Analysis and interpretation of metabolomics and proteomics data

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Technologies for systems biology studies at the cellular level





Metabolic Fluxes

Subtrates

Metabolic flux balancing

-in most cases underdetermined system
=> experimental constraints necessary

Products Biomass

Flux balancing

v₃+**v**₂-**v**₁=0

Chemostat cultures H2490: XR/XDH+XKmc

10g/L Glucose

3 g/L glucose + 27g/L xylose

Samples: •aerobic culture •anaerobic culture •5, 30, and 60 minutes after the switch off oxygen supply

Benefits of ¹³C labeling & NMR

• position sensitive • isotopomer sensitive

METAFoR (metabolic flux analysis)

Mass spectrometry

LC/MS proteomics platform and data processing

Liver Protein Profiling

Fractionation using Reversed Phase Chromatography

Plasma Protein Profiling LC/MS of digested SEC fraction

Plasma Protein Profiling Principal Component Analysis: Fraction I

Unsupervised clustering reveals differences at 9 week age

Plasma Protein Profiling Factor Spectrum: Peptides Exhibiting Differences

Peptide Sequencing using MS/MS

Metabolomics

Study of small molecules , or metabolites, contained in a cell, tissue or organ (including fluids) and involved in primary and intermediary metabolism.

We are not alone genomewise ...

From Nicholson et al., Nature Reviews Microbiology (2005)

Historical note

1500-2000BC China •Ants used to detect patients with diabetes

1940s-1970s

- •Advances in analytics
- •Pattern recognition
- \rightarrow Metabolic profiling

21st century
Advances in analytics
Biostatistics & Bioinformatics
→ Modern era of metabolomics and systems biology

Modern metabolomics platform

Experiment design + Analytical chemistry + Chemometrics + Bioinformatics

Data processing

Pre-processing & Normalization & QC			
Exploratory Analysis	Univariate Analysis		Correlation Analysis
PCA and Discriminant Analysis	Analysis of Variance (ANOVA) Selection of peaks displaying significant changes between Wild Type and Transgenic, separately from gender or age specific effects		Correlation Networks Linear and Non-Linear approach to profile association calculation
Study general trends In data	Parametric Tests (t-test)	Nonparametric Tests (Kolmogorov-Smirnov)	Select peaks with high level of correlations to strongest outliers
Prioritization of Important Peaks for Identification			
Verification of Protein or Metabolite IDs. Databases Extensions/Traversals			

Global Metabolite Analysis NMR Spectra of Plasma

Metabolite Analysis Plasma NMR Principal Component & Discriminant Analysis

Metabolite Analysis - LC/MS of Plasma Lipids

ApoE3 vs. WT: LC-MS Plasma Lipid Profiles

Metabolite Analysis ApoE3 vs. WT: Plasma Lipid Difference Factor Spectrum

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Normalized Integrated Differential Profile

- Mouse Liver
- mRNA +Protein + Metabolite
- Normalization
- Pattern recognition

Variable Index

Similarity

Example: highly correlated peaks

Similarity

Example: uncorrelated peaks

Correlation networkscan reveal patterns of changes relevant to the physiological response

A. Histogram of the distribution of peaks (lipid compounds) according to up-/down-regulation.

Cer3 (565)

C. Up-regulated lipids (mainly long chain phospholipids, short-chain triacylglycerols, and diacylglycerols)

TG (888)

FA fragment (263)

TG (878)

TG (880

LysoPL(512)

DAG(655)

TG (882)

TG(C54:4)

TG(C54:6)

TG(C56:6)

DAG(602)

LC PL (810)

TG (892)

LC PL (854)

LC PL (856)

DAG(600)

DAG(598)

LC PC (846)

LysoPL(419)

LC PL (860)

G. Medina Gomez et al., Diabetes (2005)

Subspace clustering methods

Unsupervised clustering No prior information used

Set of "objects" (e.g. samples), each described by several variables (e.g. gene expression, metabolite profiles)

Unsupervised clustering No prior information used

- Find groups of objects with small within-group distances and large between-group distances
- Several choices of distance metrics
- Examples: K-Means, Hierarchical, Subspace clustering methods

Supervised clustering Prior grouping information available \rightarrow Classification

- Find a model for each group, in order to be able to classify previously ungrouped objects
- Examples: Neural networks, Genetic algorithms, Support vector machines, Linear discriminant analysis
- Main problem in clinical applications (biomarkers, diagnostics): Lack of proper validation and overfitting.

Subspace similarity Metabolites may be dynamically (de)coupled under specific conditions

Example 2: Functional genomics *ob/ob* mouse model

- Spontaneous mutation in *ob* gene resulting in lack of leptin (product of *ob* gene)
- Leptin hormone is a satiety signal
 - hormone secreted from adipose tissue
 - modulates energy intake and utilization
- Model for ea '

e obesity

ob/ob and WT mouse white adipose tissue Lipidomic profiles reveal gender-specific differences

Oresic and Vidal-Puig

Double KO models (ob/ob and PPARγ2) WT/WT, WT/KO, KO/WT, and KO/KO

Clustering with Euclidian distance metric

Subspace clustering (no a priori grouping assumed) COSA method

Three major groups identified from lipidomic profiles: mainly WT/WT, mainly KO/KO, mainly WT/KO

ob/ob and WT mouse white adipose tissue Lipidomic profiles reveal gender-specific differences

Oresic and Vidal-Puig

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