

BIG DATA ANALYSIS: METABOLOMICS



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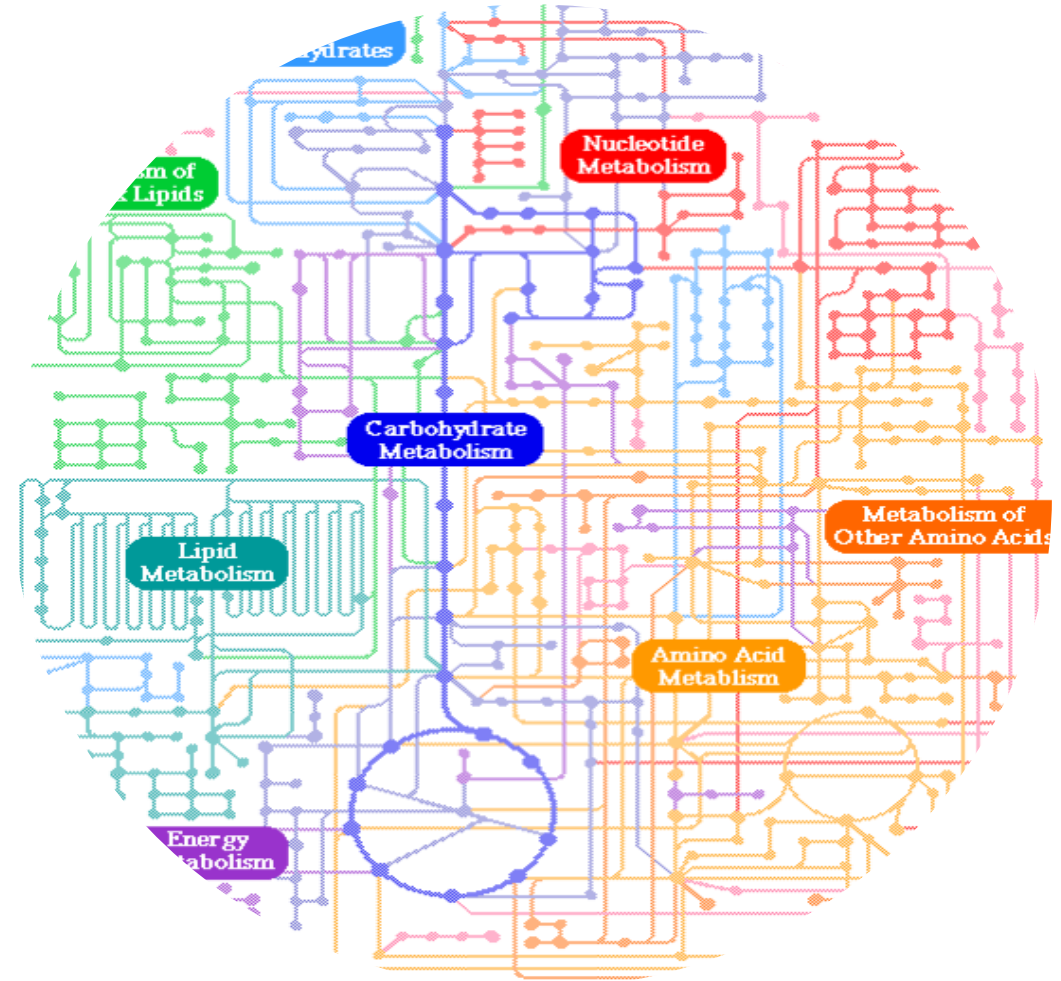
Metabolites



- Metabolites are the molecules of the metabolism
- It is estimated there are around 300,000 metabolites in humans
- Specific metabolites can be potential biomarkers of diagnosis or prognosis, or targets for treatment
- The **metabolome** is the entire set of metabolites in an organism
- **Metabolomics** is the science that studies the **metabolome**

Metabolomics

- **Metabolomics** was the last “omic” technique developed for biomedical research
- Any **phenotype** can be described by the collection of metabolites and their levels in the organism
- As a result, any **pathology** would present **specific alterations** of some metabolites
- The best example of this is **glucose** for the diagnosis of diabetes



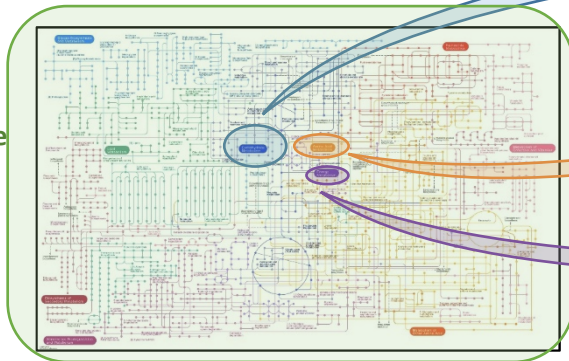
Types of strategy in metabolomics



Untargeted (metabolic fingerprinting)

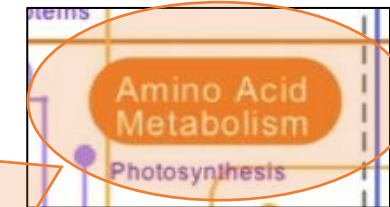
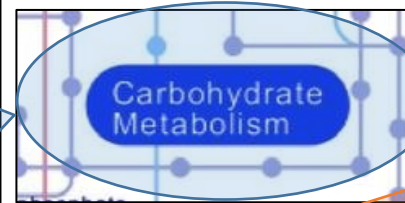
- ✓ Studies differences in metabolite **relative abundances** between groups
- ✓ Ideal for finding **novel biomarkers**
- ✓ Understand biological processes
- ✓ No previous knowledge or hypothesis needed

Whole
metabolome

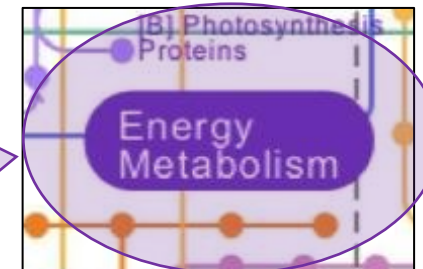


Targeted

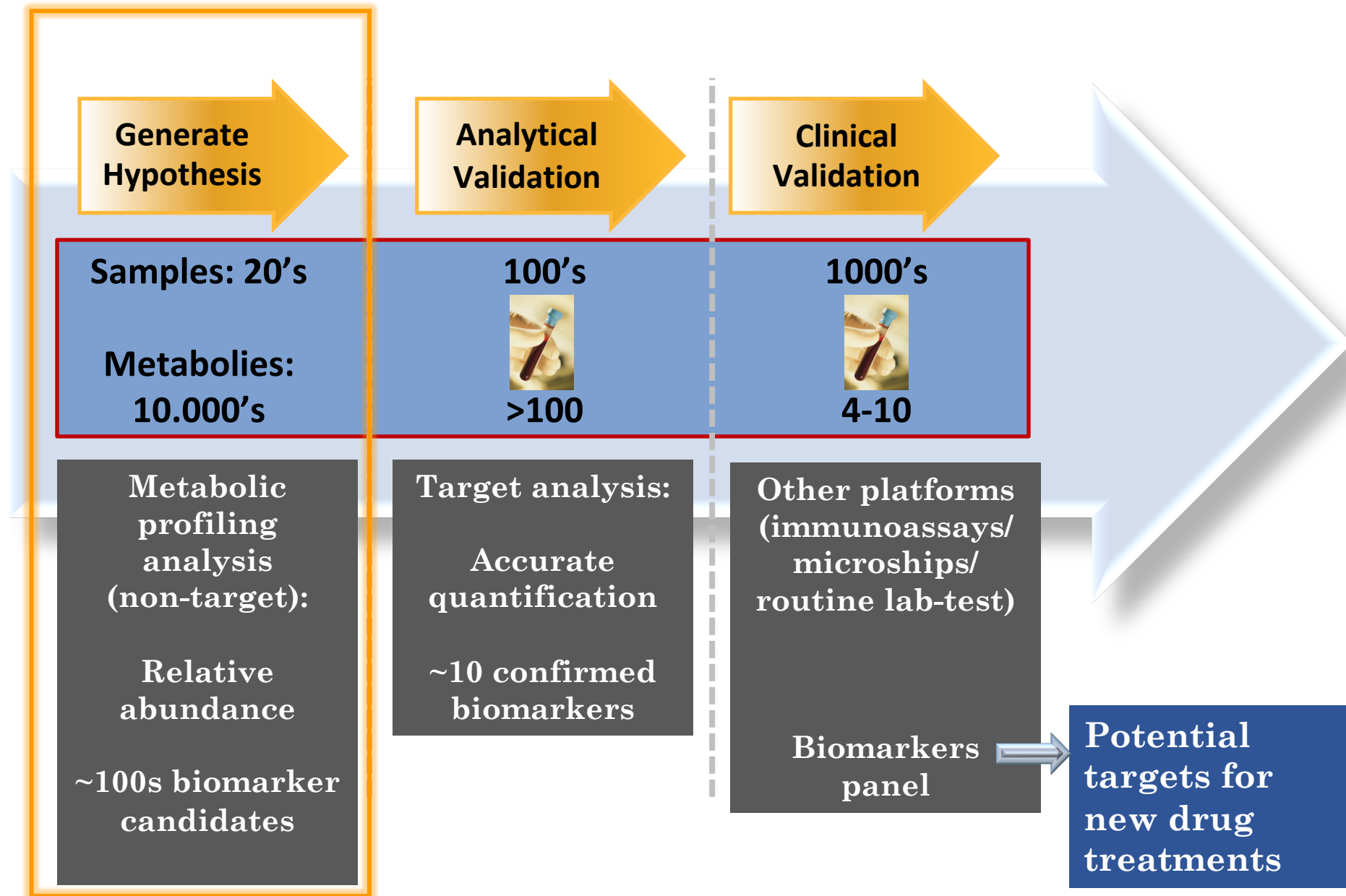
- ✓ **Accurate quantification** of a limited set of metabolites
- ✓ Needs previous knowledge



Specific sets of
metabolites



Workflow for biomarker discovery in metabolomics



MS related techniques used in metabolomics

Separation technique



High Performance
Liquid Chromatography
(HPLC)



Gas chromatography
(GC)



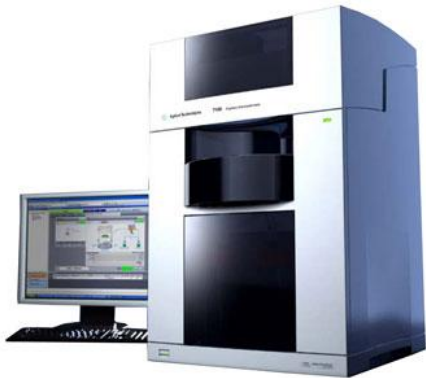
Detection technique



Single quadrupole



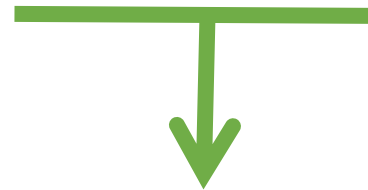
Quadrupole Time of
Flight (Q-ToF)



Capillary electrophoresis
(CE)

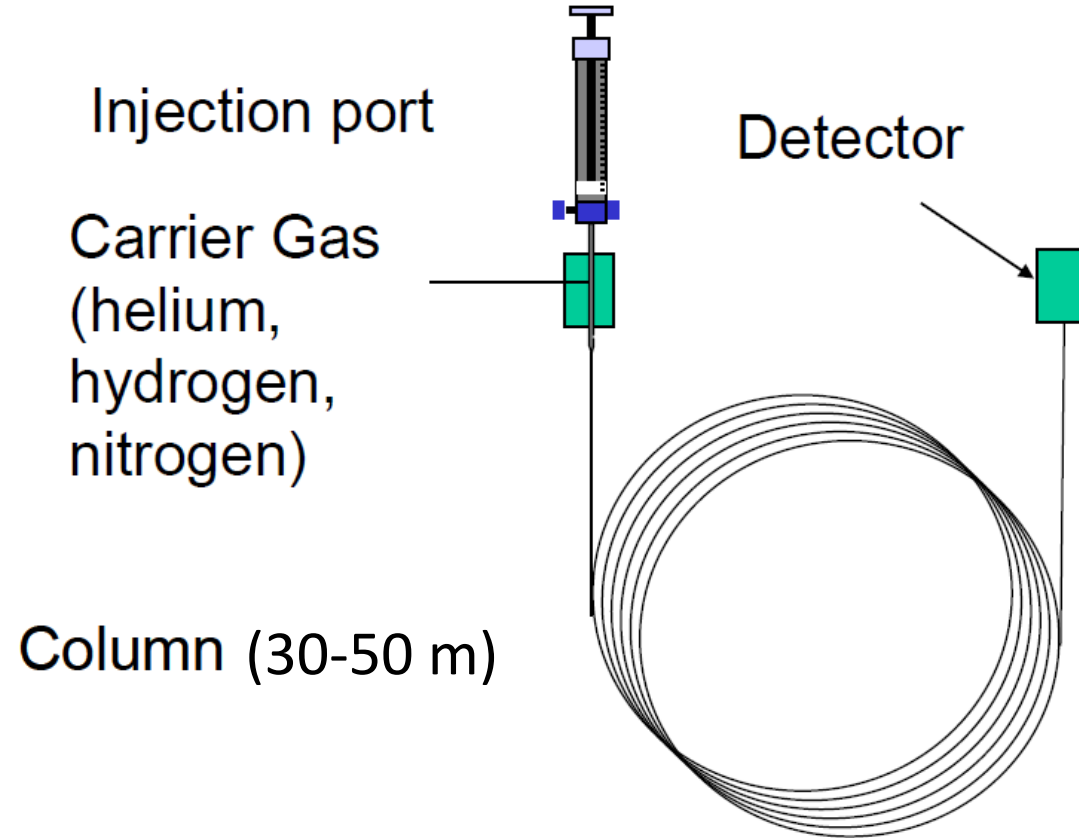
Gives a Retention Time (RT)

Gives a mass/charge ratio (m/z)



RT + m/z = Describes a specific metabolite

Gas Chromatography coupled to Mass Spectrometry (GC-MS)



- GC- MS is mainly used to study volatile metabolites
- Metabolites are separated depending on boiling points: The smaller boiling point metabolites exist first

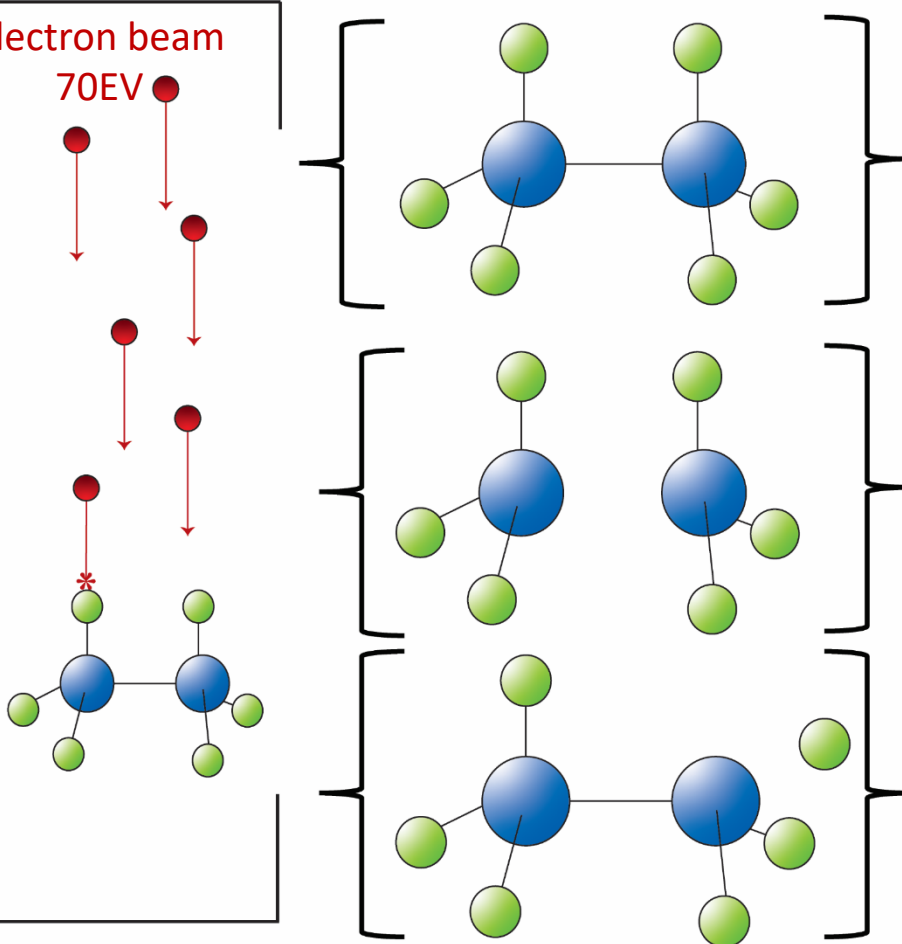
Ion source in GC-MS: Electron Ionization (EI)

Metabolites are broken
in the impact chamber

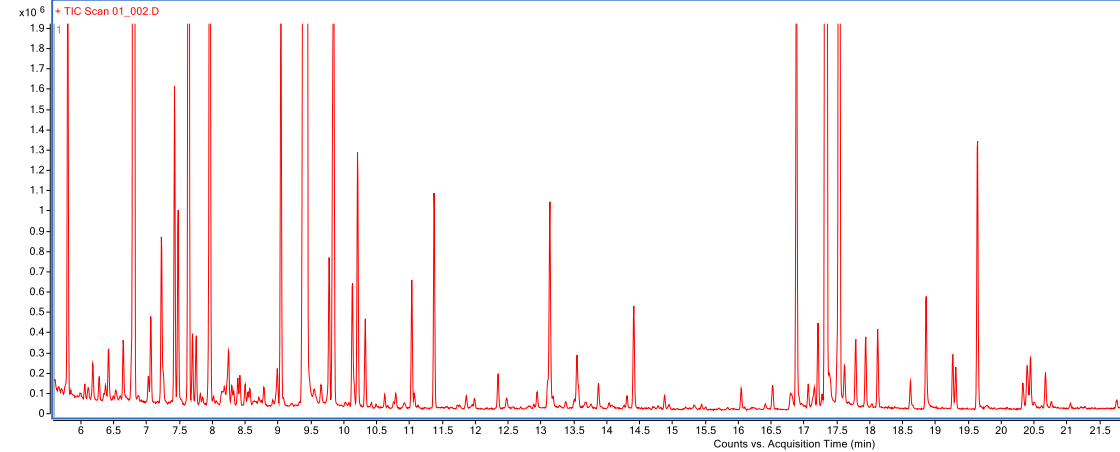
Possible fragments detected

Volatile
metabolites

Electron beam
70eV



Typical GC-MS chromatogram of a plasma sample



Advantages & Disadvantages of GC-MS



- ✓ Good separation of complex mixtures
- ✓ High precision
- ✓ Robust
- ✓ Ideal for volatile samples such as exhaled breath
- ✓ Existence of extensive databases (used since 70s)



- ✗ Complicated sample treatment in order to make compounds volatile (Derivatization)

Liquid Chromatography coupled to Mass Spectrometry (LC-MS)

Agilent 6510 Quadrupole Time-of-Flight LC/MS



Advantages & Disadvantages of LC-MS



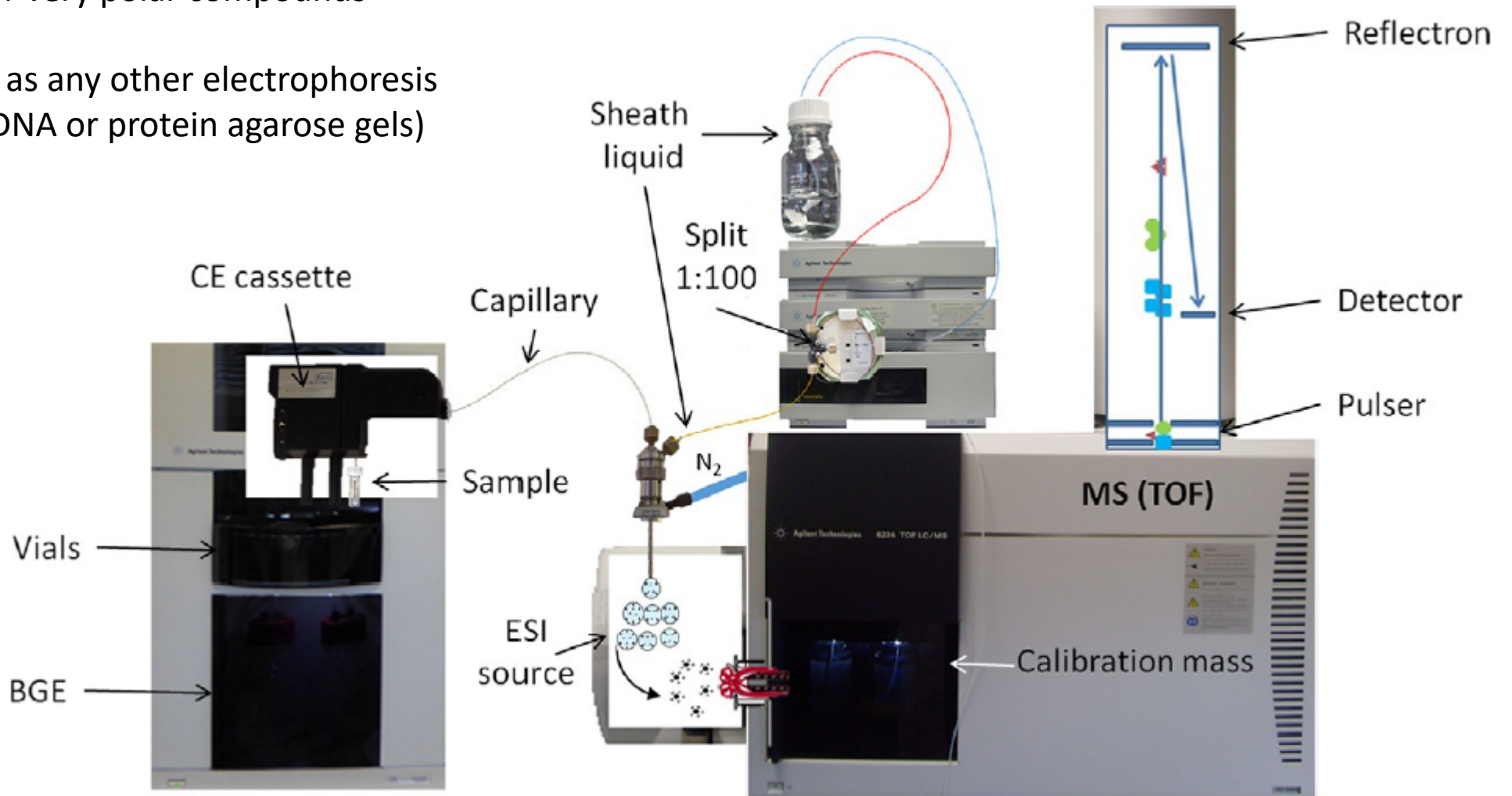
- ✓ Great coverage of metabolites detection (from small polar molecules (Aa) until big non polar molecules (triglycerides))
- ✓ High mass accuracy
- ✓ Robust



- x Identification of compounds in a non targeted study is very complex
- x Laborious data treatment

Capillary electrophoresis coupled to mass spectrometry (CE-MS)

- Ideal technique for very polar compounds
- Separation Works as any other electrophoresis experiment (e.g. DNA or protein agarose gels)



Advantages & Disadvantages of CE-MS



- ✓ Small volume required
- ✓ Sample preparation is minimal for polar samples such as urine or tears
- ✓ Separation of ionic and polar compounds



- ✗ Lower sensitivity than LC-MS: Injection of nanolitres of sample
- ✗ Complex identification: Only possible by using commercial standards and in Ion Source fragmentation

LC-MS, GC-MS and CE-MS are complementary



**Liquid Chromatography coupled
to Mass Spectrometry
(LC-MS)**

Metabolites in solution
with a full range of
polarities

**Gas Chromatography coupled
to Mass Spectrometry
(GC-MS)**



Volatile metabolites

More analytical techniques = More information



**Capillary Electrophoresis coupled
to Mass Spectrometry
(CE-MS)**

Polar metabolites

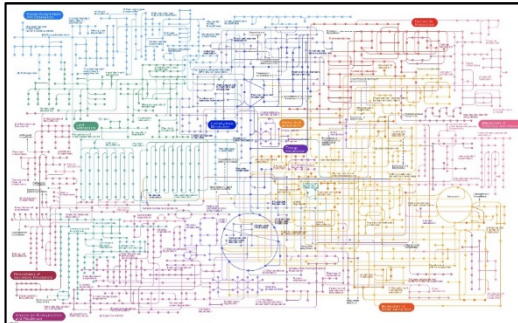
Types of strategy in metabolomics



Untargeted
(metabolic
fingerprinting)

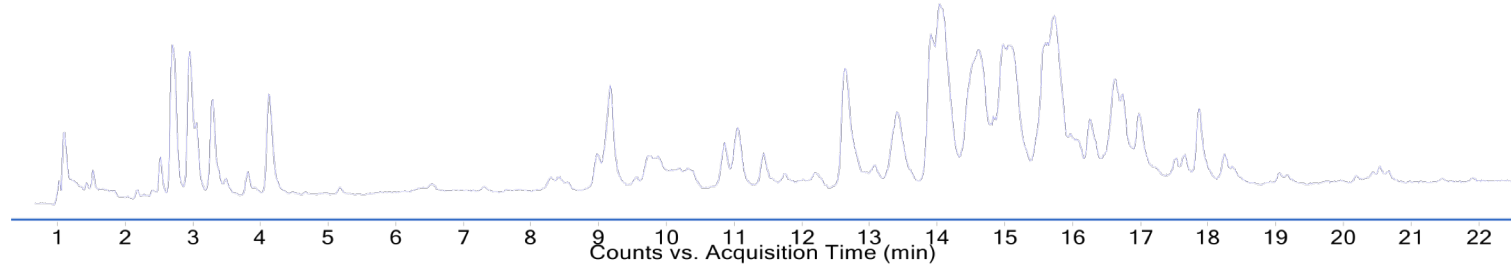
- ✓ Studies differences in metabolite **relative abundances** between groups
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Whole
metabolome

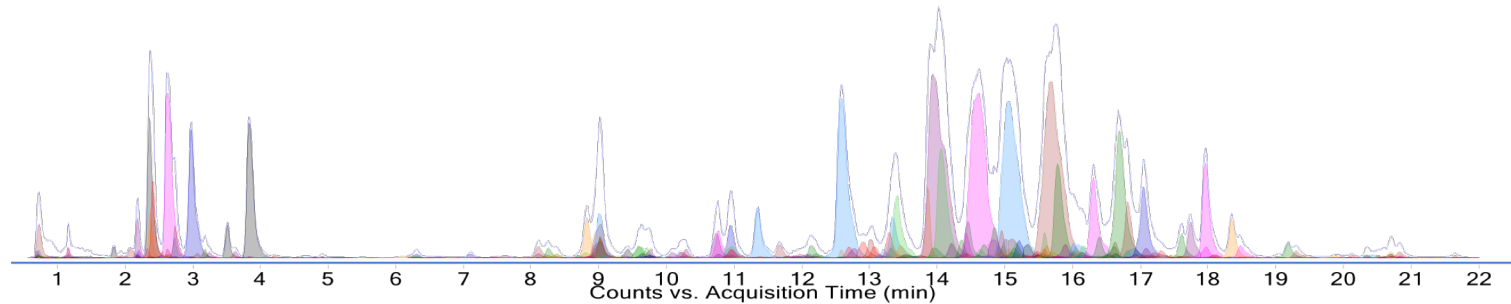


Data pre-processing

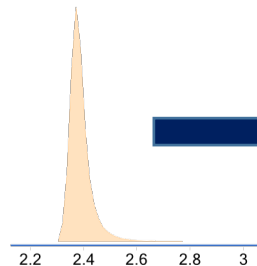
- Typical metabolic profile



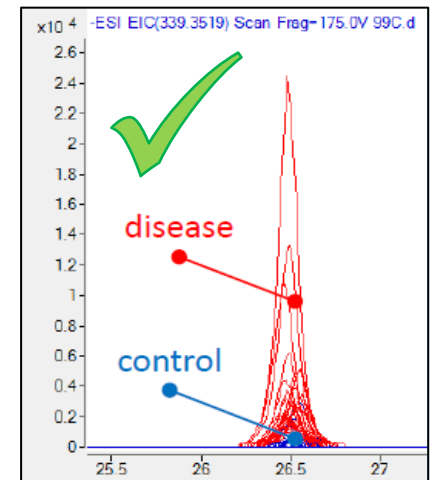
- Underneath, the profile contains metabolites



- Each metabolite is characterized by:



Mass: 543.3390
RT: 2.37
Area: 61109428



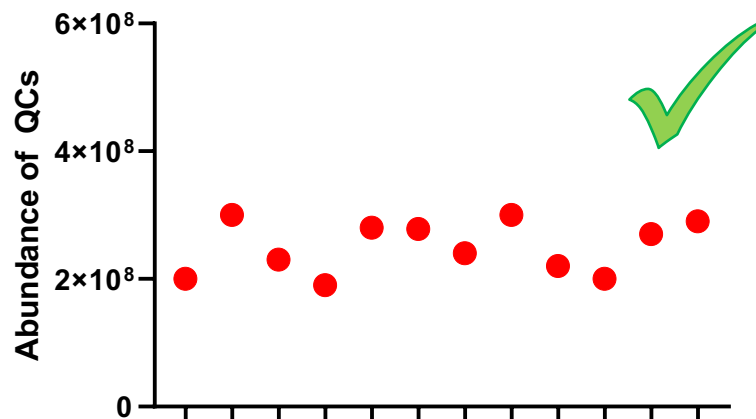
Assessing quality of data measurements: Filtering unreliable metabolites

❑ Different filters are applied to assure the quality of the data:

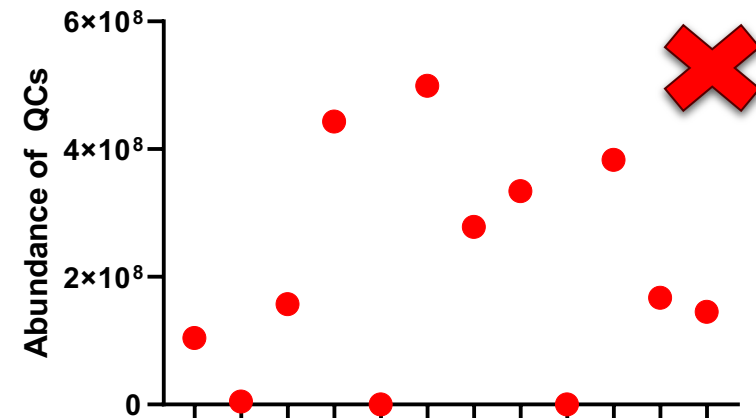
- Remove features in the blanks
- Remove metabolites that have high coefficient of variation ($>30\%$) on Quality Control samples (QCs)
- Remove metabolites that are not present in a sufficient number of samples (depends on experimental setup)

❑ * If concentration of the samples is different (e.g. in urine samples) normalization of data will be needed

Reliable metabolite

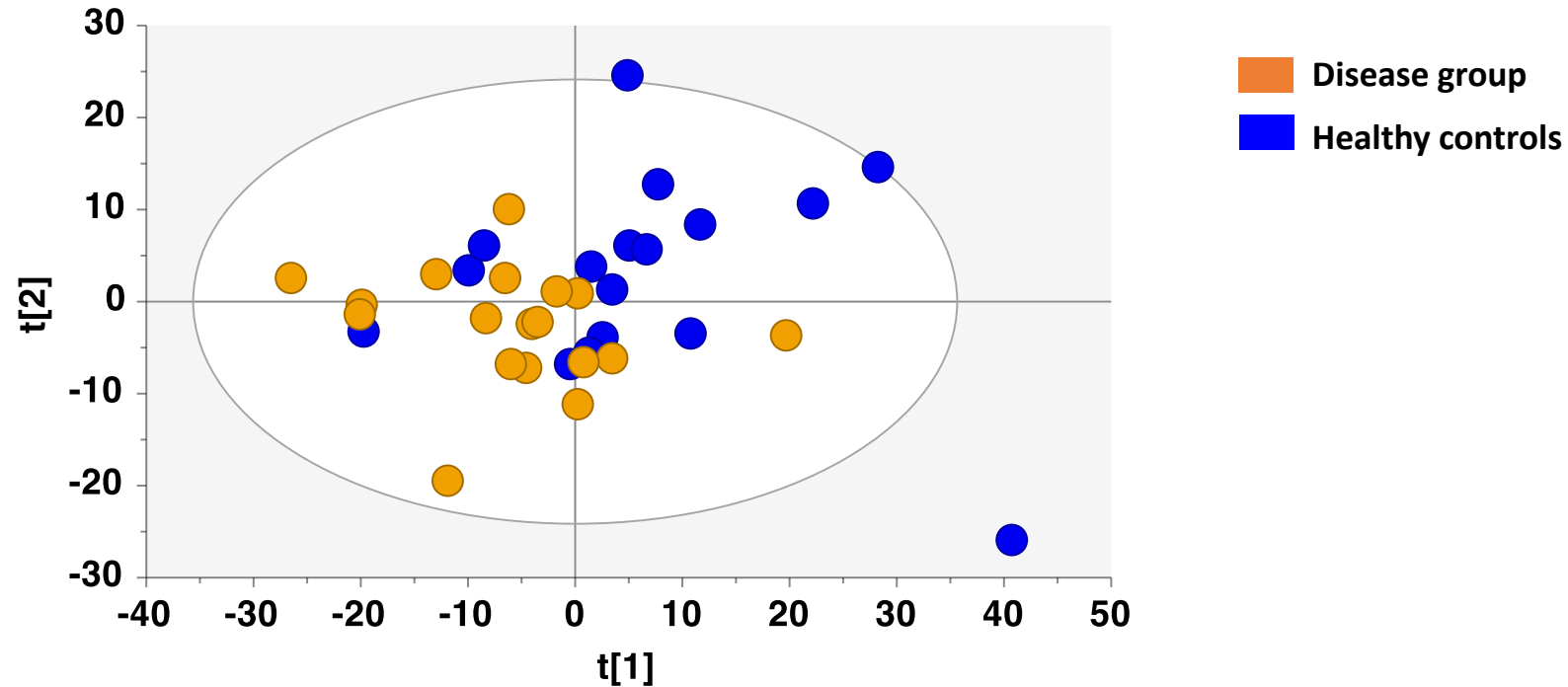


Unreliable Metabolite



Multivariate analysis: PCA

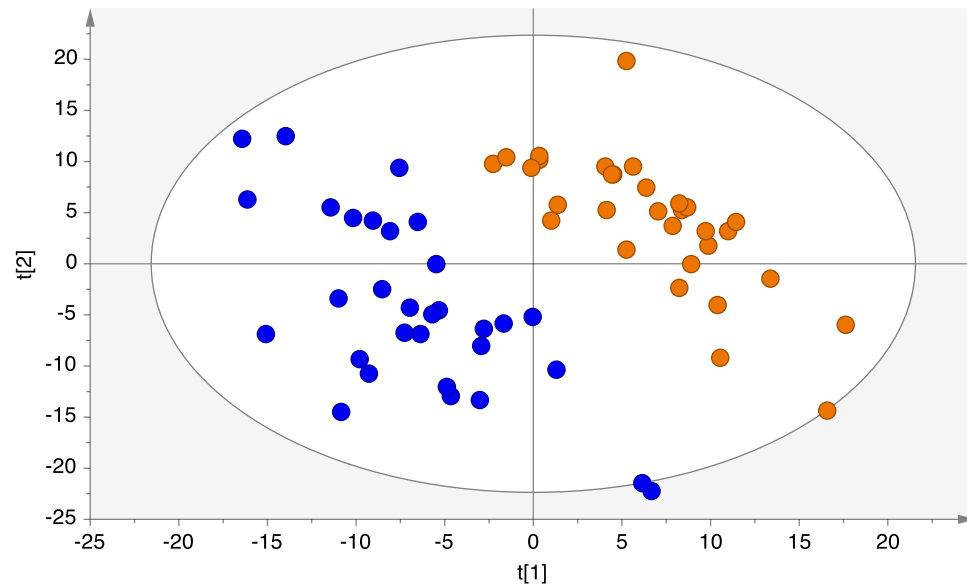
- ❑ Principal Component Analysis (PCA) is a blind no supervised analysis
- ❑ PCA looks for the similarities between samples
- ❑ It is used to observe patterns, clustering and outliers in your samples



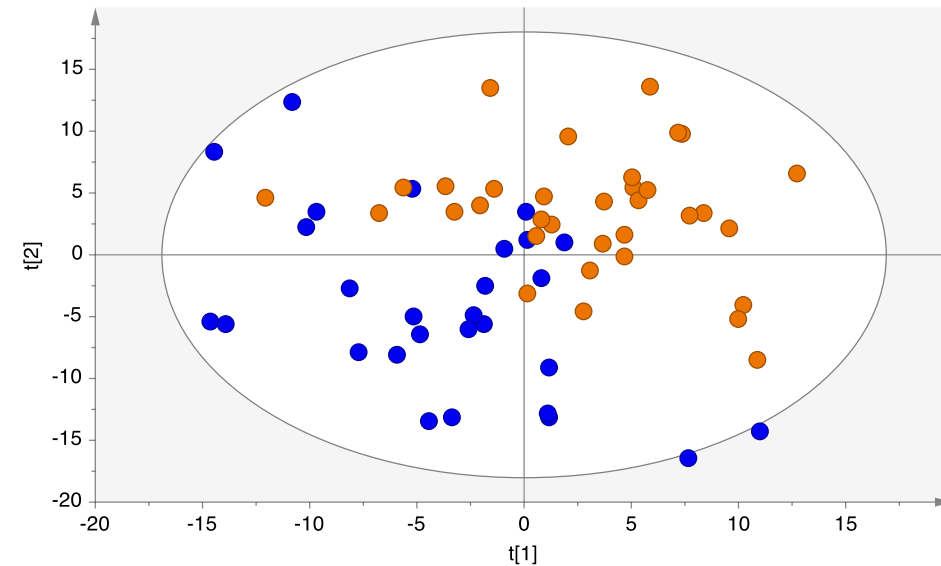
Multivariate analysis: PLS-DA

- ❑ Partial Least Square Discriminant Analysis (PLS-DA) is a supervised multivariate analysis
- ❑ It identifies if there is a real separation/difference between 2 groups.
- ❑ Separation of samples is explained by the first component (x axis, mainly) and the second component (y axis)

True biological differences



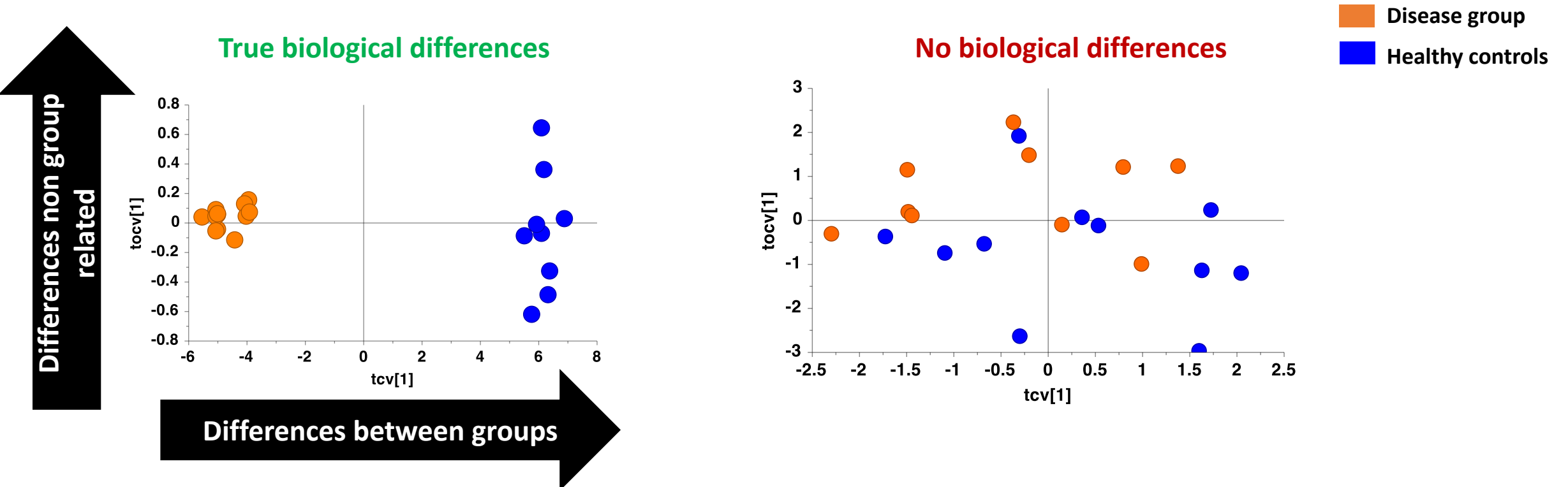
Fewer biological differences



Orange square: Disease group
Blue square: Healthy controls

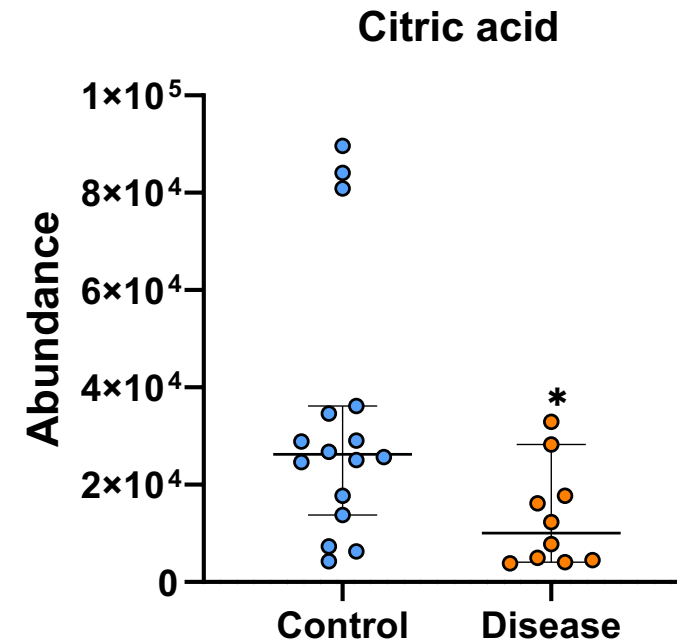
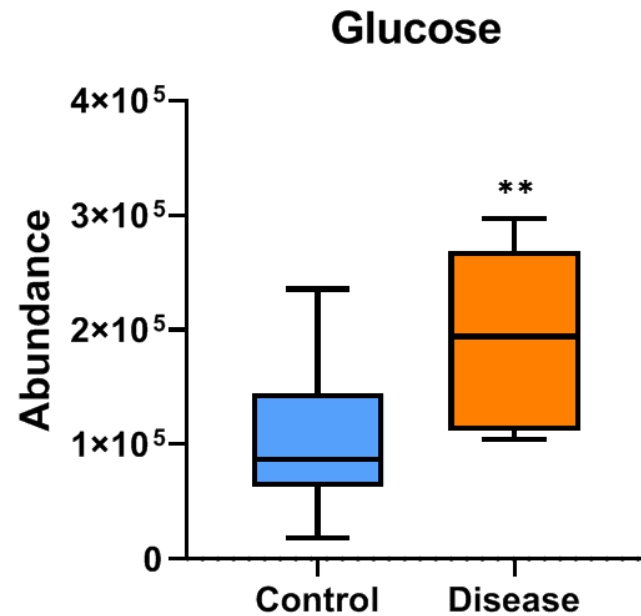
Multivariate Analysis: OPLS-DA

- ❑ Orthogonal Partial Least Square Discriminant Analysis (OPLS-DA) is also a supervised multivariate analysis which separates space the variation between samples of 2 groups. **Only used if a good PLS-DA has been obtained.**
- ❑ Separation is only based by the first component
- ❑ Commonly used for identification of potential biomarkers and prediction of samples



Univariate analysis: ANOVA and non parametric ANOVA

- ❑ To detect differences of individual metabolites between groups
- ❑ Depending of the number of patients/conditions/animals you use one or another test (t test, U-Mann Whitney, etc.)



Significant compounds need to be identified

Non allergic vs Severe				
No	<i>m/z</i> (Da)	RT (min)	% Moderate	<i>p</i> value
1	479.3366	21.44	56.9	0.017
2	553.3793	26.01	121.2	0.004
3	553.3747	22.23	47.9	0.03
4	551.3602	22.3	55.1	0.009
5	557.3327	16.11	12.9	0.537
6	541.3386	19.44	45.7	0.004
7	531.3102	20.21	17.3	0.017
8	559.3407	23.76	77.1	0.004

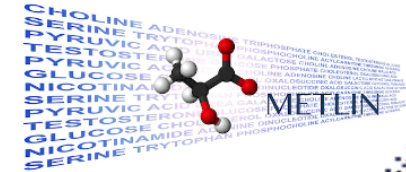
Identification of compounds in LC-MS and CE-MS

1. First step → Search into specific web databases

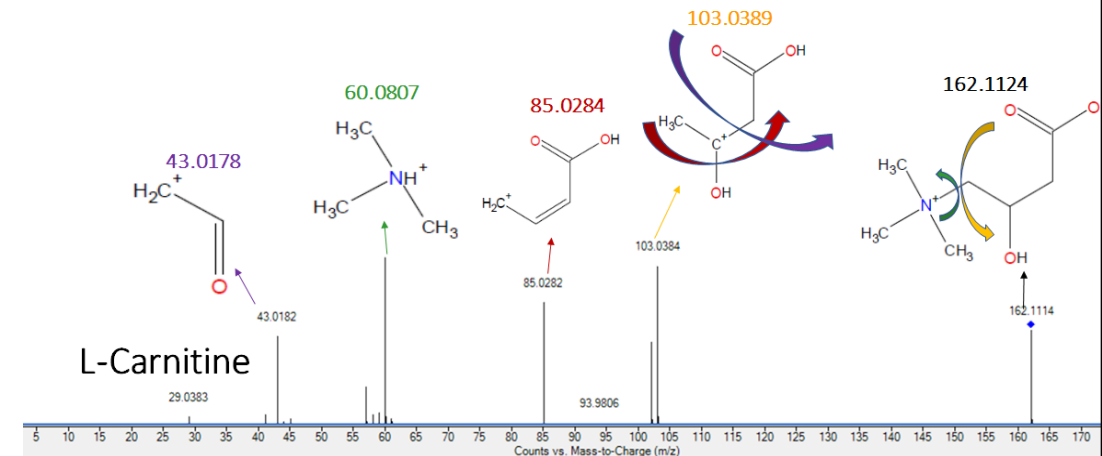
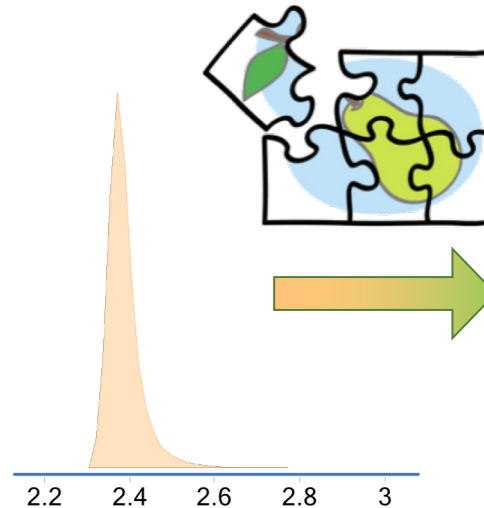
Tentative identification, based only on its mass and RT



CEU MASS
MEDIATOR



2. Second step → fragment the significant metabolite and puzzle out the structure (i.e. L-Carnitine)



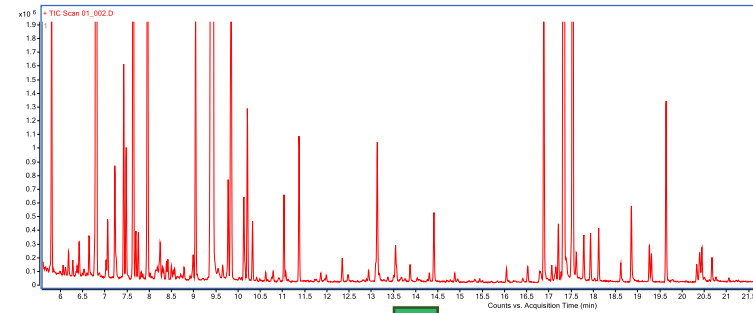
Identification in GC-MS

➤ Contrary to LC-MS and CE-MS identification is performed during data treatment

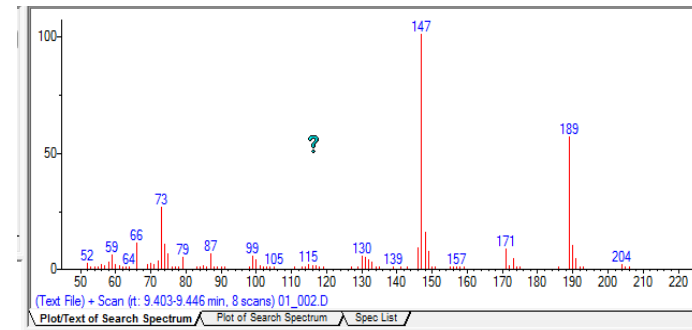
➤ Common databases used:

1.  2000s compounds

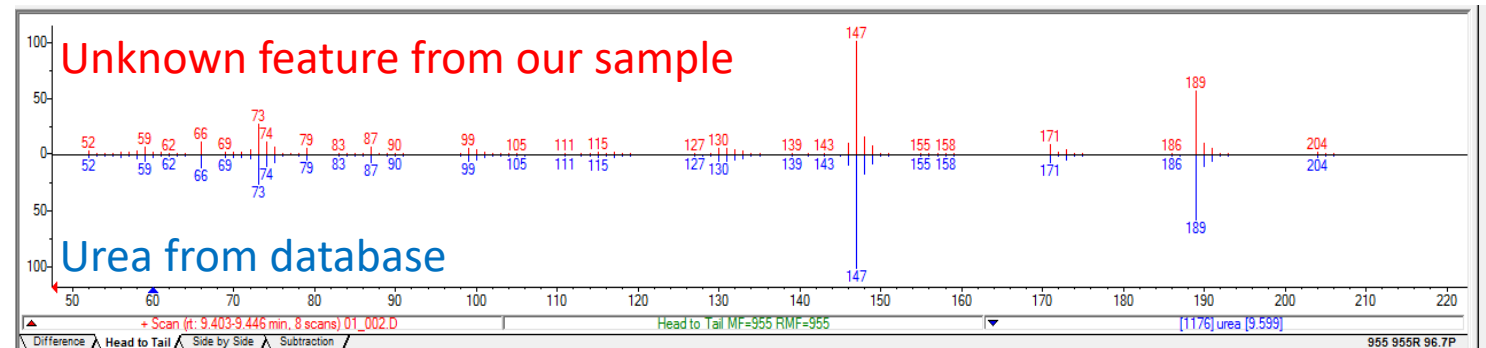
2. **Fiehn library**- 1000s compounds



Complete chromatogram



1 spectra at RT 10.32



Is compared with databases

Common problems

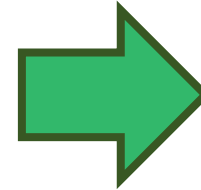


Common problems in untargeted metabolomics: Big patient cohort

Big cohort of samples may not be able to analyze continuously in a single batch



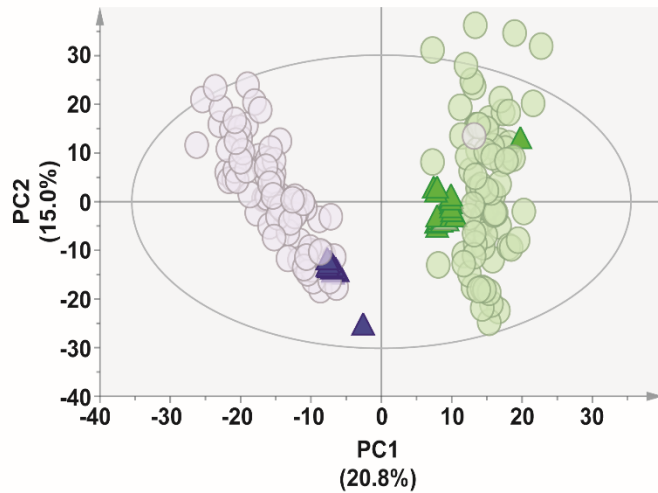
The quality between each batch can be good but does not necessary that can data can be overlapped



Normalization strategies:
Intra-batch and inter-batch normalization

N=165

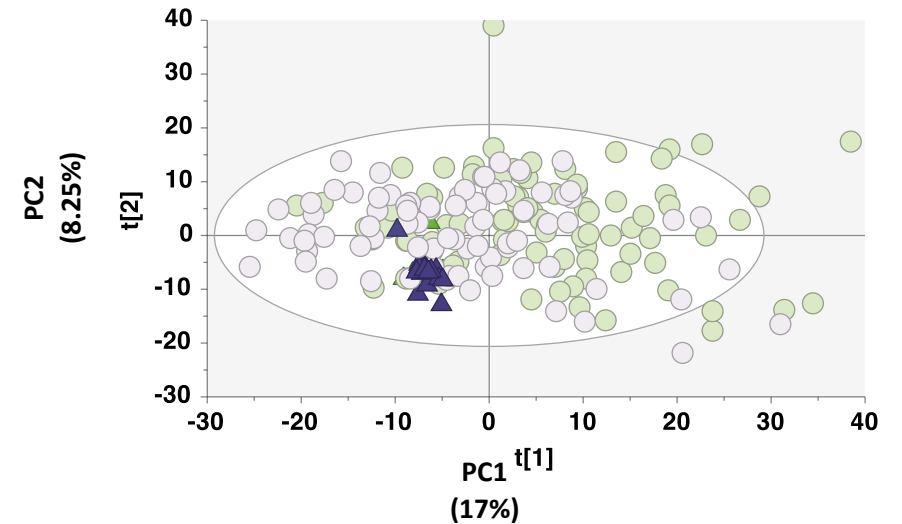
Raw data



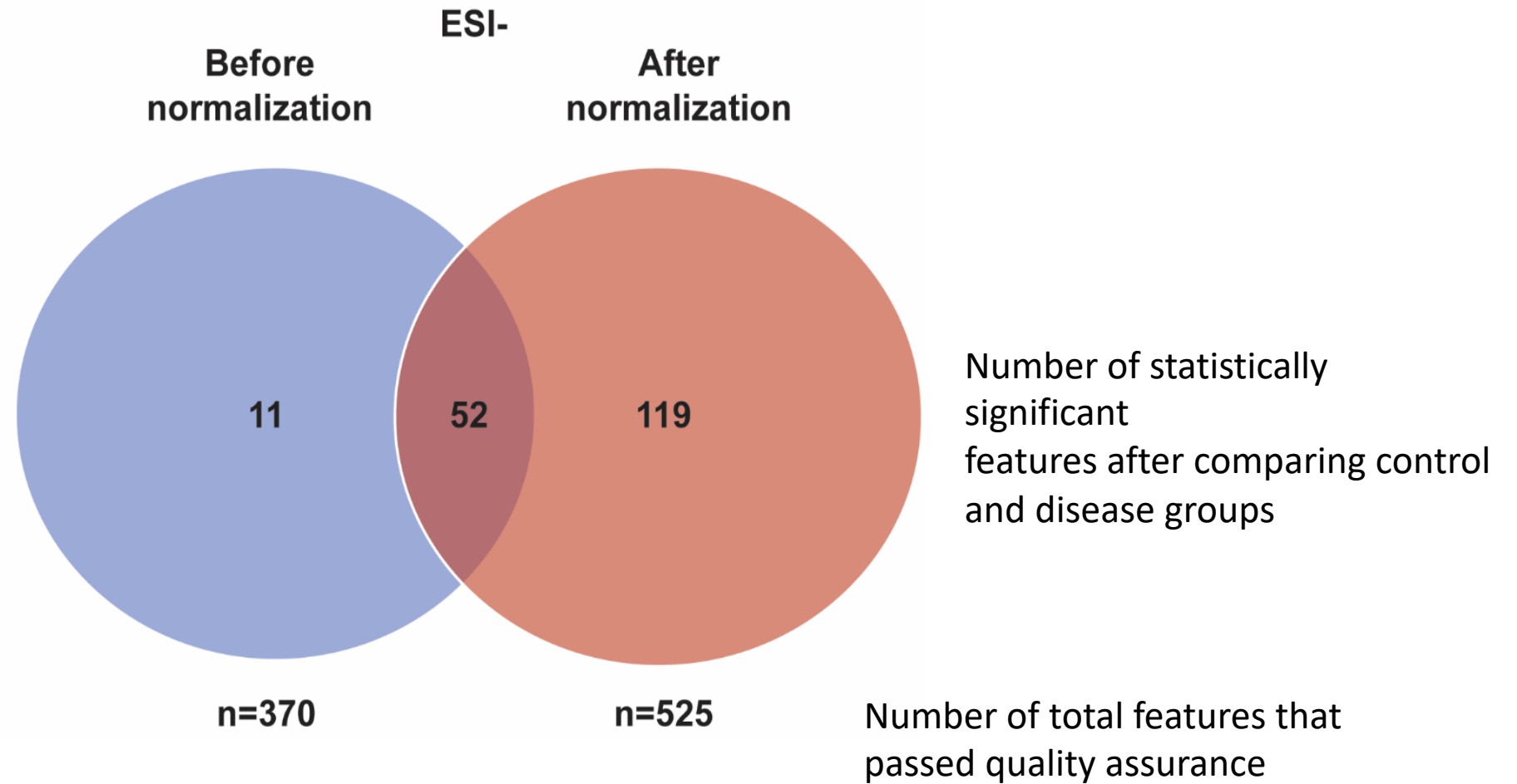
After inter- and intra-batch normalization



Normalized data



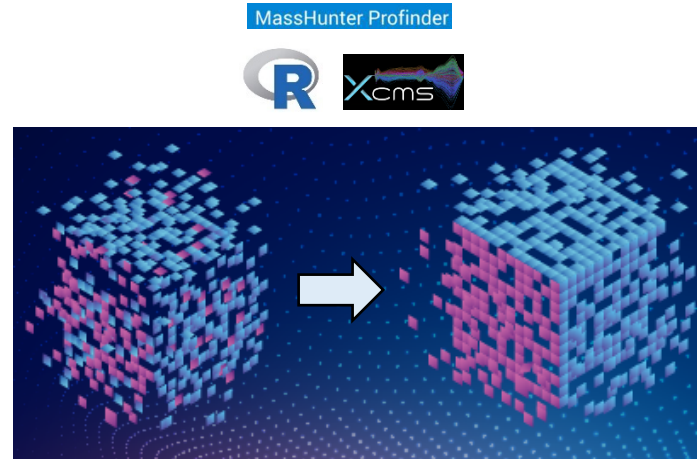
Effect of normalization in the number of significant features



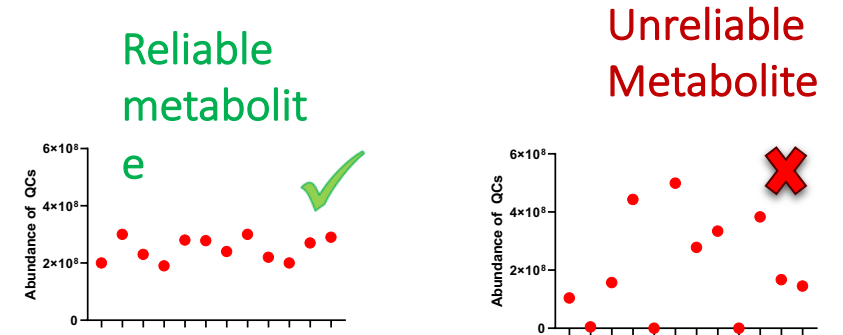
Summary of untargeted metabolomics analysis



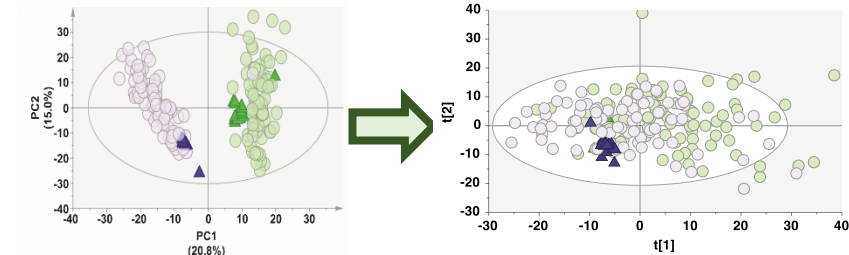
1. Measurement



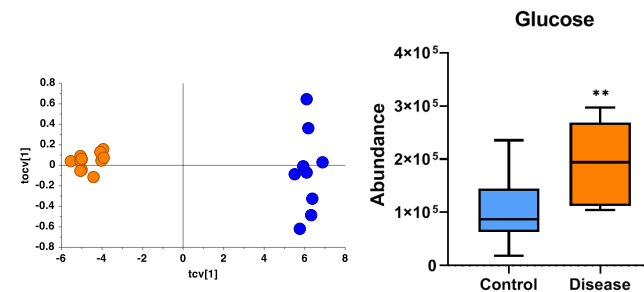
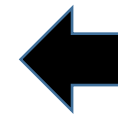
2. Data transformation



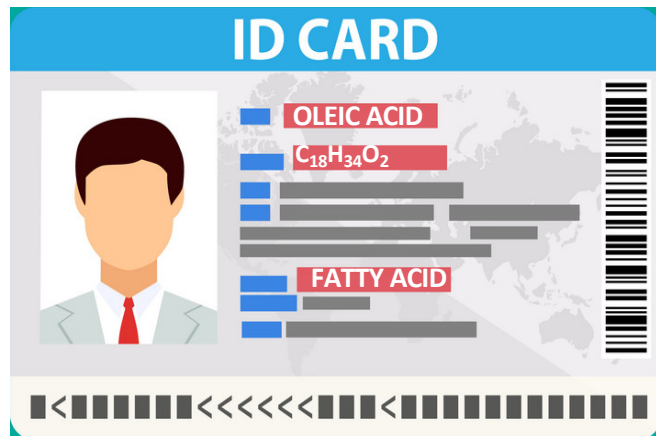
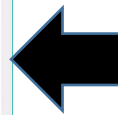
3. Data quality assessment



4. Normalization



5. Statistical analysis



6. Identification

ORAL MUCOSA: A MODEL OF EPITHELIA REMODELLING AND INFLAMMATION

- SEVERE PROFILIN FOOD ALLERGY
- SEVERE RESPIRATORY ALLERGY IN THE ABSENCE OF FOOD ALLERGY

Hypothesis: Oral mucosa integrity is compromised in respiratory allergic patients.



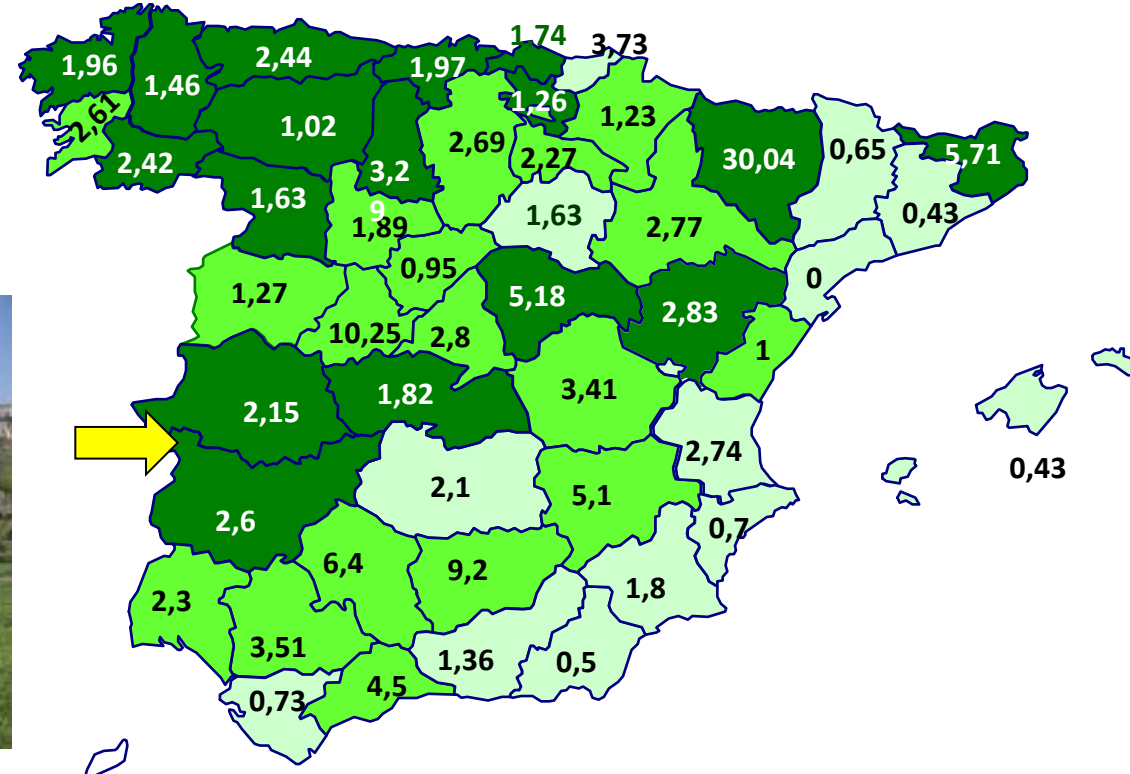
Profilin as a severe food allergen in allergic patients overexposed to grass pollen

M. I. Alvarado¹, L. Jimeno², F. De La Torre², P. Boissy², B. Rivas¹, M. J. Lázaro¹ & D. Barber³

¹Servicio de Alergia, Hospital Ciudad de Coria, Coria; ²Departamento de I+D y Medical Advisor, ALK-Abelló S.A.; ³Institute for Applied Molecular Medicine (IMMA), School of Medicine, University San Pablo-CEU, Madrid, Spain

To cite this article: Alvarado MI, Jimeno L, De La Torre F, Boissy P, Rivas B, Lázaro MJ, Barber D. Profilin as a severe food allergen in allergic patients overexposed to grass pollen. *Allergy* 2014; **69**: 1610–1616.

Coria (Caceres):
-60% of prevalence to profilin

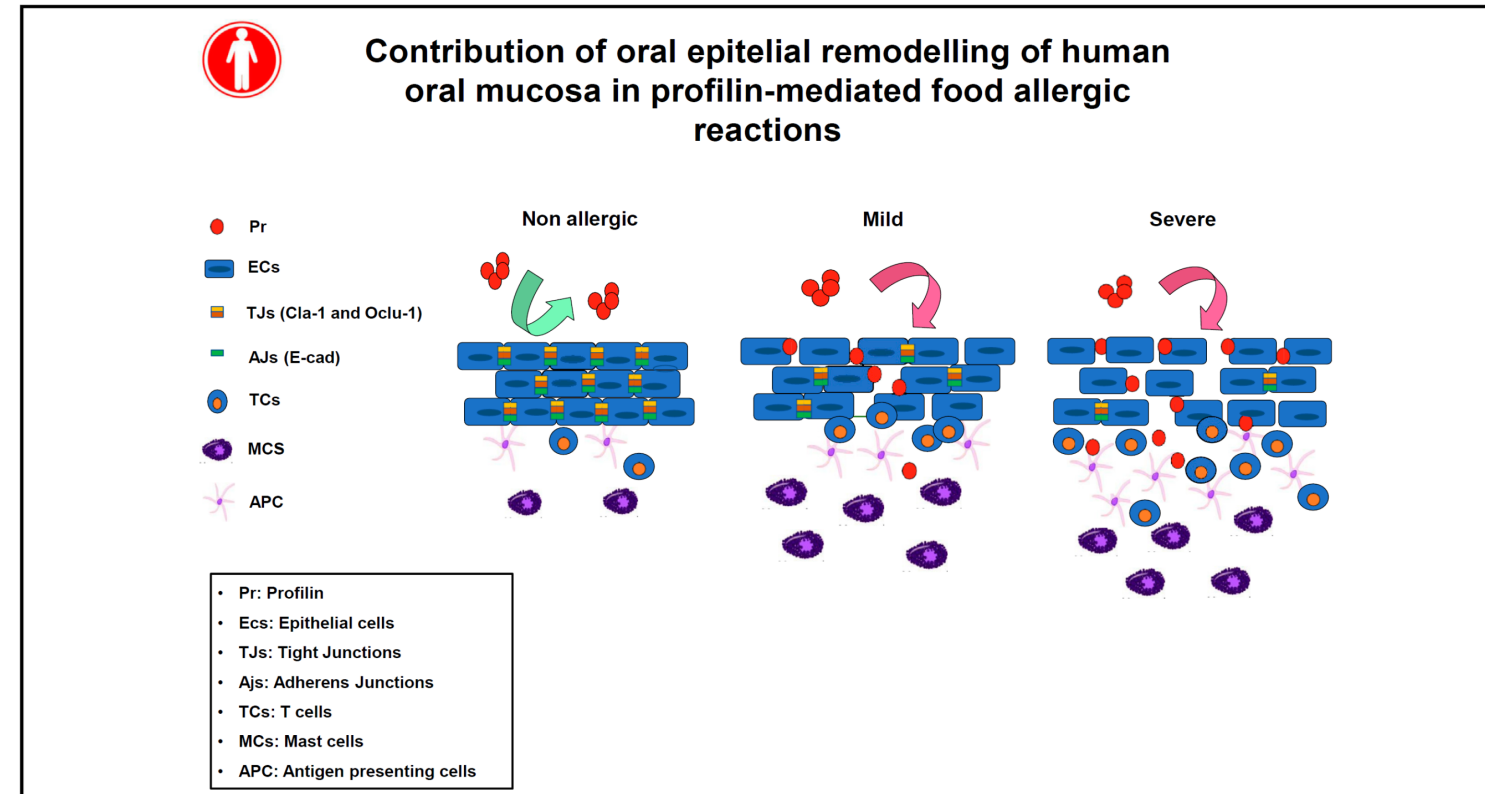


Profilin-mediated food-induced allergic reactions are associated with oral epithelia remodeling



J ALLERGY CLIN IMMUNOL
FEBRUARY 2019

Domenico Rosace, MSc,^a Cristina Gomez-Casado, PhD,^a Paloma Fernandez, PhD,^a Marina Perez-Gordo, PhD,^b María del Carmen Dominguez, MD,^c Angel Vega, MD,^c María Teresa Belver, MD,^d Tania Ramos, MD,^d Francisco Vega, MD,^d Guadalupe Marco, MD, PhD,^e Manuel de Pedro, MD,^e Leticia Sanchez, MD,^e María de las Mercedes Arnas, MD, PhD,^f Marcela Santaolalla, MD, PhD,^f Miguel Ángel Saez, MD,^g Sara Benedé, PhD,^h Montserrat Fernandez-Rivas, MD, PhD,^e Carlos Blanco, MD, PhD,^d Maria Isabel Alvarado, MD, PhD,^c María M. Escribese, PhD,^{a,b} and Domingo Barber, PhD^a *Madrid and Cáceres, Spain*

GRAPHICAL ABSTRACT



Respiratory allergies with no associated food allergy disrupt oral mucosa integrity

Javier Sanchez-Solares¹
Maria I. Delgado-Dolset¹
Leticia Mera-Berriatua¹
Gonzalo Hormias-Martin²
Jose A. Cumplido³
Vanesa Saiz⁴
Teresa Carrillo³
Carmen Moreno-Aguilar⁴
Maria M. Escribese¹
Cristina Gomez-Casado¹ 
Domingo Barber¹ 

¹Department of Basic Medical Sciences, Faculty of Medicine, Institute
of Applied Molecular Medicine, San Pablo CEU University, Madrid,
Spain

- Highly exposed Olive pollen allergic patients (Cordoba)
- Highly exposed mite allergic patients (Canary Islands)

Understanding severity:

Why, patients that had been tolerating profilin for years on a daily basis, get sensitized and develop severe reactions?


- In the three severity models: **Bad response to intervention** (side reactions, lack of effect)

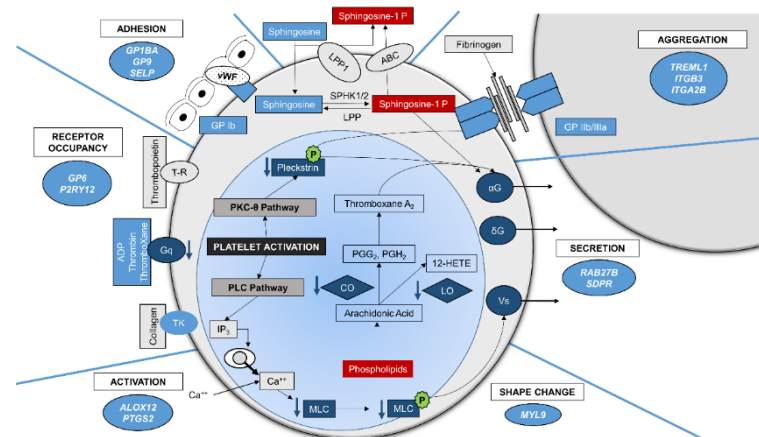
- Metabolomics of grass pollen severe allergy phenotypes.

ORIGINAL ARTICLE

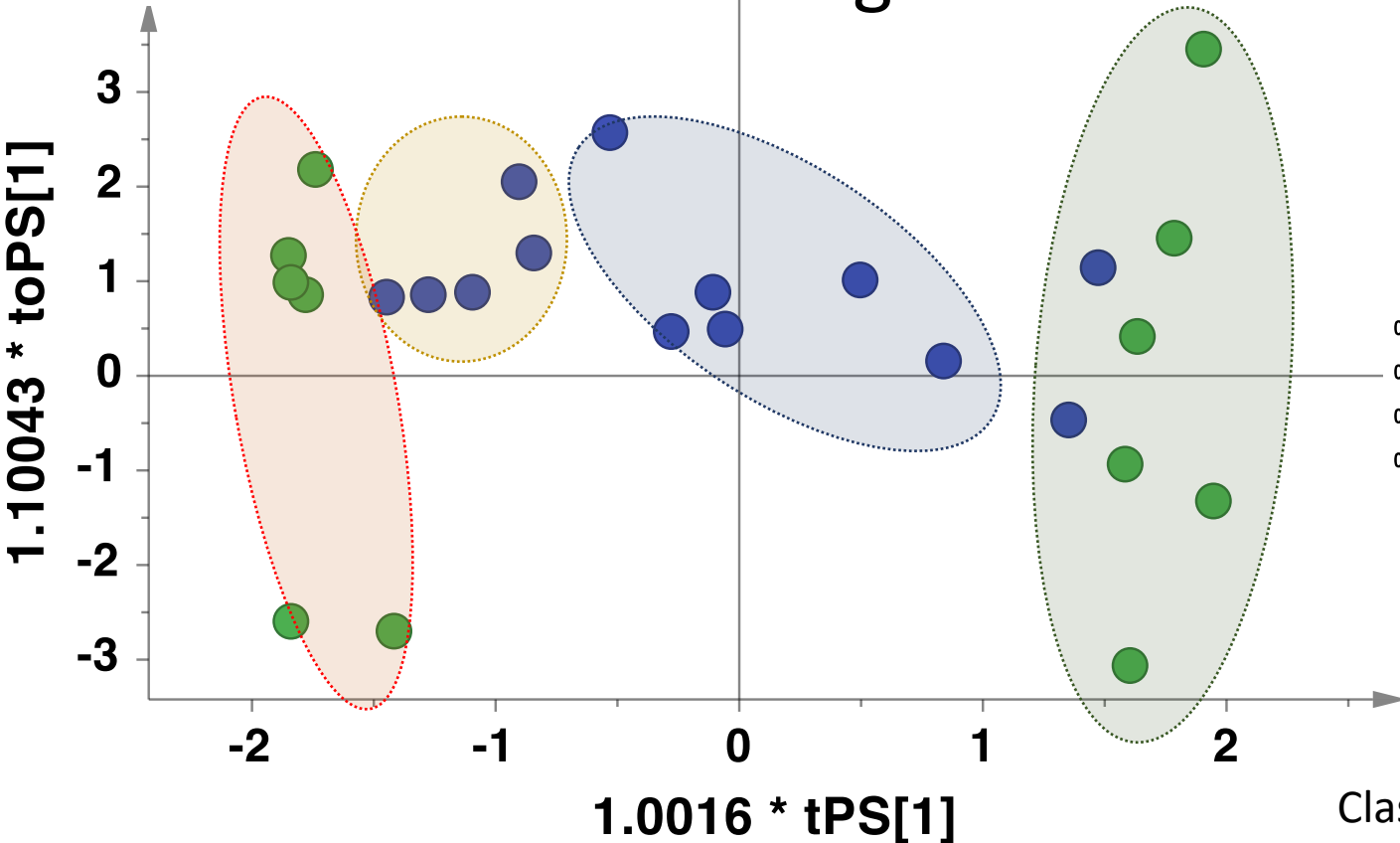
Experimental Allergy and Immunology

Multi-omics analysis points to altered platelet functions in severe food-associated respiratory allergy

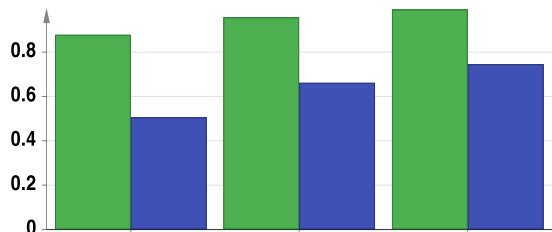
David Obeso^{1,2} | Leticia Mera-Berriatua¹ | Juan Rodríguez-Coira^{1,2} |
 Domenico Rosace¹ | Paloma Fernández¹ | Isabel Adoración Martín-Antoniano^{1,3} |
 Marcela Santaolalla⁴ | Guadalupe Marco Martín⁵ | Tomás Chivato^{1,3} | Montserrat
 Fernández-Rivas⁵ | Tania Ramos⁶ | Carlos Blanco⁶ | María I. Alvarado⁷ |
 Carmen Domínguez⁷ | Santiago Angulo⁸ | Coral Barbas² | Domingo Barber¹  |
 Alma Villaseñor¹ | María M. Escribese^{1,9}



Background results. LC-MS (ESI +)

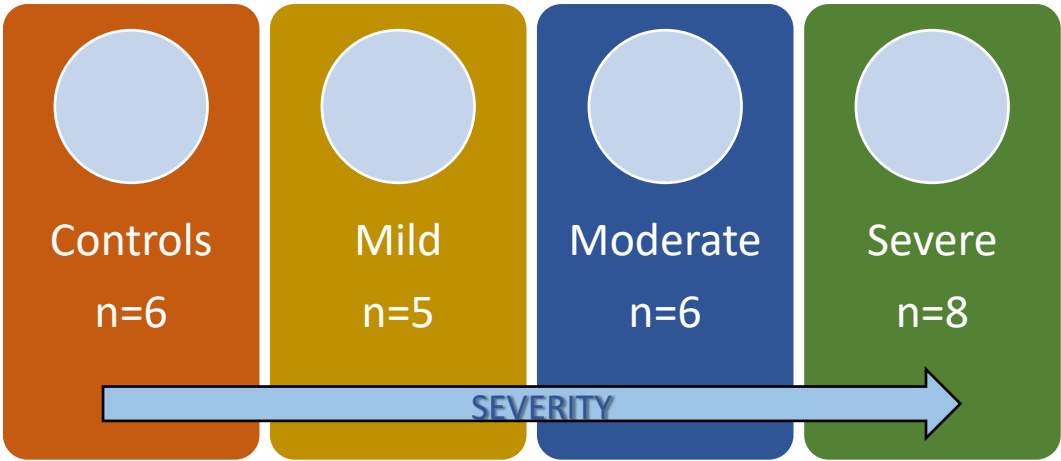


OPLS-DA predicted model



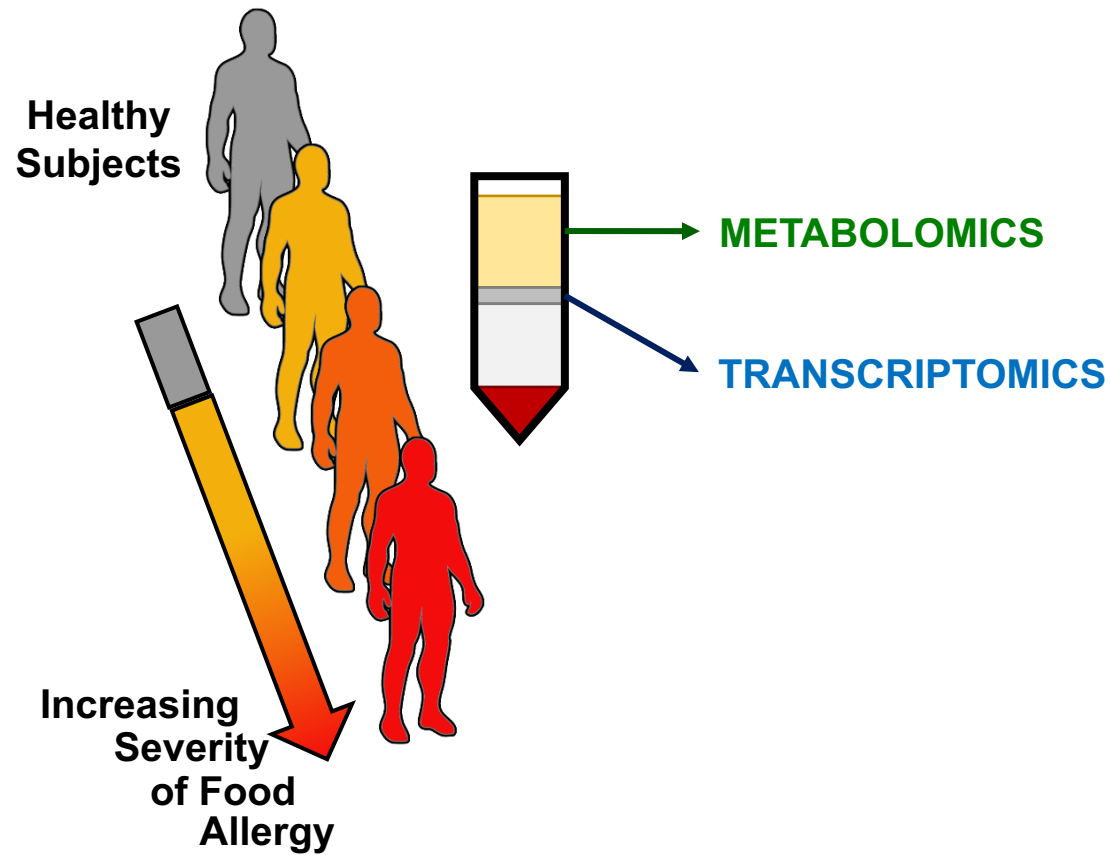
R² = 0.99
Q²= 0.75

Classes were assigned based on the prediction ecuation:

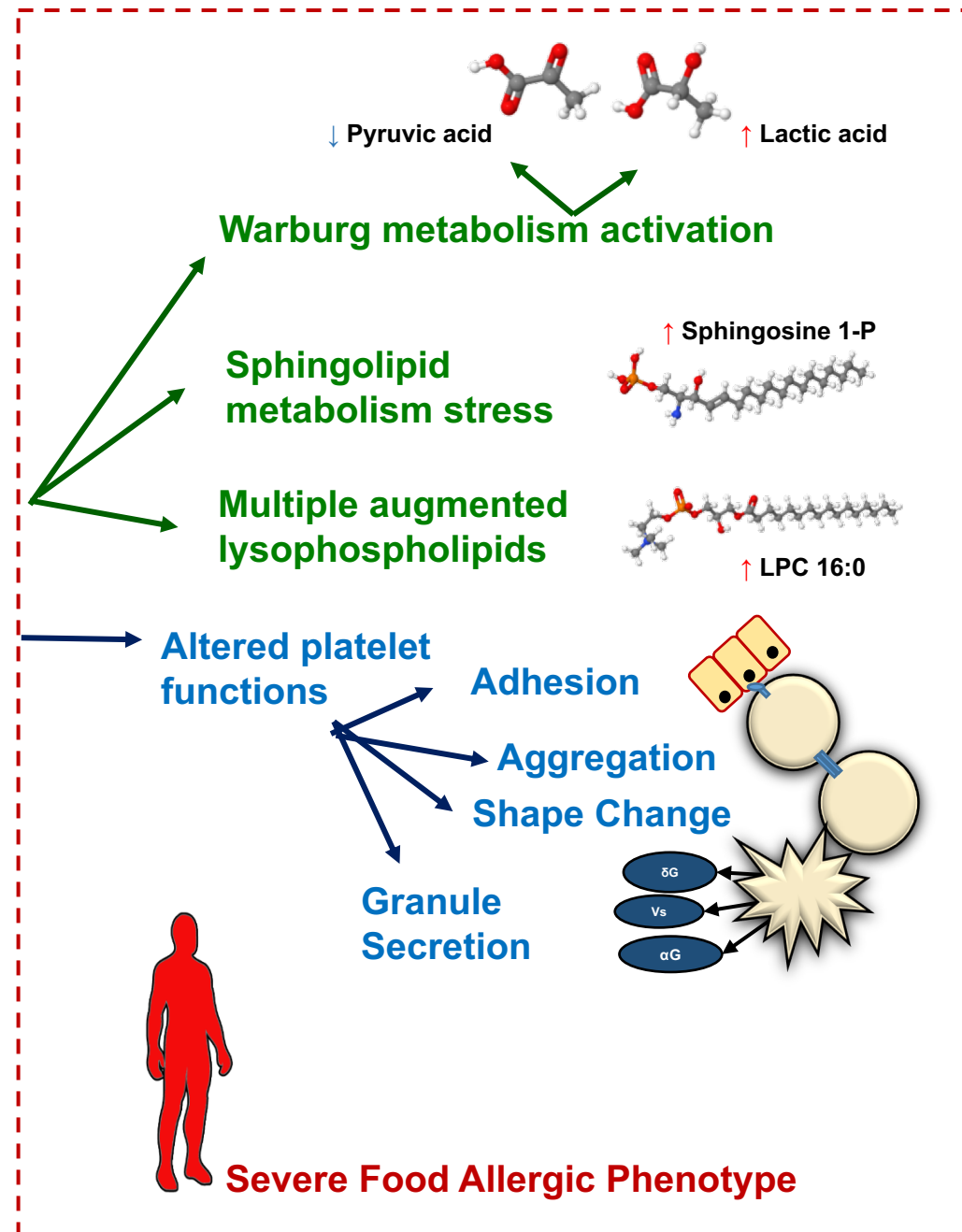


M29.YVarPS(\$M29.DA(1))	M29.YPredPS[1](\$M29.DA(1))	M29.YVarPS(\$M29.DA(4))	M29.YPredPS[1](\$M29.DA(4))
1	1.00646	0	-0.00645721
1	1.02588	0	-0.0258775
1	1.02419	0	-0.0241894
1	0.904015	0	0.0959849
1	1.0238	0	-0.0238008
1	0.994343	0	0.00565687
--	0.740211	--	0.259789
--	0.260185	--	0.739815
--	0.531348	--	0.468652

SIGNATURES LINKED TO SEVERE PHENOTYPE

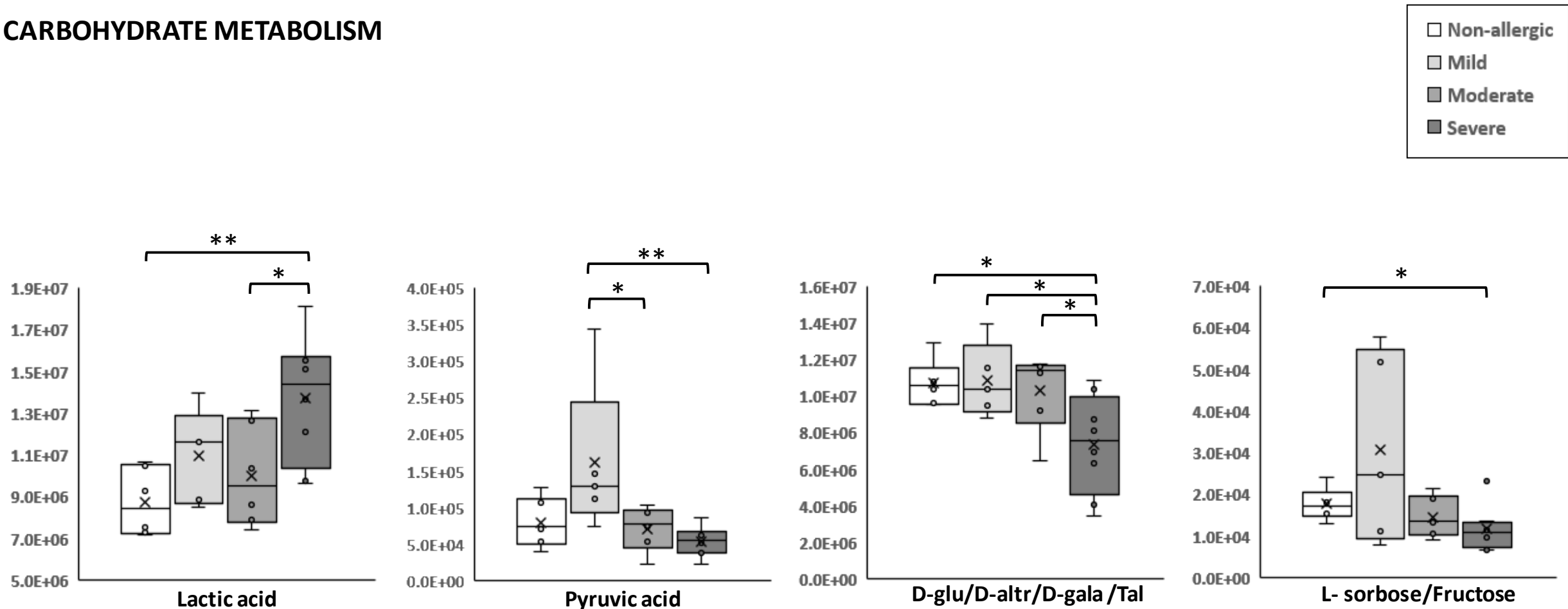


Obeso et al Allergy. 2018



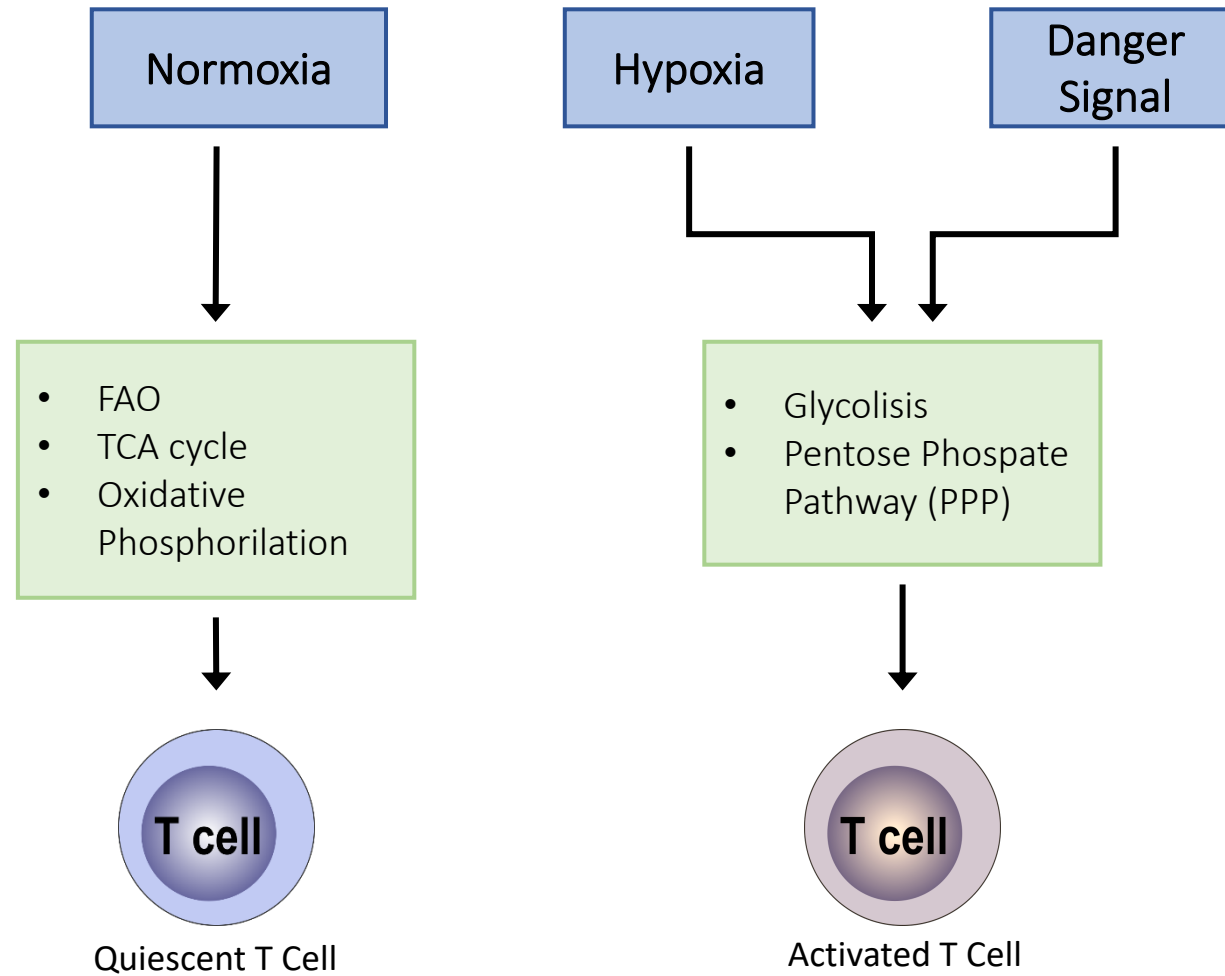
Aerobic Glycolysis (Warburg) metabolism activation

CARBOHYDRATE METABOLISM

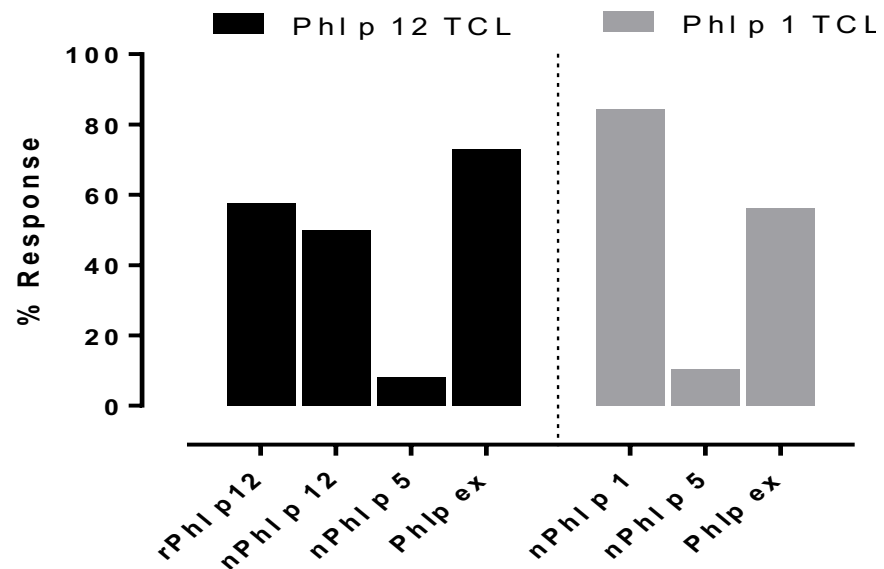


Obeso et al Allergy. 2018

T cell metabolism



Profilin induces strong T cell proliferation in Spanish sensitized patients compared to Nordic ones.

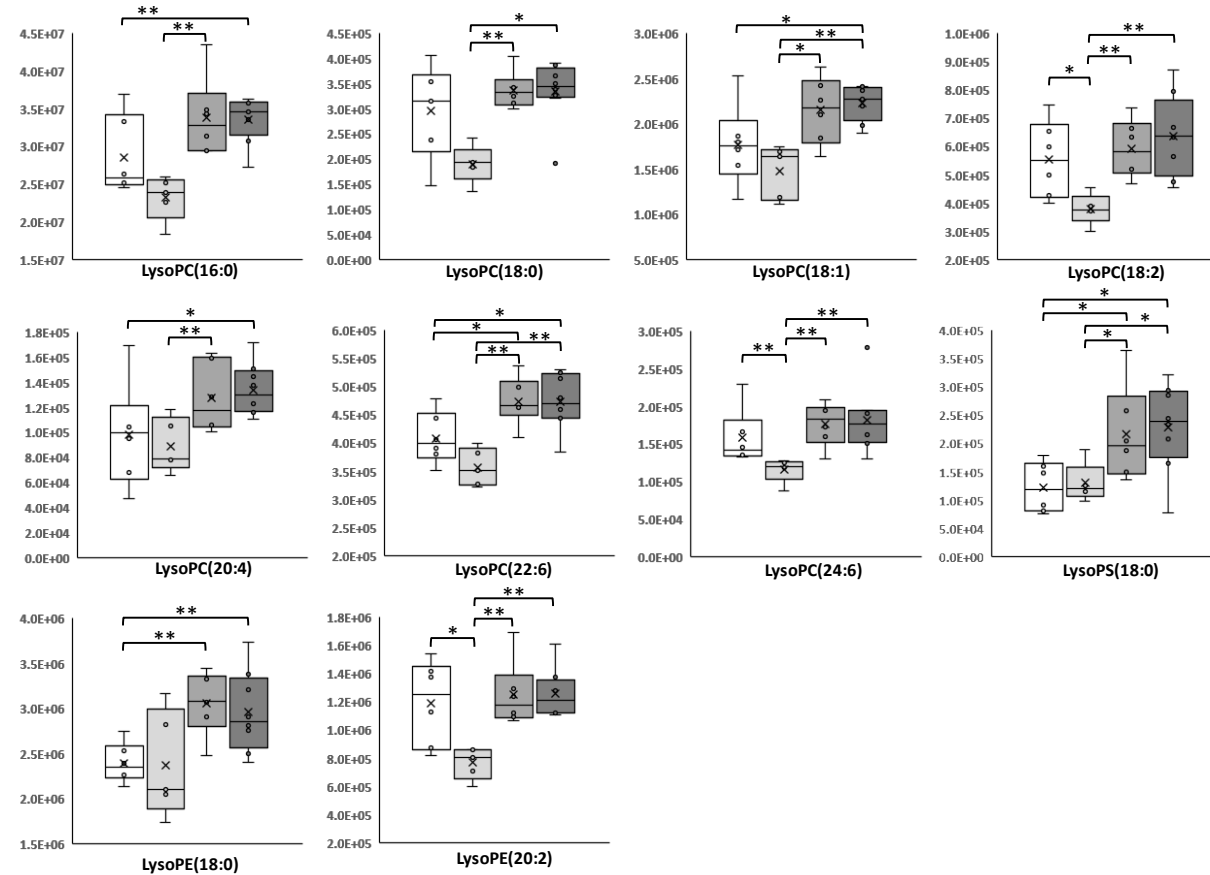


found in association with PFS. In contrast to the Danish cohort, T cells from the Spanish patients responded vigorously to profilin and were comparable to the major allergen Phl p 1, in terms of both response prevalence and strength. Thus, the T-cell response to Phl

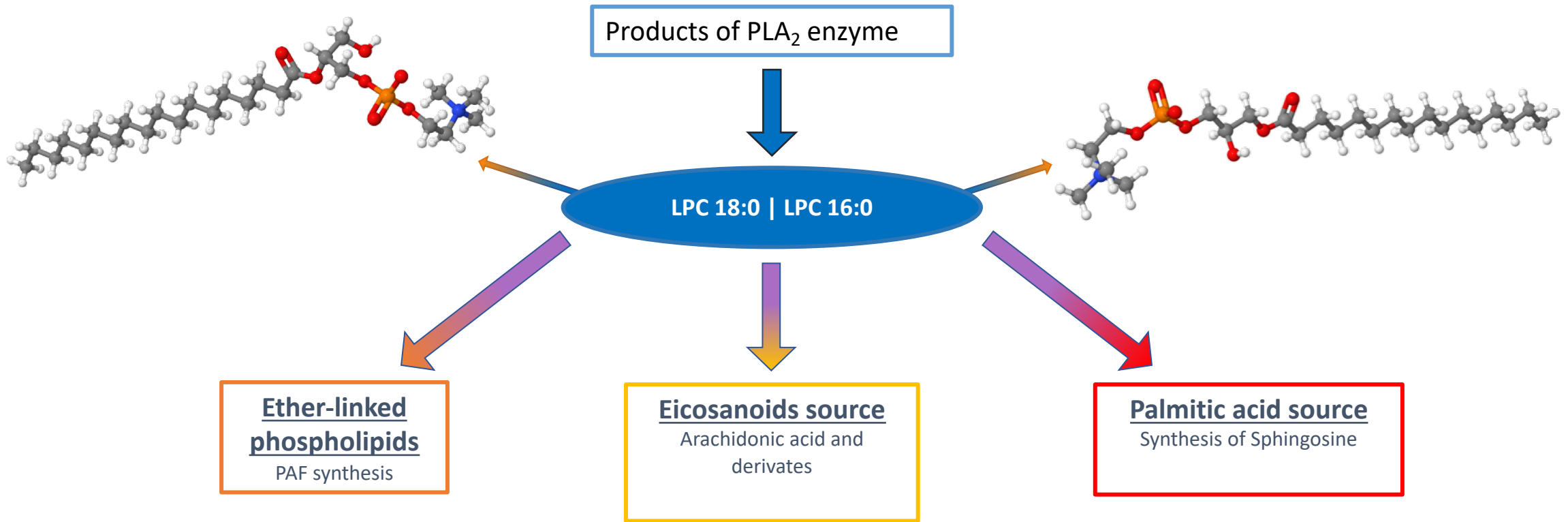
Lund G et al. Allergy 2018

LYSOPHOSPHOLIPIDS SIGNALLING

D. LYSOPHOSPHOLIPIDS METABOLISM



Alteration of LYSOPHOSPHOLIPID metabolism: Lysophosphocholine 16:0 and 18:0 (LPC 16:0 & LPC 18:0)



Allergy. 2013;68(5):629-36. doi: 10.1111/ail.12110. Epub 2013 Mar 1.

Integrative genetic and metabolite profiling analysis suggests altered phosphatidylcholine metabolism in asthma.

Ried JS¹, Baurecht H, Stückler F, Krumsiek J, Gieger C, Heinrich J, Kabesch M, Prehn C, Peters A, Rodriguez E, Schulz H, Strauch K, Suhre K, Wang-Sattler R, Wichmann HE, Theis FJ, Illig T, Adamski J, Weidinger S.

Allergy Asthma Immunol Res. 2014 Jan; 6(1): 61-65.
Published online 2013 Dec 5. doi: 10.4168/aaair.2014.6.1.61

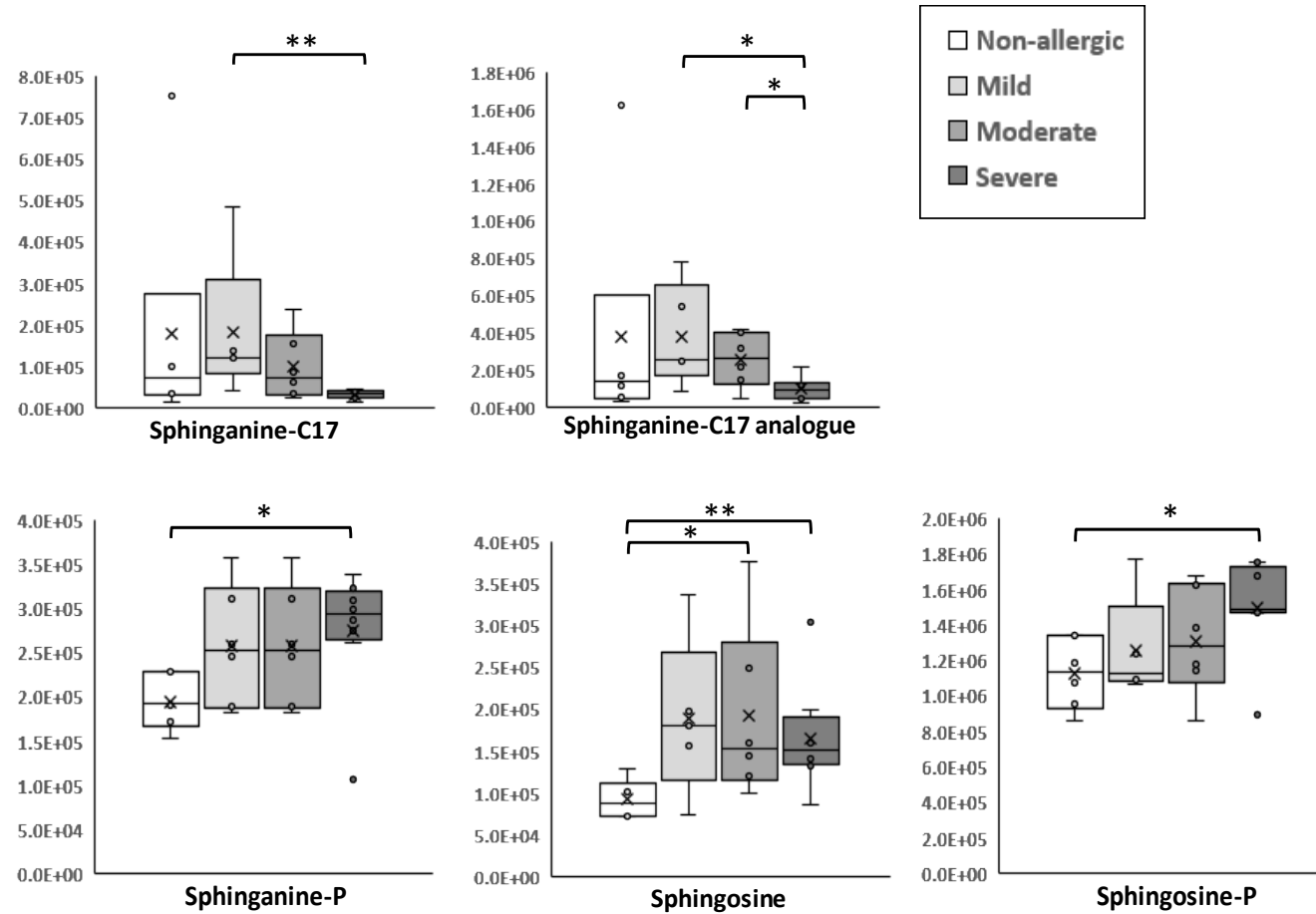
PMCID: PMC3881403
PMID: 24404395

Bioactive Lysophosphatidylcholine 16:0 and 18:0 Are Elevated in Lungs of Asthmatic Subjects

Mark Yoder,¹ Yan Zhuge,² Yang Yuan,⁴ Oksana Holian,² Sherry Kuo,¹ Richard van Breemen,⁴ Larry L. Thomas,³ and Hazel Lum⁰²

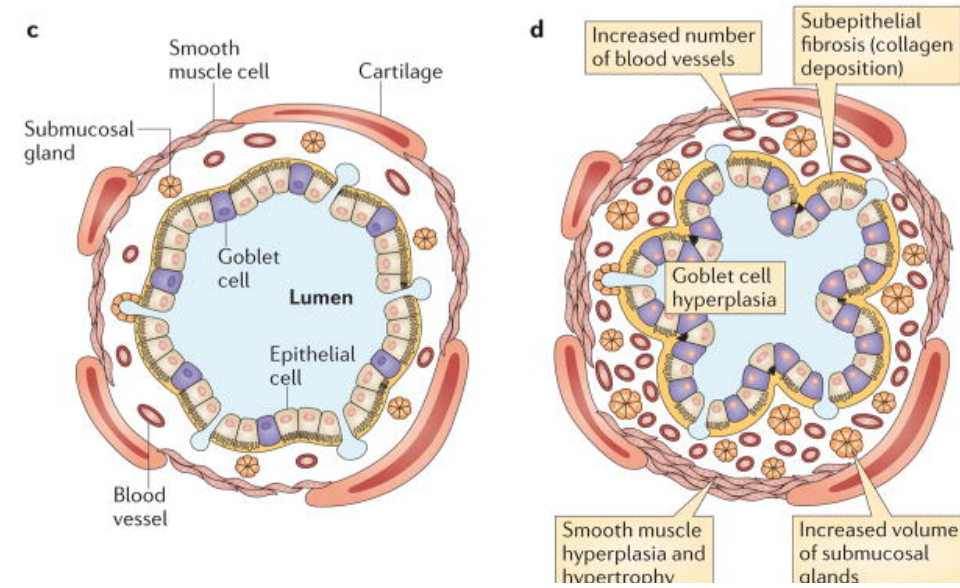
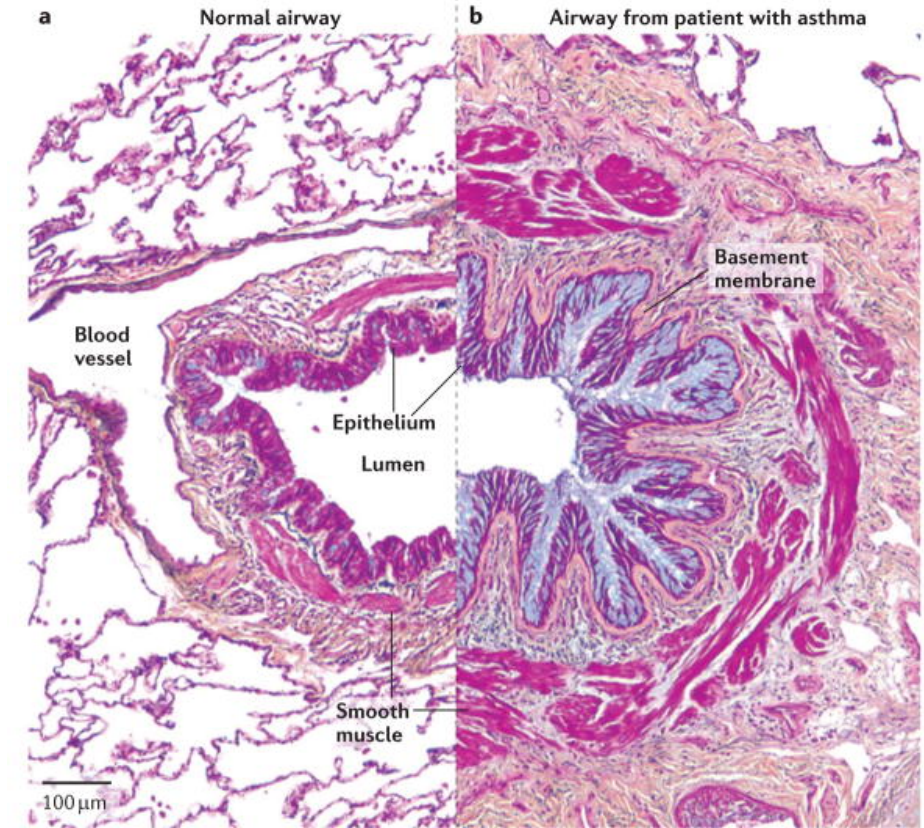
Author information ► Article notes ► Copyright and License information ► Disclaimer

Sphingolipid metabolism



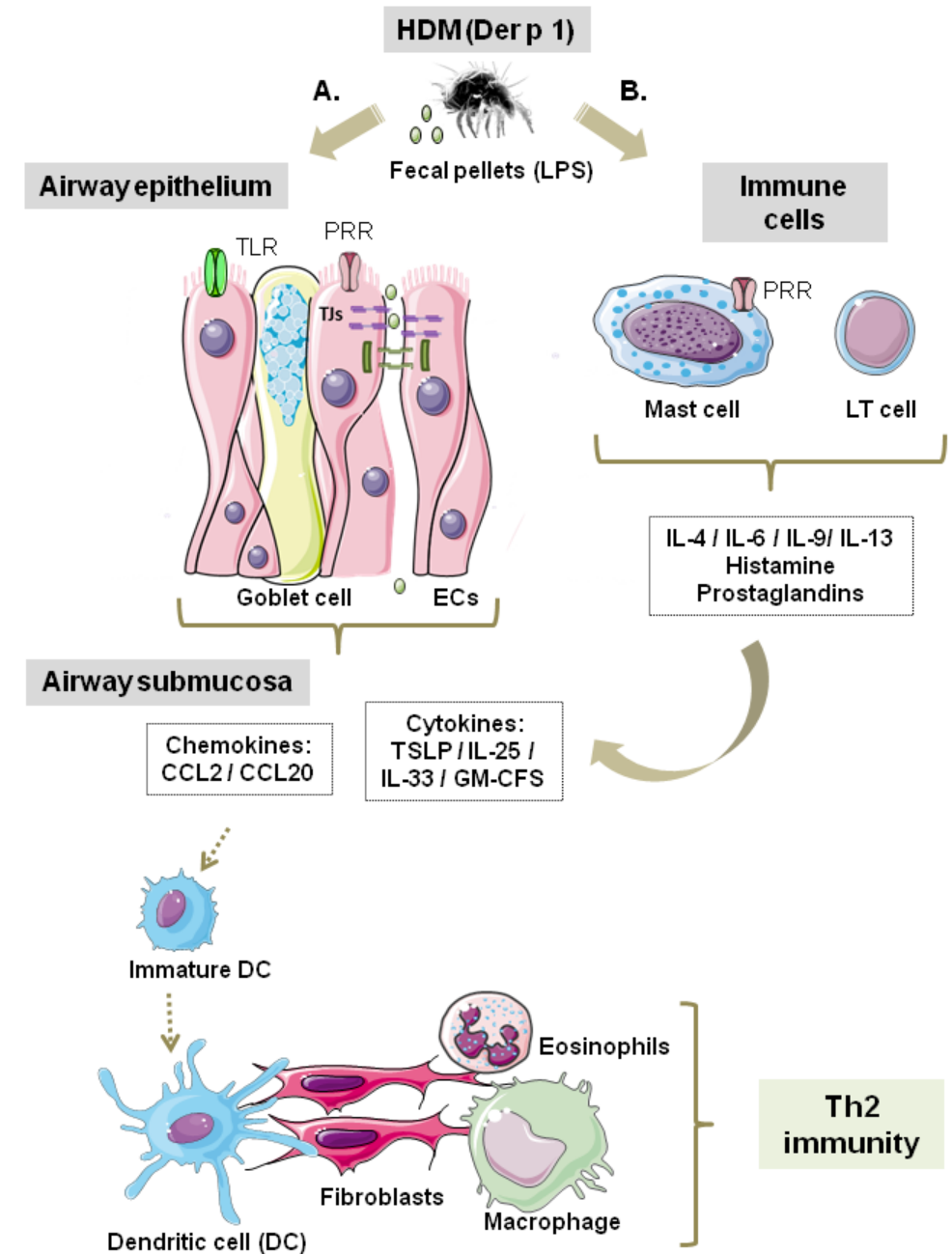
Asthma

- Asthma is a multifactorial, chronic syndrome, which varies over time and involves genetic and environmental interactions.
- It is characterized by:
 - Airway obstruction
 - Mucus hypersecretion
 - Airway hyper-responsiveness
 - Inflammatory cell infiltration
 - Airway epithelial remodeling



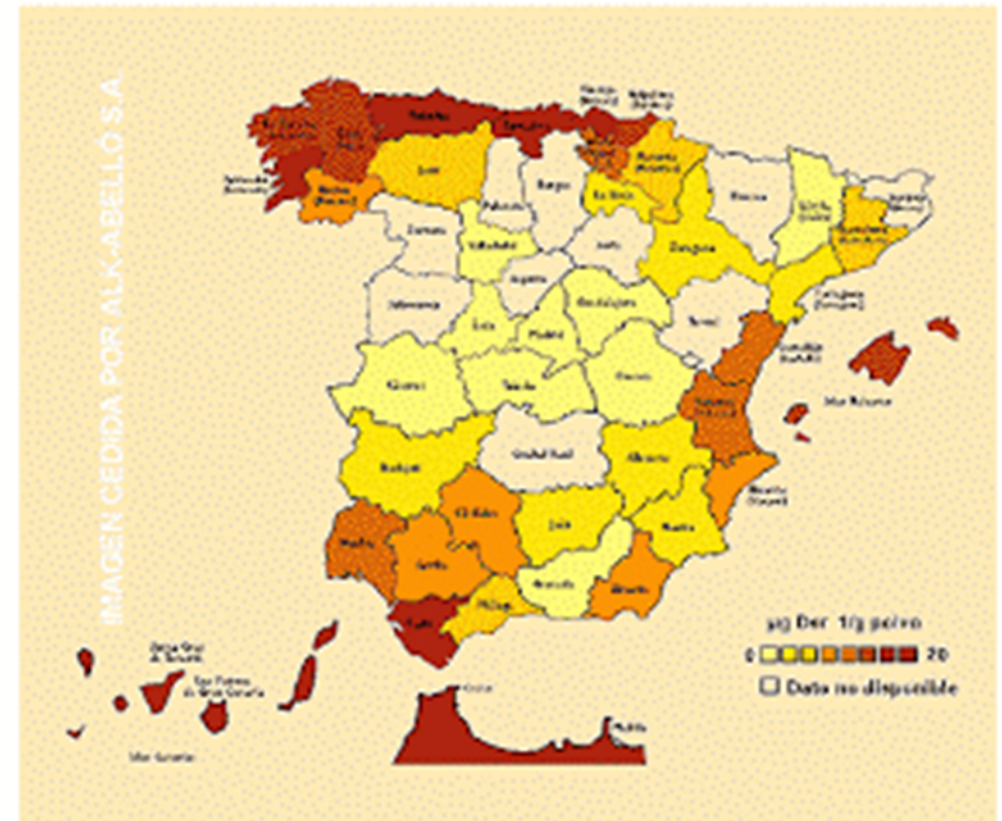
HDM Allergic Asthma

- House dust mites (HDM) are the most prevalent sensitizers associated with allergic asthma.
- The major mite allergens Der p 1 and Der p 2 have the ability to induce asthmatic status through different mechanisms:
 - Der p 1 is a cysteine protease capable of inducing tissue damage and inflammation by cleaving tight-junction
 - Der p 2 displays an allergenic role by mimicking the function of MD-2 in the activation of TLR4.

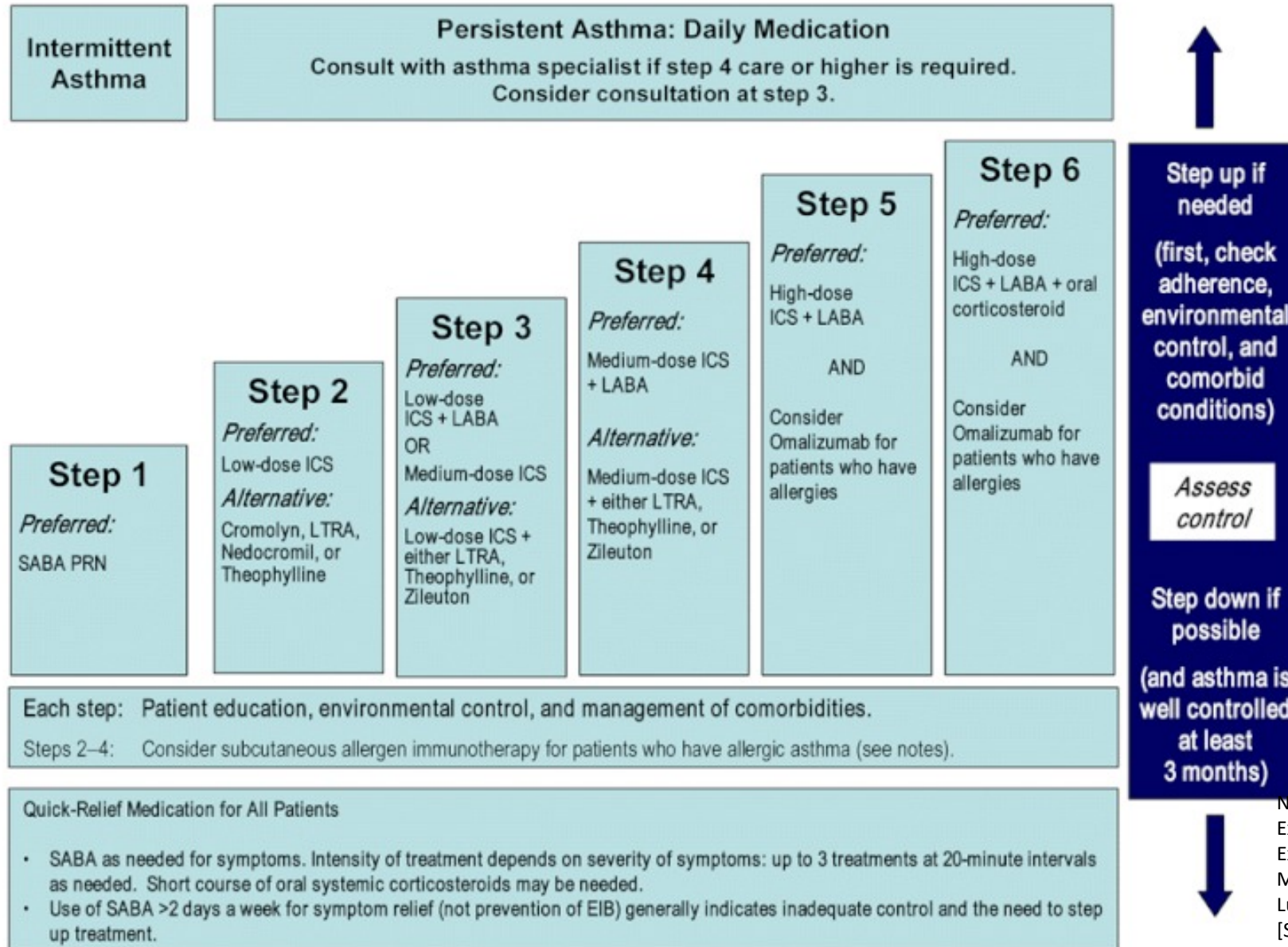


HDM High exposure area

- Canary Islands present the highest levels of HDM exposure in Spain.
- Tropical temperatures and high humidity.
- Around 80% of allergic patients are sensitized to HDM



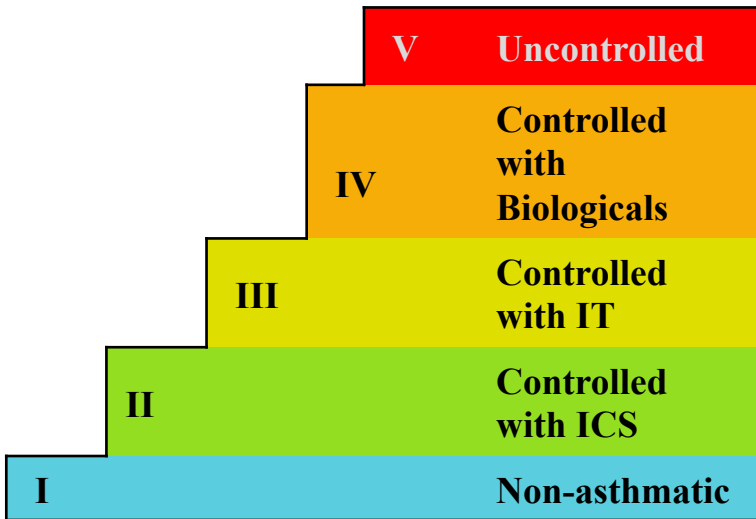
Stepwise approach to managing asthma



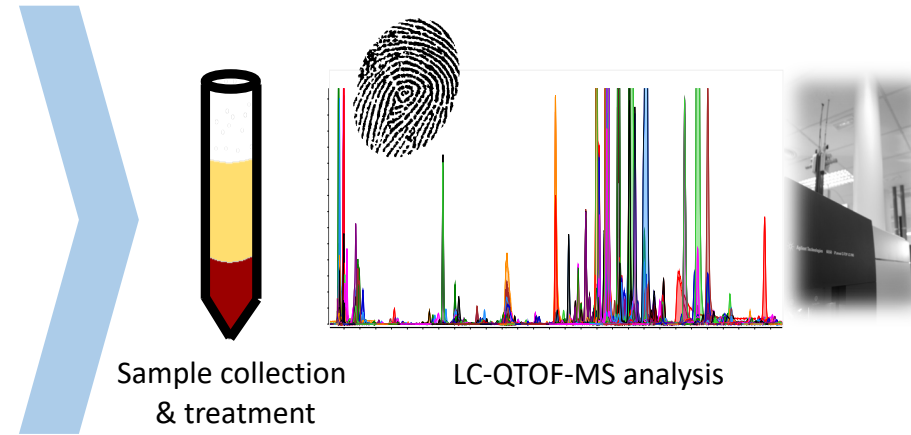
National Asthma Education and Prevention Program, Third Expert Panel on the Diagnosis and Management of Asthma. Expert Panel Report 3: Guidelines for the Diagnosis and Management of Asthma. Bethesda (MD): National Heart, Lung, and Blood Institute (US); 2007 Aug. Figure 4-5, [STEPWISE APPROACH FOR MANAGING ASTHMA IN YOUTHS ≥12 YEARS OF AGE AND ADULTS].

Metabolomic fingerprint

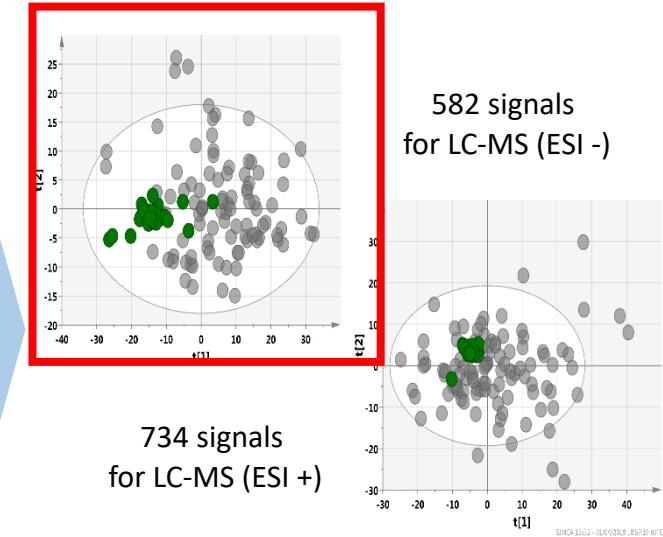
Patient Stratification



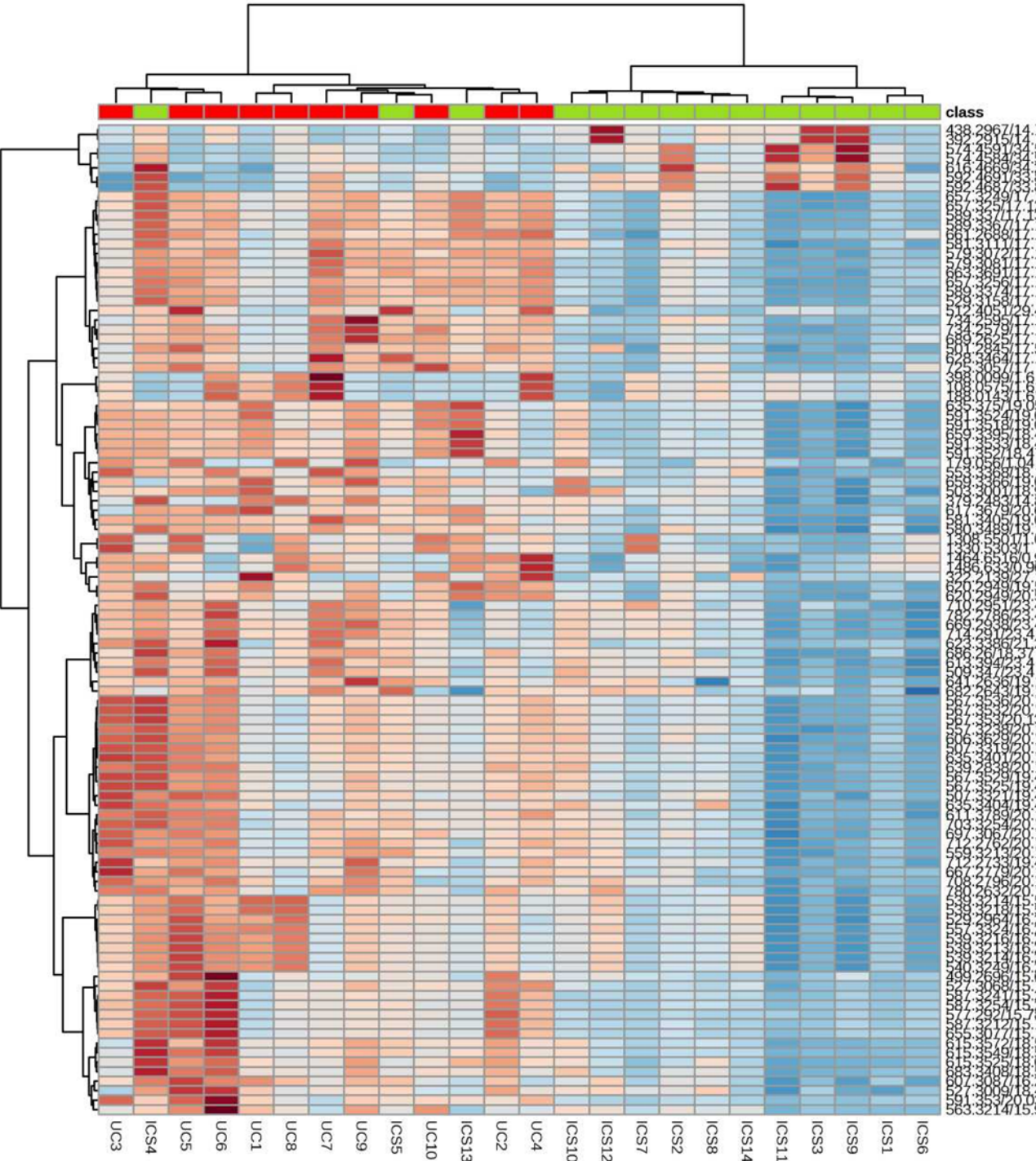
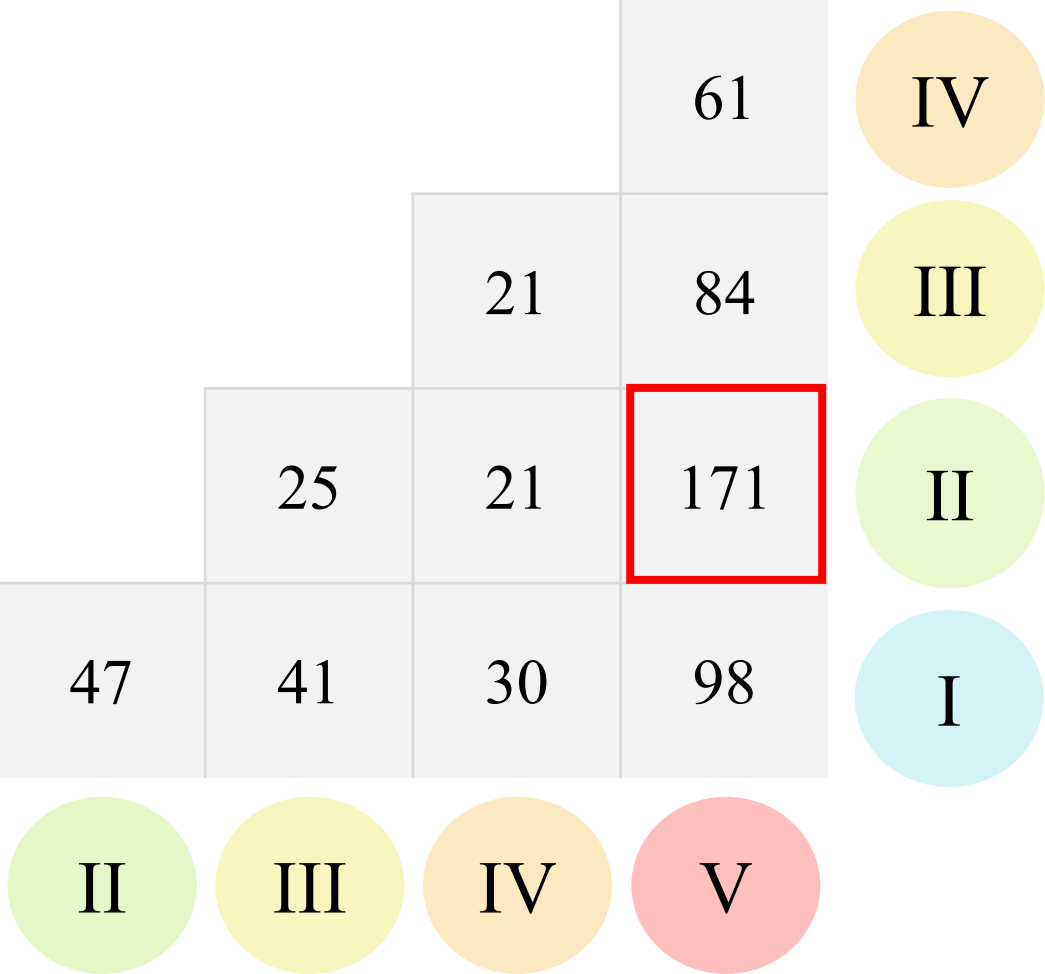
Global Metabolomic Profiling



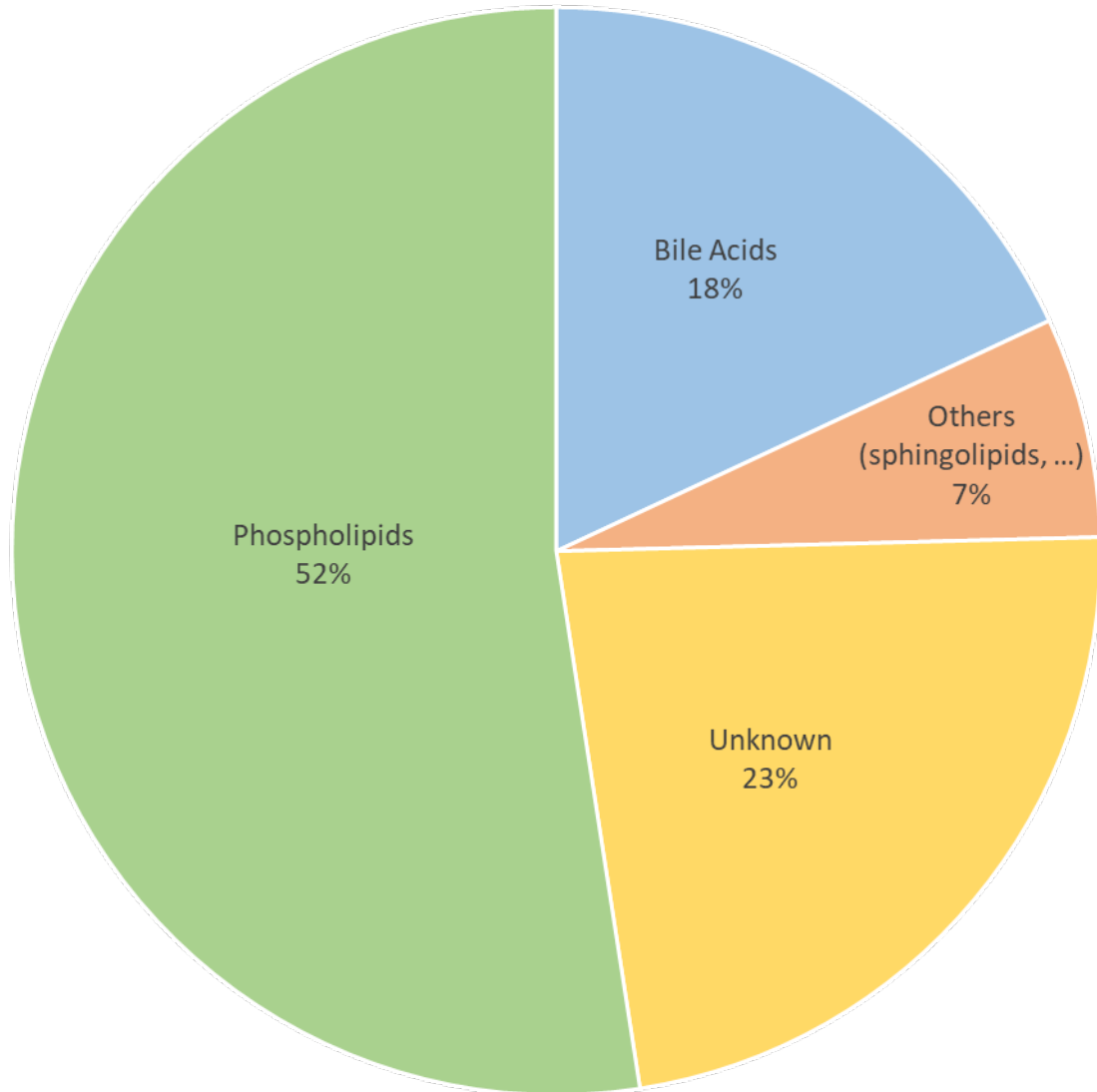
Data treatment & Analysis



Uncontrolled severe allergic
asmathic patients show a
differential metabolic fingerprint.



Tentative identification of differential metabolites in severe uncontrolled patients



Recommendations

-Working with metabolomics in allergy needs:

-A perfect technical execution (Skilled analytical team)

-Adequate Clinical Models

-Biochemical Interpretation

-Complementary approaches: Other omics, Immunological data, Immunohistochemistry.....)

-In summary , a multidisciplinary team



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