May 16th-17th

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May 16th-17th

May 16th

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---- 04:30 pm Finish ----

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May 16th-17th

May 16th CHOLINE ADENOSINE TRIPHOSPHATE CHOLESTEROL TESTOSTERONE OF CHOLESTEROL TESTOSTERONE OF CHOLESTEROL TESTOSTERONE GIVEN AN PHOSPHOCHOLINE ACYLCARNITINE THREE ON THE CHOLINE THREE ON THE CHOLINE THREE ON THE CHOLINE THREE ON THE CHOLINE CHOL SERINE TRYTOPHAN PHOSPHOCHOLINE ACYLCARNITINE THREONE GLUCEN CAL ACTOSE CHOLINE ALEXANTINE THREONE GLUCEN CAL ACTOSE CHOLINE ADENOSINE CHOLINE MALEXAL ---- 12:30 pm Begin ----PYRUVIC ACID URFA GALACTOSE CHOLINE ACYLCARNITINE THREONIE GLUCOSE GALACTOSE CHOLINE ADENOSINE CHOLINE THREONIE GLUCOSE UCOSE PHOSPHATE CHOLESTEROL OXALOSUCCINIC ACID GALACTOSE GLUCEMIC ACID UFFA A CHOLINE ADENOSINE CHOLINE LACTICACID KETOGLUTA DURCINIC ACID GALACTOSE GLUCEMIC COLID UFFA A CHOLINE ADENOSINE CHOLINE LACTICACID KETOGLUTA DURCINIC ACID GALACTOSE GLUCEMIC DURCINIC ACID GUL ---- 3:00 pm Break -------- 04:30 pm Finish ----PYRUVIC ACID JE A CHOLINE ADENOSINE CHOLINE MALICACID GLUCOSE CHOLINE ACHOLINE ADENOSINE CHOLINE LACTOSE GLYCEROL JCLEOTIDE OXALOSUCCINIC ACID GALACTOSE GLYCEROL JCLEOTIDE OXALOSUCCINIC ACID GALACTOSE GLYCEROL NICOTINAMIDE APENANDUCLEOTIDE OXALOSUCCINIC ACID GALACTOSE G SERINE TRYTO PHOSTHOCHOLINE ACYLCARNITINE THREE PYRUVIC ACID REA GALACTOSE CHOLINE ADENOSINE CHOLINE PYRUVIC ACID REA GALACTOSE PHOSPHATE CHOLESTEROL OXALO DOVE DE CONTRACTORE CHOLINE ACID GALACTOSE G TESTOSTERONE GLUCOSE PHOSPHATE CHOLESTEROL OXALOSUCCINIC ACID GALACTOSE GLYCEROL FUNAL GLUCOSE CHOLESTEROL OXALOSUCCINIC ACID GALACTOSE GLYCEROL IMARATE NICOTINAMIDE ADENINE DINUCLEOTIDE OXALOSUCCINIC ACID GALACTOSE GLYCEROL FURANCE ADENINE DINUCLEOTIDE OXALOSUCCINIC ACID GALACTOSE GLYCEROL FURANCE ADENINE DINUCLEOTIDE OXALOSUCCINIC ACID GALACTOSE GLYCEROL SERIE TRYTOPHAN PHOSPHOCHOLINE ACYLCARNITINE THREONINE GYCERU May 17th ---- 09:00 am Begin -------- 10:30 am Break -------- 12:00 pm Lunch ----

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Gary Siuzdak



Gary Siuzdak



Elizabeth Billings



Gary Siuzdak



Elizabeth Billings



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Amelia
Palermo
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Gary Siuzdak



Elizabeth Billings



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Amelia
Palermo
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Tao Huan



Gary Siuzdak



Elizabeth Billings



Amelia Palermo



Tao Huan



Bill Webb



Gary Siuzdak



Elizabeth Billings



Amelia Palermo



Tao Huan



Bill Webb



H. Paul Benton



Xavi Domingo



Erica Forsberg



Carlos Guijas



Rafa Montenegro

Objectives and Challenges

May 16th

May 16th

- ---- 12:30 pm Begin ----
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- Objectives and Challenges
- Experimental Design

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• Primary Experimental and Informatic Challenges

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- Primary Experimental and Informatic Challenges
- Key Algorithms in Creating Reproducible Data

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Pre-analytical

Sample amount



cell cultures (~ 1.10⁶ cells)



Metabolism quenching



snap freezing (liquid N₂) heat fixation





freezing -80°C



Fundamental Metabolomics Advanced



Fundamental Metabolomics Advanced



Experimental Design

Biology





is a discipline in which the complete set of within cells or an organism is analyzed.



Metabolomics is a discipline in which the complete set of within cells or an organism is analyzed.



Metabolomics is a discipline in which the complete set of metabolites within cells or an organism is analyzed.














Riboswitches





Riboswitches

Enzyme substrates/Inhibitors Post-translational Modification Allosteric Modulation







Riboswitches

Enzyme substrates/Inhibitors Post-translational Modification Allosteric Modulation



Metabolomics Activity Screening



Fundamental Metabolomics Advanced



Fundamental Metabolomics Advanced



Experimental Design

Biology



Untargeted Metabolomics



Untargeted Metabolomics

> Targeted Metabolomics



Untargeted Metabolomics





Untargeted Untargeted Metabolomics Extraction MeOH / ACN / plasma (2:2:1)

- 200μL plasma aliquot Reconstitution ACN / H2O (1:1)

Dry metabolite extract





Extracted Ion Chromatograms







Extracted Ion Chromatograms





Extracted Ion Chromatograms











Experimental Design **Biological Question Control Design**

Experimental Design **Biological Question Control Design**

Experimental Design **Biological Question Control Design**







1 3 5 10 20

1 3 5 10 20 50

1 3 5 10 20 50 100 1000

Experimental Design **Biological Question Control Design** Numbers/Statistics **Biomarkers/Pathways/Mechanism**
Experimental Design **Biological Question Control Design** Numbers/Statistics **Biomarkers/Pathways/Mechanism Biological Activity**

Metabolomics Papers PDFs Included

Metabolomics Activity Screening Identifies Metabolites that Modulate Phenotype Nature Biotechnology 2018 Data Processing, Multi-Omic Pathway Mapping, and Metabolite Activity Analysis Nature Protocols 2018 Metabolomics-Based Discovery of a Metabolite that Enhances Oligodendrocyte Maturation Nature Chemical Biology 2018 Metabolite-Induced Protein Expression Guided by Metabolomics and Systems Biology Cell Metabolism 2018 Systems Biology guided by Metabolomics Nature Methods 2017 Nature Reviews 2016 Metabolomics: Beyond Biomarkers and Towards Mechanisms XCMS: Processing MS Data using Nonlinear Alignment and Metabolite ID Analytical Chemistry 2006 Mzmine 2: Modular framework for processing, visualizing, and analyzing MS data **BMC Bioinformatics 2010** Bioinformatics: The Next Frontier of Metabolomics **Analytical Chemistry 2015** Predicting Network Activity from High Throughput Metabolomics PLOS Computational Biol. 2013 **Analytical Chemistry 2014** Interactive XCMS Online: Simplifying Advanced Data Processing and Statistical Autonomous Metabolomics for Rapid Metabolite Identification in Global Profiling **Analytical Chemistry 2015 Analytical Chemistry 2015** Thermal Degradation of Small Molecules: A Global Metabolomics Investigation Arteriovenous Blood Metabolomics: A Readout of Intra-Tissue Metabostasis **Scientific Reports 2015** Cell Metabolism 2015 Metabolism Links Bacterial Biofilms and Colon Carcinogenesis CFM-ID: a web server for annotation, prediction and metabolite ID Nucleic Acid Research 2014 Determining Conserved Metabolic Biomarkers from a Million Database Queries **Bioinformatics 2015** Autonomous Metabolomics for Rapid Metabolite Identification in Global Profiling Analytical Chemistry 2015 Metabolomic data streaming for biology-dependent data acquisition Nature Biotechnology 2014 Comprehensive bioimaging with fluorinated nanoparticles Nature Comm. 2015 Liquid chromatography quadrupole time-of-flight mass spectrometry Nature Protocols 2013 Multivariate Analysis in Metabolomics Current Metabolomics 2013 Intra- and Interlaboratory Reproducibility of UPLC TOF MS for Urinary Metabolic Profiling Analytical Chemistry 2012 A Guideline to Univariate Statistical Analysis for LC/MS Metabolites 2012 An accelerated workflow for untargeted metabolomics using METLIN database Nature Biotechnology 2012 Within-Day Reproducibility of an HPLC-MS-Based Method **Journal Proteome Research 2007** HMDB: the Human Metabolome Database Nucleic Acid Research 2007 XCMS: Processing MS Data using Nonlinear Alignment and Metabolite ID **Analytical Chemistry 2006** METLIN: A Mass Spectral Database Therap. Drug Monitoring 2005

Fundamental Metabolomics

- Objectives and Challenges
- Experimental Design

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May 16th

Sample Preparation May 16th

Elizabeth Billings

Fundamental Metabolomics



Experimental Design

Fundamental Metabolomics



Experimental Design

Sample Types

Biofluids (20-100µL)

urine, cerebrospinal fluid (CSF), blood plasma/serum, saliva, etc.

Cell Cultures (varies by cell type, typically 1x10⁶ cells) adherent and non-adherent cells

Tissues (~10 mg fresh weight) liver, kidney, muscle, fat, etc.

• Remove proteins and particulates



• Remove proteins and particulates



• Quench metabolism





- Rapid drop of temperature in solvent and efficient protein precipitation
- Extraction of polar and non-polar molecules
- Polar solvent
 - MeOH, EtOH, H₂O, MeOH:H₂O (4:1)
- Non-polar solvent
 - Acetone, chloroform, hexane





- Cold is recommended
 - liquid nitrogen or dry ice ethanol bath
 - very fast quenching
 - much safer for metabolites and metabolomics than heat fixation







• Remove proteins and particulates



• Quench metabolism

• Recover hydrophobic and hydrophilic metabolites



Yanes et al. 2011, Ivanisevic et al. 2013 AnalChem

Experimental design

toward 'omic scale metabolite profiling



Profiling of both polar and non-polar metabolites with ONE single extraction

Ivanisevic, J., et al. Anal. Chem, 2014

Experimental design

toward 'omic scale metabolite profiling



Profiling of both polar and non-polar metabolites with ONE single extraction

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Experimental design

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Experimental design

toward 'omic scale metabolite profiling



When time and sample are limited the highest number of unique, biologically relevant metabolites can be detected in:



Methods for extraction

Dependent on sample type

-non-mechanical methods (Liquids: plasma, urine, cells, CSF)
-freeze/thawing to break open the cell
-addition of solvent

-mechanical method (Solids: organs, tissues, feces)
-homogenizer

Cell pellet extraction

5-10 million cells + ice cold water: acetonitrile: methanol (1:2:2 v/v/v)



Cell pellet extraction



Cell pellet extraction



Cell pellet extraction

Transfer to centrifuge tubes



Evaporate solvent





Cell pellet extraction



Cells in suspension vs. adherent cell lines

• Avoid using trypsin

Cells in suspension vs. adherent cell lines

• Avoid using trypsin

Without protein measurement

Cells in suspension vs. adherent cell lines

• Avoid using trypsin

Without protein measurement

- Wash cells with PBS
- Add 1 mL ice cold solvent and scrape cells into a vial

Cells in suspension vs. adherent cell lines

• Avoid using trypsin

Without protein measurement

- Wash cells with PBS
- Add 1 mL ice cold solvent and scrape cells into a vial
- Dry samples in a lyophilizer, extract same weight per sample, and reconstitute in 1 mg per 100 µL solvent.

Cells in suspension vs. adherent cell lines

• Avoid using trypsin

With protein measurement

Cells in suspension vs. adherent cell lines

• Avoid using trypsin

With protein measurement

- Wash cells with PBS
- Add 1 ml ice cold water on liquid nitrogen and scrape cells into a vial

Cells in suspension vs. adherent cell lines

• Avoid using trypsin

With protein measurement

- Wash cells with PBS
- Add 1 ml ice cold water on liquid nitrogen and scrape cells into a vial
- Carry out freeze-thawing steps and collect aliquot for protein assay
- Then add solvent
Biofluid Specifics

Plasma/Urine/CSF

•Add 400 μL of cold solvent to 100 μL plasma to maintain ratio of 2:2:1 (MeOH:ACN:H2O)

•Vortex and sonicate 10 min

Methods for extraction

Dependent on sample type

-non-mechanical methods (Liquids: plasma, urine, cells, CSF)
 -freeze/thawing to break open the cell
 -addition of solvent

-mechanical method (Solids: organs, tissues, feces)
 -homogenizer

Tissue extraction

10 mg tissue + Ice cold water: methanol (1:4 v/v) + Homogenization Beads → 1mm Zirconia beads 1mm Glass beads



Tissue extraction



Homogenizer



Store –20°C

Overnight/1 h

Sonicate

Tissue extraction

Transfer to centrifuge tubes



Evaporate solvent





Tissue extraction



Normalization Strategies

Tissues – Weight – Protein

Normalization Strategies

- Tissues Weight
 - Protein
- Cells Cell number
 - Protein or DNA concentration/estimation

Normalization Strategies

Tissues – Weight – Protein

- Cells Cell number – Protein or DNA concentration/estimation
- Biofluids Volume for most biofluids – Challenging to normalize urine

Quality Sample Prep

Reduce background ions: salts/buffers/surfactants, PEG, solvents (DMSO), polymers/plasticizers

Reduce biological contamination: keratin, cross contamination, cellular media

Reduce sample degradation: properly store samples after preparation

Quality sample prep \rightarrow Higher quality results

Fundamental Metabolomics

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Mobile Phase



Stationary Phase





1. Reduce ion suppression for MS Better sensitivity and increase in detected molecules

Reduce ion suppression for MS
 Better sensitivity and increase in detected molecules

 Separate isobaric molecules

1. Reduce ion suppression for MS

Better sensitivity and increase in detected molecules

2. Separate isobaric molecules



- Reduce ion suppression for MS
 Better sensitivity and increase in detected molecules

 Separate isobaric molecules
- 3. Retention time for metabolite ID

- 1. Reduce ion suppression for MS Better sensitivity and increase in detected molecules
- 2. Separate isobaric molecules
- 3. Retention time for metabolite ID
- 4. High-quality MS/MS data

Factors affecting Chromatography

- Mobile phase (MP) (composition, pH, salts content, elution gradient)
- Temperature
- Type of stationary phase (SP)

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- Mobile phase (MP) (composition, pH, salts content, elution gradient)
- Temperature
- Type of stationary phase (SP)



+ salts for buffer effect
 (pH and ionic strength control)



+ salts for buffer effect
 (pH and ionic strength control)

Reversed-phase

- ESI + A: 100% H₂0 + 0.1% FA
 - B: 100% ACN + 0.1% FA
- ESI- A: 100% H₂0 + 1mM NH₄F

B: 100% ACN

HILIC

ESI- A: 95% H₂0 + 20mM NH₄Ac + 20mM NH₄OH B: 95% ACN



- + salts for buffer effect
 (pH and ionic strength control)
- Isocratic elution



Organic



- + salts for buffer effect
 (pH and ionic strength control)
- Isocratic elution
- Gradient elution



Organic

Factors affecting Chromatography

- Mobile phase (MP) (composition, pH, salts content, elution gradient)
- Temperature
- Type of stationary phase (SP)

Column Temperature



- Usually 27°C
- T > 27 °C for the elution of highly retained compounds (e.g. lipids in RP)

Column Temperature



- Usually 27°C
- T > 27 °C for the elution of highly retained compounds (e.g. lipids in RP)

Increase of T:

- Increase elution of highly retained compounds
- Allows higher <u>flow</u> rate for faster gradients
- Caution, can affect metabolite stability and column lifetime!

Factors Affecting Chromatography

- Mobile phase (MP) (composition, pH, salts content, elution gradient)
- Temperature
- Type of stationary phase (SP)

How do we choose the appropriate type of LC?

• **Time** & sample **number** -High-throughput?
How do we choose the appropriate type of LC?

- **Time** & sample **number** -High-throughput?
- **Type of metabolites** you wish to see?
 - Polar vs. non-polar
 - Specific metabolite class
 - Isomers

Speed: HPLC vs. UPLC

- Time & sample number
 - High-throughput?
 - A) High Performance Liquid Chromatography (HPLC)B) Ultra Performance Liquid Chromatography (UPLC)

Speed: HPLC vs. UPLC

A) High Performance Liquid Chromatography (HPLC)B) Ultra Performance Liquid Chromatography (UPLC)



UPLC

- Operates at higher pressure
- Smaller particles size

Speed: HPLC vs. UPLC

UPLC

- Improved resolution
- Generally higher sensitivity
- Higher pressure stability
- Higher mass spec scan speed required
- Shorter gradients

HPLC

- Lower likelihood of column clogging
- Lower back pressure
- Can use mass spec with slower scan speed





Speed: LC vs. NO LC ?



- Flow Injection Analysis (FIA) 1-2min/sample
- No chromatography → <u>cannot separate</u> <u>isobars</u>, <u>high ion suppression</u> and <u>lower sensitivity</u>.
- Useful for:
 - **real-time** metabolomic profiling (Link, H., Nat. Met. 2015)
 - high-throughput studies > 1000 samples

How do we choose the appropriate type of LC?

- **Time** & sample **number** -High-throughput?
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 - Isomers

LC Choices in Metabolomics

• HPLC (High Performance Liquid Chromatography)

- Reversed Phase
- Hydrophilic Interaction Liquid Chromatography: HILIC

• UPLC (Ultra Performance Liquid Chromatography)

- Reversed Phase
- Hydrophilic Interaction Liquid Chromatography: HILIC

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Hydrophobic Interactions



Hydrophobic Interactions

Non-polar Metabolites



Hydrophobic Interactions

Non-polar Metabolites

Elution Gradient: From High Water to High Organic Solvents (ACN or IPA)





Hydrophobic Interactions

Non-polar Metabolites

Elution Gradient: From High Water to High Organic Solvents (ACN or IPA)



• Large number of metabolomic studies use C18 RP LC



• Large number of metabolomic studies use C18 RP LC



- Large number of metabolomic studies use C18 RP LC
- Highly polar molecules are not retained

void volume: glycolysis, pentose-phosphate, TCA,... (lots of important structural isomers)



LC Choices in Metabolomics

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 - Reversed Phase
 - Hydrophilic Interaction Liquid Chromatography: HILIC
- UPLC (Ultra Performance Liquid Chromatography)
 - Reversed Phase
 - Hydrophilic Interaction Liquid Chromatography: HILIC

- **Derivatization** of silica stationary phase enhances retention of polar molecules by hydrogen bonding or ionic interactions.
- Elution gradient: from high organic with low % water and salts, to high water and salts.



- MF forms a water-rich layer on the surface of the polar stationary phase, creating a liquid/liquid extraction system.
- The retention is based on the hydrophilic partitioning of the analytes into the water-enriched SP and electrostatic interactions with the charged SP.

- **Derivatization** of silica stationary phase enhances retention of polar molecules by hydrogen bonding or ionic interactions.
- Elution gradient: from high organic to high water.



• Increasingly popular, particularly for targeted analysis of metabolites in central carbon metabolism.

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- Highly hydrophobic compounds are not retained.

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- Increasingly popular, particularly for targeted analysis of metabolites in **central carbon metabolism.**
- Highly hydrophobic compounds are not retained.
- Long equilibration times and shorter column lifetime.
- At high water/salt/pH buffer, SP can degrade rapidly.

HILIC for Untargeted Metabolomics

HILIC COLUMN for untargeted metabolomics:

 HPLC: Luna NH₂ (3 μm, 150 x 1 mm) column Phenomenex (Ivanisevic, J, Anal. Chem. 85(14), 2013)



Fold change Metabolite **Fold change** p-value Metabolite p-value 1.10 ± 0.09 19 Docosahexaenoic acid Leucine 1.03 ± 0.03 ns 1 ns 2 Isoleucine 1.03 ± 0.03 1 ns 20 Arachidonic acid 1.06 ± 0.07 1 ns 3 Valine 1.03 ± 0.05 1 21 Hypoxanthine 1.77 ± 0.39 4 ns ns 22 Phenylalanine 0.0033 4 Methionine 1.05 ± 0.06 🕹 ns 1.09 ± 0.02 1 5 Proline 1.02 ± 0.03 + ns 23 Tryptophan 1.11 ± 0.06 4 ns 6 Alanine 1.17 ± 0.04 + 0.0003 24 Inosine 1.10 ± 0.11 4 ns + 25 7 Tyrosine 1.03 ± 0.02 ns Hippuric acid 1.03 ± 0.04 ns 8 Glycine 1.04 ± 0.02 👃 ns 26 Glutamine 1.17 ± 0.06 0.0259 27 < 0.0001 9 Threonine 1.02 ± 0.03 🕹 ns Lactate 1.31 ± 0.06 4 10 1.03 ± 0.03 🕹 28 Sialic acid (Neu5Ac) 1.09 ± 0.02 4 0.0007 Asparagine ns 1.07 ± 0.03 1 29 < 0.0001 11 Serine 0.0144 Aspartate 1.51 ± 0.09 + + < 0.0001 12 Histidine 1.02 ± 0.03 ns 30 Glutamate 3.02 ± 0.32 1 13 Malate 1.76 ± 0.23 + 0.0012 31 Cystine 1.06 ± 0.03 ns + 14 α-ketoglutarate 1.14 ± 0.06 ns 32 Hexadecanedioic acid 1.04 ± 0.03 ns 1.06 ± 0.05 1 Tetradecanedioic acid 1.04 ± 0.02 15 Arginine ns 33 ns + 16 Ornithine 1.03 ± 0.04 34 Dodecanedioic acid 1.03 ± 0.03 1 ns ns 1.04 ± 0.04 4 17 Lysine 35 3-methylglutaric acid 1.25 ± 0.12 4 ns ns 18 Allantoin 1.07 ± 0.03 🕹 ns 36 Succinate 1.56 ± 0.09 < 0.0001

Mobile Phase (pH: 9.7)

A: 95% H20 +20mM NH₄Ac +20mM NH₄OH B: 95% ACN

Elution Gradient: From High Organic to High Water



Gradient Time

Dual Separation In Metabolomics

When **time and sample are limited** the highest number of unique, biologically relevant metabolites can be detected in:

Dual Separation In Metabolomics

When **time and sample are limited** the highest number of unique, biologically relevant metabolites can be detected in:



Dual Separation In Metabolomics



Good coverage:

RPLC ESI(+) AND HILIC ESI (-)

(Ivanisevic, J, Anal. Chem. 85(14), 2013)

LC: Take-Home Message



- Objectives and Challenges
- Experimental Design

May 16th

May 16th

- ---- 12:30 pm Begin ----
- ---- 3:00 pm Break ----
- ---- 04:30 pm Finish ----
- Sample Preparation and Chromatography
- Untargeted Metabolomics
- Targeted Metabolomics
- Metabolite Databases and Informatics
- Statistical Analysis

- Objectives and Challenges
- Experimental Design

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Nuclear magnetic resonance (NMR)

- Good for absolute quantification
- □ Not sensitive enough for broad metabolome coverage

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Gas chromatography-mass spectrometry (GC-MS)

- Good chromatographic separation
- Not suitable for thermo-labile metabolites

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Liquid chromatography-mass spectrometry (LC-MS)

Good sensitivity and wide metabolome coverage

LC-MS based Untargeted Metabolomics

Choice of MS

- LC-MS combination
- Analytical sequence
- Data processing
- Metabolite identification



Choice of MS

Mass resolution Mass accuracy




How Much Resolution Is Required

• The higher the better, there may never be enough resolution





How Much Resolution Is Required

- The higher the better, there may never be enough resolution
- Typical metabolomic profiling requires mass resolution higher than 15,000



Mass Accuracy



Mass Accuracy

• Mass error = (theoretical m/z) – (measured m/z)



Mass Accuracy

- Mass error = (theoretical m/z) (measured m/z)
- Mass error in parts per million (ppm) =

X 10⁶

• Accurate mass is important for metabolite identification



• Accurate mass is important for metabolite identification



- Accurate mass is important for metabolite identification
- Accurate mass measurement can be used to determine the elemental composition

- Accurate mass is important for metabolite identification
- Accurate mass measurement can be used to determine the elemental composition
- Typical MS profiling requires mass accuracy better than 10 ppm



Achieve good mass accuracy through mass calibration

250 mM NaFA





Calibration list: ESI -*Na Formate (pos) <Method> Auto Search I Ref. Mass Cur. Mass Res. (m/z) Error [ppm] Substance Remove Na(NaCOOH)1 90.9766 90.9761 90.9766 -0.230 133282 Remove All Na(NaCOOH)2 158.9641 158.9636 158.9641 0.152 158408 Na(NaCOOH)3 226.9515 226.9499 226.9516 0.325 528956 Na(NaCOOH)4 294,9389 294,9376 294,9389 0.043 24502 Na(NaCOOH)5 362.9263 362.9254 362.9262 -0.443 148970 430.9138 430.9131 430.9137 -0.183 204534 Na(NaCOOH)6 Na(NaCOOH)7 498.9012 498,9005 498.9013 0.149 83322 Na(NaCOOH)8 566.8886 566.8876 566.8888 0.294 81710 Na(NaCOOH)9 634.8760 634.8743 634.8761 0.114 82924 702.8634 -0.042 97920 Na(NaCOOH) 10 702.8635 702.8612 770.8482 770.8507 -0.238 78144 Na(NaCOOH)11 770.8509 Na(NaCOOH)12 838.8355 -0.311 67734 838.8383 838.8380 Na(NaCOOH)13 906.8257 906.8235 906.8260 0.325 55494 Na(NaCOOH)14 974.8132 974.8107 974.8133 0.101 45624 Na(NaCOOH)15 1042.8006 1042.8006 0.030 35778 1042.7977 Na(NaCOOH)16 1110.7880 1110.7844 1110.7878 -0.178 25296 Na(NaCOOH)17 1178.7754 1178.7715 1178.7755 0.071 14880 Standard deviation [ppm]: 0,295 Minimal number of calibration points: 7 Abd. 0.4 0 0 0.2 0 \odot 0.0 0 0 0 -0.2 0 -0.4 • 200 1200 1400 400 600 800 1000 m/z Mode: HPC Ŧ Search range (m/z): Intensity threshold: 0.05 1000 Zoom: off •

Q-TOF

- Resolution: > 20,000
- Mass accuracy: < 1 ppm
- Mass range: up to 20,000 m/z
- Dynamic range: five orders of magnitude with femtogram-level sensitivity



Orbitrap

- Resolution: up to 140,000
- Mass accuracy: < 1 ppm
- Mass range: up to 6,000 m/z
- Dynamic range: four orders of magnitude with femtogramlevel sensitivity



LC-MS based Untargeted metabolomics

- Choice of MS
- LC-MS combination
- Analytical sequence
- Data processing
- Metabolite identification

Toward 'omic scale metabolite profiling

Profiling of both polar and non-polar metabolites with ONE single extraction

Ivanisevic, J., et al. Anal. Chem, 2014











LC-MS based Untargeted Metabolomics

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- LC-MS combination
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Fundamental Metabolomics LC-MS Analytical sequence

Blank (50/50 ACN/H2O)

Standard mixture (mixture of metabolite standards)

QC sample (pooled sample solution)

Sample 1 - 10

QC sample

Sample 11 - 20

:

Fundamental Metabolomics Metabolomic Profiling

•Sreekumar et al. (Nature 2009) used a 16-min gradient to examine 262 prostate-related samples (tissue, plasma, urine) to look for markers of prostate cancer aggressiveness

•Wang et al. (Nature Medicine 2011) used a 30-min run to analyze 1500 plasma samples for predictors of diabetes

•Wang et al (Nature 2011) used 14.5-min run to analyze 2000 plasma samples for cardiovascular disease.

LC-MS based Untargeted Metabolomics

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Web-based metabolomics data processing platform



Web-based metabolomics data processing platform

- Comprehensive data processing algorithms
- Interactive tools for rapid data exploration
- Over 15,000 registered users (May, 2018)
- Freely available at http://xcmsonline.scripps.edu/





Home	9	MRM	Databases -	Create	View	XCMS	XCMS	Stored	Account	Toolbox	Help+	😃 Logout [thuan]	
				Job -	Results	Public	Institute	Datasets					

(CMS

The original and most widely used metabolomic and lipidomic platform

Latest News and Articles

Nature Protocols - Data Processing with XCMS Nature Methods - Systems Biology guided by Metabolomics Visit our new cloud-based targeted MRM technology: XCMS-MRM













Single Job

Peak picking & identification for a single sample group, no comparison Pairwise Job

Two group comparison (control vs. treatment)

Meta XCMS Job

Identify the common dysregulated features across several comparisons Multigroup Job

XCMS Stream

Three or more group comparisons (time series)

Visit our new cloud-based targeted MRM technology: XCMS-MRM

Home У MRM Da	tabases≁ Create Vie Job≁ Res	ew XCMS XCMS ults Public Institu	S Stored te Datasets	Account Toolb	ox Help+ 🕲 Logout [thuan]
1 Dataset 1 Load New Dataset OR Select Dataset (See <u>File Formats</u> for more information)	2 Dataset 2 Load New Dataset OR (See File Formats for more	elect Dataset information)	Parameters	~	Job ID: 1217570 User: thuan@scripps.edu (9032) Job Name: pair_2018-05-10_1. Edit Dataset 1: Not Defined (control) Dataset 2: Not Defined
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Directly upload new data files

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Select from a list of existing stored datasets

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View/Edit Parameters for Job

Polarity is defined on the General tab and will affect values on the Annotation and Identification (adducts) tabs. Job results will be misleading if this value is not correctly defined. The current parameter set is read-only. Use **Create New** button below to modify parameters to suit your job.

General	Feature Detection	Retention Time Correction	Alignment	Statistics	Annotation	Identification	Visualization	Miscellaneous			
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Create New O Cancel



Simplified mechanism of peak extraction
Fundamental Fundamental Metabolomics Raw LC-MS data





Combined Chromatogram: 268.1 - 268.2 m/z









Combined Chromatogram: 268.1 - 268.2 m/z











Mechanism of peak extraction

	Home	MRM	Databases -	Create Job -	View Results	XCMS Public	XCMS Institute	Stored Datasets	Account	Toolbox	Help≁	😃 Logout	[thuan]	
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	MULTI	VIEW	1194929	job complete	D	DvH Late vs Cys vs ND132		DvH-WT_lat (#275833) DvH+cys_RN (#275827) DvH-WT_med (#275834)	2018-01-05 12:43:08	DvH_Bru	iker (34096)		Shared [Stop sharing]	×
	PAIR	VIEW	1194927	job complete		DvH Late vs. ND132		DvH-WT_lat (#275833) ND132_RN (#275831)	2018-01-05 12:41:06	DvH_Bru	ıker (34096)		Shared [Stop sharing]	×
	PAIR	VIEW	1194921	job complete		DvH Late vs Cys		DvH-WT_lat (#275833) DvH+cys_RN (#275827)	2018-01-05 11:08:06	DvH_Bru	ıker (34096)		Shared [Stop sharing]	×
	SINGLE	VIEW	1194920	job complete		DvH S4/cys		DvH+cys_RN (#275827)	2018-01-05 11:06:36	DvH_Bru	ıker (34096)		Shared [Stop sharing]	×
	SINGLE	VIEW	1194912	job complete		DvH Mid Spent Me	edia	DvH Mid Sp (#292029)	2018-01-05 10:23:55	DvH_Bru	ıker (34096)		Shared [Stop sharing]	×
	MULTI	VIEW	1194907	job complete	DvH Mid	Late_Ecoli_RCH2	Spent Media	DvH Late (#292024) DvH_Mid (#292022) RCH2 anaer (#292026)	2018-01-05 09:59:48	DvH_Bru	iker (34096)		Shared [Stop sharing]	×
	PAIR	VIEW	1194905	job complete		DvH Late vs. ND1	32	DvH+34S_la (#275836) ND132_RN (#275831)	2018-01-05 09:54:44	DvH_Bru	iker (34096)		Shared [Stop sharing]	×
	SINGLE	VIEW	1194837	job complete		RCH2 anaerobic		RCH2 anaer (#292026)	2018-01-04 22:29:18	DvH_Bru	ıker (34096)		Shared [Stop sharing]	×
	SINGLE	VIEW	1194836	job complete		E. coli anaerobi	с	E.coli ana (#292028)	2018-01-04 22:28:29	DvH_Bru	iker (34096)		Shared [Stop sharing]	×
	SINGLE	VIEW	1194833	job complete		DvH Late Spent M	edia	DvH Late S (#292030)	2018-01-04 22:21:18	DvH_Bru	ıker (34096)		Shared [Stop sharing]	×

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	SINGLE	VIEW	1194912	job complete	DvH Mid Spent N	Vledia	DvH Mid Sp (#292029)	2018-01-05 10:23:55	DvH_Bruker (34096)		Shared [Stop sharing]	×	
	MULTI	VIEW	1194907	job complete	DvH Mid_Late_Ecoli_RCH2	2_Spent Media	DvH Late (#292024) DvH_Mid (#292022) RCH2 anaer (#292026)	2018-01-05 09:59:48	DvH_Bruker (34096)		Shared [Stop sharing]	×	
	PAIR	VIEW	1194905	job complete	DvH Late vs. ND	0132	DvH+34S_la (#275836) ND132_RN (#275831)	2018-01-05 09:54:44	DvH_Bruker (34096)		Shared [Stop sharing]	×	
	SINGLE	VIEW	1194837	job complete	RCH2 anaerol	bic	RCH2 anaer (#292026)	2018-01-04 22:29:18	DvH_Bruker (34096)		Shared [Stop sharing]	×	
	SINGLE	VIEW	1194836	job complete	E. coli anaerol	bic	E.coli ana (#292028)	2018-01-04 22:28:29	DvH_Bruker (34096)		Shared [Stop sharing]	×	
	SINGLE	VIEW	1194833	job complete	DvH Late Spent M	Media	DvH Late S (#292030)	2018-01-04 22:21:18	DvH_Bruker (34096)		Shared [Stop sharing]	×	

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Pairwise Results Summary: RPLC_colon cancer_lipid (#1180800)												
Submit Dat	е	Finish Date		Paired Samples		Total Aligned Features		Paramet	er ID#		Log	Shared



2017-10-03 01:31:05 : iHeatMap data prep, memory requires limiting to top 1000 features <0.000136367 p-values 2017-10-03 01:37:03 : There are regions with poor chromatographic resolution. Feature annotations (CAMERA) were omitted for these regions.













	Home	¥	MRM	Databases +	Create Job -	View Results	XCMS Public	XCMS Institute	Stored Datasets	Account	Toolbox	Help+	🕲 Logout	[thuan]
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2017-10-02 22:36:37 2017-10-03 01:53:24 View 19713 RPLC_Bruker_positive (35164) View Log											View Log	NOT SHARED		
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2017-10-03 01:31:05 : iHeatMap data prep, memory requires limiting to top 1000 features <0.000136367 p-values 2017-10-03 01:37:03 : There are regions with poor chromatographic resolution. Feature annotations (CAMERA) were omitted for these regions.









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	2	12.3	6.03231e-1	DOWN	597.6742	41.10	990	8,467	686			289		
Submit Date	3	5.3	3.60958e-9	UP	99.9262	11.41	5,582	11,005	58,045			32		
Cubinit Bato	4	5.1	6.82561e-9	DOWN	555.3299	14.87	2,600	15,831	3,093	[1753][M]-	[M+CI]- 52	(167		
2017-10-02 22:36:37	5	5.6	8.38870e-9	DOWN	134.0178	32.66	6,822	75,826	13,618	[60][M+1]-		192		
	6	22.2	1.59534e-8	UP	817.3058	29.31	978	140	3,119			419		
	7	3.4	2.08921e-8	DOWN	348.0748	15.21	8,510	125,545	36,406	[883][M]-		25		
	8	4.8	2.62550e-8	UP	334.0658	16.51	3,116	12,069	58,134	[809][M+1]-		70		
	9	6.9	3.32163e-8	UP	119.0351	24.43	58,434	178,433	1,223,464	[37][M]-	[M-H]- 120	120		
	10	9.4	3.86507e-6	UP	102.9236	11.41	50,622	60,953	573,057			32		
	11	17.8	6.62694e-8	DOWN	128.9597	22.07	11,560	72,577	4,076			78		
	12	7.9	7.27733e-8	DOWN	333.0639	16.48	7,408	82,894	10,434	[809][M]-	[2M+CI]- 1	70		
	13	13.3	9.83814e-8	UP	322.0449	41.40	1,112	897	11,958			436		
	14	2.9	1.12502e-7	DOWN	329.9648	20.89	6,186	96,825	33,867			109		
Results Table	15	5.4	1.16648e-7	UP	255.0964	18.48	3,016	7,925	42,449			13		
	16	2.8	1.27953e-7	UP	159.0777	21.88	73,674	311,558	869,355	[125][M]-	[M-H]- 160	6		
Metabolomic Cloud Plot	17	3.7	1.33541e-7	UP	532.3506	14.81	2,154	3,781	13,888	[1665][M+1]-		167		
	18	4.7	1.47236e-7	' UP	236.1733	2.23	1,836	865	4,094			51		
Interactive Heatmap	19	8.7	1.51071e-7	UP	219.0512	26.89	3,104	3,849	33,501		[M-H]- 220	122		
	20	2.2	1.58493e-7	UP	132.9964	5.82	501,612	5,460,592	11,803,119	[59][M]-		12		
iPCA	21	4.7	1.59126e-7	UP	467.3741	2.13	1,138	2,052	9,669		[M-H-CO]-	177		
	22	2.9	1.59983e-7	' UP	495.3289	12.94	1,532	4,239	12,082	[1516][M+1]-		11		
Activity Network (Connections)	23	1.5	1.69323e-7	UP	640.1753	2.36	506	43	1,212			62		
	24	2.8	1.96208e-7	DOWN	273.0103	20.77	1,070	11,820	4,164	[502][M+1]-		109		
/ulti-Omics Data +	25	9.4	2.25296e-7	UP	103.9209	11.41	169,682	201,688	1,890,454	[17][M]-		32		
	26	2.3	2.46060e-7	UP	502.3042	15.22	984	3,051	6,959		[M-H]- 503	25		
Systems Biology Results	27	4.1	2.63478e-7	UP	304.2026	15.74	1,832	4,832	19,839			339		
	28	4.2	2.71609e-7	UP	160.0617	21.96	5,410	12,315	51,353		[M+CI]- 12	83		
Pathway Cloud Plot	29	4.9	2.88932e-7	UP	521.4579	2.08	752	554	2,693			177		
	30	4.9	3.14046e-7	UP	173.0933	18.44	4,658	16,549	80,343			13		
	31	10.9	3.57576e-7	UP	805,2954	29.32	2,942	802	8,705	[2779][M+2]-		307		



Please click on a row to view feature details

Feature #9 m/z : 119.0351 Retention Time (min): 24.43

LC-MS based Untargeted Metabolomics

- Choice of MS
- LC-MS combination
- Analytical sequence
- Data processing
- Metabolite identification

Metabolite identification

- Accurate mass
- Retention time
- MS/MS spectra



Identification confidence

Example

Minimum data requirements

H ₃ C~s	Level 1:	Confirmed structure by reference standard	MS, MS ² , RT, Reference Std.
	Level 2:	<i>Probable structure</i> a) by library spectrum match b) by diagnostic evidence	MS, MS ² , Library MS ² MS, MS ² , Exp. data
	Level 3:	Tentative candidate(s) structure, substituent, class	MS, MS ² , Exp. data
C6H2N3O4 -{	Level 4:	Unequivocal molecular formula	MS isotope/adduct
192.0757	Level 5:	Exact mass of interest	MS

Adapted from Schymanski et. al., Environ. Sci. Technol. 2014, 48, 2097-2098



Databases

Databases

SERINE TRYPTOPHAN PHOSPHATE CHOLESTERN. INFORMATION AND A CHORAGE ACTION AND A CHORAGE ACTION









National Institute of Standards and Technology



Databases



- The largest MS/MS collection of data at multiple collision energies and in positive and negative ionization modes.
- It now includes 961,829 molecules ranging from lipids, steroids, plant & bacteria metabolites, small peptides, carbohydrates, exogenous drugs/metabolites, central carbon metabolites and toxicants.
- Over 14,000 metabolites have been individually analyzed and another 200,000 has in silico MS/MS data.



Databases



KEGG is a database resource for understanding highlevel functions and utilities of the biological system, such as the cell, the organism and the ecosystem, from metabolomic information.

Databases

- A freely available electronic database containing detailed information about small molecule metabolites found in the human body.
- 42,003 metabolite entries including both watersoluble and lipid soluble metabolites as well as metabolites that would be regarded as either abundant or relatively rare.



Databases

LIPID Metabolites And Pathways Strategy (LIPID MAPS) is a multi-institutional effort to identify and quantify lipd species in mammalian cells, as well as to identify the changes in response to perturbation.

- Detailed lipid pathways
- Analytical tools and experimental protocols
- 500 mass spectrometric standards
- Experimental data



Databases

The NIST Chemistry WebBook provides chemical and physical property data for chemical species. The data provided are from collections maintained by the NIST Standard Reference Data Program and outside contributors.





Databases

- A public repository of mass spectra of small chemical compounds
- It contains spectra from EI-MS, FAB-MS, ESI-MS²



Home

isoMETLIN

Simple Search Advanced Search Batch Search Fragment Similarity Search

TRYPTOPHAN PHOSPHOCHOL

VIC ACID UREA GALAC

RINE TRYPTOPHAN PHOSPHOCHOL

ERONE

Neutral Loss Search

MS/MS Spectrum Match Search

MRM-😃 Logout [thuan]

The original and most comprehensive MS/MS metabolite database

GLUCOSE CHOLESTEROL OXALOS INAMIDE ADENINE DINUCLEOTION

Latest News and Articles

Analytical Chemistry 2018 - METLIN: A Technology Platform for Identifying Knowns and Unknowns







Home	y isoMETLIN Simple Search	Advanced Search	Batch Search Frag	ment Similarity Search	Neutral Loss Search	MS/MS Spectrum Match Search M	RM 👻 😃 Logout [thuan]
	Simple Search	METLIN ID	.↓↑ Mass	↓↑ ΔΡΡΜ ↓≟	Name	IT MS/MS	Structure
Mass Tolerance	147.0771 5 PPM	63630	[M+H] ⁺ <u>m/z</u> 147.0764 M 146.0691	4	D-Glutamine Formula: C5H10N2O3 CAS: 5959-95-5	experimental	HO NH ₂ NH ₂
Charge Adducts	Neutral Positive Negative	58589	[M+H] ⁺ <u>m/z</u> 147.0764 M 146.0691	4	Ala-Gly Formula: C5H10N2O3 CAS: 687-69-4	experimental	H ₃ C H
	M+H-2H2O M+H-H2O M+K M+ACN+H M+ACN+Na M+2Na-H M+2H M+3H	18	[M+H] ⁺ <u>m/z</u> 147.0764 M 146.0691	4	L-Glutamine Formula: C5H10N2O3 CAS: 56-85-9	experimental	
	M+H+Na M+2H+Na M+2Na M+2Na+H M+Li M+CH3OH+H	85603	[M+H] ⁺ <u>m/z</u> 147.0764 M 146.0691	4	Alanyl-Glycine Formula: C5H10N2O3 CAS:	in silico	
Peptides Toxicants	Remove Peptides from Search ~ Remove Toxicants from Search ~	2819	[M+H]⁺ <u>m/z</u> 147.0764	4	Isoglutamine Formula: C5H10N2O3 CAS: 328-48-3	in silico	но он
Sea	Clear		M 146.0691				NH ₂

Home	y isoMETLIN Simple Search	Advanced Search	Batch Search Frag	ment Similarity Search	Neutral Loss Search	MS/MS Spectrum Match Search M	RM 👻 😃 Logout [thuan]
	Simple Search	METLIN ID	.↓↑ Mass	↓↑ ΔΡΡΜ ↓≟	Name	IT MS/MS	Structure
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	M+H+Na M+2H+Na M+2Na M+2Na+H M+Li M+CH3OH+H	85603	[M+H] ⁺ <u>m/z</u> 147.0764 M 146.0691	4	Alanyl-Glycine Formula: C5H10N2O3 CAS:	in silico	
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Sea	Clear		M 146.0691				NH ₂





- Objectives and Challenges
- Experimental Design

- May 16th
- ---- 12:30 pm Begin ----
- ---- 3:00 pm Break ----
- ---- 04:30 pm Finish ----
- Sample Preparation and Chromatography
- Untargeted Metabolomics
- Targeted Metabolomics
- Statistical Analysis

May 16th

- Objectives and Challenges
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- Preparative LC for collection of metabolite for NMR
- Elemental composition of MS² and MS³ fragment ions
- Synthesize authentic standard

Science 1995

Science 1995



It took about 8 months to identify oleamide



SER It took about 8 months to identify oleamide JVIC ACID UREA GALACTOSE SINE TRIPHOSPHATE CHOLESTEROL TEET SERINE TRYTOPHAN PHOSPHOCHOLINE ACYLCARNITINE TH

1 Million Molecules in METLIN

Science 1995

It took about 8 months to identify oleamide Within seconds we can now identify oleamide and most other metabolite oleamide and most other metabolites N PHOSPHOCHOLIN SERINE

1 Million Molecules in METLIN

Within seconds we can now identify oleamide and most other metabolites

20180115_Siuzdak.Metabolomics

It took about 8 months to identify oleamide



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20180115_Siuzdak.Metabolomics


CHOLINE ADENOSINE TRIPHOSPHATE CHOLESTEROL TEST SERINE TRYTOPHAN PHOSPHOCHOLINE SERINE TRYTOPHAN PHOSPHOCHOLINE ACYLCARNITINE HAR

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The Standards

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The Standards Sample Preparation

CHOLINE ADENOSINE TRIPHOSPHATE CHOLESTEROL TECHNOLINE ACYL CARNET SERINE TRYTOPHAN PHOSPHOCHOLINE SERINE TRYTOPHAN PHOSPHOCHOLINE ACYLCARNITNE TH

The Standards Sample Preparation Compound Standards Info Automated OLINE ADENOSINE TRIPHOSPHATE CHOLESTEROL SERINE TRYTOPHAN PHOSPHOCHOU SERINE TRYTOPHAN PHOSPHOCHOL **1 Million Molecules in METLIN**

60,000 Standards with MS/MS data

The Standards Sample Preparation Compound Standards Info Automated Reliable & Accurate MS Data Acquisition CUVIC ACID UREA GALACTOSE NE TRIPHOSPHATE CHOLESTEROL ES RYTOPHAN PHOSPHOCHO EC NAMID SERINET **1 Million Molecules in METLIN**

60,000 Standards with MS/MS data

The Standards Sample Preparation Compound Standards Info Automated Reliable & Accurate MS Data Acquisition Data Streamed into METLIN Autonomously SERINE TRYTOPHAN PHOSPHOCH

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Untargeted Metabolomics



Extracted Ion Chromatograms



Targeted Metabolomics

QqQ LC/MS



Multiple reaction monitoring (MRM)





- Targeted metabolomics
- Know which compounds to measure
- Concentration



Triple Quadrupole Mass Spectrometers





May 16th

A mass selected precursor ion is chosen with Q1 and the collision cell generates fragment ions. Q3 is set to look for specific fragment ions. This is known as multiple reaction monitoring, or MRM.





Single quad in Selected Ion Monitoring mode





Triple Quad in MRM mode Specificity and sensitivity





• Internal standards take into account losses during prep



• Internal standards take into account losses during prep

May 16th

• Will adjust for matrix effects and suppression



• Internal standards take into account losses during prep

- Will adjust for matrix effects and suppression
- Chemically similar, but differ in mass



- Internal standards take into account losses during prep
- Will adjust for matrix effects and suppression
- Chemically similar, but differ in mass





Internal standards

- Internal standards are added to samples and standards at the same concentration
- Absolute response will differ due to losses, but ratio of response will remain the same





Internal standards Addition to samples



Internal standards are At the same concentration In samples and standards





Internal standards Addition to samples



For liquid samples – plasma, urine, csf spike directly into vial prior to adding extraction solvent



Internal standards Addition to samples

For tissue samples add I.S. to extraction









May 16th

Results in a linear standard curve



May 16th



Results in a linear standard curve Concentrations should bracket what is expected In the samples



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Statistics is the mathematics of impression

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Α	В	С	D	E	F	G	Н	1	J	K	L
Sample	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11
Label	Normal	Normal	Normal	Normal	Normal	Disease	Disease	Disease	Disease	Disease	Disease
1	5.2E+06	6.1E+06	5.8E+06	5.1E+06	4.6E+06	4.7E+06	5.1E+06	3.5E+06	3.0E+06	3.8E+06	3.1E+06
2	2.7E+06	2.4E+06	2.6E+06	9.8E+05	8.5E+05	1.1E+06	8.3E+05	2.1E+06	1.8E+06	1.7E+06	1.5E+06
3	1.8E+06	1.8E+06	1.8E+06	1.3E+06	1.3E+06	1.5E+06	1.6E+06	1.3E+06	1.2E+06	1.3E+06	1.1E+06
4	8.4E+05	9.4E+05	8.2E+05	4.4E+05	4.6E+05	4.5E+05	4.5E+05	9.0E+05	8.7E+05	8.6E+05	8.3E+05
5	6.5E+05	4.0E+05	5.3E+05	9.1E+04	7.5E+04	9.3E+04	1.2E+05	5.5E+04	4.1E+04	4.0E+04	4.3E+04
6	4.8E+05	4.6E+05	4.7E+05	3.6E+05	3.2E+05	3.9E+05	3.9E+05	3.4E+05	2.7E+05	3.0E+05	2.7E+05
7	4.1E+05	4.3E+05	4.5E+05	1.2E+05	2.6E+05	1.7E+05	2.5E+05	8.4E+04	3.7E+04	1.8E+05	1.3E+05
8	4.0E+05	3.8E+05	4.0E+05	2.9E+05	2.7E+05	3.0E+05	3.2E+05	2.6E+05	2.1E+05	2.4E+05	2.0E+05
9	2.9E+05	2.8E+05	2.8E+05	1.6E+05	1.6E+05	1.6E+05	1.5E+05	2.4E+05	2.0E+05	2.3E+05	2.6E+05
10	2.5E+05	2.6E+05	2.3E+05	1.7E+05	1.8E+05	1.9E+05	1.9E+05	1.7E+05	1.9E+05	1.8E+05	1.8E+05
11	2.4E+05	2.6E+05	2.3E+05	6.9E+04	1.0E+05	6.7E+04	1.2E+05	8.6E+04	7.2E+04	7.3E+04	5.5E+04
12	1.8E+05	1.6E+05	2.1E+05	9.2E+04	8.7E+04	8.5E+04	9.3E+04	1.6E+05	1.9E+05	1.9E+05	1.7E+05
13	1.7E+05	1.8E+05	1.8E+05	2.0E+05	2.0E+05	1.8E+05	2.1E+05	3.0E+05	3.1E+05	2.8E+05	2.6E+05
14	1.4E+05	1.4E+05	1.4E+05	1.0E+05	1.0E+05	1.1E+05	1.3E+05	9.5E+04	8.6E+04	9.8E+04	8.4E+04
15	1.2E+05	1.2E+05	1.2E+05	9.0E+04	8.7E+04	9.9E+04	1.1E+05	8.3E+04	7.3E+04	8.3E+04	7.1E+04
16	9.3E+04	9.1E+04	7.9E+04	5.2E+04	5.1E+04	5.8E+04	5.7E+04	6.6E+04	6.6E+04	6.9E+04	6.7E+04
17	8.0E+04	7.3E+04	8.2E+04	4.9E+04	3.9E+04	5.3E+04	5.1E+04	4.9E+04	2.9E+04	3.7E+04	2.8E+04
18	7.8E+04	7.2E+04	7.7E+04	5.3E+04	4.2E+04	5.3E+04	4.7E+04	5.3E+04	4.4E+04	4.0E+04	4.3E+04
19	7.3E+04	7.3E+04	7.4E+04	3.9E+04	3.2E+04	3.6E+04	3.1E+04	7.1E+04	5.5E+04	5.4E+04	5.1E+04
20	6.5E+04	6.1E+04	6.5E+04	3.7E+04	3.2E+04	4.2E+04	4.2E+04	3.8E+04	2.4E+04	3.1E+04	2.4E+04

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Α	В	С	D	E	F	G	Н	1	J	K	L
Sample	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	s11
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2	2.7E+06	2.4E+06	2.6E+06	9.8E+05	8.5E+05	1.1E+06	8.3E+05	2.1E+06	1.8E+06	1.7E+06	1.5E+06
3	1.8E+06	1.8E+06	1.8E+06	1.3E+06	1.3E+06	1.5E+06	1.6E+06	1.3E+06	1.2E+06	1.3E+06	1.1E+06
4	8.4E+05	9.4E+05	8.2E+05	4.4E+05	4.6E+05	4.5E+05	4.5E+05	9.0E+05	8.7E+05	8.6E+05	8.3E+05
5	6.5E+05	4.0E+05	5.3E+05	9.1E+04	7.5E+04	9.3E+04	1.2E+05	5.5E+04	4.1E+04	4.0E+04	4.3E+04
6	4.8E+05	4.6E+05	4.7E+05	3.6E+05	3.2E+05	3.9E+05	3.9E+05	3.4E+05	2.7E+05	3.0E+05	2.7E+05
7	/ 10-05	4 25105	4 55405	1 25405	2 65405	1 75+05	2 55405	0 1ETU1	2 75+04	1 95105	1 25405

How to discover features associated with certain condition?

10	2.5E+05	2.6E+05	2.3E+05	1.7E+05	1.8E+05	1.9E+05	1.9E+05	1.7E+05	1.9E+05	1.8E+05	1.8E+05
11	2.4E+05	2.6E+05	2.3E+05	6.9E+04	1.0E+05	6.7E+04	1.2E+05	8.6E+04	7.2E+04	7.3E+04	5.5E+04
12	1.8E+05	1.6E+05	2.1E+05	9.2E+04	8.7E+04	8.5E+04	9.3E+04	1.6E+05	1.9E+05	1.9E+05	1.7E+05
13	1.7E+05	1.8E+05	1.8E+05	2.0E+05	2.0E+05	1.8E+05	2.1E+05	3.0E+05	3.1E+05	2.8E+05	2.6E+05
14	1.4E+05	1.4E+05	1.4E+05	1.0E+05	1.0E+05	1.1E+05	1.3E+05	9.5E+04	8.6E+04	9.8E+04	8.4E+04
15	1.2E+05	1.2E+05	1.2E+05	9.0E+04	8.7E+04	9.9E+04	1.1E+05	8.3E+04	7.3E+04	8.3E+04	7.1E+04
16	9.3E+04	9.1E+04	7.9E+04	5.2E+04	5.1E+04	5.8E+04	5.7E+04	6.6E+04	6.6E+04	6.9E+04	6.7E+04
17	8.0E+04	7.3E+04	8.2E+04	4.9E+04	3.9E+04	5.3E+04	5.1E+04	4.9E+04	2.9E+04	3.7E+04	2.8E+04
18	7.8E+04	7.2E+04	7.7E+04	5.3E+04	4.2E+04	5.3E+04	4.7E+04	5.3E+04	4.4E+04	4.0E+04	4.3E+04
19	7.3E+04	7.3E+04	7.4E+04	3.9E+04	3.2E+04	3.6E+04	3.1E+04	7.1E+04	5.5E+04	5.4E+04	5.1E+04
20	6.5E+04	6.1E+04	6.5E+04	3.7E+04	3.2E+04	4.2E+04	4.2E+04	3.8E+04	2.4E+04	3.1E+04	2.4E+04

- Univariate analysis examines each variable separately, providing a ranking of potentially important features
 - ✓ T-test
 - ✓ Volcano plot

- Univariate analysis examines each variable separately, providing a ranking of potentially important features
 - ✓ T-test
 - ✓ Volcano plot
- Multivariate analysis considers two or more variables simultaneously and takes into count relationships between variables
 - ✓ PCA: Principle Component Analysis
 - ✓ PLC-DA: Partial Least Squares-Discriminant Analysis


Univariate analysis: Student's t-Test

- Also called the t-test
- Used to determine if 2 populations are different



Data distribution

A basic way of presenting univariate data is to create a frequency distribution of the individual cases



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Gaussian distribution

$$\varphi(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\left(\frac{x-\mu}{\sigma}\right)^2}$$

mean = μ

variance =
$$\sigma^2$$

standard deviation = σ



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Sample mean:
$$\overline{\mathbf{X}} = \frac{1}{n} \sum_{i=1}^{n} X_i$$

Sample variance: $S^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \overline{X})^2$

Sample standard deviation: $S = \sqrt{S^2}$

One-sample t-test: is the sample belong to a known population

Null hypothesis
$$H_0$$
: $\mu = \mu_0$

Test statistic:
$$t = \frac{\overline{x} - \mu_0}{s/\sqrt{n}}$$

Sample standard deviation: $s = \sqrt{\frac{1}{n-1}\sum_{i=1}^n (x_i - \overline{x})^2}$





Test statistic:
$$t = \frac{\overline{x} - \mu_0}{s / \sqrt{n}}$$

The test statistic *t* follows a student's *t* distribution.



- P-value is the area in the tail of a probability distribution.
- If p-value is smaller than the critical significance level α, the null hypothesis is rejected and the tested sample is significant different from the population



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Equivalent statement:

 If the t-test statistic gives a p = 0.01, it means there is only 1% of the chance that these two populations are the same, i.e. is statistically significant



Student's t-Test

- **Paired t-Test**: Measurements made on the same individuals before and after the treatments. e.g., what is the effect of a treatment.
- **Unpaired t-Test**: used for the statistical analysis of 2 groups of unrelated samples



Student's t-Test

- **Parametric t-test**: If the two population are normally distributed
- Non-parametric t-test (Mann-Whitney t-test): if the two populations are non-normally distributed. More powerful and robust than the Parametric t-test. Commonly used in metabolomics



- Lots of extreme values far away from mean
- Hard to do useful statistical tests



Apply a log transformation to fixing a skewed distribution

Apply a log transformation to fixing a skewed distribution





Analysis of variance (ANOVA)



Analysis of variance (ANOVA)

- Used to determine if 3 or more populations are different
- A generalization of the t-test
- It provides a statistical test of whether or not the means of several groups are all equal or whether 3+ groups of values are different









- Objectives and Challenges
- Experimental Design

- May 16th
- ---- 12:30 pm Begin ----
- ---- 3:00 pm Break ----
- ---- 04:30 pm Finish ----
- Sample Preparation and Chromatography
- Untargeted Metabolomics
- Targeted Metabolomics
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May 16th

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Visualization of Data Variability

Targeted Metabolomics

• E.g. **3** metabolite concentrations measured for each sample.

Metabolite abundances



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3-D Plot

For 3 variables, we can estimate and visualize the distribution of the variability within our data.

Visualization of Data Variability

Targeted Metabolomics

• E.g. **3** metabolite concentrations measured for each sample.

Samples

2-D Correlation Matrix



For 3 variables, we can estimate and visualize the distribution of the variability within our data by plotting pairs of variables.

Data Dimensionality in Metabolomics

Targeted Metabolomics

• Generally < 100 metabolite concentrations measured for each sample.

Metabolite abundances



Samples

Data Dimensionality in Metabolomics

Targeted Metabolomics

• Generally < 100 metabolite concentrations measured for each sample.

Untargeted Metabolomics

 N >> 100 metabolic feature abundances measured for each sample.

Metabolite abundances


The Data Visualization Problem in Metabolomics

Metabolomics provides high-dimensional data sets (big data).

Metabolite abundances



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• We can not use 3-D plots to visualize the variability in the data.

The Data Visualization Problem in Metabolomics

 Metabolomics provides high-dimensional data sets (big data).

Metabolite abundances

- We can not use 3-D plots to visualize the variability in the data.
- 2-D correlation matrix interpretation requires too much time and plots redundant variability (correlation between variables).

Why PCA of Metabolomic Data?

 Visual estimation of the latent variability in the data set at a glance (e.g. spontaneous group clustering).

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- Visual estimation of the latent variability in the data set at a glance (e.g. spontaneous group clustering).
- **2. Outliers detection** (e.g. quality control).
- **3. Interpretation of the variability** in high-dimensional data by using all the variables simultaneously.

Before PCA: Data Scaling

PCA is a maximum variance projection method, therefore variables with larger range can bias the model.

SCALING and MEAN CENTERING before PCA

e.g. Auto-Scaling:

Mean Centering: the average value for each variable is calculated and subtracted from the data.

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 SD: standard deviation, consequently each variable has equal (unit) variance.

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Other options: Pareto scaling, Log Transformation

Data Auto-Scaling



How Does PCA Work?



 PCA performs an orthogonal transformation to convert a set of observations of linearly correlated variables in a set of linearly uncorrelated variables (Principal Components, or eigenvectors)

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- PCA performs an orthogonal transformation to convert a set of observations of linearly correlated variables in a set of linearly uncorrelated variables (Principal Components, or eigenvectors)
- It computes new coordinates (eigenvectors or Principal Components) from the original coordinates.
- The PCs are ordered according to the amount of explained variability.

How Does PCA Work?

• We can **discard low-variance variables to visualize the variability** in our data set in a 2-D or 3-D plot.



PCA of High-Dimensional Metabolomics Data



• For high-dimensional data sets, this operation is repeated for all the dimensions in our experiment.

PCA Scree Plot

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Example 1: Colon Cancer Study

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- Scree plot: visual aid to determine the number of PCs to plot.
- e.g. Colon Cancer Vs. Normal Colon Tissue in Human. 17130 total aligned features, 10 samples/class



PCA Score Plot

• Each observation can be projected on the PCs in order to get a coordinate value along the PC-line: this value is known as a score. Scores for PCs can be plotted to visualize variability.

e.g. score plot of the first 2 PCs define a model plane.



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PCA Loading Plot

• The loading plot represents the relationship between the original variables and the computed dimensions (PCs).



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Which variables have the largest effect on each Principal Component?



Score Vs. Loading Plot

• Loadings range from -1 to +1. As closer to <u>+</u>1, as more influence the variable has on the component.



Score Vs. Loading Plot

• Loading ranges from -1 to +1. As closest to <u>+</u> 1, as more influence has the variable on the component.



• e.g. Spermine and spermidine may be dysregulated in colon cancer.

Example 2: Quality Control

• PCA can highlight the presence of outliers.

This suggests lack of reproducibility/errors in sample preparation or data acquisition. Careful interpretation of data acquired in proximity of the outlier should be performed and the outliers excluded from further analysis.

e.g. Multigroup study: 12913 detected features, 10/Lung Adenocarcinoma, 10/Small Cells Lung Cancer, 10/Control, 10/QCs(pools).



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PCA is a data dimensionality reduction method.

Use PCA for:

- 1. Unravel spontaneous group **clustering** /**trends** in the data (score plot).
- 2. Evaluate variables contribution in clustering and variables correlation (score and loading plots).
- 3. Unravel strong **outliers** (score plot).

Fundamental Metabolomics

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