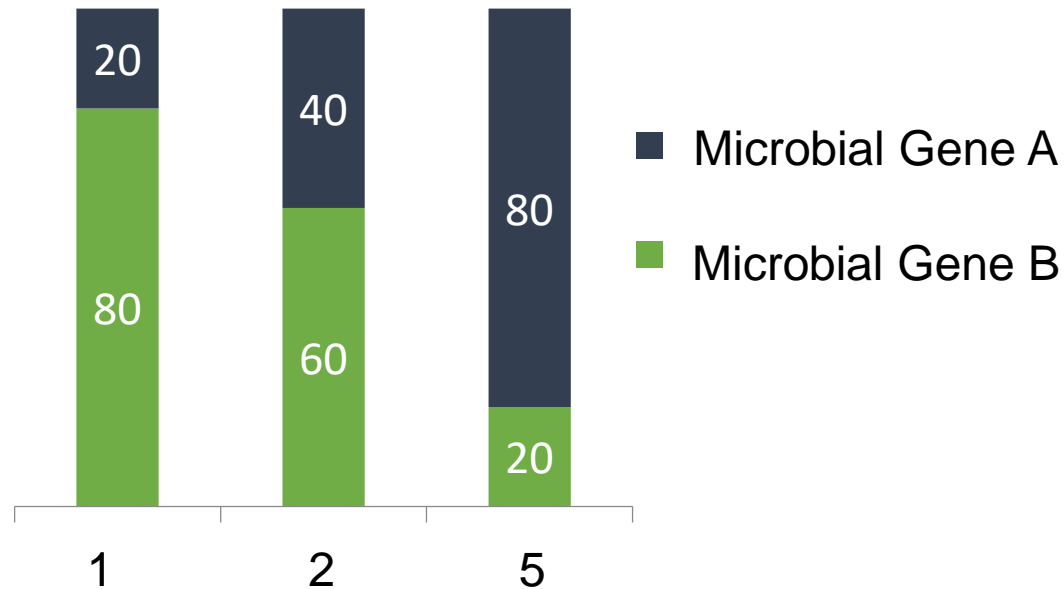


IMF



Microbial Genes A & B

RELATIVE VALUES



STATISTICAL ANALYSIS OF METAGENOMIC DATA



INTERPRETATION PROBLEM

ABSOLUTE VALUES

IMF (g/100 g)	1	2	5
Microbial gene A	1	10	40
Microbial gene B	4	6	8

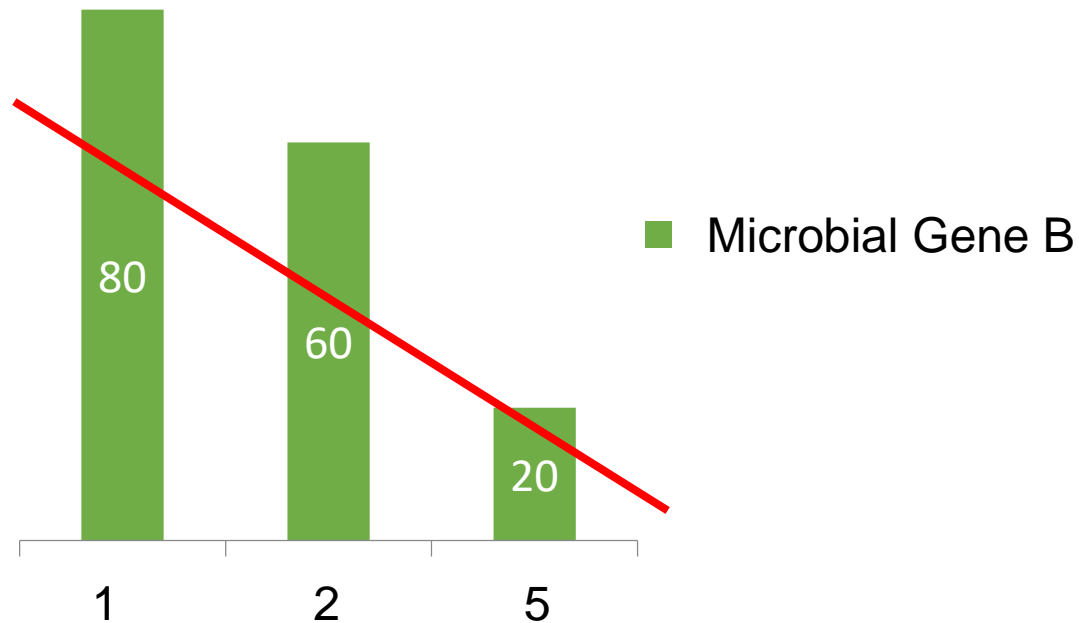


IMF



Microbial Genes A & B

RELATIVE VALUES



STATISTICAL ANALYSIS OF METAGENOMIC DATA



INTERPRETATION PROBLEM

ABSOLUTE VALUES

IMF (g/100 g)	1	2	5
Microbial gene A	1	10	40
Microbial gene B	4	6	8

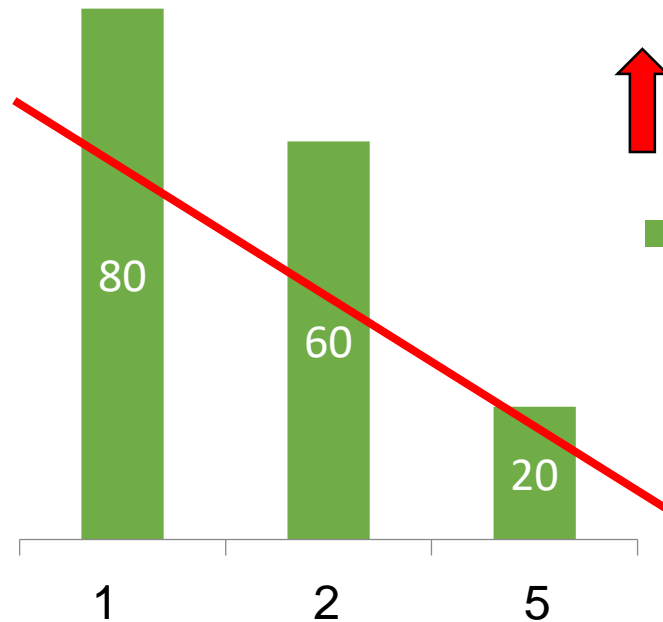


IMF



Microbial Genes A & B

RELATIVE VALUES



IMF



Microbial Gene B

■ Microbial Gene B

CONFUSION



STATISTICAL ANALYSIS OF METAGENOMIC DATA



COMPOSITIONAL DATA

SIMPLEX
restricted space

Aitchison geometry
(not real)

STATISTICAL ANALYSIS OF METAGENOMIC DATA



COMPOSITIONAL DATA

SIMPLEX
restricted space

Aitchison geometry
(not real)

Transformations

Log ratio

Clr

Alr

Ilr

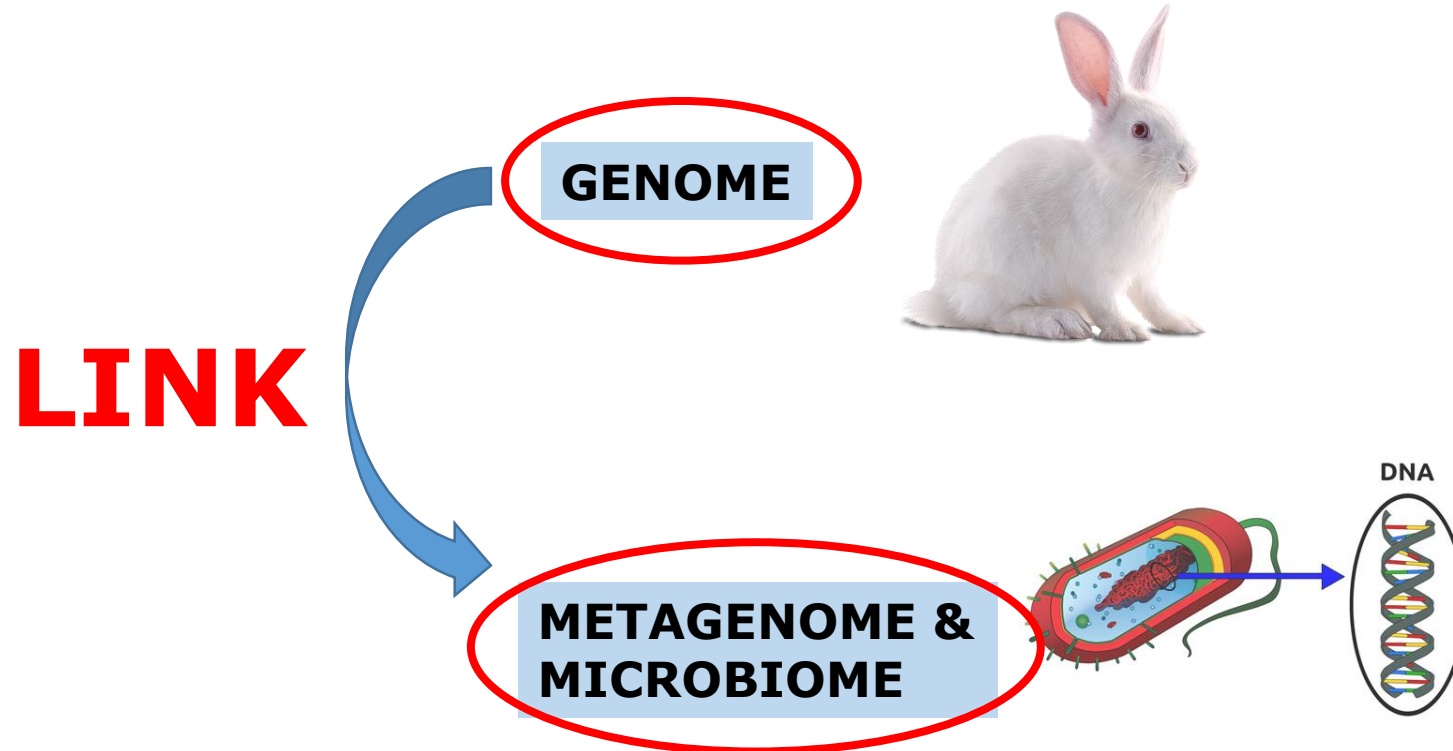
From Simplex to Real Space

Metrics in Euclidean
geometry of real space



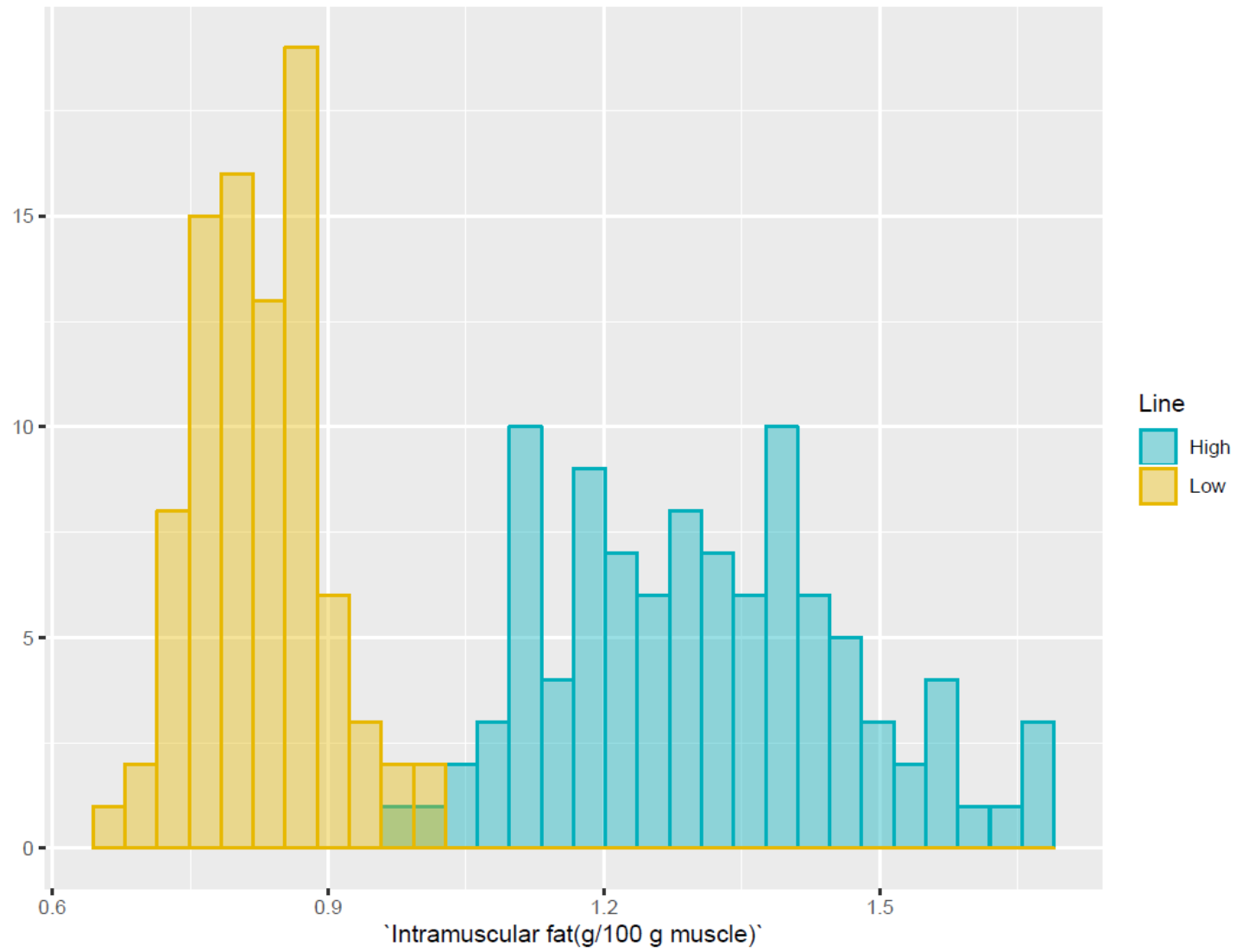
OBJECTIVE

CORRELATED RESPONSES IN MICROBIALS GENOME

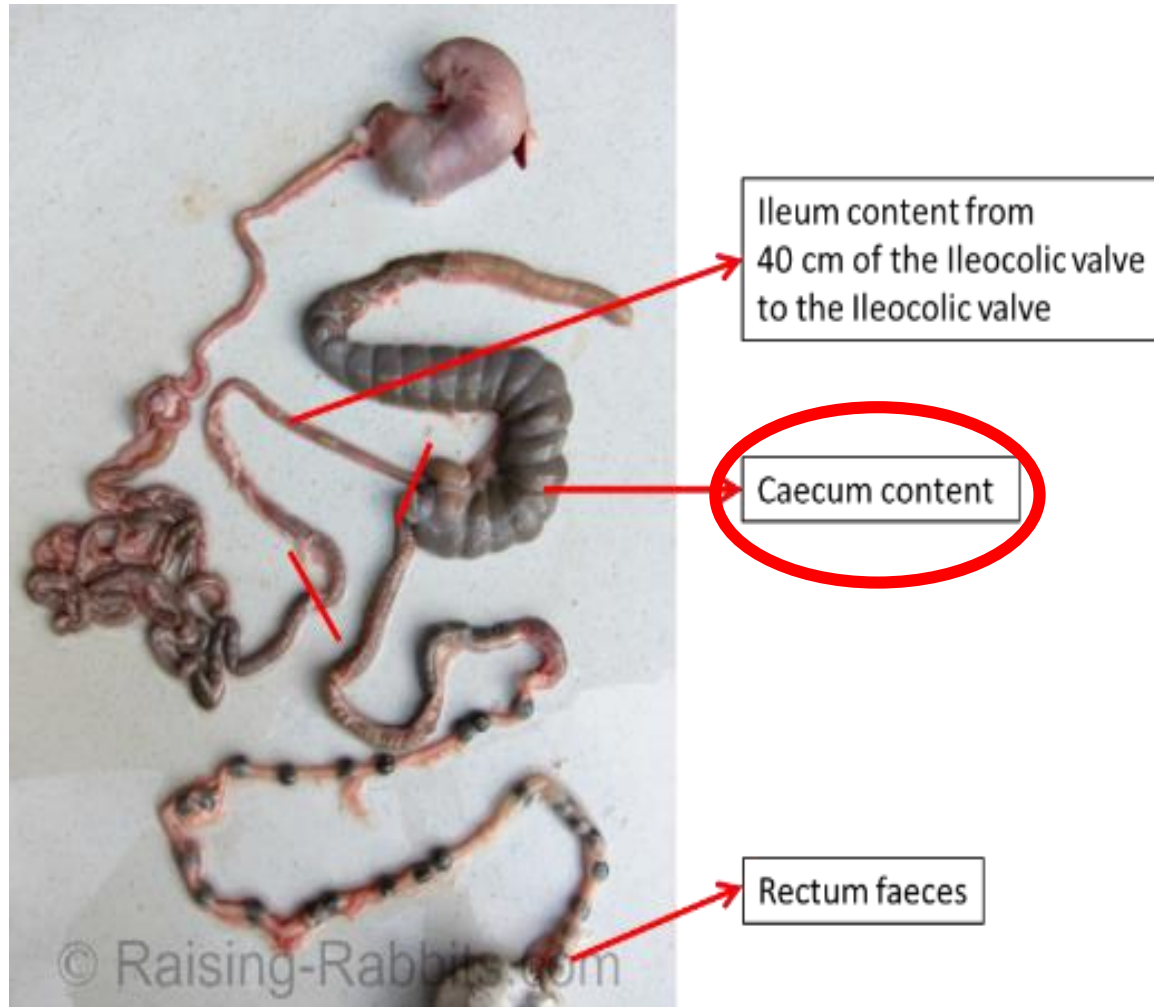


ANIMALS

Distribution of IMF fat data in the 10th generation



METAGENOMIC MEASUREMENTS



N = 33 (16 H & 17 L)

- Illumina NextSeq
- Reads (2 x 150 bp)
- KEGG database

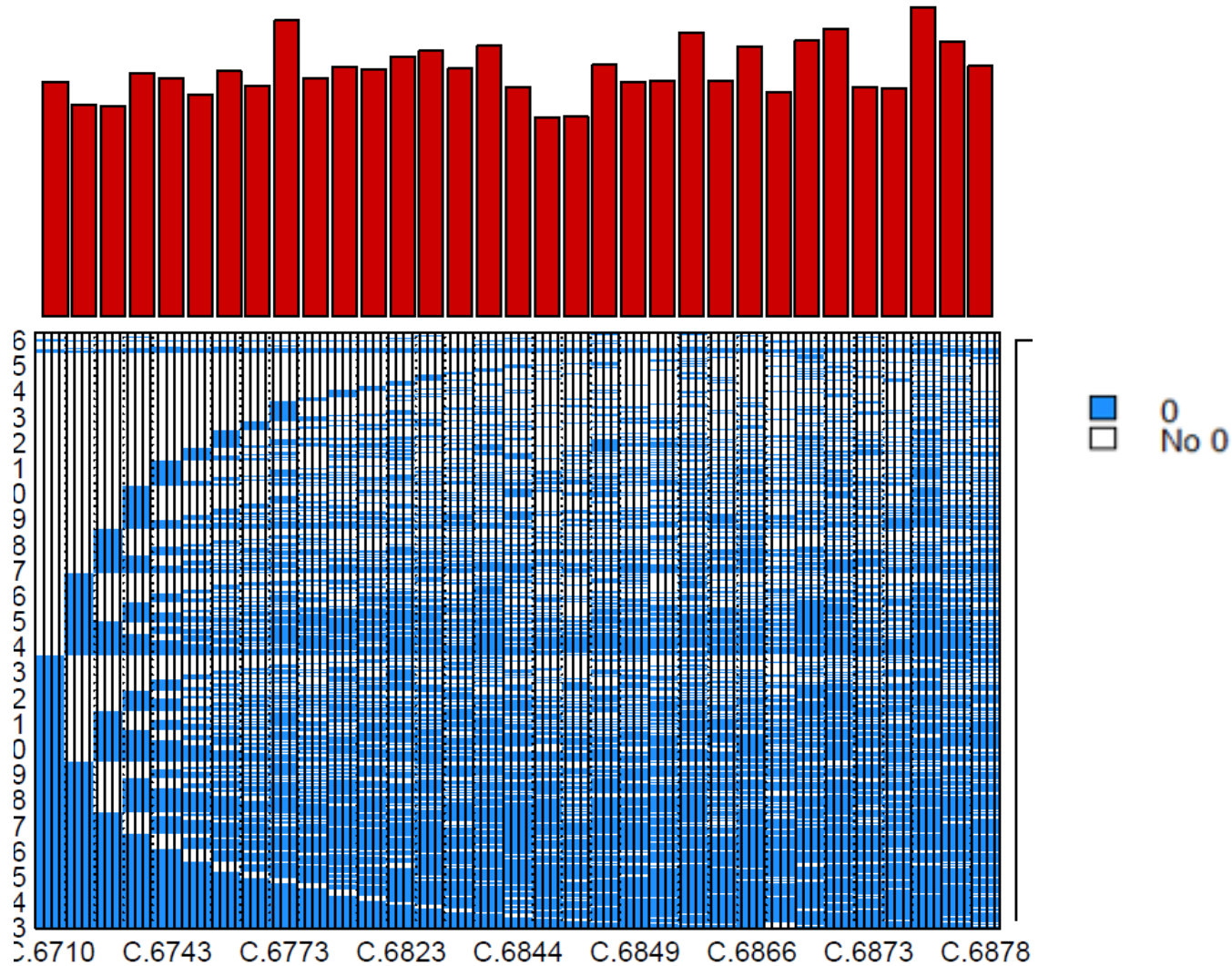
STATISTICAL PIPELINE

1. "0s" study and replacement (zCompositions R)

STATISTICAL PIPELINE

1. "0s" study and replacement (zCompositions R)

16 % of 0s



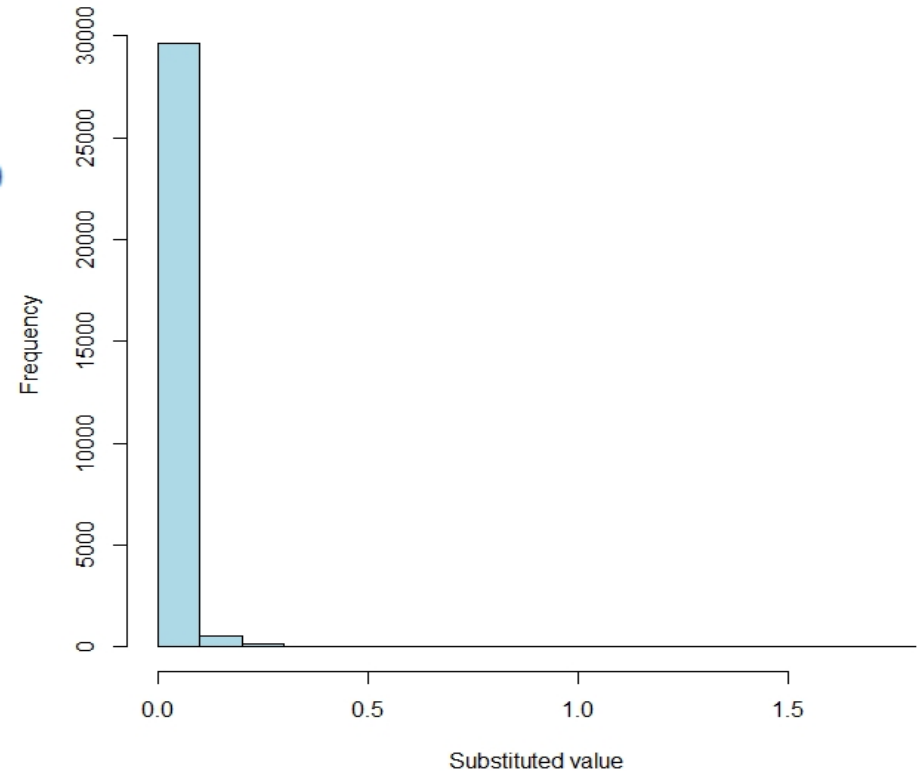
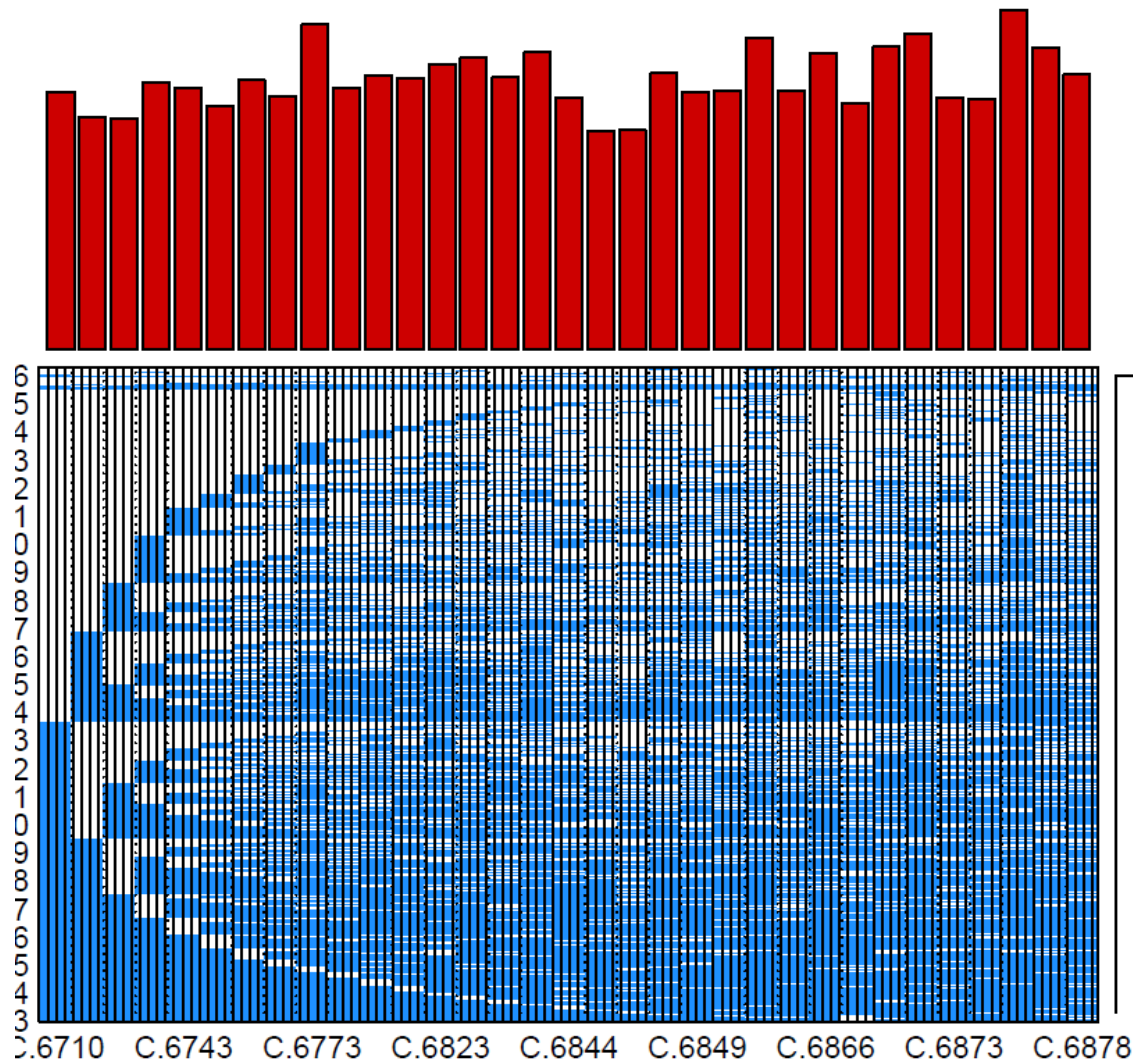
STATISTICAL PIPELINE

1. "0s" study and replacement (zCompositions R)

16 % of 0s

Bayesian-multiplicative replacement
Martín-Fdez et al. 2104

Zero substitution using GBM in zCompositions-Genes



STATISTICAL PIPELINE

1. "0s" study and replacement (zCompositions R)
2. Estimation of relative abundances

STATISTICAL PIPELINE

1. "0s" study and replacement (zCompositions R)
2. Estimation of relative abundances
3. **Weighed** centered log ratio transformation

$$\text{clr}(x_i) = \lg \frac{x_i}{G} = \lg x_i - \frac{1}{n} \sum_1^n \lg(x_i)$$

STATISTICAL PIPELINE

1. "0s" study and replacement (zCompositions R)
2. Estimation of relative abundances
3. **Weighed** centered log ratio transformation

$$\text{clr}(x_i) = \lg \frac{x_i}{G} = \lg x_i - \frac{1}{n} \sum_{i=1}^n \lg(x_i)$$

Weighed mean

1/n → Mean relative abundance

STATISTICAL PIPELINE

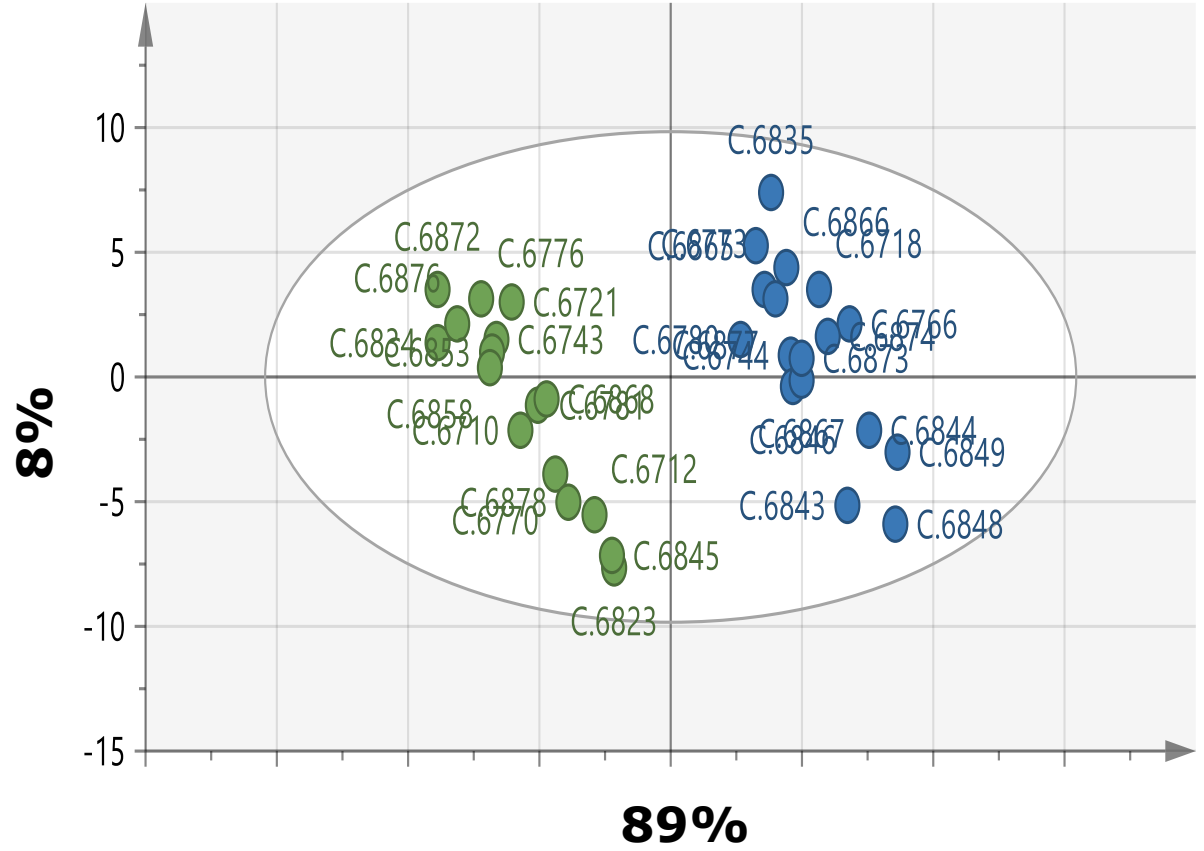
1. "0s" study and replacement (zCompositions R)
2. Estimation of relative abundances
3. **Weighed** centered log ratio transformation
4. Selection of discriminant microbial genes with DA - PLS
 - VIP
 - Regression coefficients

RESULTS

DISCRIMINATING MICROBIAL GENES DA-PLS

PC	R ²	Q ²
1	0.89	0.84
2	0.97	0.91
3	0.99	0.92

SCORE PLOT



251 GENES INCLUDED IN THE MODEL

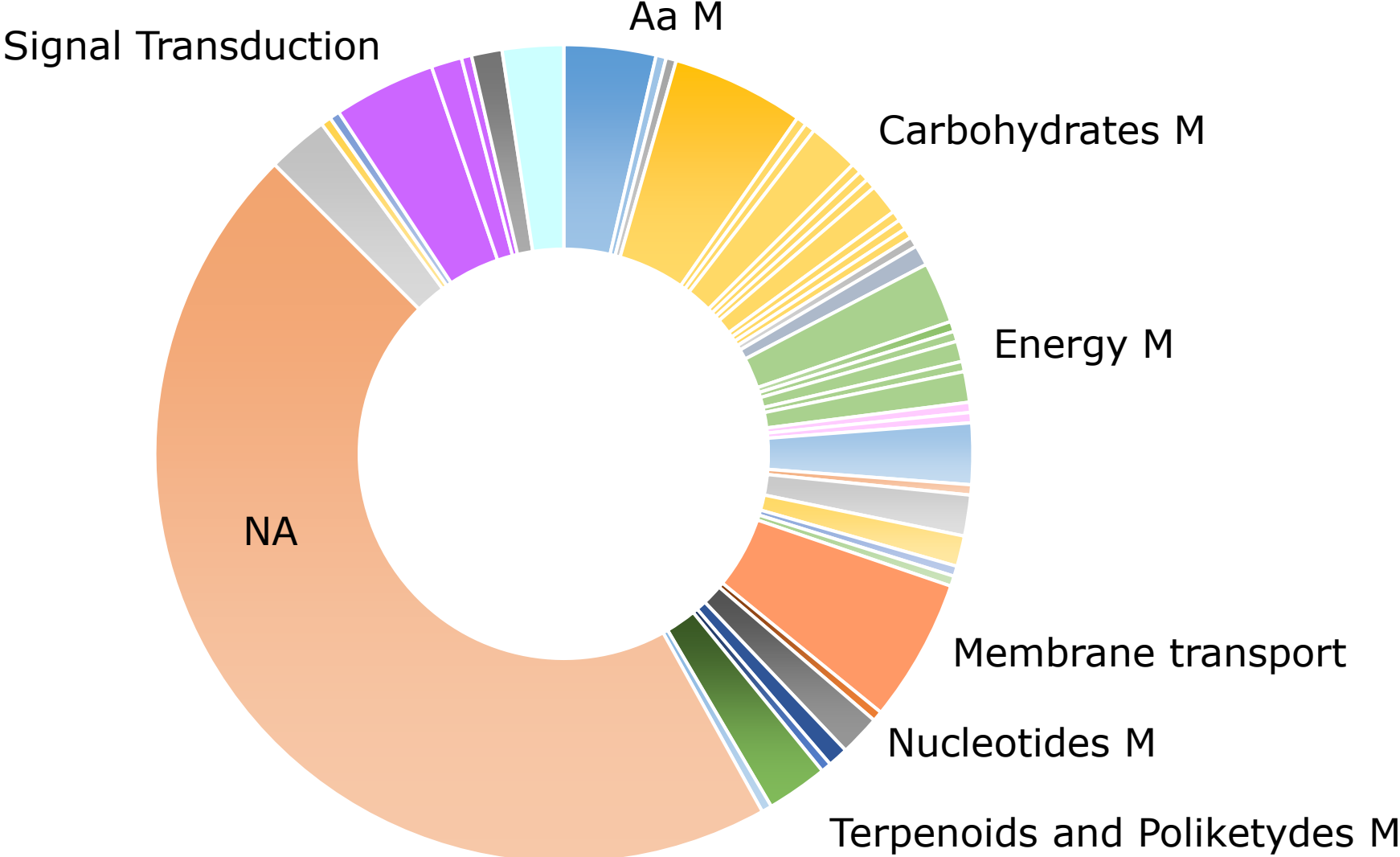
**SELECTION FOR IMF
MODIFIED THE MICROBIAL
GENOME OF THE LINES!!!**



**LINK
HOST GENOME-METAGENOME**

RESULTS

WHICH 251 MICROBIAL GENES?



RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE

ANALYSIS WITHOUT $wclr$ TRANSFORMATION

RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE **ANALYSIS WITHOUT wclr TRANSFORMATION**

PREDICTION ABILITY OF DA-PLS MODEL

	PC	R ²	Q ²	Number of genes
Rel. abundances	3	0.987	0.917	227

RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE **ANALYSIS WITHOUT wclr TRANSFORMATION**

PREDICTION ABILITY OF DA-PLS MODEL

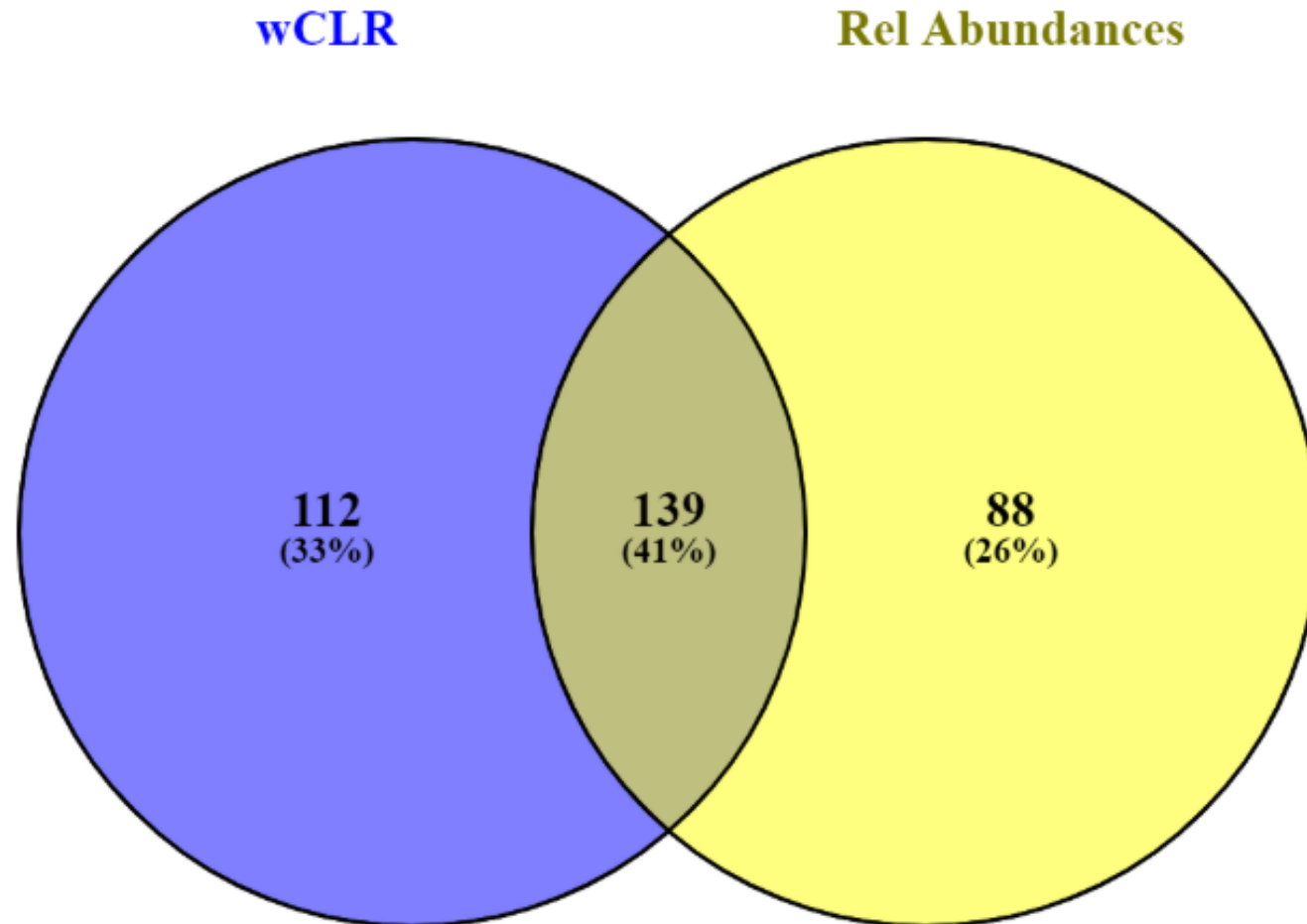
	PC	R ² Y	Q ²	Number of genes
Rel. abundances	3	0.987	0.917	227
wClr	3	0.987	0.922	251

RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE

ANALYSIS WITHOUT *wclr* TRANSFORMATION

OVERLAPPING BETWEEN MICROBIAL GENES SELECTED BY DA-PLS



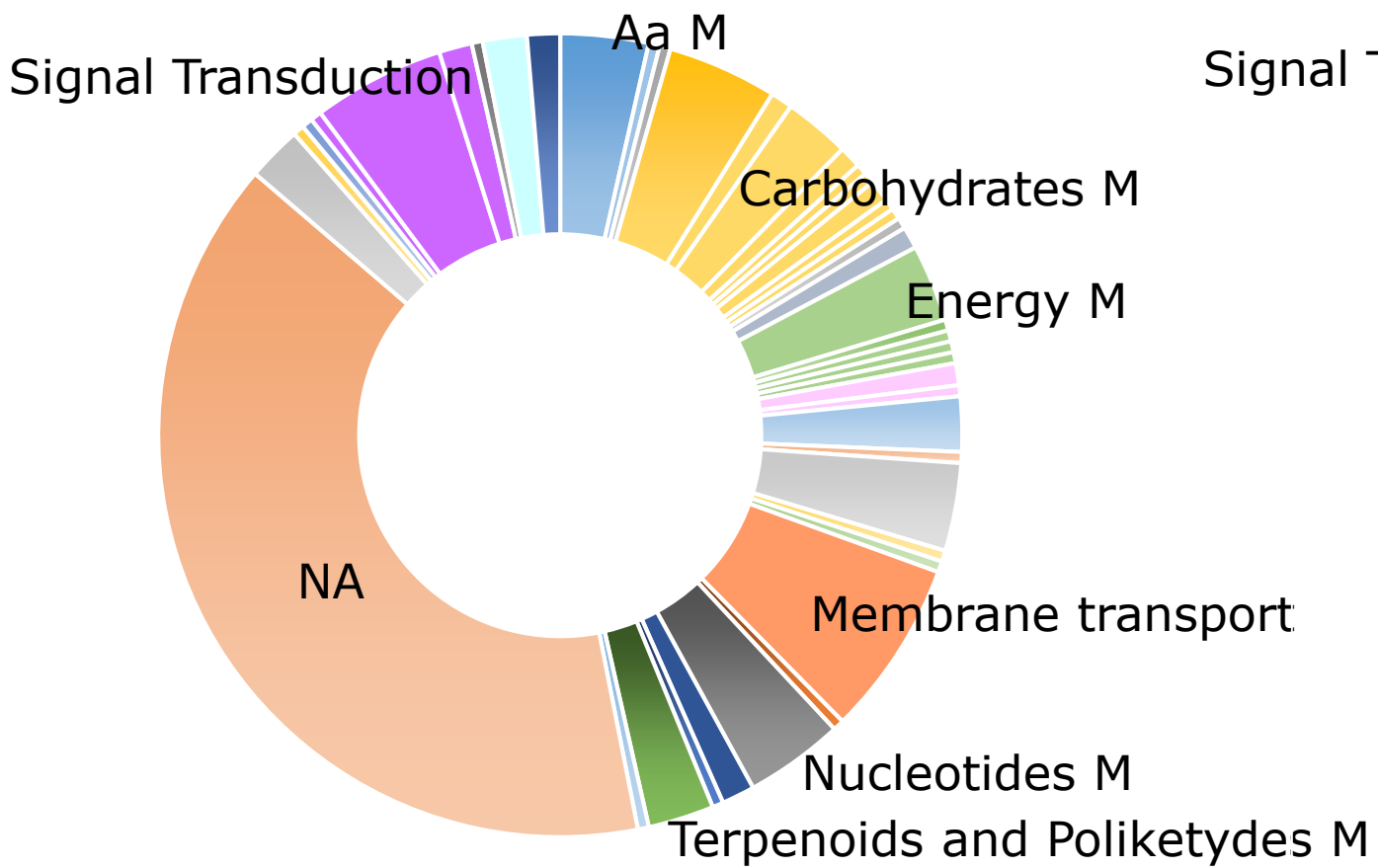
RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE

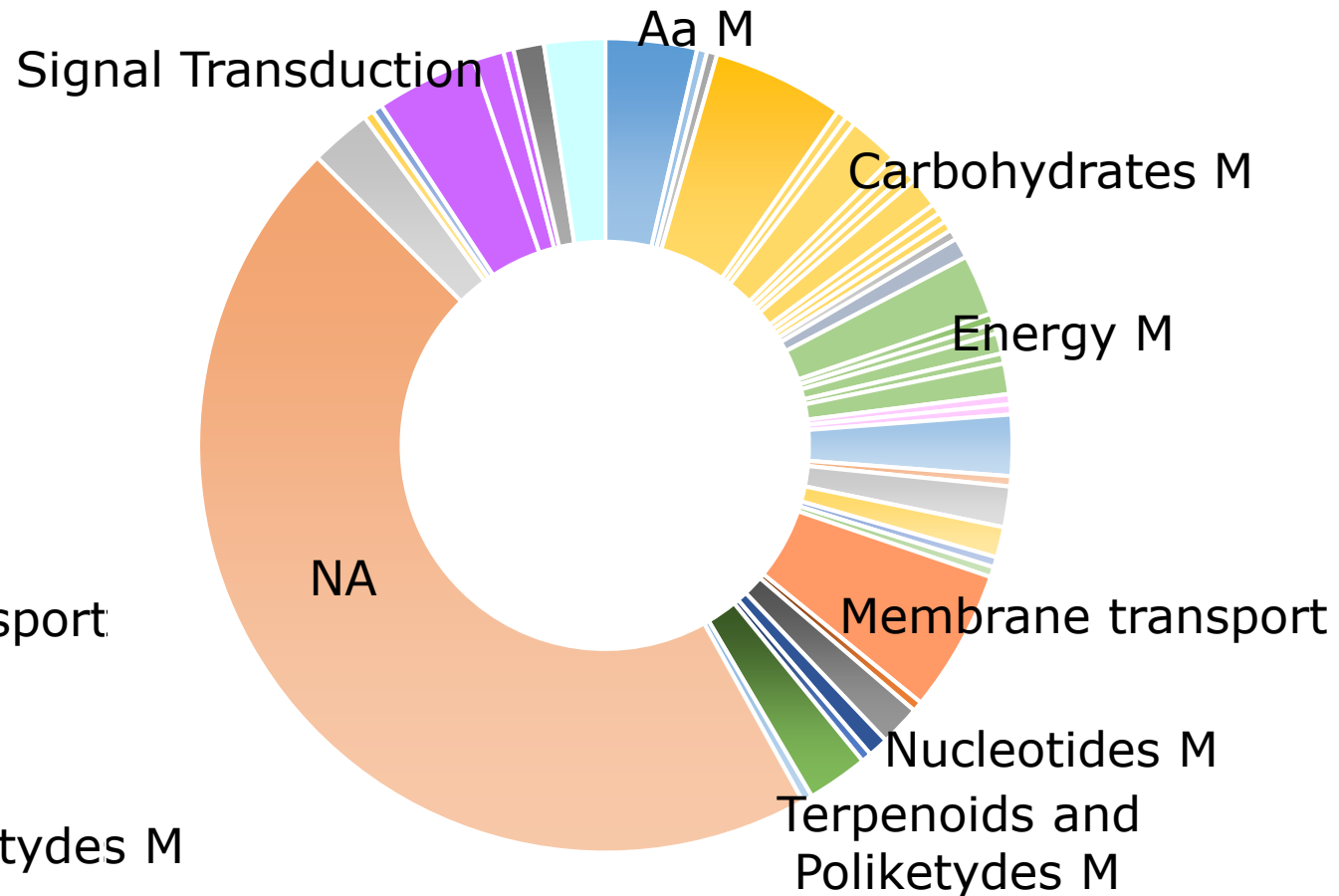
ANALYSIS WITHOUT wCLR TRANSFORMATION

OVERLAPPING BETWEEN MICROBIAL GENES SELECTED BY DA-PLS

RELATIVE ABUNDANCES



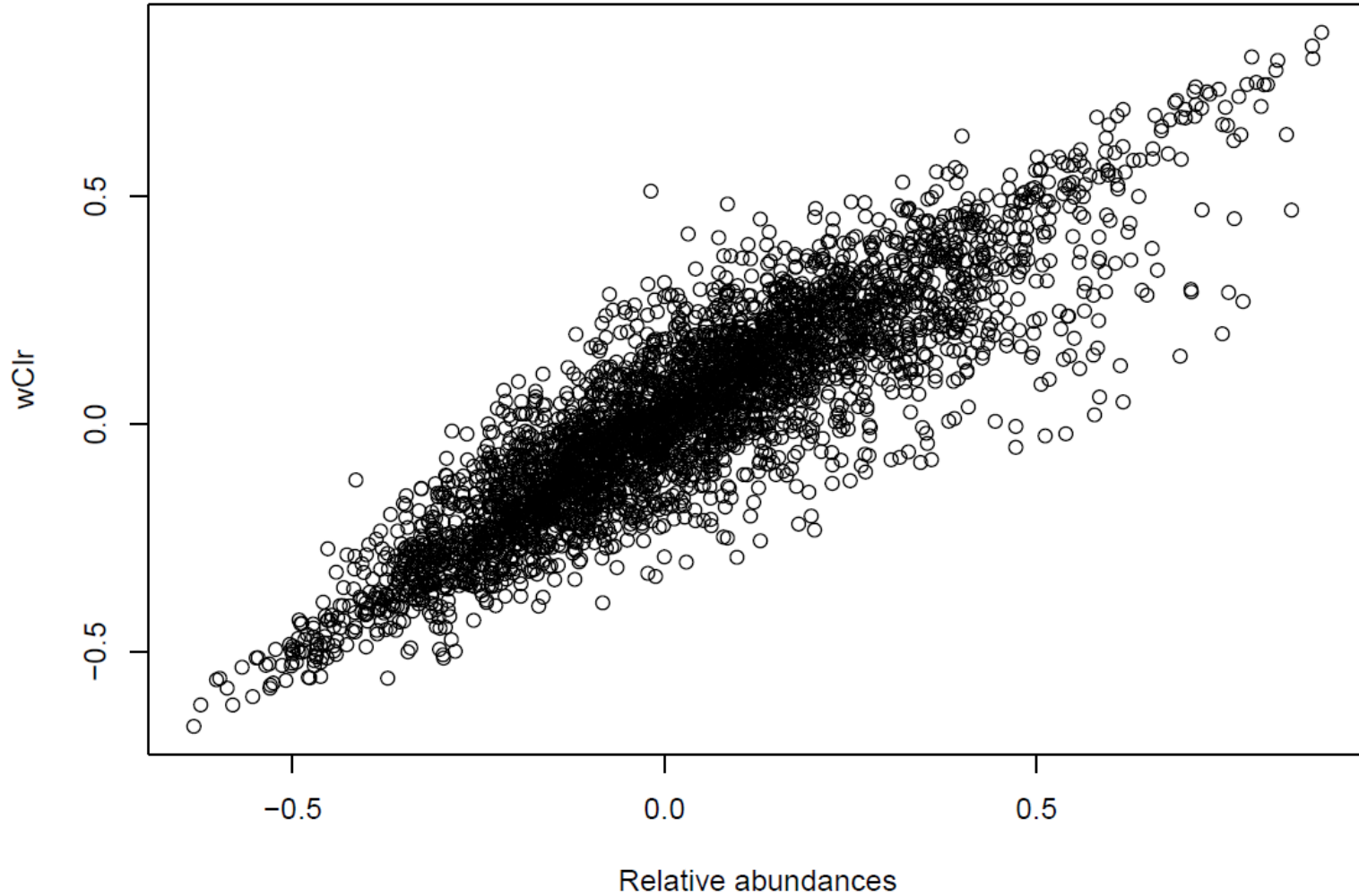
wCLR



RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE

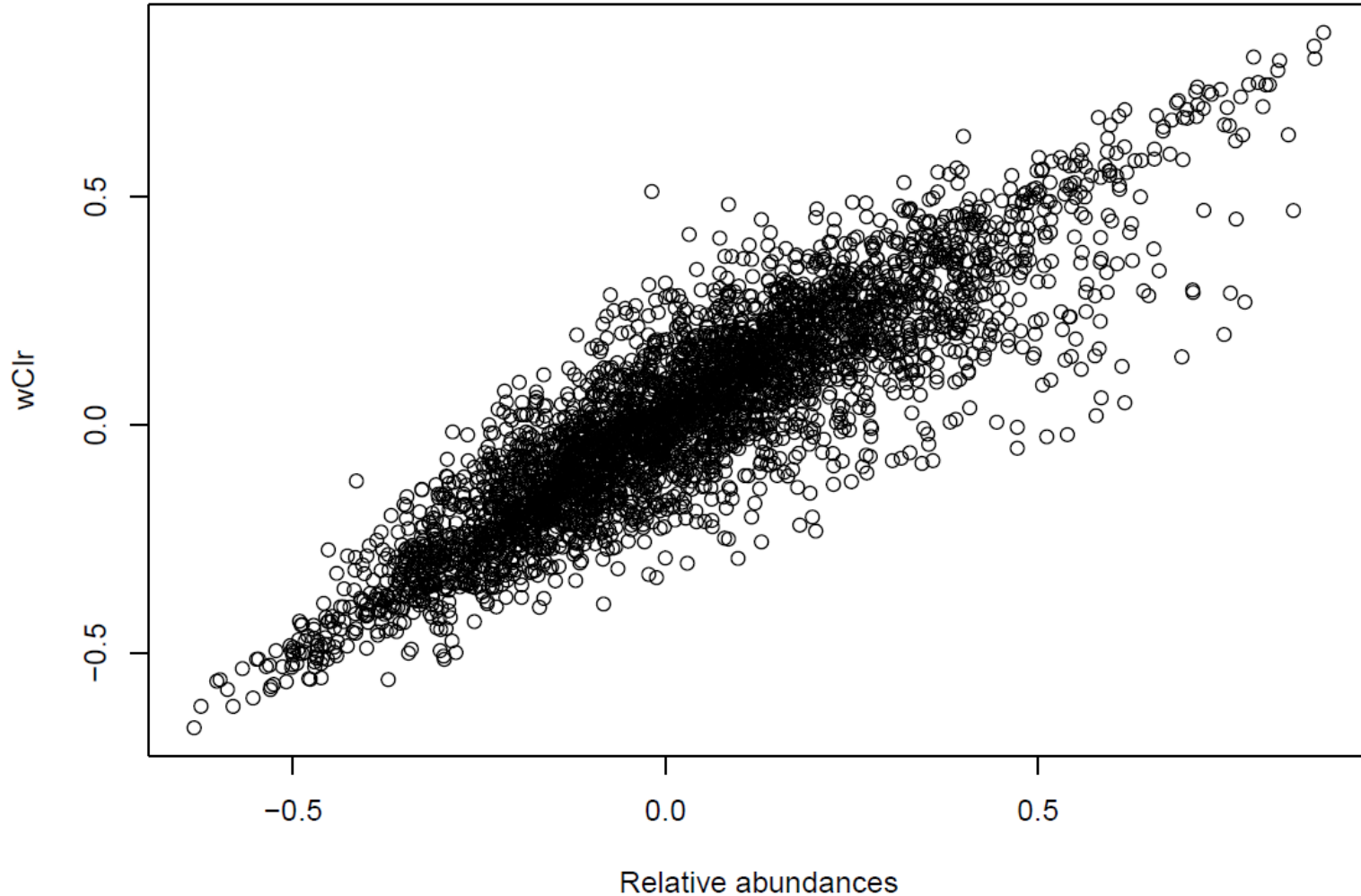
CORRELATIONS BETWEEN MICROBIAL GENES IN wCLR VS. REL. ABUNDANCES



RESULTS

LOG TRANSFORMATION EFFECTS IN PRACTISE

CORRELATIONS BETWEEN MICROBIAL GENES IN wCLR VS. REL. ABUNDANCES



**Rank of relative abundances
[1×10^{-6} , 1×10^{-1}]**

**MAY BE NOT LIKE THIS
IN OTHER DATABASES**

CONCLUSIONS



Selection for IMF modifies the microbial genome

CONCLUSIONS



Selection for IMF modifies the microbial's genome

Link genome - metagenome

CONCLUSIONS



Selection for IMF modifies the microbial's genome

Link genome - metagenome

Correlated responses in genes involved in several metabolic pathways, as carbohydrates and energy metabolism

CONCLUSIONS



Selection for IMF modifies the microbial's genome

Link genome - metagenome

Correlated responses in genes involved in several metabolic pathways, as carbohydrates and energy metabolism

In our study, log transformations did not change results



UNIVERSITAT
POLITÈCNICA
DE VALÈNCIA



Unión Europea
Fondo Social Europeo



ueeeca

UNIÓN DE ENTIDADES ESPAÑOLAS DE CIENCIA ANIMAL

THANKS!



GENERALITAT
VALENCIANA