

75th EAAP Annual Meeting
1-5 September 2024 - Florence, Italy



ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA



Animal and Food Genomics Group

Molecular phenotyping through metabolomic analyses in pig breeds

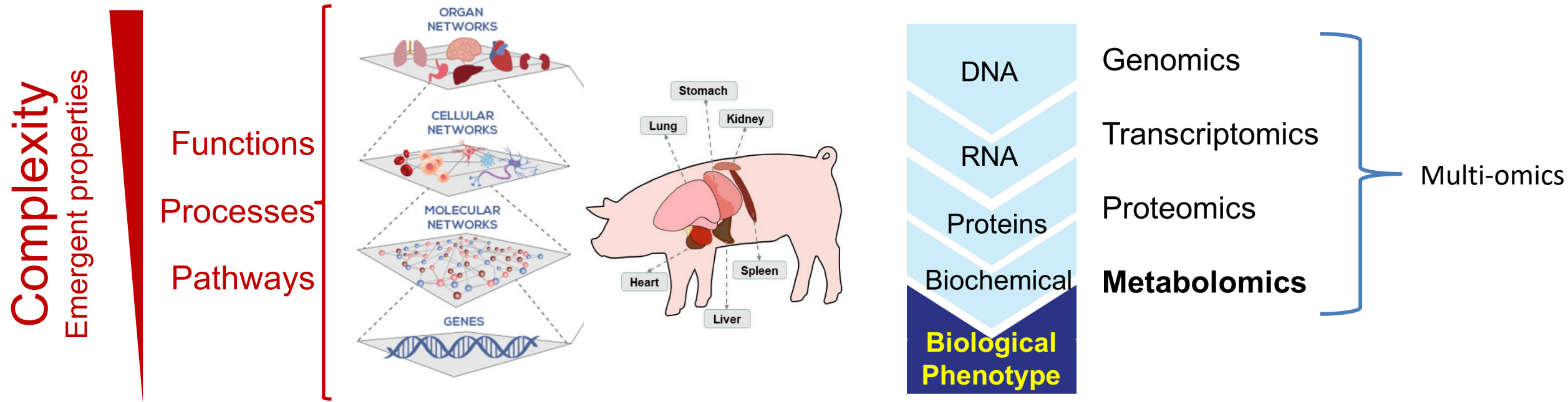
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Biological complexity: an overview

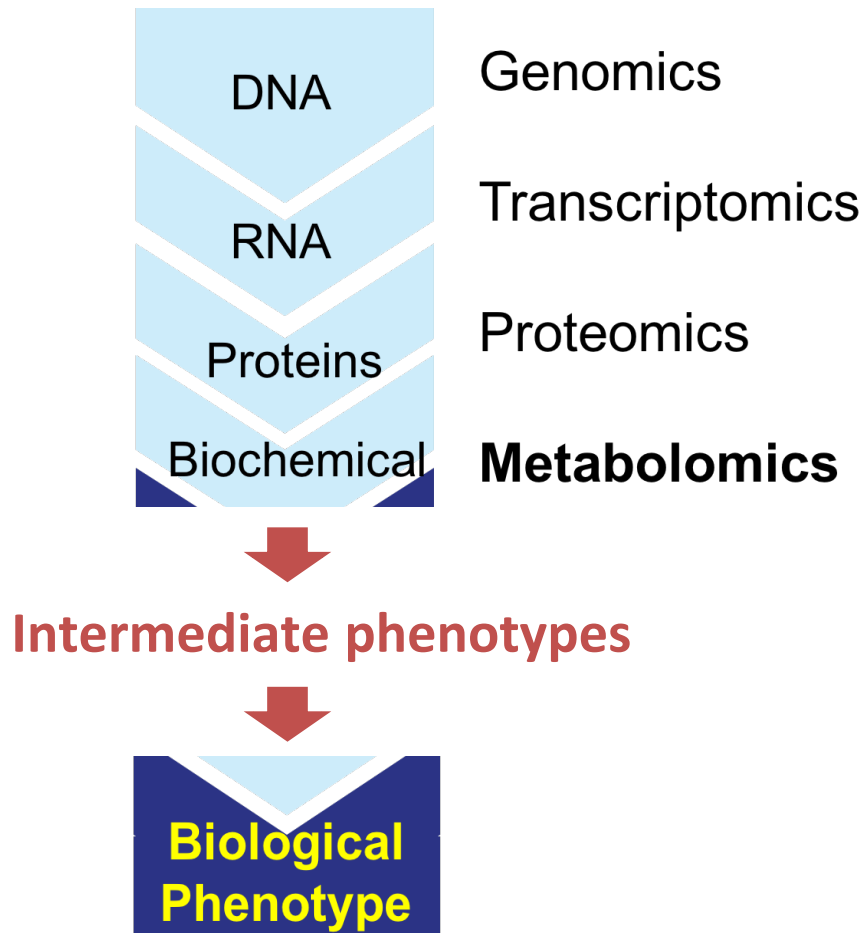
The different **layers of organization** establish complex links allowing properties to emerge.



Processes and pathways interact with each other, defining cell types, organs, and the organism as a whole.

Metabolomics as a molecular phenotyping approach

Metabolites are the end products of cellular processes.



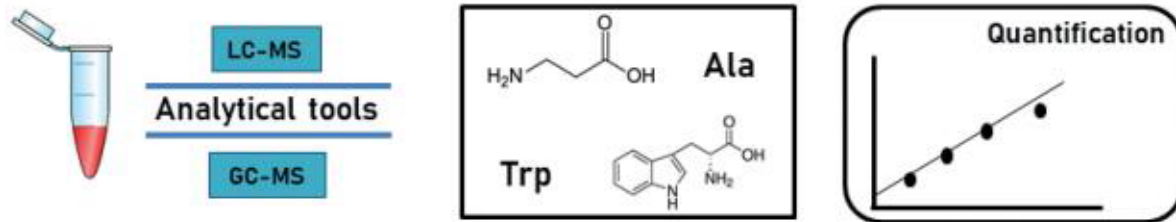
They can help define **intermediate phenotypes**, i.e. precursors to final phenotypes and complex traits

Metabolomics aims to characterize and quantify low molecular weight metabolites (<1.5 kDa) in a biological sample.

Metabolomics as a molecular phenotyping approach

Main approaches:

Targeted Metabolic Profile

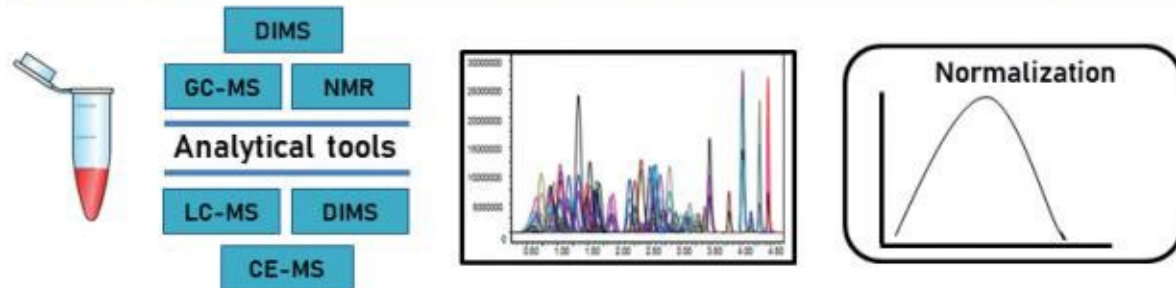


50 - 200 Metabolites



- Low detection limit
- Quantitative
- Limited targets
- Requires standards

Untargeted Metabolic Profile



~1000 Metabolites

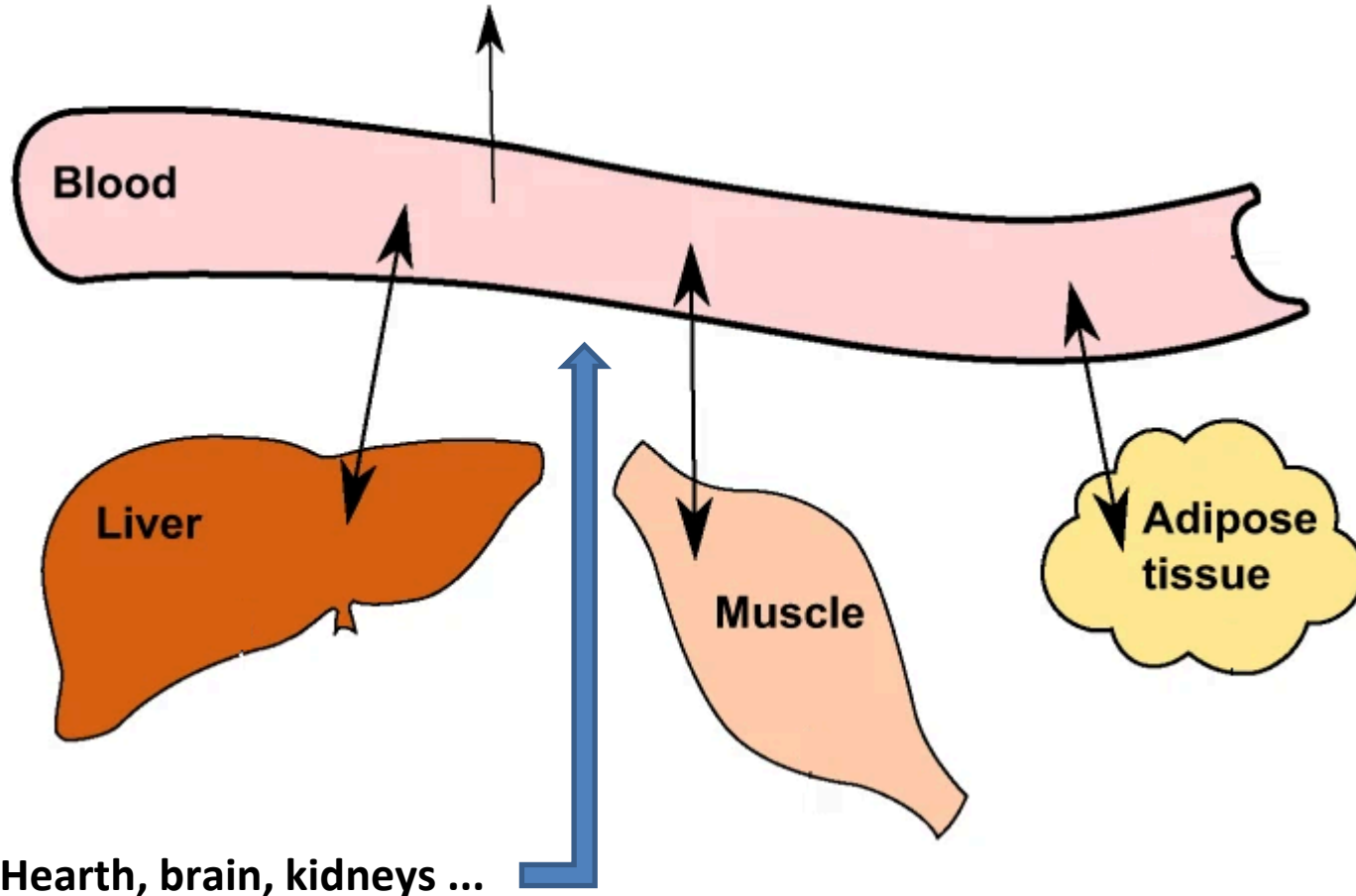


- Comprehensive
- High throughput
- Unexpected/novel metabolites
- Semi-quantitative
- Unknown compounds

Source: De San-Martin et al. 2021
10.20945/2359-3997000000300

Biological matrices for metabolomics

Urine, semen, milk ...



Blood is one of the most widely used matrices

- Each organ is fed and drained by blood
- Blood is sensitive to the effects of health or disease, genetic variation, environment, nutrition, or the impact of toxicants
- It can be easily obtained.

Applications of metabolomic phenotyping: Pilot study on Italian heavy pigs



Animal

Volume 10, Issue 10, 2016, Pages 1741-1748



Metabolomics evidences plasma and serum biomarkers differentiating two heavy pig breeds

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- Biofluid: **Plasma and serum**
- Analysis : **Targeted**
- Comparison: **Between breeds (ILW vs IDU)**

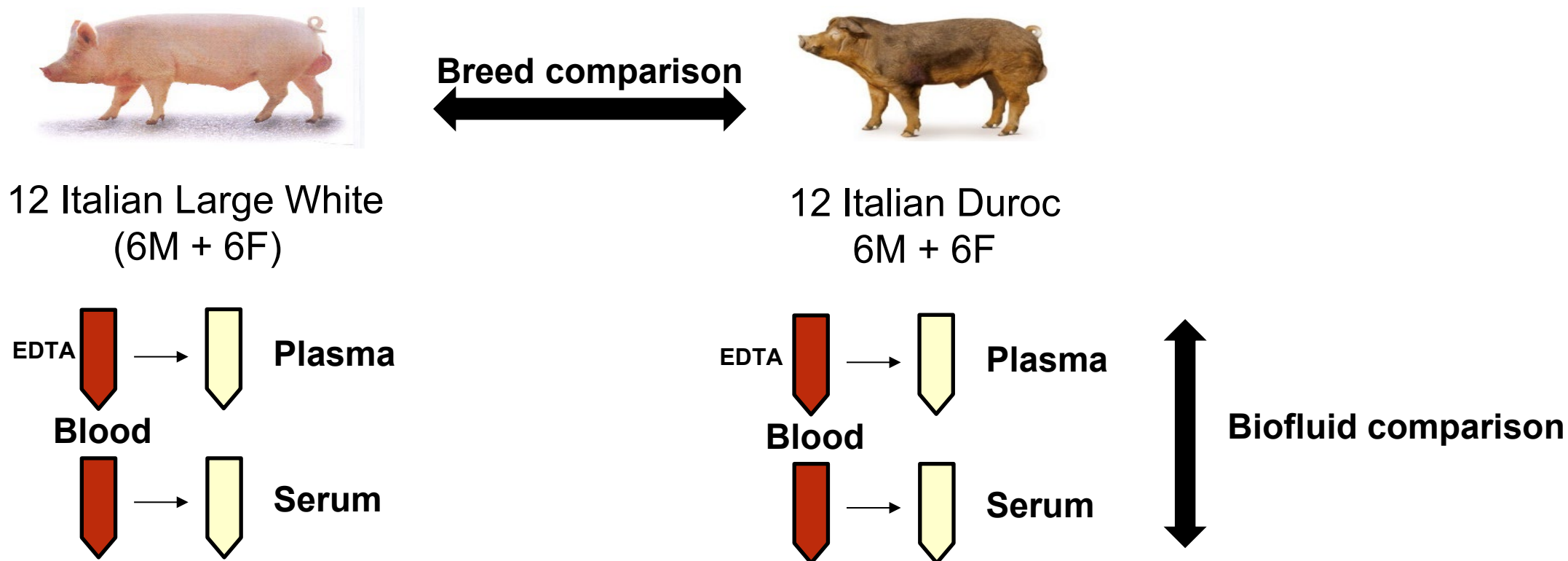
Targeted metabolomics Biocrates AbsoluteIDQ p180 Kit



Metabolite classes	No.	Biological relevance (selected)
Acylcarnitines	40	Energy metabolism fatty acid transport
Amino acids	21	Amino acid metabolism, neurotransmitter metabolism
Biogenic amines	19	Neurological disorders DNA stability, oxidative stress
Hexoses	1	Carbohydrate metabolism
Glycerophospholipids	90	
- lysoPhosphatidylcholine acyl - lysoPC a Cx:x	14	Degradation of phospholipids fatty acid profile
- Phosphatidylcholine diacyl – PC aa Cx:x	38	Dyslipidemia, Membrane composition and damage
- Phosphatidylcholine acyl- alkyl – PC ae Cx:x	38	
Sphingolipids	15	Signalling cascades membrane damage



Applications of metabolomic phenotyping: Pilot study on Italian heavy pigs



Applications of metabolomic phenotyping: Pilot study on Italian heavy pigs

**Sparse Partial Least
Square Discriminant
Analysis (sPLS-DA)**

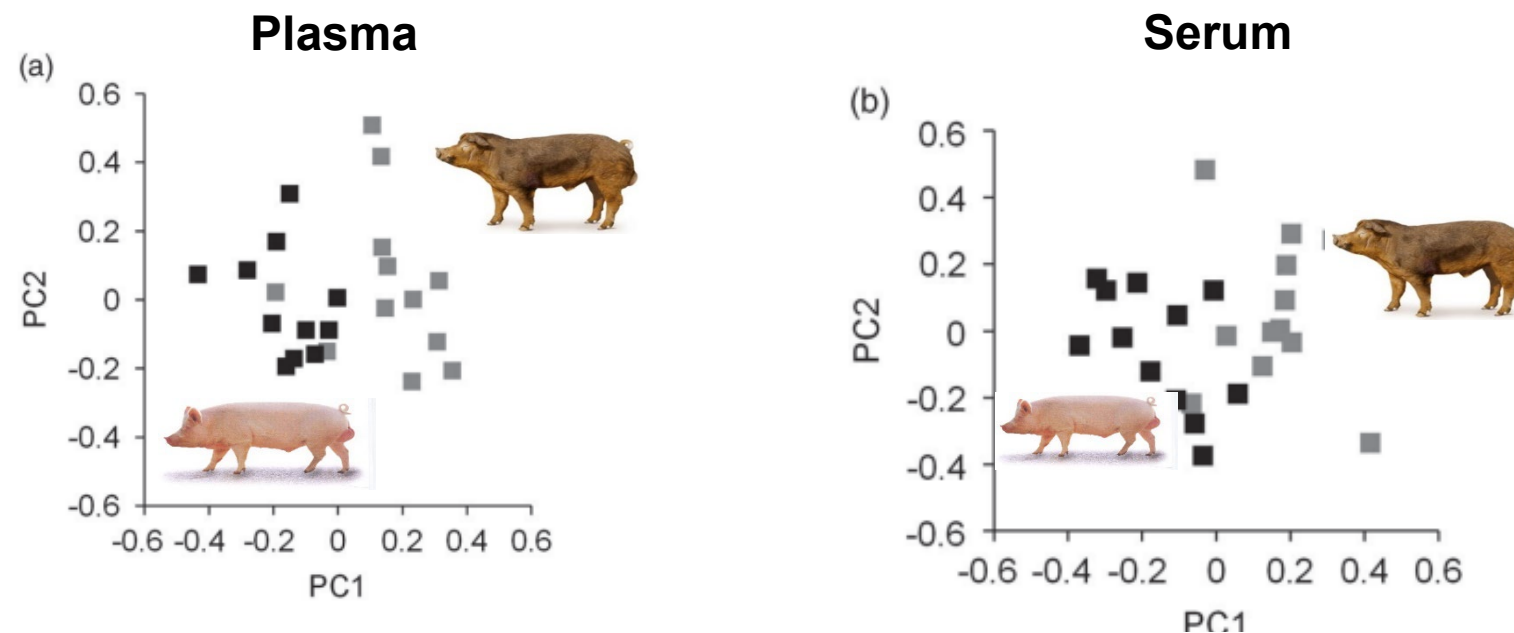
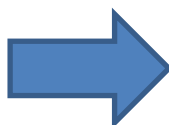


Table 2 Metabolites selected by sPLS-DA that were stable and significant in plasma and serum ($P < 0.20$)

Biofluid	Metabolic class	Metabolite ¹	ID				ILW				Stability ²		Significance ³		Direction ⁴
			Mean _R	SD _R	Mean _r	SD _r	Mean _R	SD _R	Mean _r	SD _r	<i>t</i>	<i>P_{st}</i>	<i>t</i>	<i>P_{si}</i>	
Plasma	Sphingomyelins	SM (OH) C14:1	1.69	0.18	0.14	0.18	1.40	0.50	−0.14	0.15	24	0.037	0.9066	0.000	ID
	Biogenic Amines	Ac.Orn	6.93	3.62	−3.42	3.84	14.11	3.07	3.42	3.01	24	0.064	−1.0855	0.001	ILW
		Kynurenine	0.48	0.25	−0.18	0.27	1.01	0.27	0.18	0.21	24	0.066	0.1169	0.177	ILW
Serum	Sphingomyelins	SM (OH) C14:1	1.74	0.21	0.15	0.20	1.37	0.18	−0.15	0.21	24	0.029	0.2798	0.008	ID
		SM (OH) C16:1	2.43	0.39	0.22	0.34	1.83	0.29	−0.22	0.34	22	0.084	0.2957	0.012	ID
		SM C16:0	74.36	7.12	4.77	6.42	61.78	5.13	−4.77	6.41	24	0.021	0.3759	0.002	ID
	Biogenic Amines	Ac.Orn	6.24	3.48	−3.15	3.77	12.98	2.36	3.15	2.38	24	0.052	−1.1162	0.001	ILW

**7 metabolites
discriminate
between breeds**

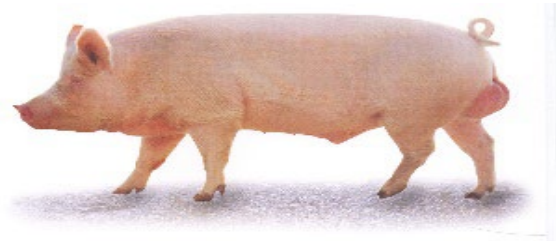


Scaling up

Scaling up the analysis using **untargeted** metabolomics on around **1000 samples**

Italian Large White

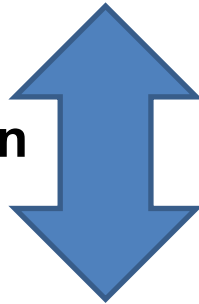
- 727 samples



243 Castrated males

484 Entire gilts (females)

Comparison



Italian Duroc

- 271 samples

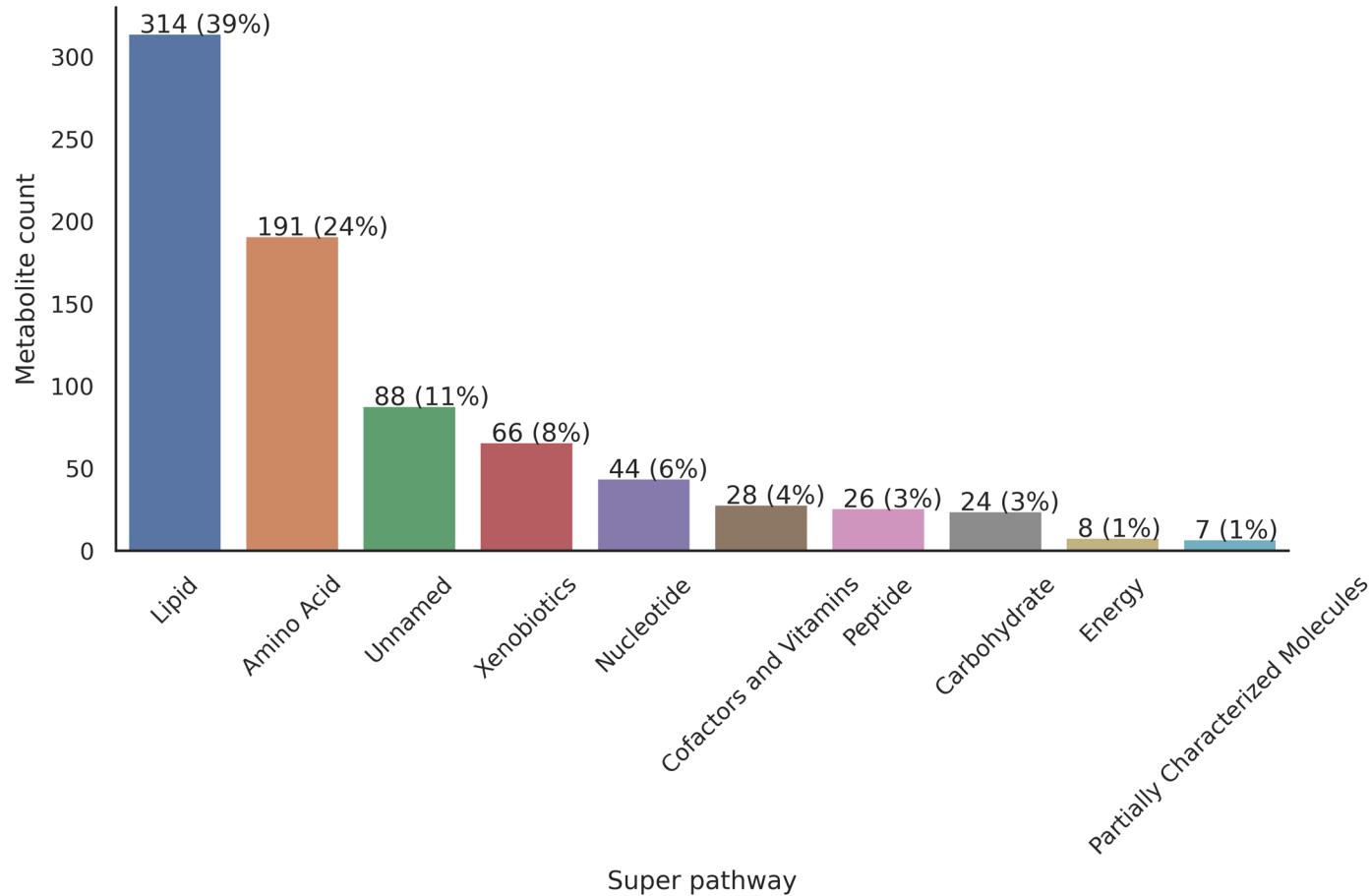


78 Castrated males

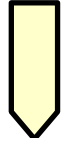
193 Entire gilts (females)



Approach: Untargeted metabolomics



Biofluid: **Plasma**



Platform: **Metabolon**
SMALL MOLECULES, BIG INSIGHTS™

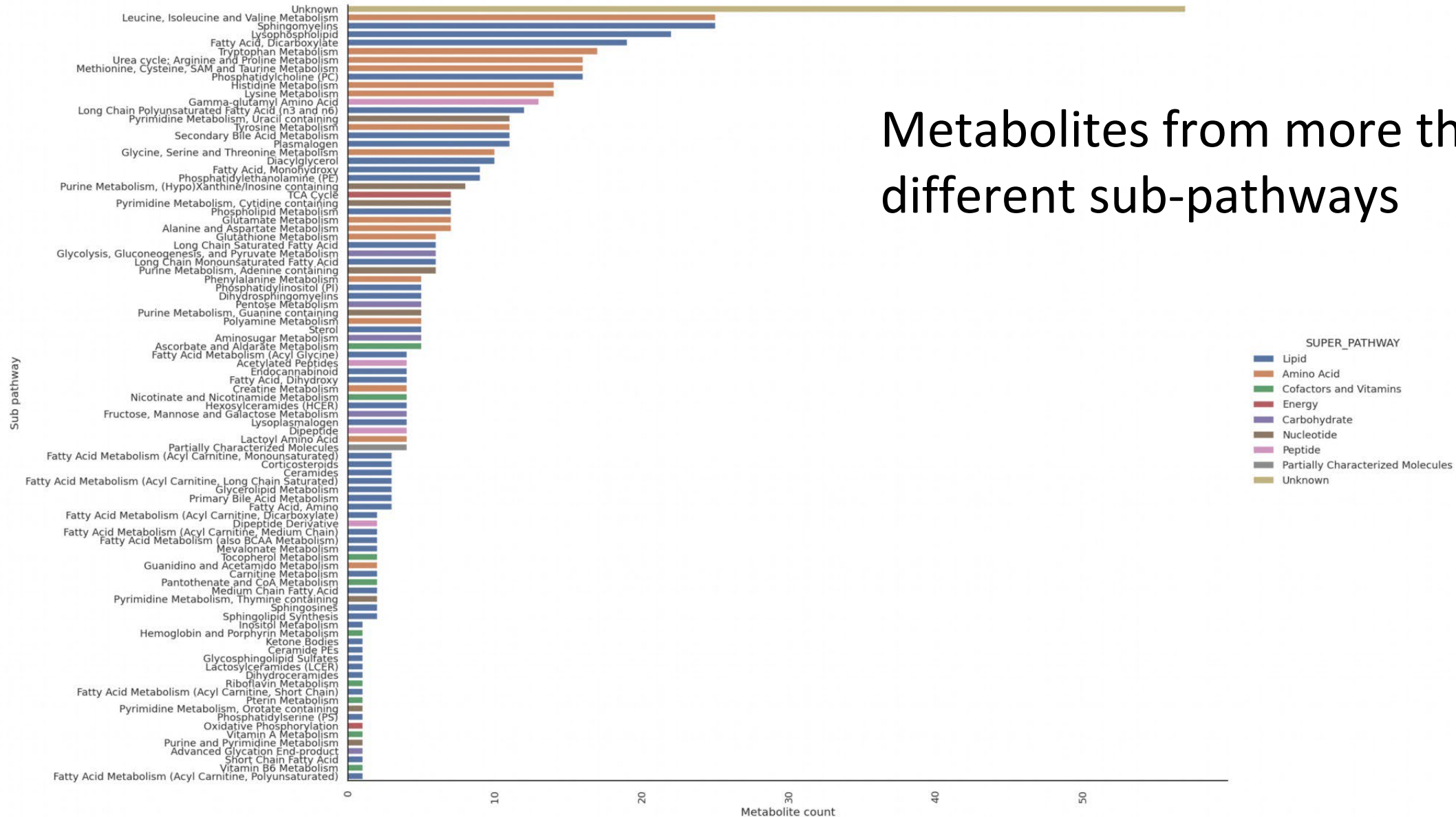
796 metabolites measured:

- 642 Endogenous
- 88 Unnamed
- 66 Xenobiotic



Approach: Untargeted metabolomics

Metabolites from more than 60 different sub-pathways



Quality control

- Internal QC practices implemented by the data providers:
 - QC-normalization
 - Anchor sample merging
- Additional QCs (within breed) :
 - Identified and removed outlier metabolite values (> 5 times outside the interquartile range)
 - Removed metabolites with $> 25\%$ of missing values or outliers
 - Excluded Xenobiotic metabolites from the analysis

580 metabolites passed all QCs and were used in the analysis



Missing data imputation

Missing metabolite values imputed with MICE (Missing data Imputation with Chained Equations)

- Imputation algorithm: Predictive Mean Matching (PMM)
- Predictors: Top 10 correlated metabolites (Endogenous only)
- 5 MICE runs generating 5 datasets each => to account for the random component

Total of **25 imputed datasets**



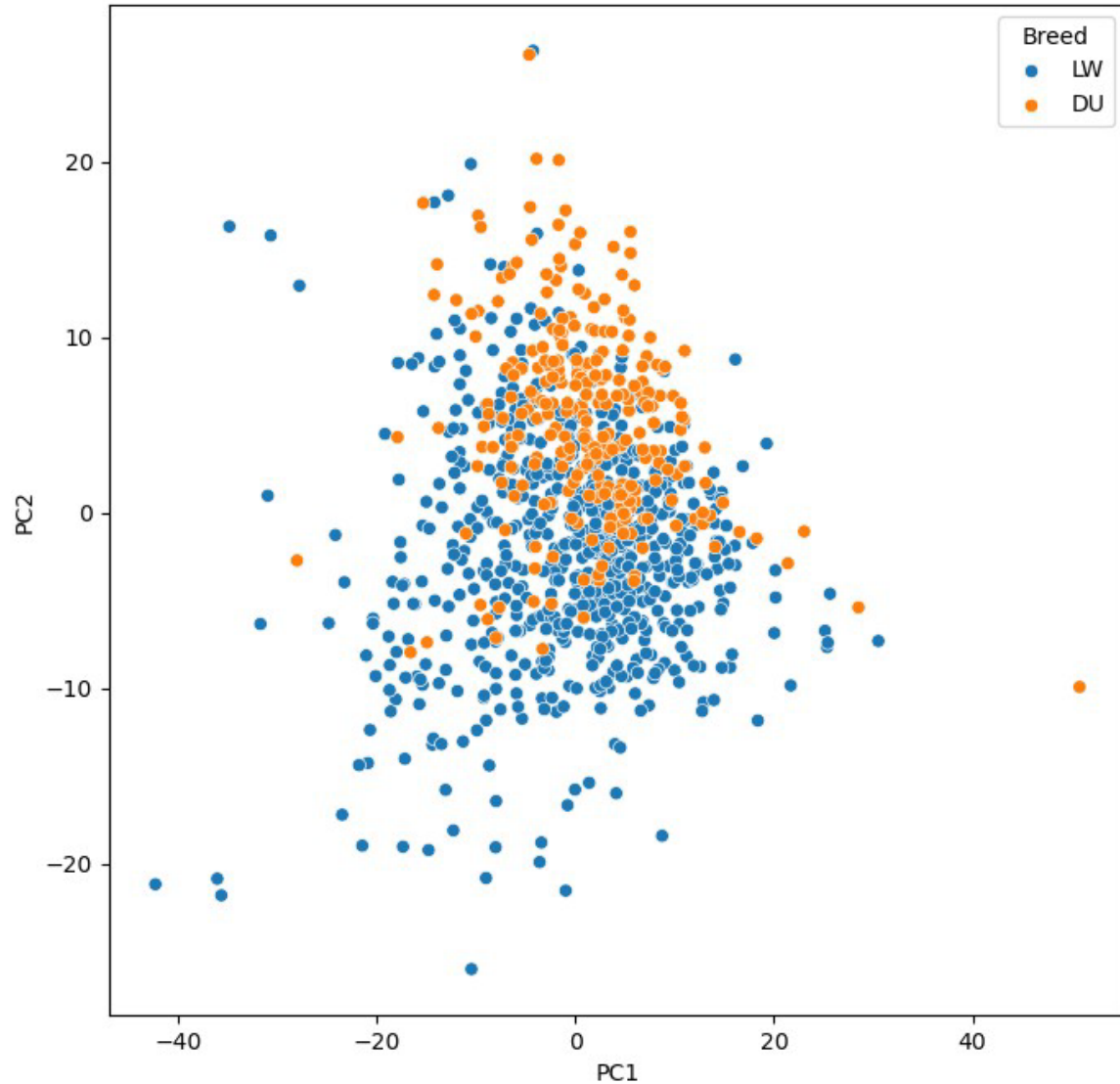
Removal of confounding effects

Confounding effects removed with a linear model:

- Slaughter date
- Weight of the animal
- Sex



Principal component analysis



PCA on all 580 metabolite residuals analyzed after missing data imputation

PC2 shows the most difference between the two breeds



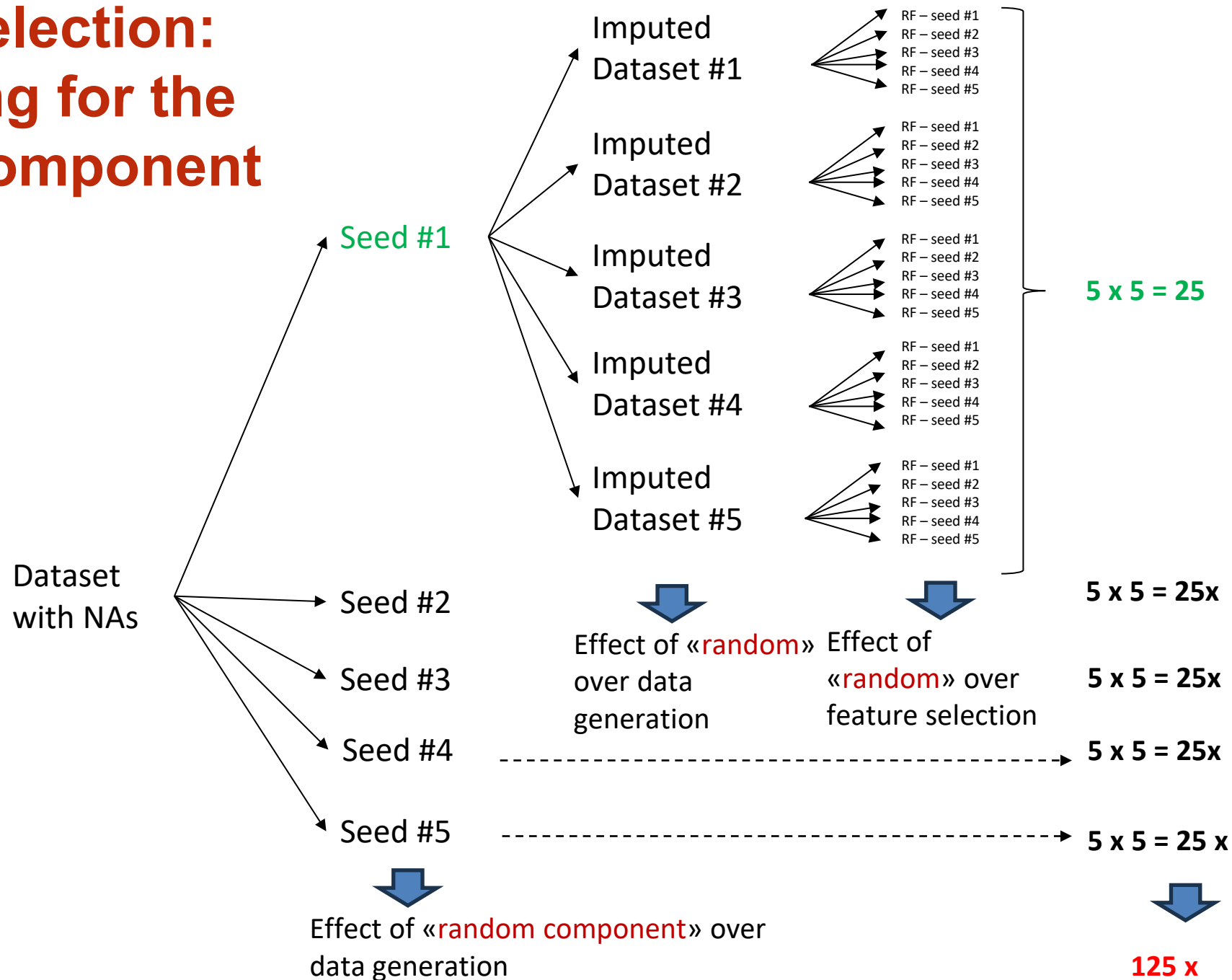
Detection of differentially abundant metabolites

Two methods applied in this study:

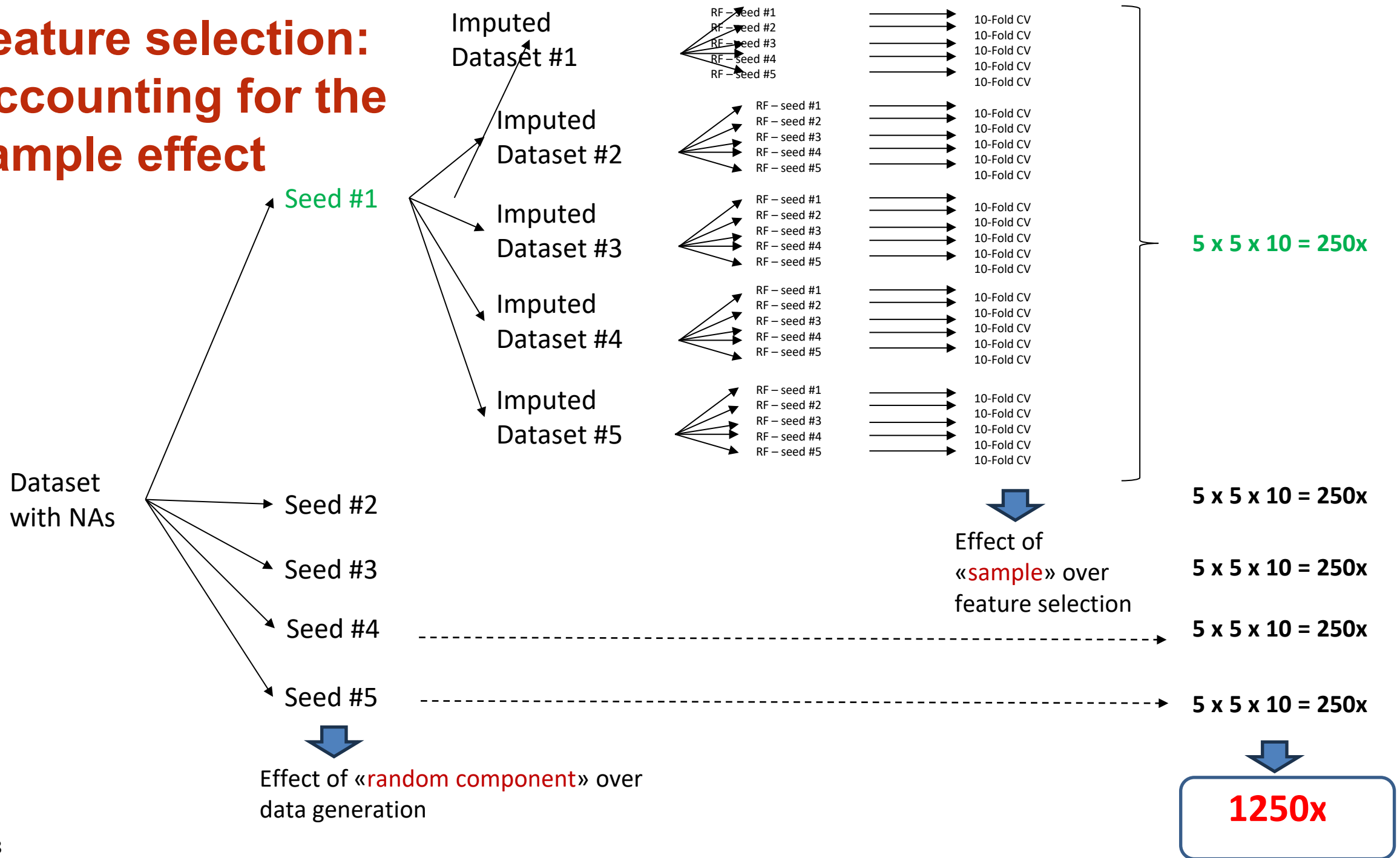
- Sparse Partial Least Squares Discriminant Analysis (**sPLS-DA**): multivariate method best suited for analysing multicollinear data with a high number of features
- **Boruta**: All-relevant feature selection method based on Random Forest classification (machine learning)



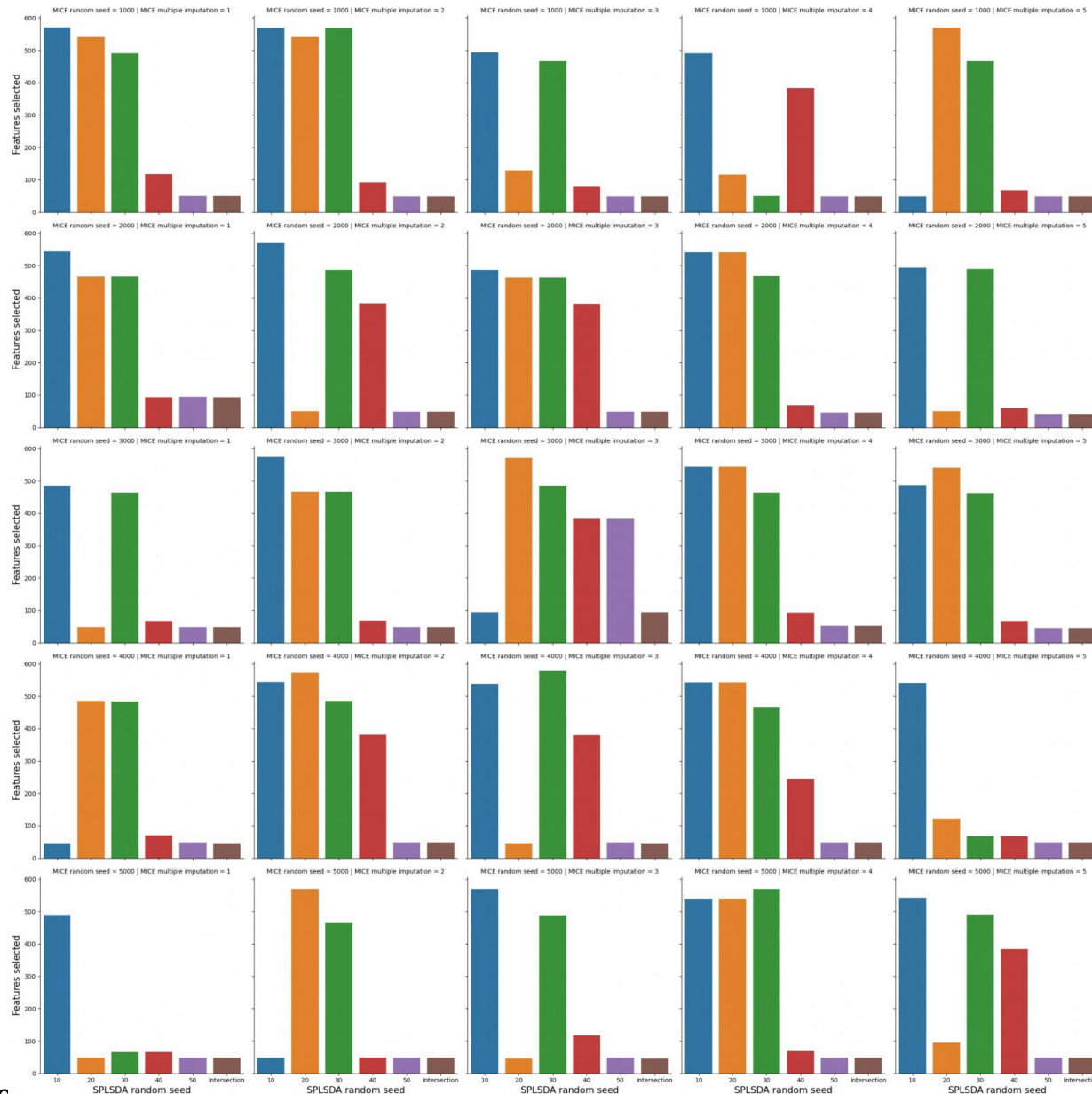
Feature selection: Accounting for the random component



Feature selection: Accounting for the sample effect

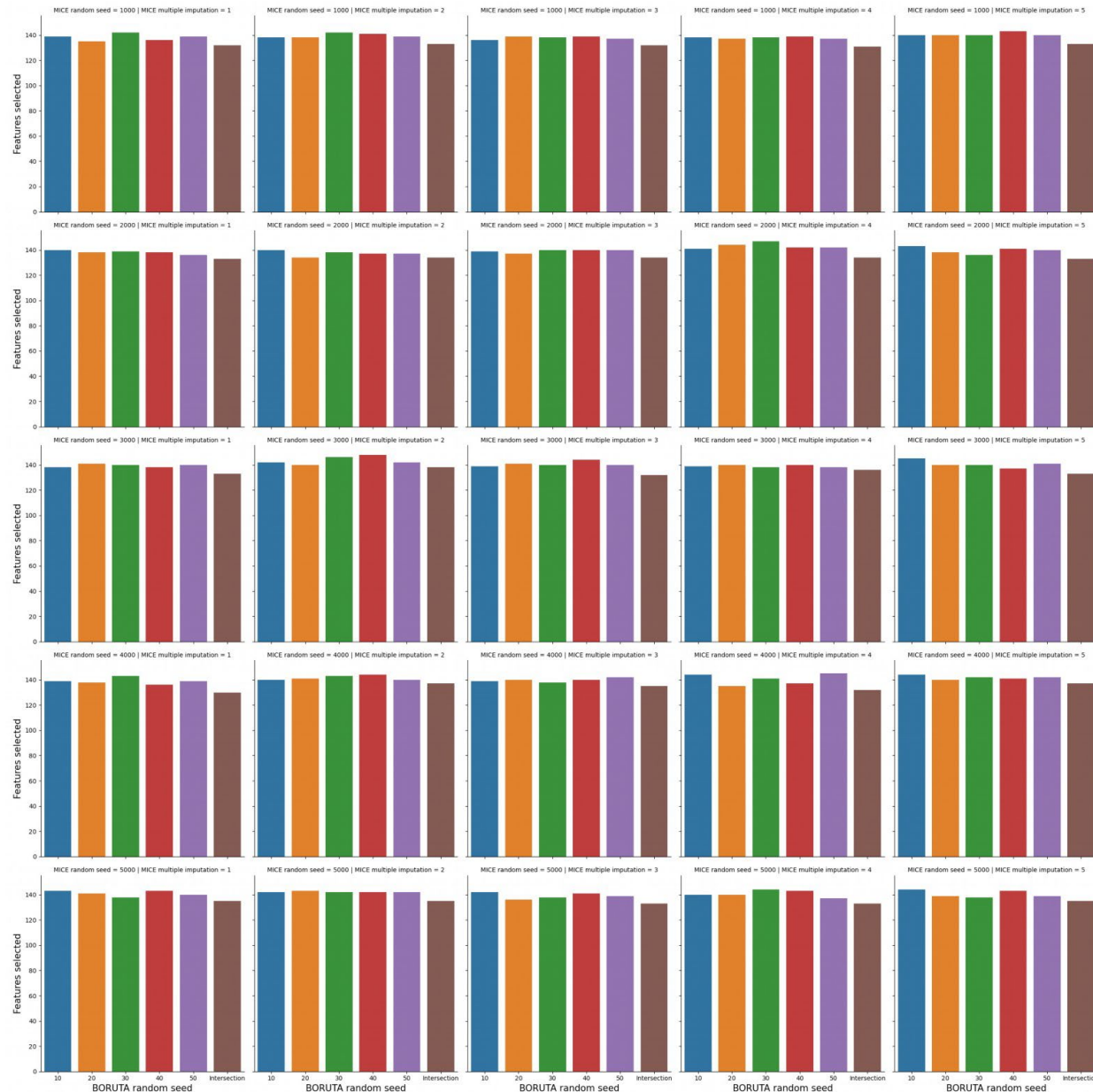


Feature selection results - sPLS-DA



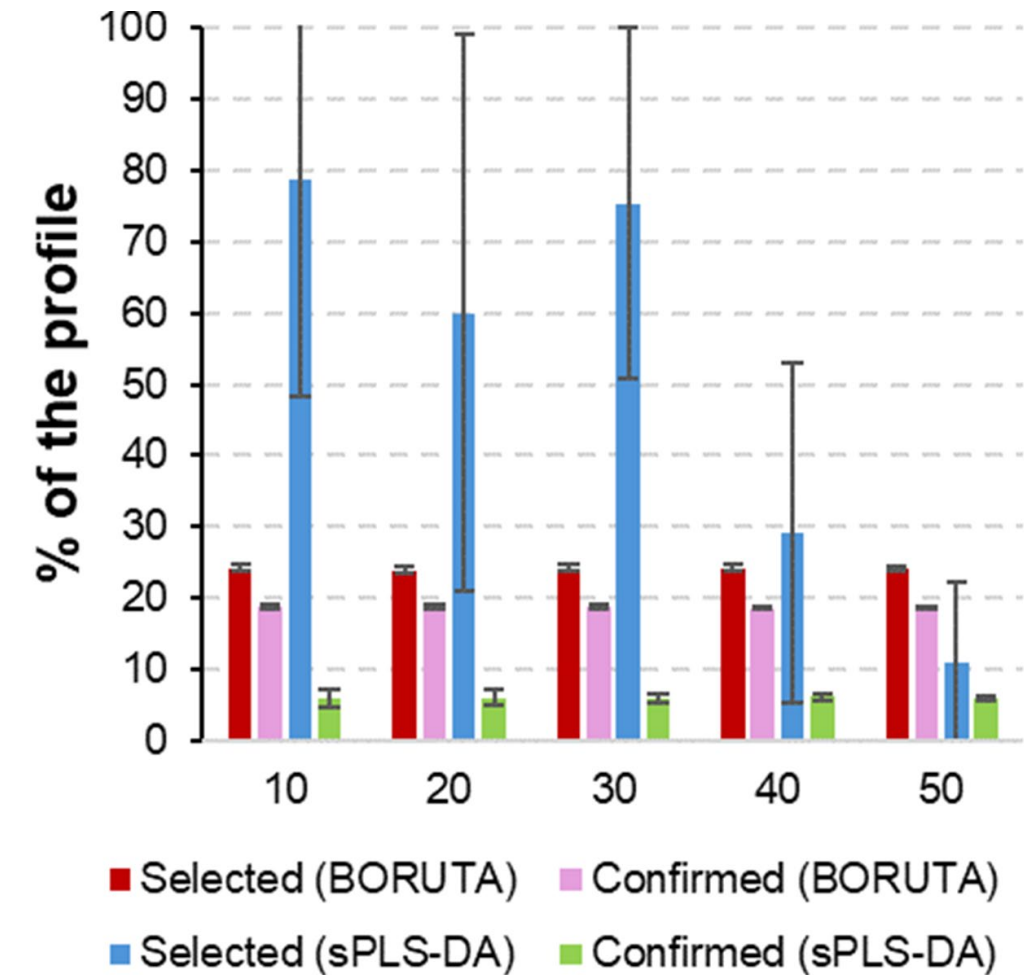
- Each bar represents a feature selection iteration
- sPLS-DA is unstable across runs => **random component**
- 31 metabolites are selected in all iterations and CVs

Feature selection results - Boruta



- Boruta is mostly stable
- 100 metabolites are selected in all iterations and CVs

Comparison between Boruta and sPLS-DA results



- All 31 metabolites selected by sPLS-DA are also selected by Boruta
- 69 metabolites are selected only by Boruta

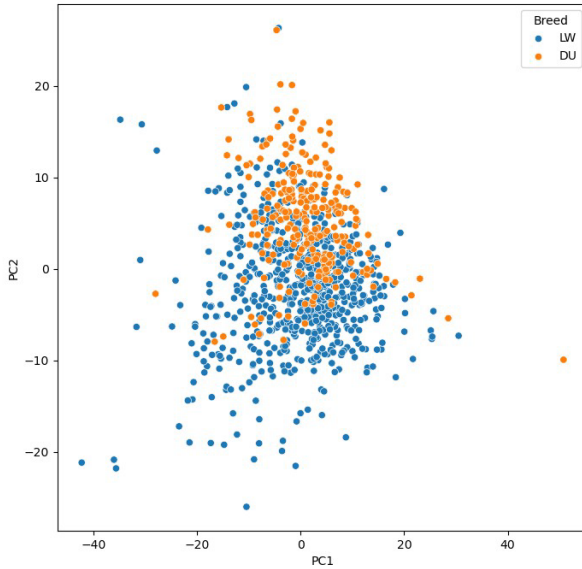


- Total of 100 metabolites selected
- All 7 metabolites from the pilot study were selected again

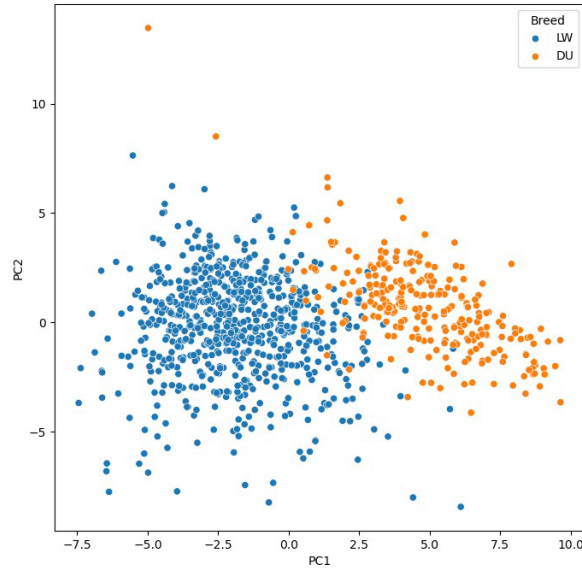


Principal Component Analysis on selected features

a)



b)

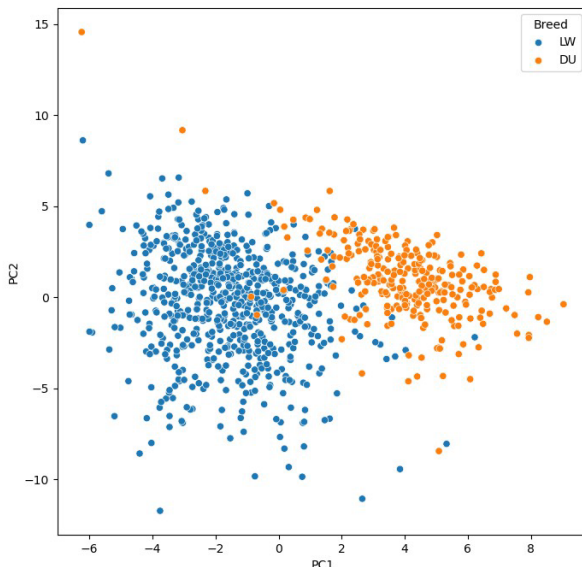


a) All 580 metabolites

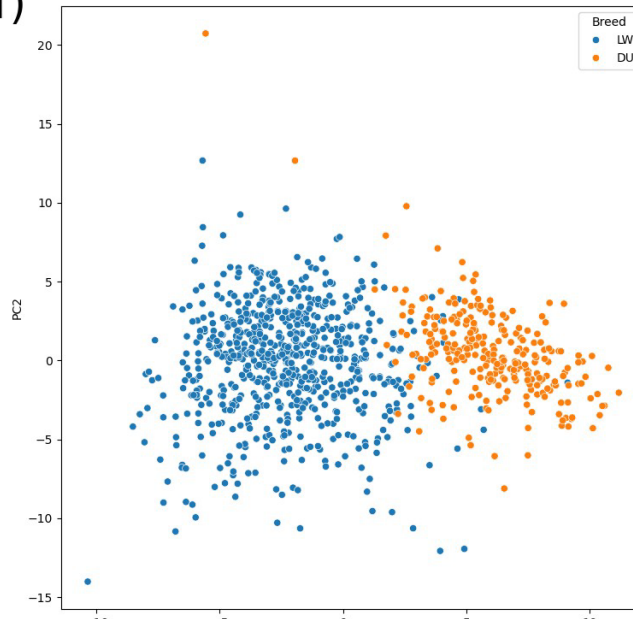
b) 31 metabolites selected by both methods

c) 69 metabolites selected by Boruta only

c)



d)



d) All 100 metabolites selected by Boruta

The selected metabolites show a clear distinction between the two breeds



Pathway analysis of selected metabolites



Conclusions

- We identified several metabolites that could be used as biomarkers to study the biological basis of complex traits in pigs
- We observed intrinsic differences between breeds at the metabolomic level -> due to the **genetic background**



- Five metabolites from the **tryptophan** metabolism pathway discriminate between breeds
- Further investigation on the genetic background determining these differences is warranted
- Metabolomics offers a promising approach for molecular phenotyping



Animal and Food Genomics Group



Luca Fontanesi
Full Professor



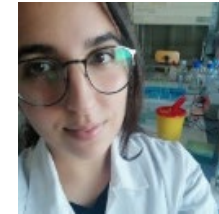
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Acknowledgments



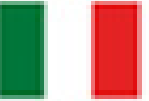
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A N A S
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SUIS.2 [Suinicoltura
Italiana
Sostenibile]



**Thank you !
Questions ?**



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Molecular phenotyping through metabolomic analyses in pig breeds

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