

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

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70<sup>th</sup> Annual Meeting of EAAP  
27<sup>th</sup> August 2019, Ghent



# WHY INTRAMUSCULAR FAT?

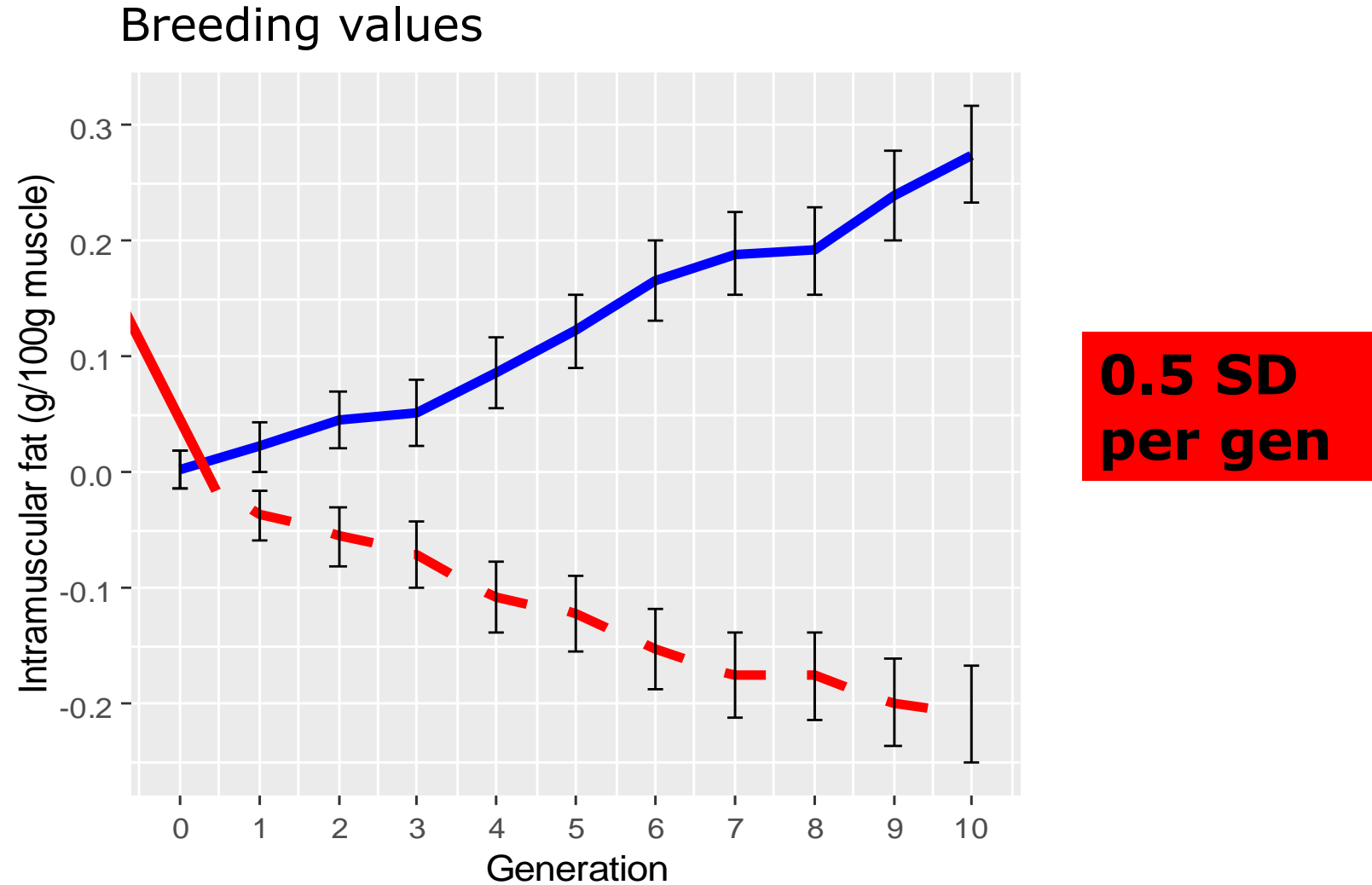


# WHY IN RABBITS?



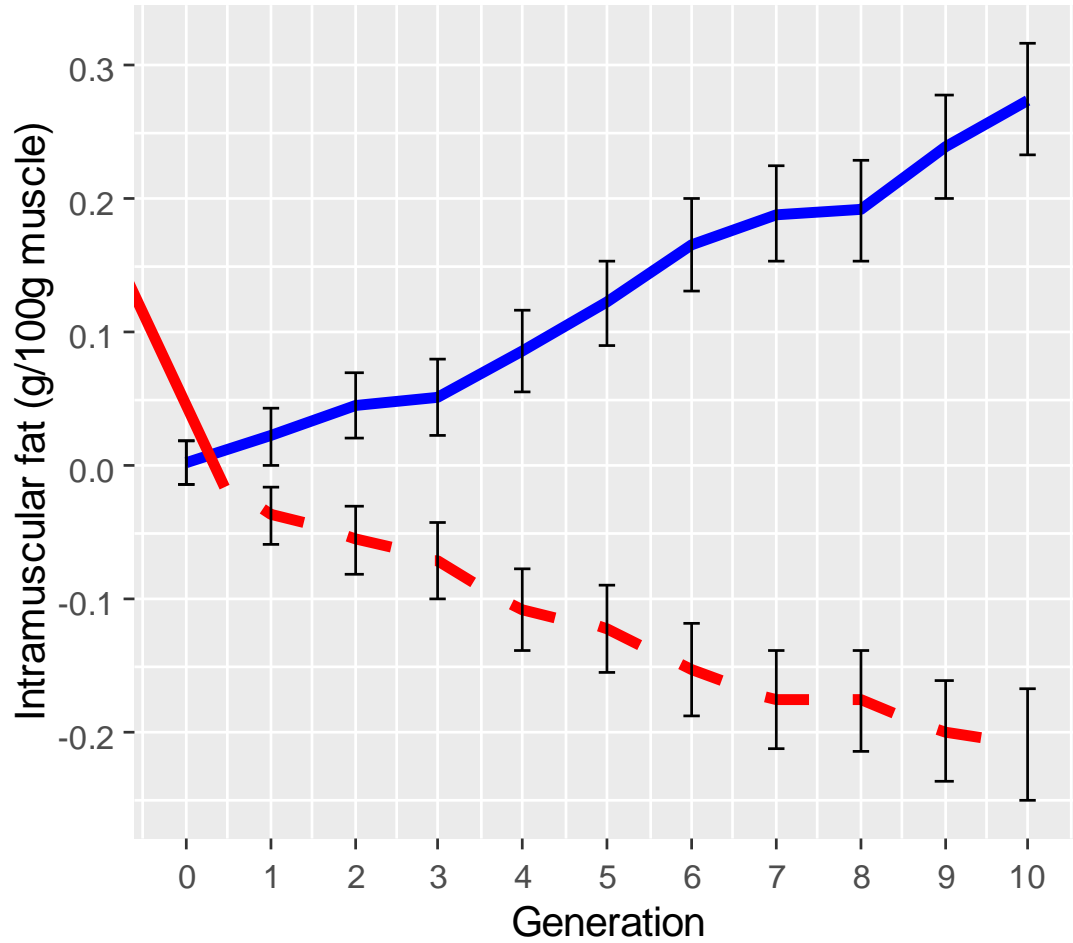
## Divergent selection for IMF

# Response to selection for IMF



# Divergent selection for IMF

**SAME ENVIRONMENT!!**



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

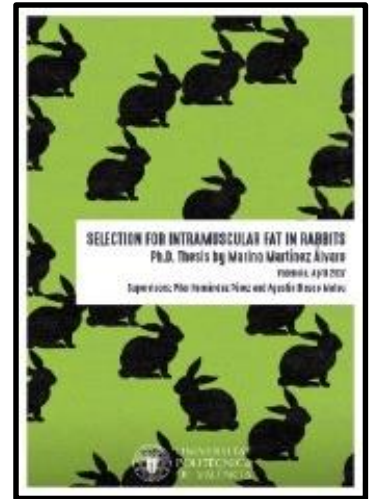


**PHENOTYPIC  
DIFFERENCES  
HIGH LINE - LOW LINE**

# Divergent selection for IMF

## CORRELATED RESPONSES IN MEAT QUALITY TRAITS

Carcass fat



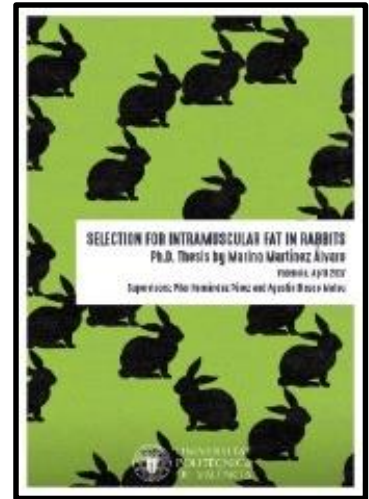
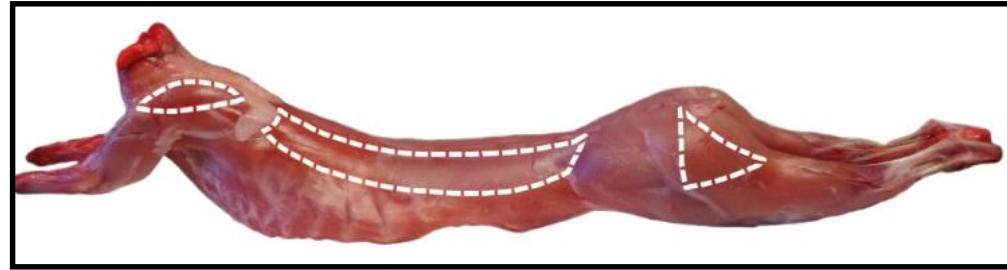
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## CORRELATED RESPONSES IN MEAT QUALITY TRAITS

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IMF in other muscles



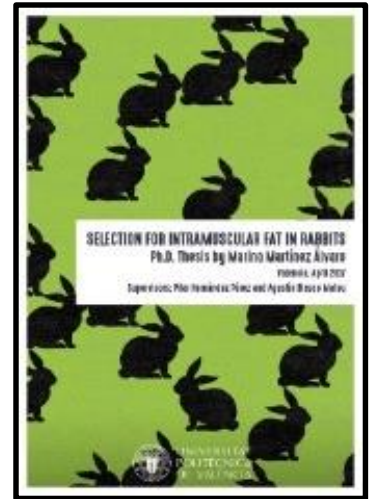
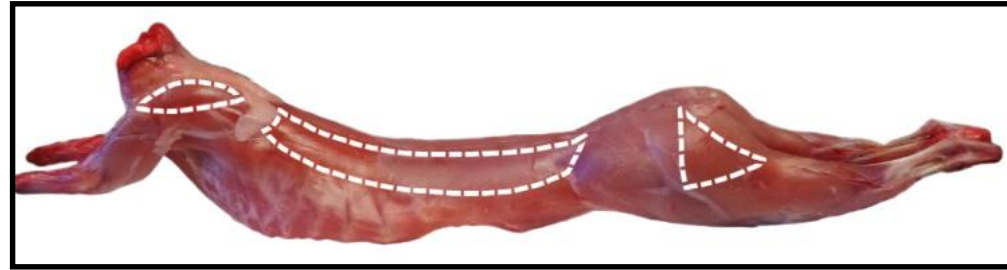
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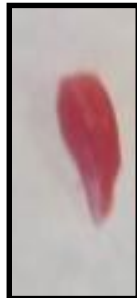
IMF in other muscles



Lipogenic activity



G6PDH





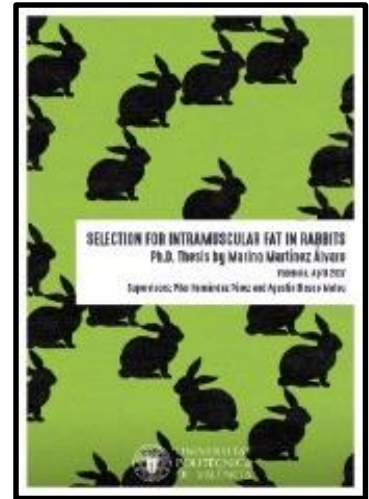
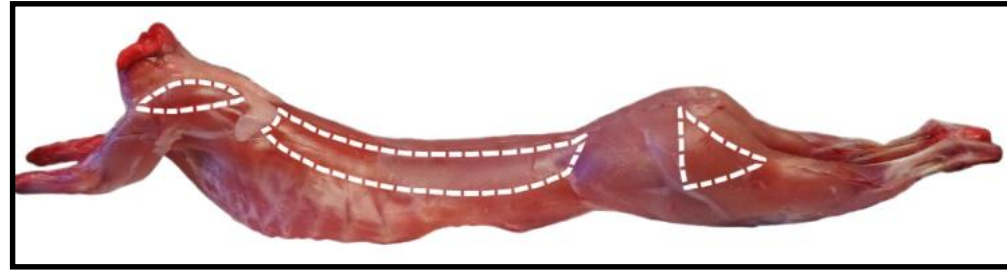
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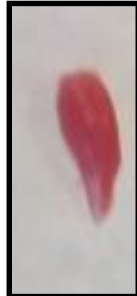
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Lipogenic activity



**G6PDH**



Adipocytes size



Liver size



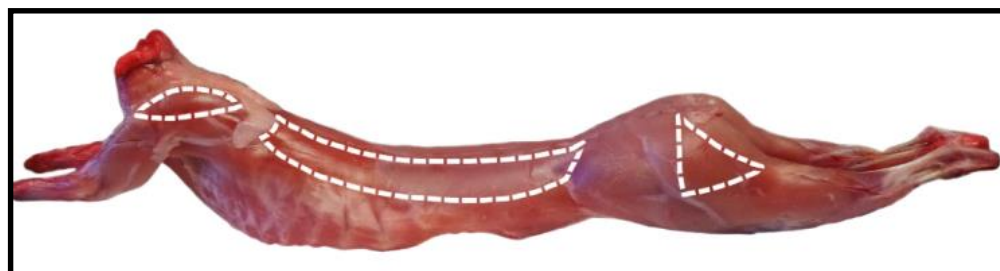
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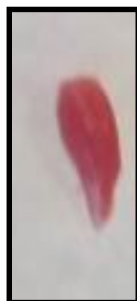
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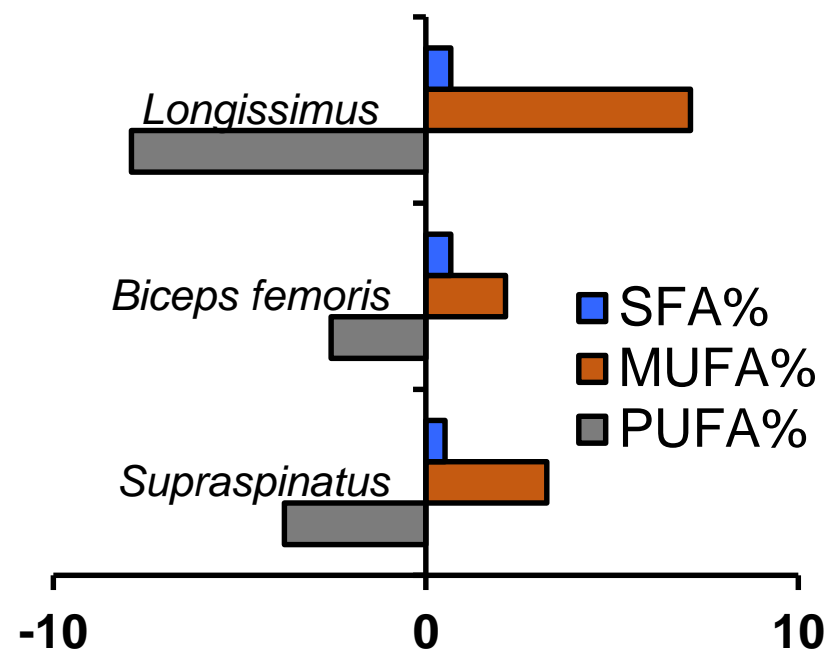
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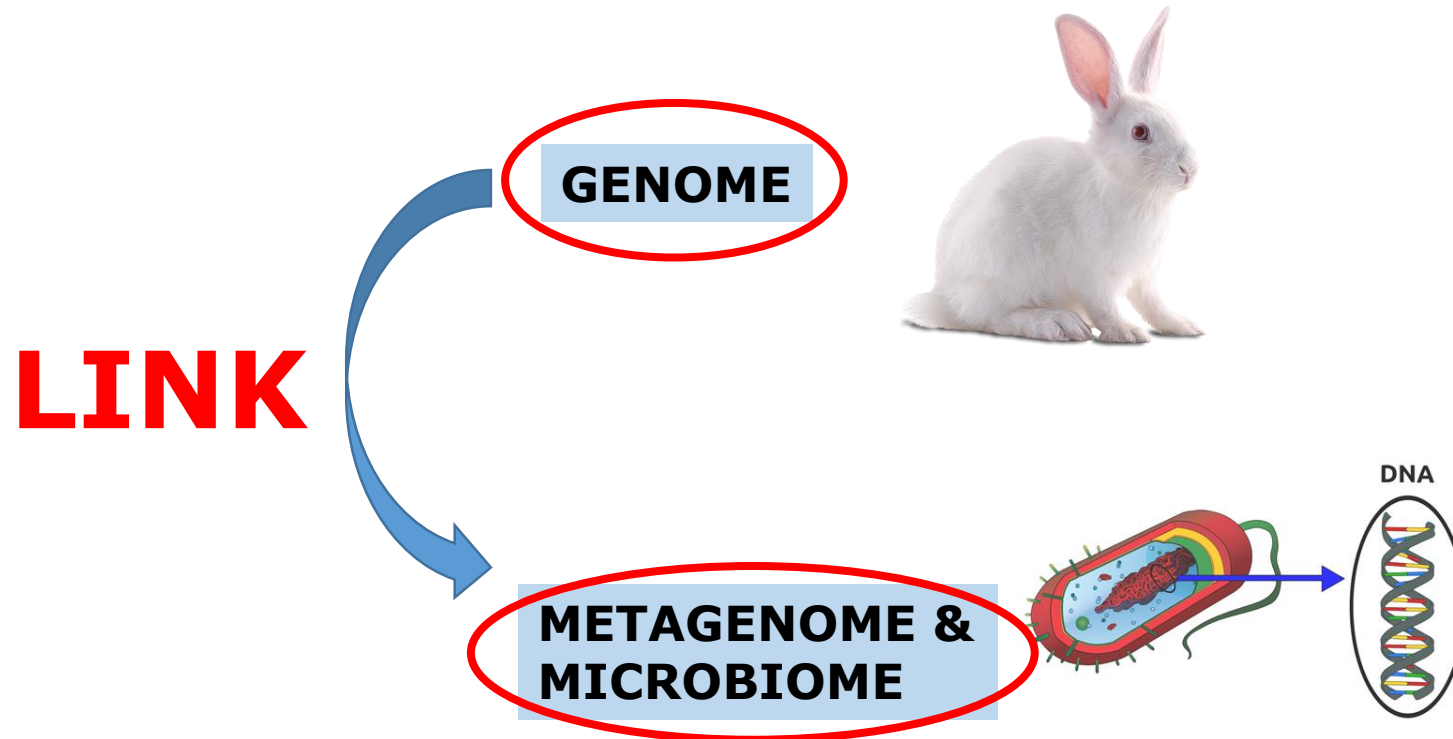


Meat Fatty Acid profile



# OBJECTIVE

## CORRELATED RESPONSES IN MICROBIALS GENOME



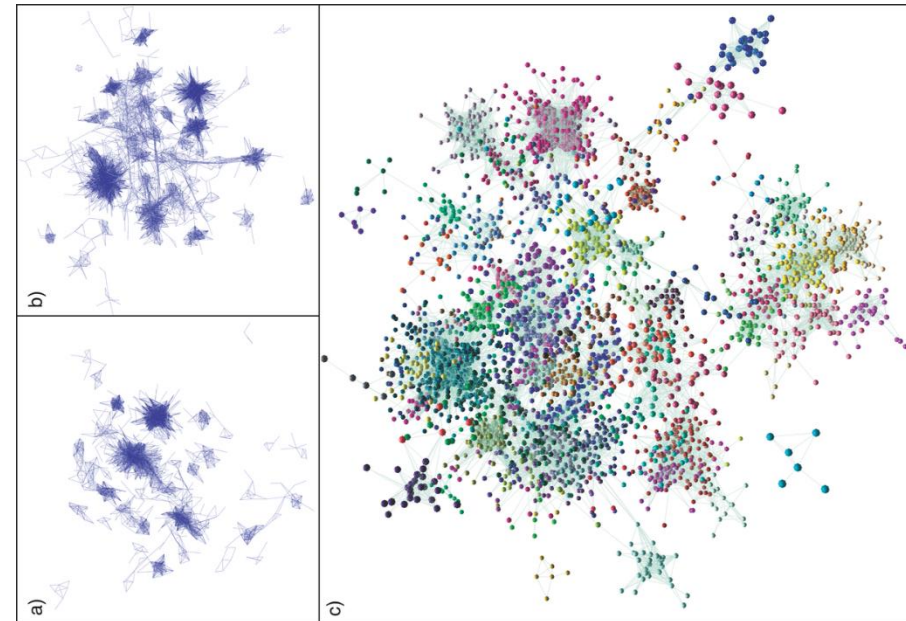
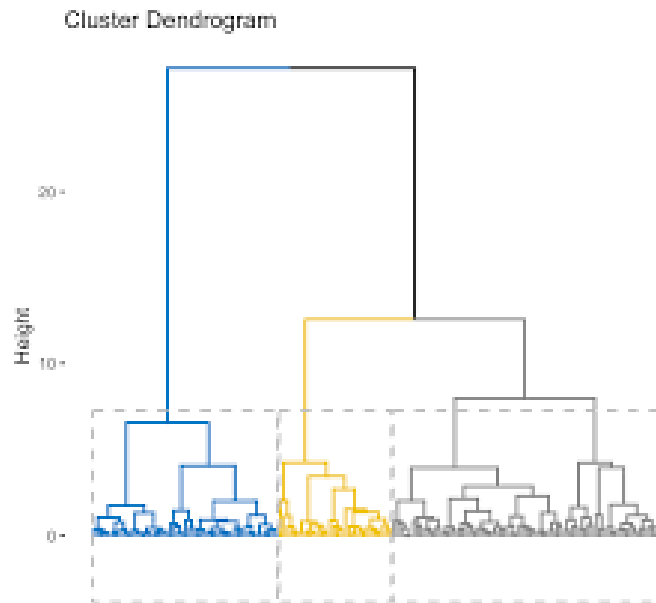
# **SOME IDEAS ABOUT COMPOSITIONAL DATA ANALYSIS...**

# 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



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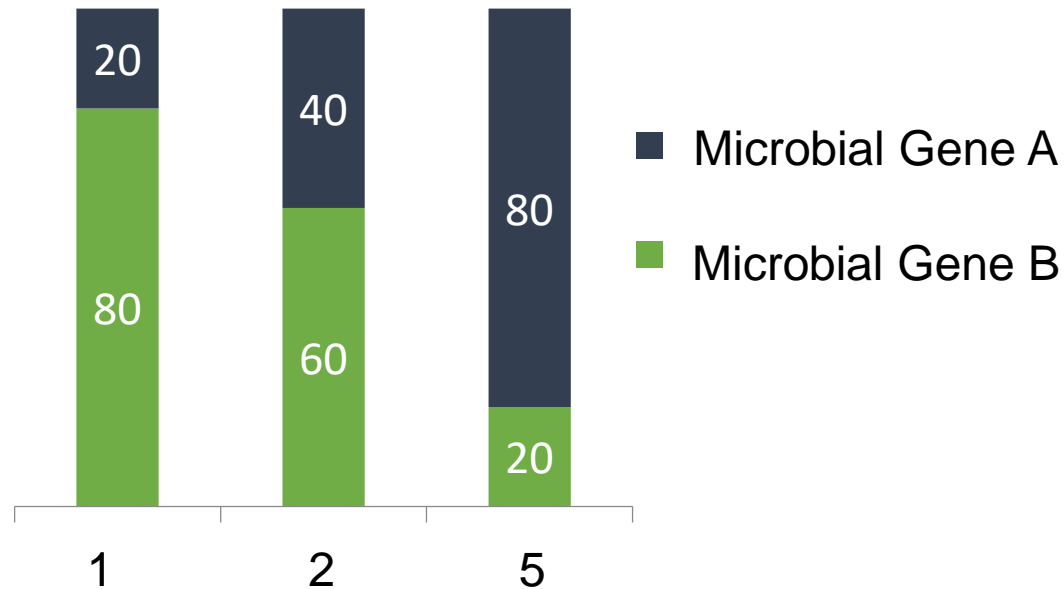


IMF



Microbial Genes A & B

### RELATIVE VALUES



# STATISTICAL ANALYSIS OF METAGENOMIC DATA



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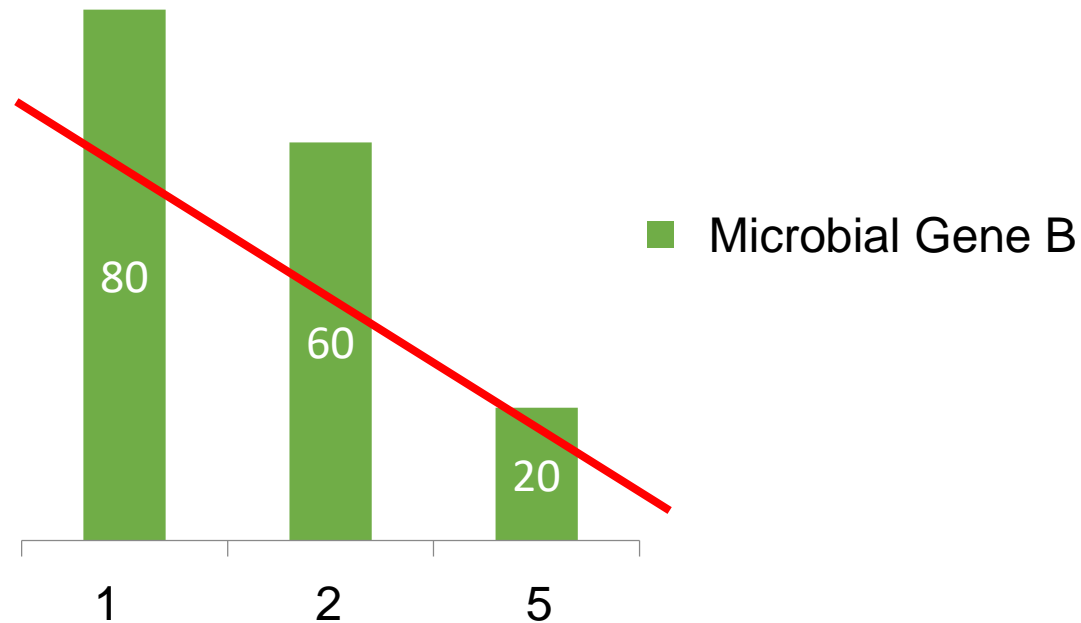


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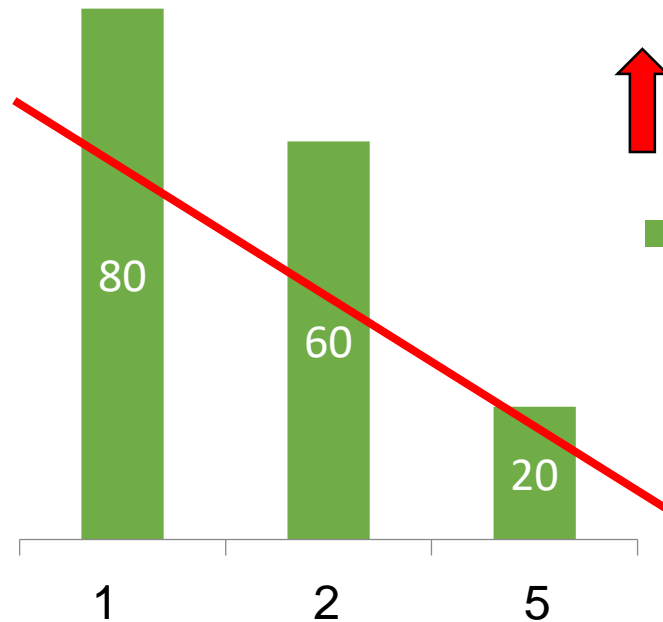


IMF



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

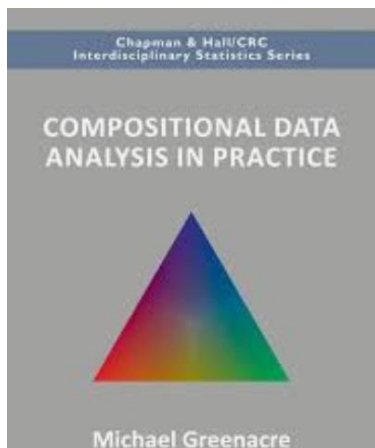
Clr

Alr

Ilr

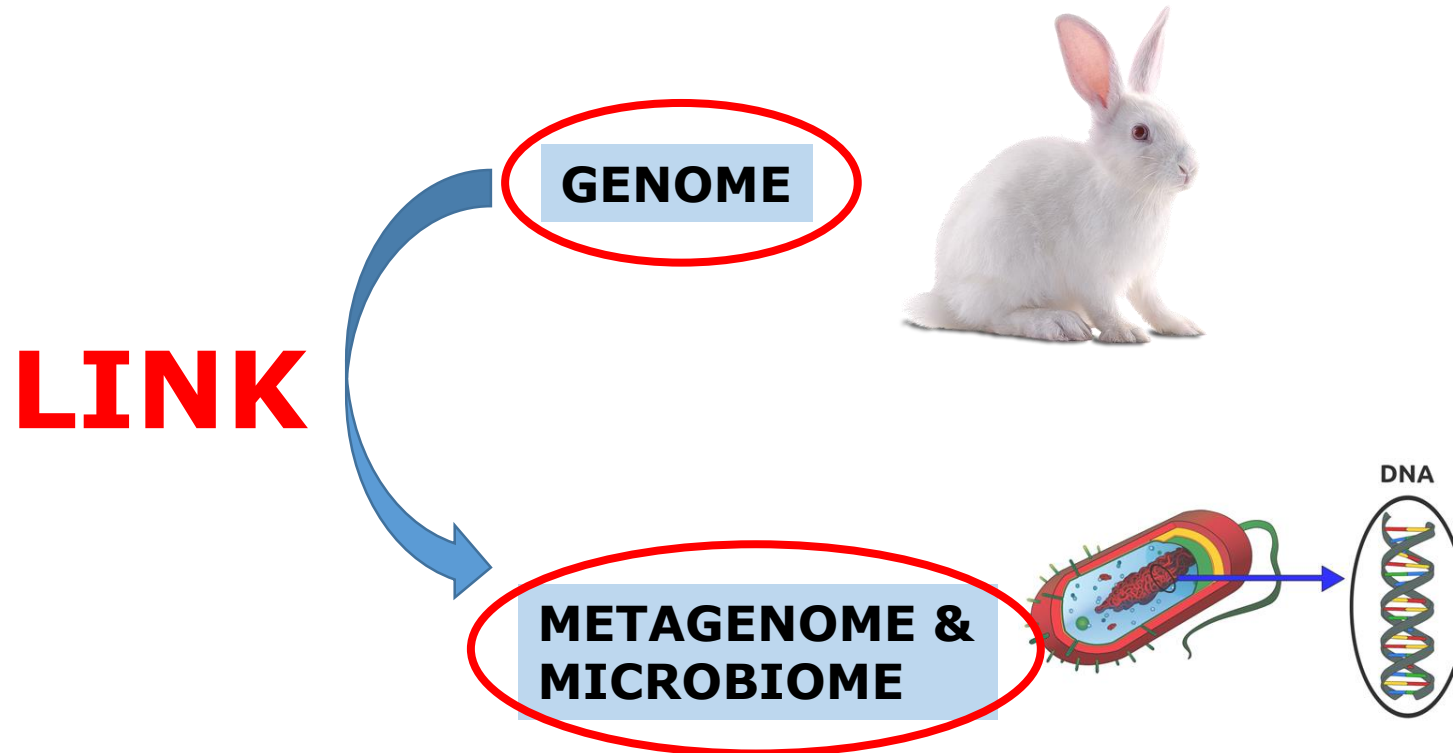
From Simplex to Real Space

Metrics in Euclidean  
geometry of real space



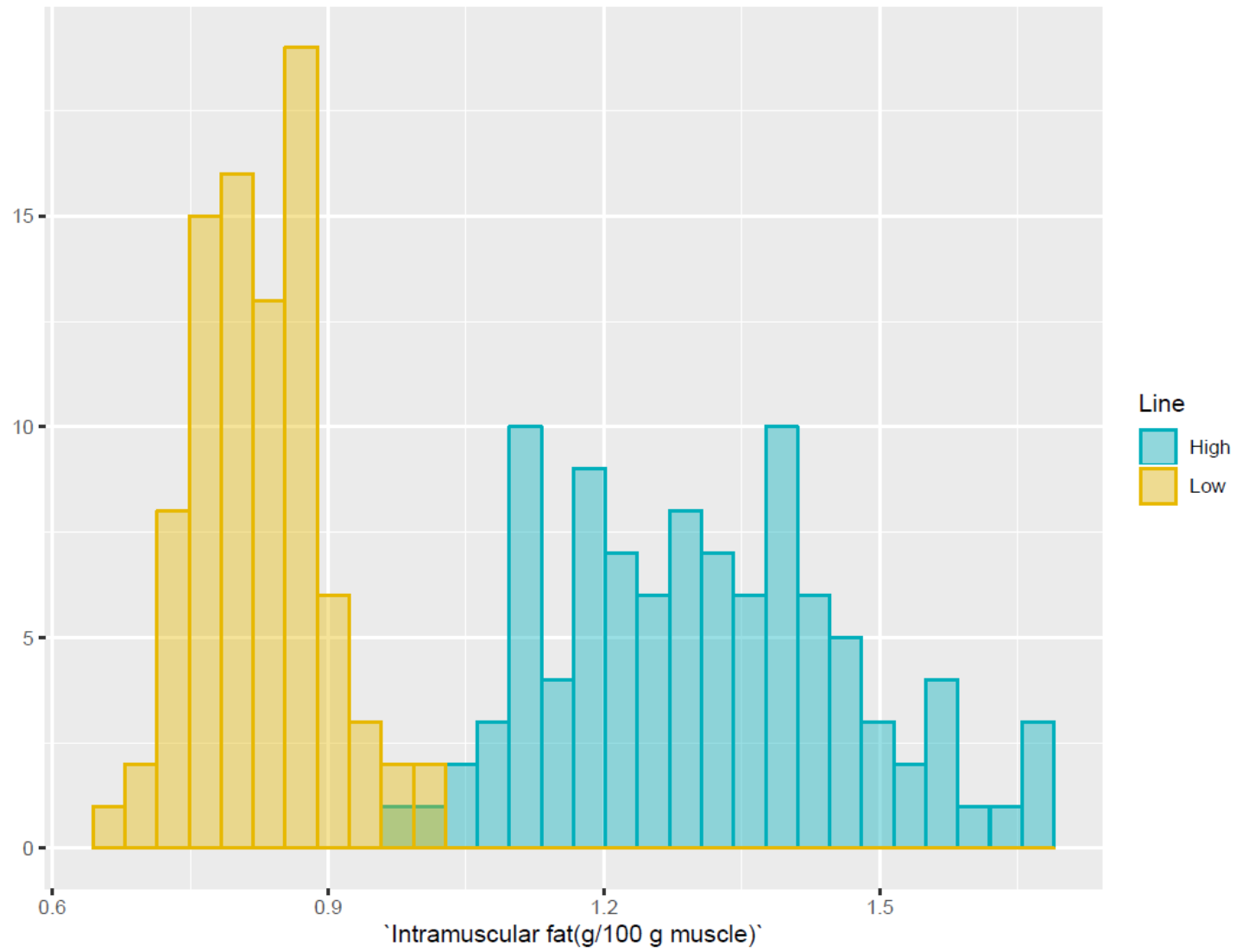
# OBJECTIVE

## CORRELATED RESPONSES IN MICROBIALS GENOME

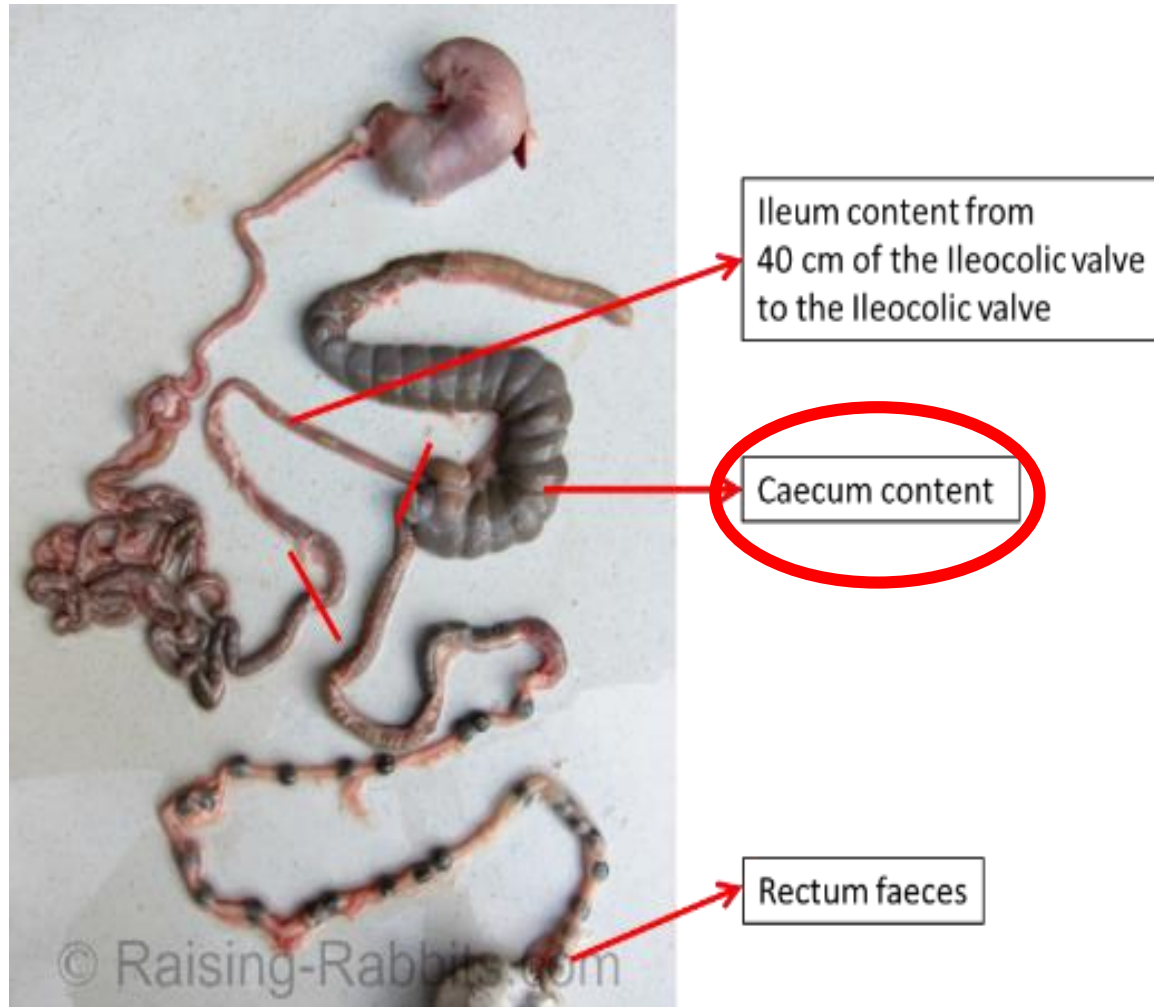


# ANIMALS

Distribution of IMF fat data in the 10<sup>th</sup> generation



## METAGENOMIC MEASUREMENTS



N = 33 ( 16 H & 17 L)

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

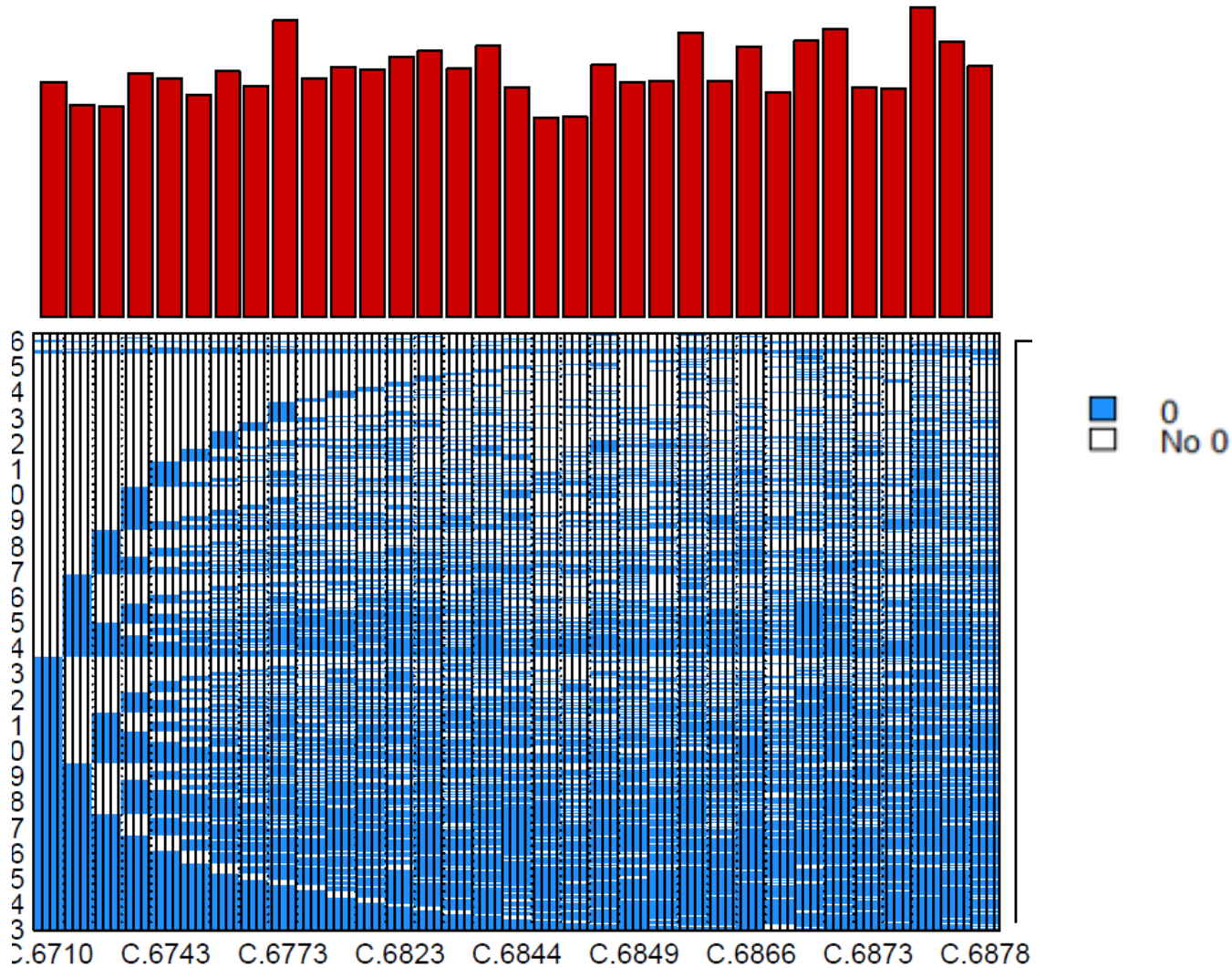
## **STATISTICAL PIPELINE**

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

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16 % of 0s

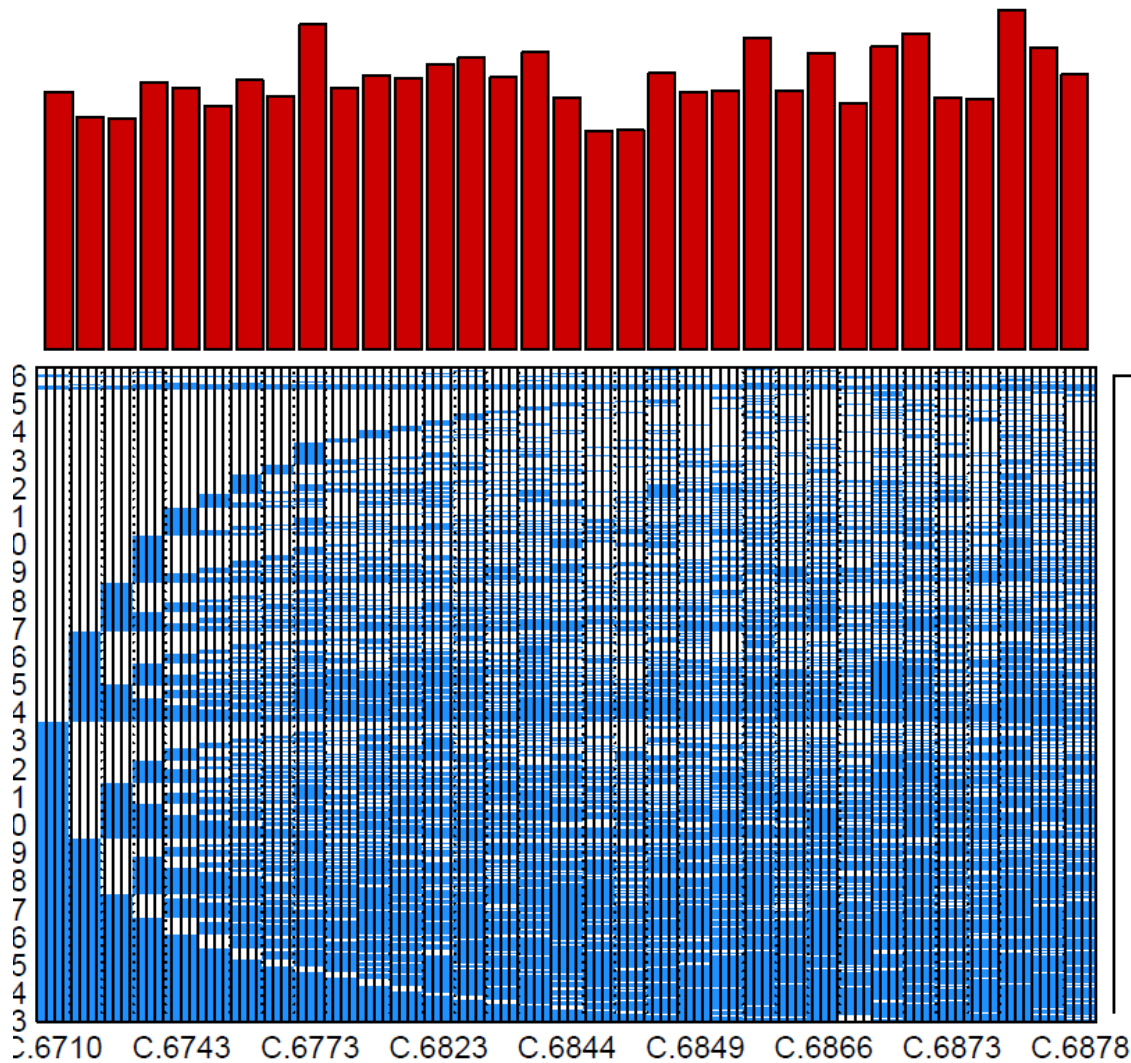




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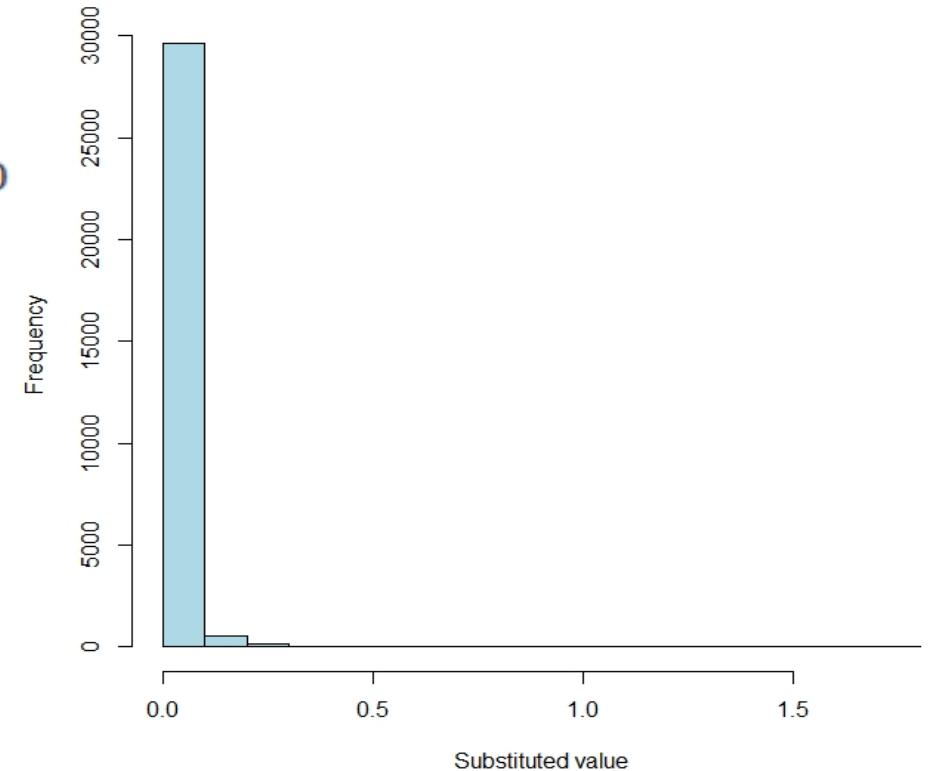
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16 % of 0s



Bayesian-multiplicative replacement  
Martín-Fdez et al. 2104

Zero substitution using GBM in zCompositions-Genes



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2. Estimation of relative abundances

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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**

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

**Weighed mean**

1/n → Mean relative abundance

## STATISTICAL PIPELINE

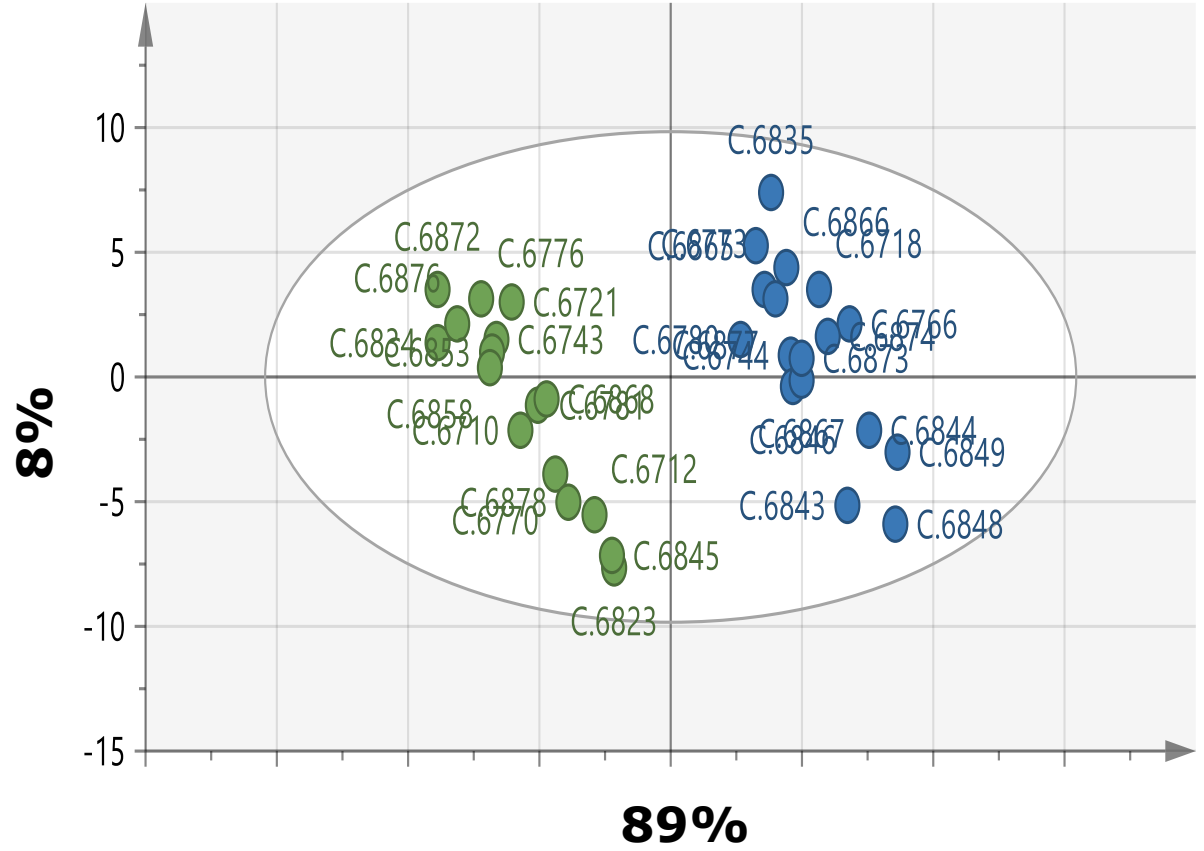
1. "0s" study and replacement (zCompositions R)
2. Estimation of relative abundances
3. **Weighed** centered log ratio transformation
4. Selection of discriminant microbial genes with DA - PLS
  - VIP
  - Regression coefficients

# RESULTS

## DISCRIMINATING MICROBIAL GENES DA-PLS

PC	R <sup>2</sup>	Q <sup>2</sup>
1	0.89	0.84
2	0.97	0.91
3	0.99	0.92

### SCORE PLOT



251 GENES INCLUDED IN THE MODEL

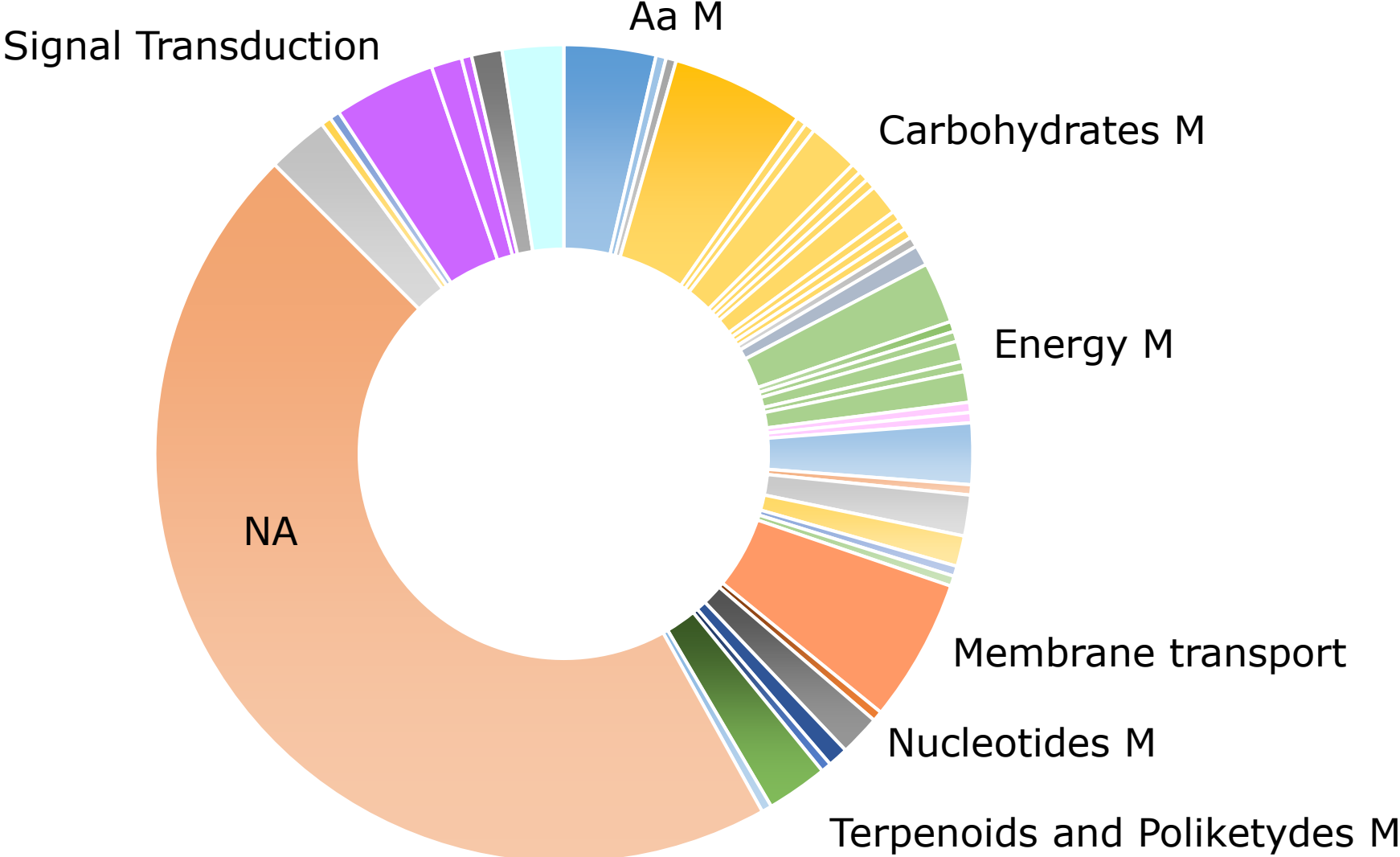
**SELECTION FOR IMF  
MODIFIED THE MICROBIAL  
GENOME OF THE LINES!!!**



**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 <sup>2</sup>	Q <sup>2</sup>	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

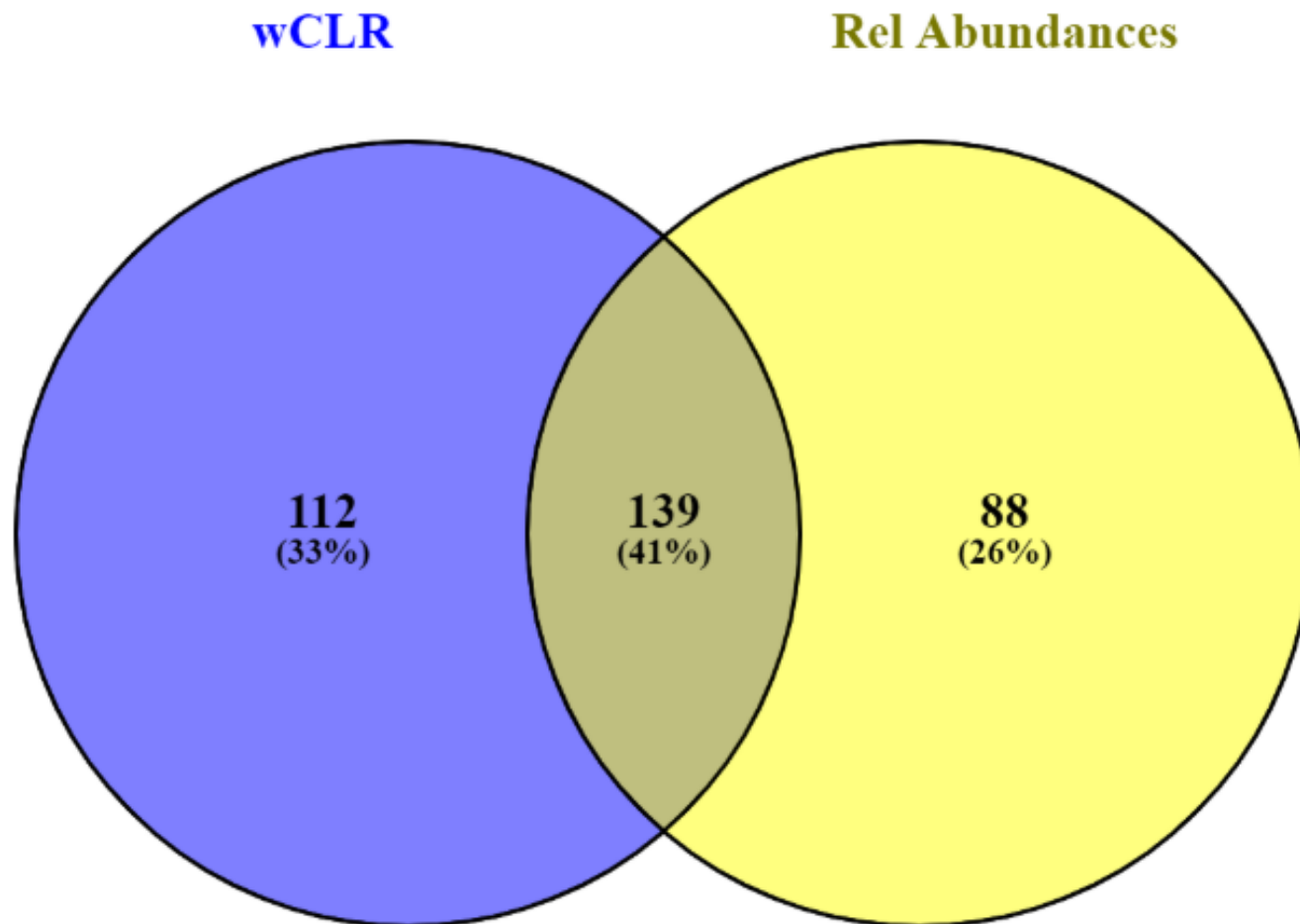
	PC	R <sup>2</sup> Y	Q <sup>2</sup>	Number of genes
Rel. abundances	3	0.987	0.917	227
wClr	3	0.987	0.922	251

# RESULTS

## LOG TRANSFORMATION EFFECTS IN PRACTISE

### ANALYSIS WITHOUT *wclr* TRANSFORMATION

#### OVERLAPPING BETWEEN MICROBIAL GENES SELECTED BY DA-PLS



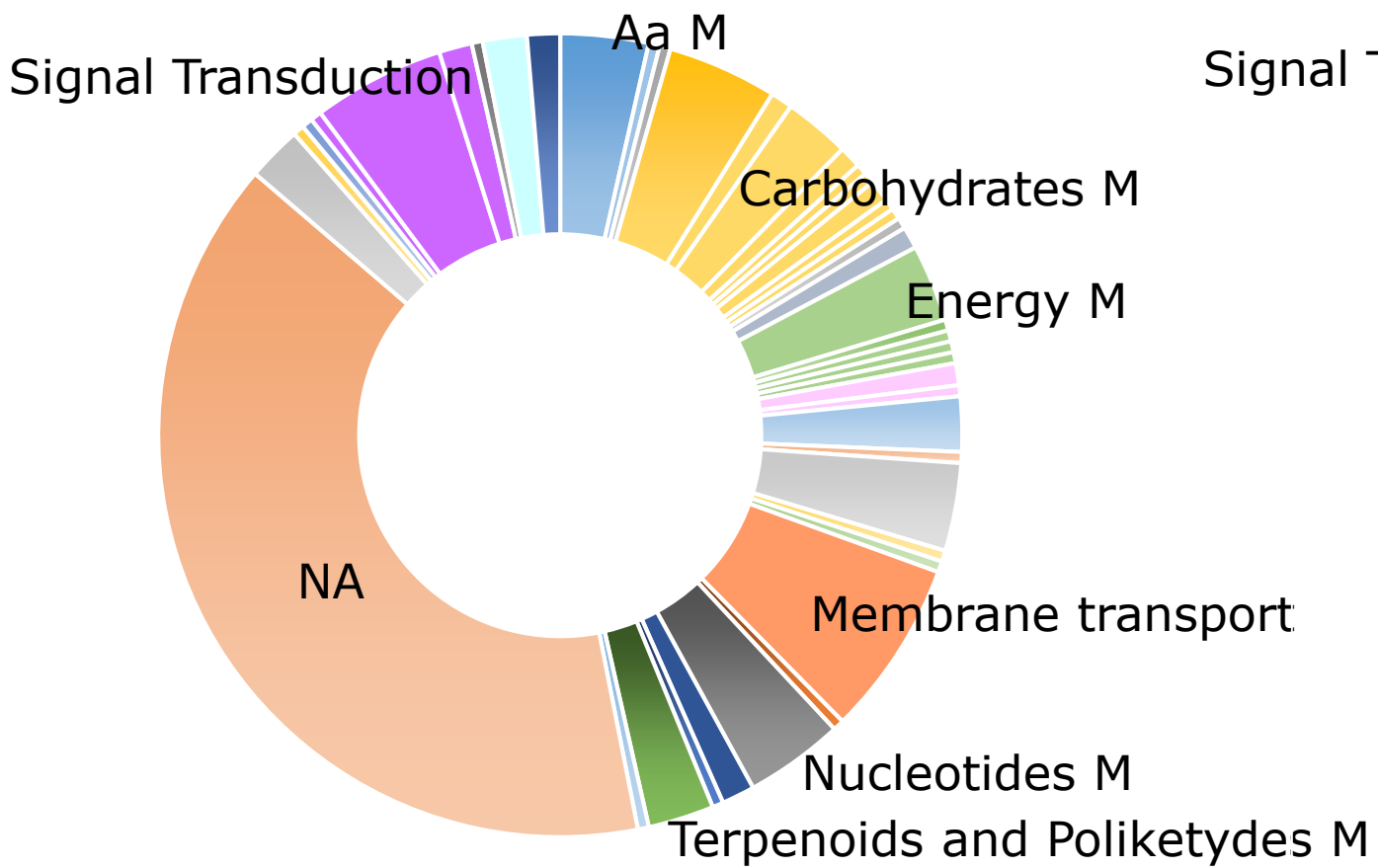
# RESULTS

## LOG TRANSFORMATION EFFECTS IN PRACTISE

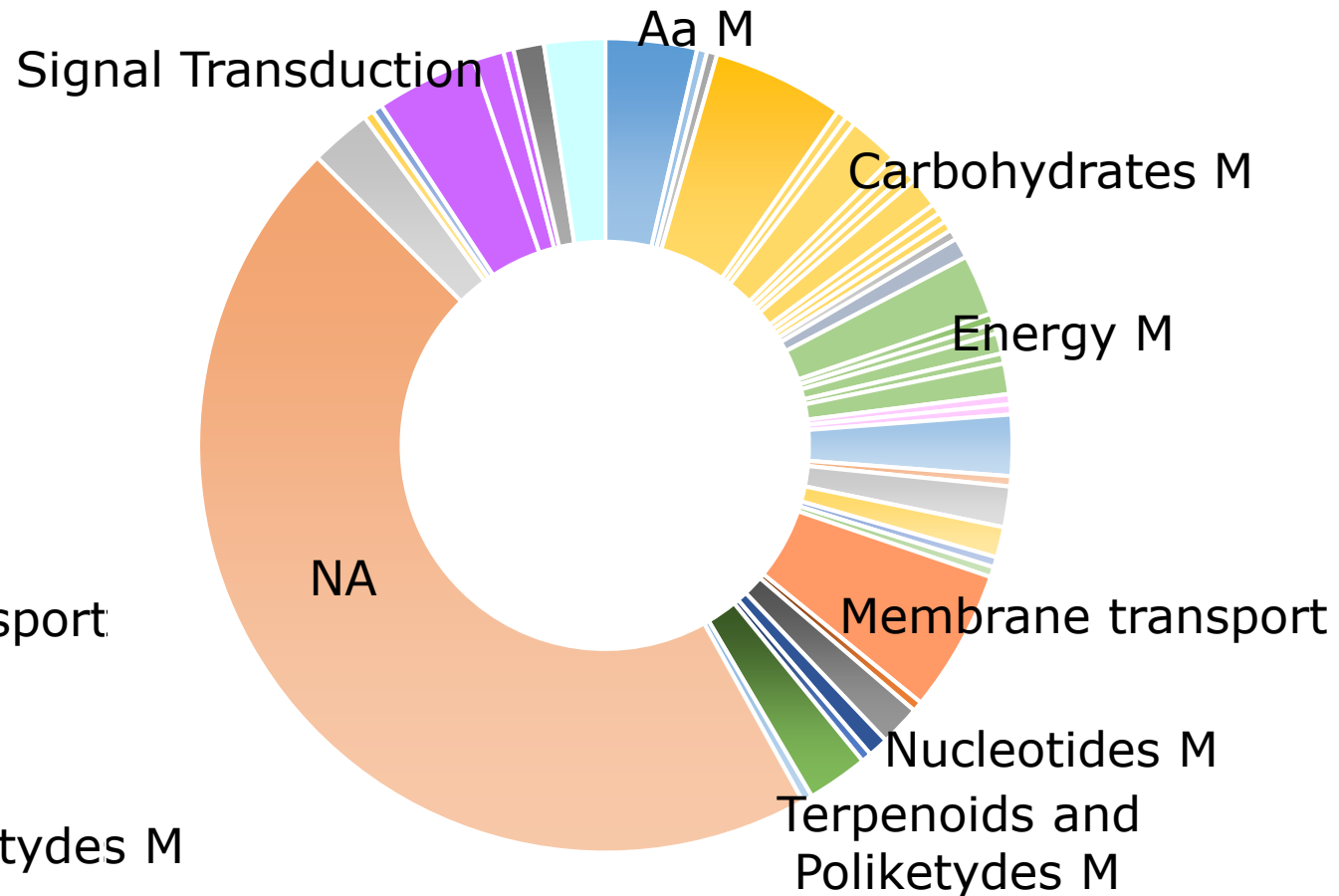
### ANALYSIS WITHOUT wCLR TRANSFORMATION

#### OVERLAPPING BETWEEN MICROBIAL GENES SELECTED BY DA-PLS

##### RELATIVE ABUNDANCES



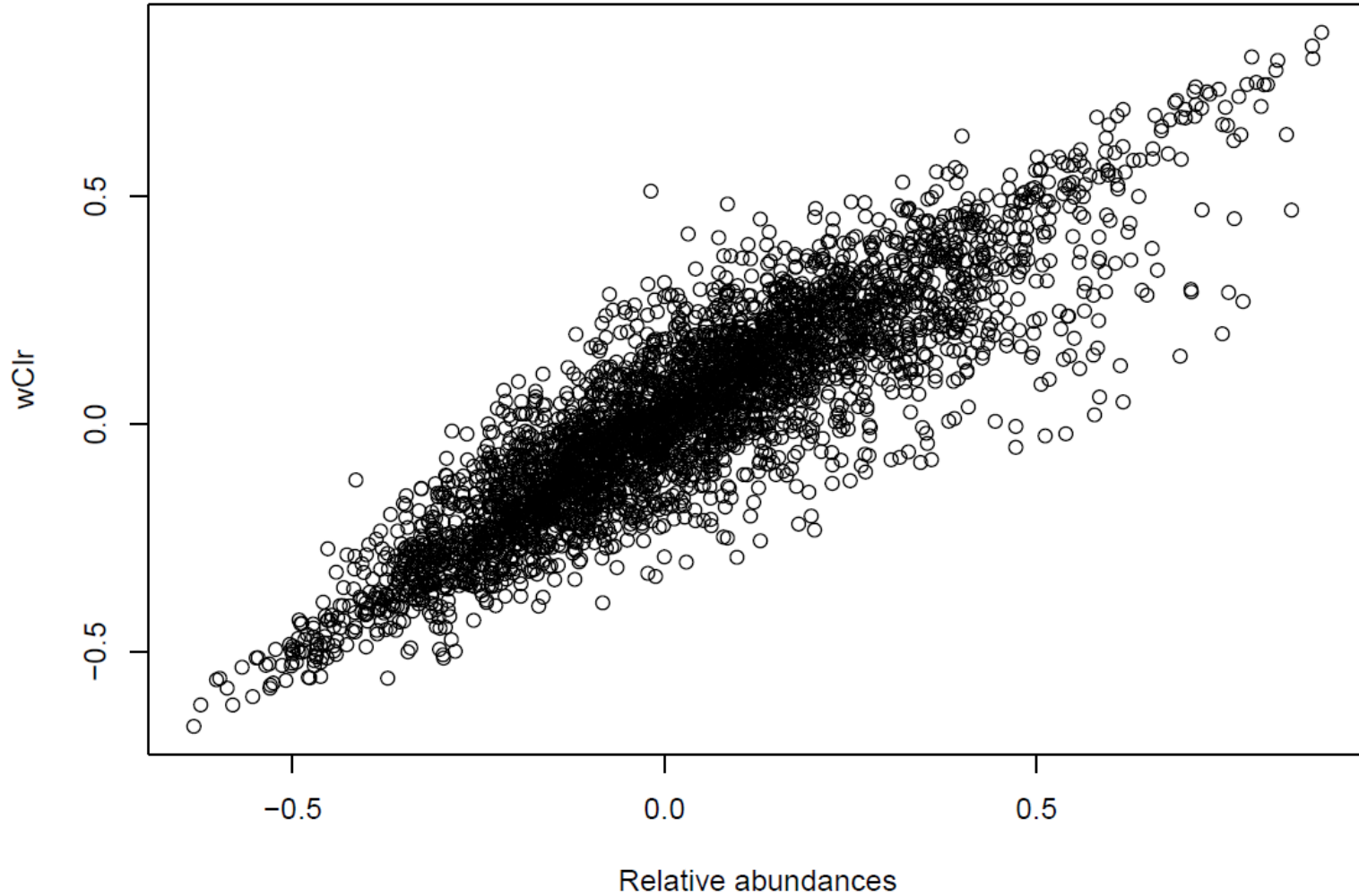
##### wCLR



# RESULTS

## LOG TRANSFORMATION EFFECTS IN PRACTISE

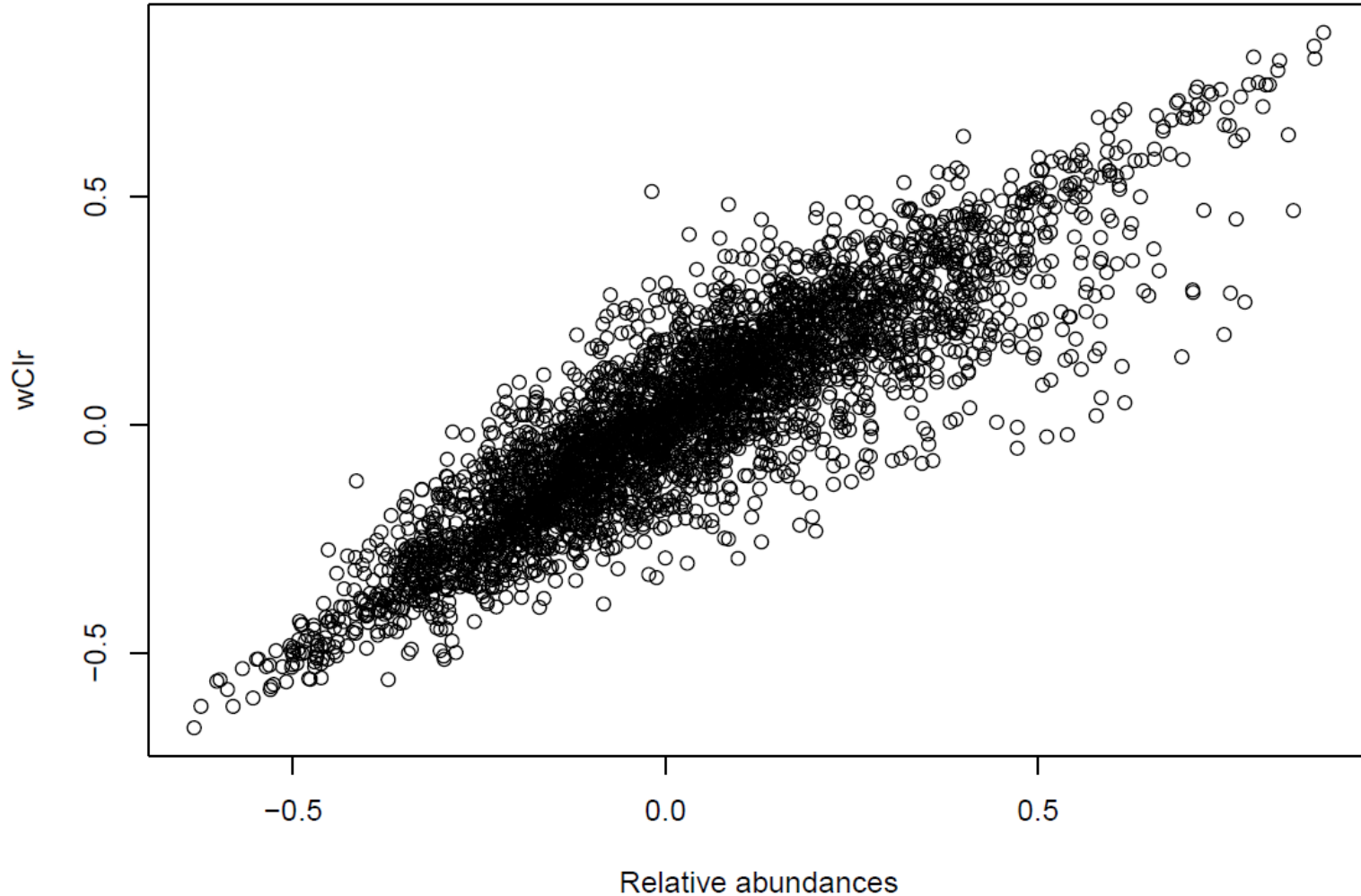
### CORRELATIONS BETWEEN MICROBIAL GENES IN wCLR VS. REL. ABUNDANCES



# RESULTS

## LOG TRANSFORMATION EFFECTS IN PRACTISE

### CORRELATIONS BETWEEN MICROBIAL GENES IN wCLR VS. REL. ABUNDANCES



**Rank of relative abundances  
[ $1 \times 10^{-6}$ ,  $1 \times 10^{-1}$ ]**

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

# CONCLUSIONS



**Selection for IMF modifies the microbial genome**

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**Selection for IMF modifies the microbial's genome**

**Link genome - metagenome**



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

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**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**



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UNIÓN DE ENTIDADES ESPAÑOLAS DE CIENCIA ANIMAL

**THANKS!**



GENERALITAT  
VALENCIANA