

Using MetaCore for multi-omics analysis

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Customer Education Specialist

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Agenda

1. Learn:

- How to approach analyzing multi-omics data in MetaCore.
- Use metabolic networks (endogenous) enrichment to analyze metabolites and expression data.
- Find pathways where the metabolic and proteomic data are both involved.

2. Questions:

- What relationships can we find between the metabolic and RNA-seq data?
- What changes in metabolites and protein concentrations could be biomarkers for disrupted processes?

MetaCore, a Cortellis solution

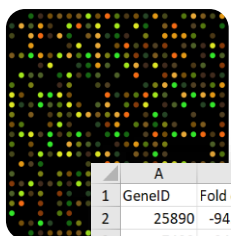
Your GPS in pathway analysis

INPUT

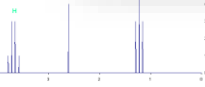

Data mining
Content Browsing



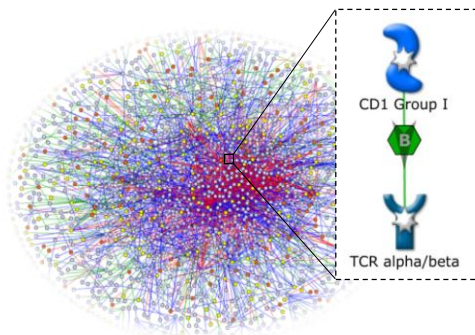
Gene lists or
OMICS analysis



	A	B	C
1	GeneID	Fold change	p-value
2	25890	-94.7858701	4.03E-07
3	7432	-94.6483041	0.00016
4	91851	-67.9404389	2.94E-06
5	1191	-66.5434408	4.90E-07
6	10351	-58.0187396	4.03E-07



METABASE



> 3,300,000 molecular interactions

From Human, mouse and rat

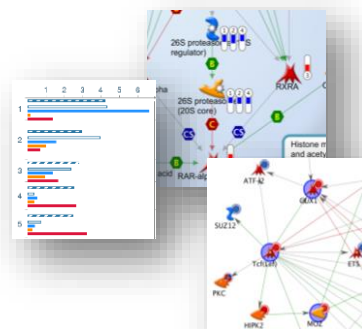
Manually curated by editorial team

(>50 PhD, MD)



3,701 journals

METACORE



1,500+ Pathway Maps

- Search & browse
- Enrichment analysis
- Compare experiments
- Network building
- Interactome analysis
- Pathway Map creation

- Understand omics data in the context of validated biology.
- Generate and confirm hypotheses for novel targets, biomarkers or drug mechanisms of action.

MetaCore, a Cortellis solution

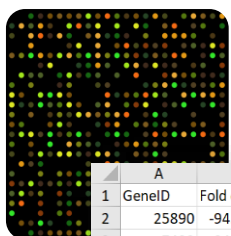
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Data mining
Content Browsing

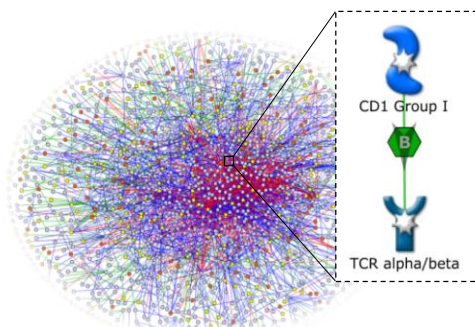


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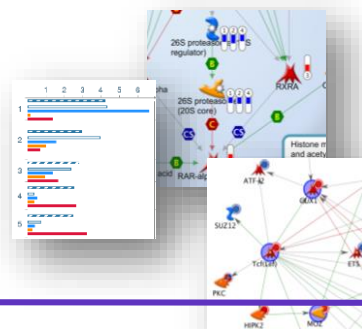
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Type

Number

All	3,301,030
Protein - Protein	1,455,811
Compound - Protein	1,012,689
Compound - Compound	12,291
Metabolic enzyme - Reaction	62,070
Substrate, Product - Reaction	136,068
RNA - Protein	616,754

MetaCore, a Cortellis solution

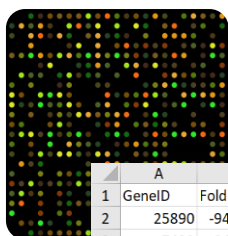
Your GPS in pathway analysis

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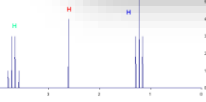

Data mining
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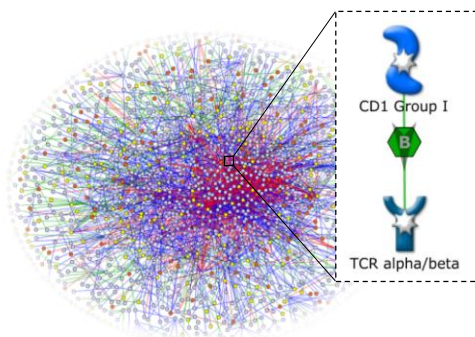
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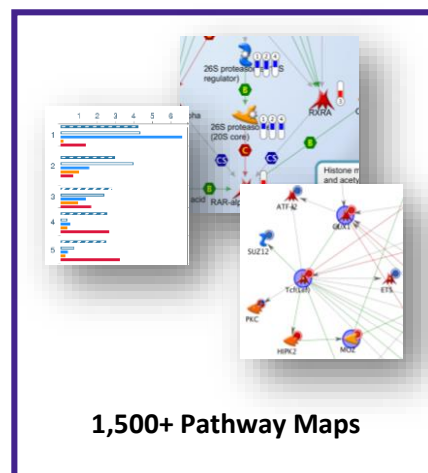
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METACORE



- Search & browse
- Enrichment analysis
- Compare experiments
- Network building
- Interactome analysis
- Pathway Map creation

- ~ 1600 canonical and disease signaling pathways
- 250 metabolic networks
- 118 endogenous metabolic networks

Multi-omics simultaneous analysis

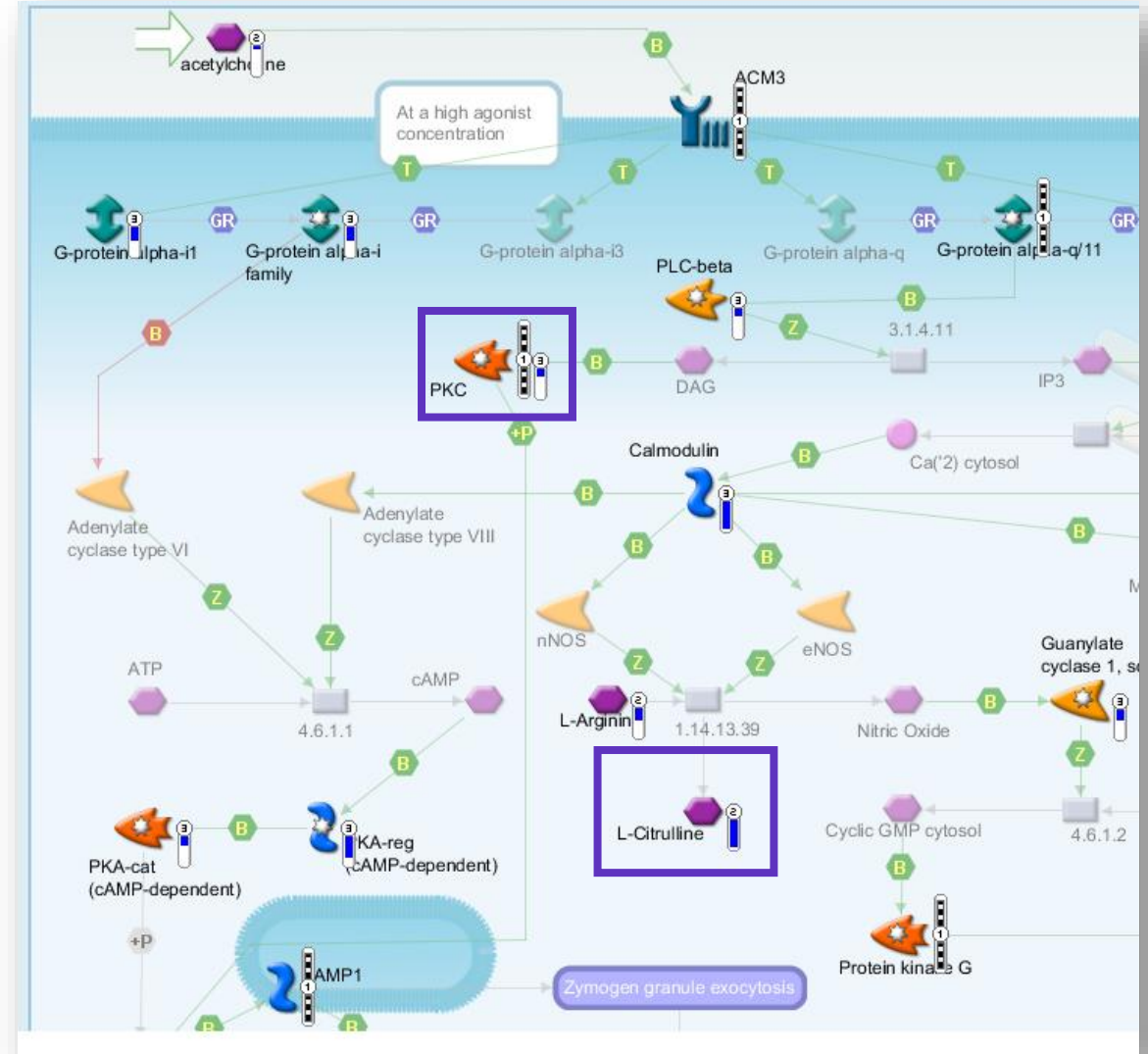
Combining metabolomic, transcriptomic and gene variants for side by side –omics enrichment analysis

You can upload your experimental data as well as list of genes/proteins/metabolites.

- [Upload Experiments with Gene or Protein IDs](#)
- [Upload Metabolites](#)
- [Upload Interactions](#)
- [Upload Structures](#)
- [Upload Gene Variants](#)


Home ▸ Active Data		
	Name	Type
[...] Active Data		
<input checked="" type="checkbox"/>	T2D Genetic Variants	VX
<input checked="" type="checkbox"/>	pre diabetic metabolites	MX
<input checked="" type="checkbox"/>	Diabetes vs. Normal Gene Expression	GX

<input checked="" type="checkbox"/>	Experiment name	Species	Network Objects
<input checked="" type="checkbox"/>	T2D Genetic Variants	Homo sapiens	1135
<input checked="" type="checkbox"/>	pre diabetic metabolites		187
<input checked="" type="checkbox"/>	Diabetes vs. Normal Gene Expression	Homo sapiens	1535



Acute kidney injury (AKI) public datasets

- **CAPSOD study** - 150 patients with sepsis or pneumonia with varying renal dysfunction.
- Renal dysfunction was classified using the **Acute Kidney Injury Network (AKIN)** criteria.
 - **AKI0** (no significant increase in serum creatinine) n=65 (**control**)
 - **AKI1** (serum creatinine increase of ≥ 0.3 mg/dl, or 150% to 200% above baseline) n=41
 - **AKI2/3** (serum creatinine increase more than 200% above baseline, or ≥ 4.0 mg/dl with an acute increase of at least 0.5 mg/dl) n=20
 - **HD** (Chronic hemodialysis) n=24

 **HHS Public Access**
Author manuscript
Kidney Int. Author manuscript; available in PMC 2016 April 01.

Published in final edited form as:
Kidney Int. 2015 October ; 88(4): 804–814. doi:10.1038/ki.2015.150.

Renal systems biology of patients with systemic inflammatory response syndrome

Ephraim L. Tsalik, MD, PhD^{1,2,3}, Laurel K. Willig, MD⁴, Brandon J. Rice, BS^{5,6}, Jennifer C. van Velkinburgh, PhD⁵, Robert P. Mohny, PhD⁷, Jonathan McDunn, PhD⁷, Darrell L. Dinwiddie, PhD^{5,8}, Neil A. Miller, BA⁴, Eric Mayer, MMB, MBA⁷, Seth W. Glickman, MD, MBA⁹, Anja K. Jaehne, MD¹⁰, Robert H. Glew, PhD¹¹, Mohan L. Sopori, PhD¹², Ronny M. Otero, MD^{10,13}, Kevin S. Harrod, PhD¹⁴, Charles B. Cairns, MD⁹, Vance G. Fowler Jr, MD, MHS², Emanuel P. Rivers, MD, MPH¹⁰, Christopher W. Woods, MD, MPH^{2,3,15}, Stephen F. Kingsmore, MB, BAO, ChB, DSc, FRCPath^{4,5,16}, and Raymond J. Langley, PhD^{5,12,16}

Datasets

- Levels of plasma proteins
 - Measured with mass spectrometry
 - 164 proteins were identified using peptide sequences
 - 46 were significantly different from the AKI0 control group using ANOVA with 5% false discovery rate correction.
- Levels of plasma metabolites
 - Measured with mass spectrometry
 - 241 metabolites were annotated
 - Clinical assays of serum creatine, capillary lactate, and serum glucose was used to validate the use of the MS data in a semiquantitative fashion.
 - 138 annotated metabolites were significantly different from the AKI0 control group using ANOVA with 1% false discovery rate correction.
- Blood transcriptome
 - Measured with RNA-seq
 - 133 out of 150 patients were used due to poor insufficient quality.
 - 1,997 genes were significantly differentially expressed across all groups using ANOVA with 1% false discovery rate correction.

AKI0 (control)

AKI1
Stage 1

AKI2-3
Stage 2

HD
Stage 3

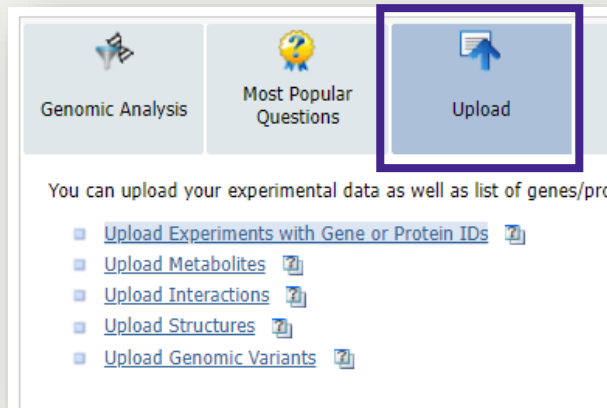
TIPS FOR ANALYZING MULTI OMICS DATA

1. Calculate enrichment p-values for each experiment independently using the appropriate background list.
2. When comparing different omics types, think about how they would be related.
 - ✓ Metabolites concentration and transcriptome expression could **identify channels and enzymes impacting the metabolites.**
 - ✓ Proteome abundance and transcriptome expression could be useful for **correlating expression to translation.**
 - ✓ Metabolites and proteome abundance could be useful for **finding biomarkers** from non-invasive mediums.

Let's go live

➤ What is the relationship between the metabolomic and expression data?

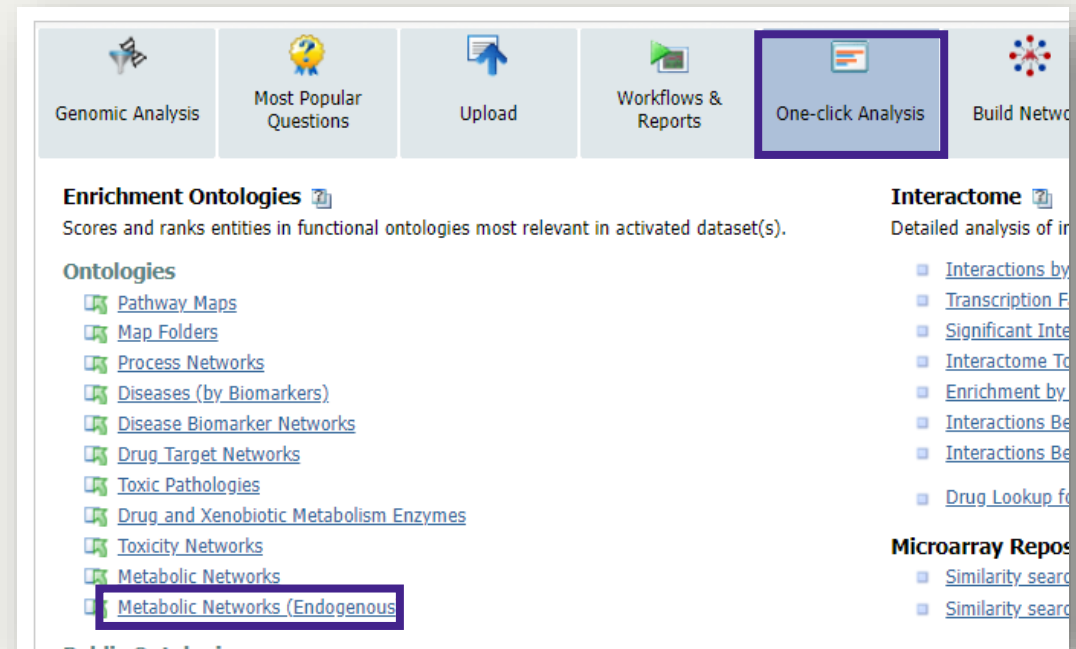
1. Upload your data



Home ▶ Active Data

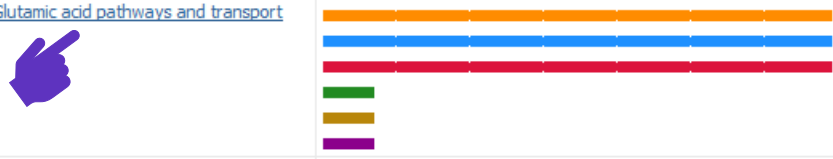



	Name	Type	Date
[-] Active Data			
Metabolomics_stage 1		MX	04/25/2022 12:14:05
Metabolomics_stage 2		MX	04/25/2022 12:14:41
Metabolomics_stage 3		MX	04/25/2022 12:15:13
RNA-seq_Stage 1		GX	04/25/2022 12:16:17
RNA-seq_Stage 2		GX	04/25/2022 12:16:17
RNA-seq_Stage 3		GX	04/25/2022 12:16:17

2. Use metabolic networks (endogenous) to analyze metabolite and transcriptomic data



➤ What is the relationship between the metabolomic and expression data?

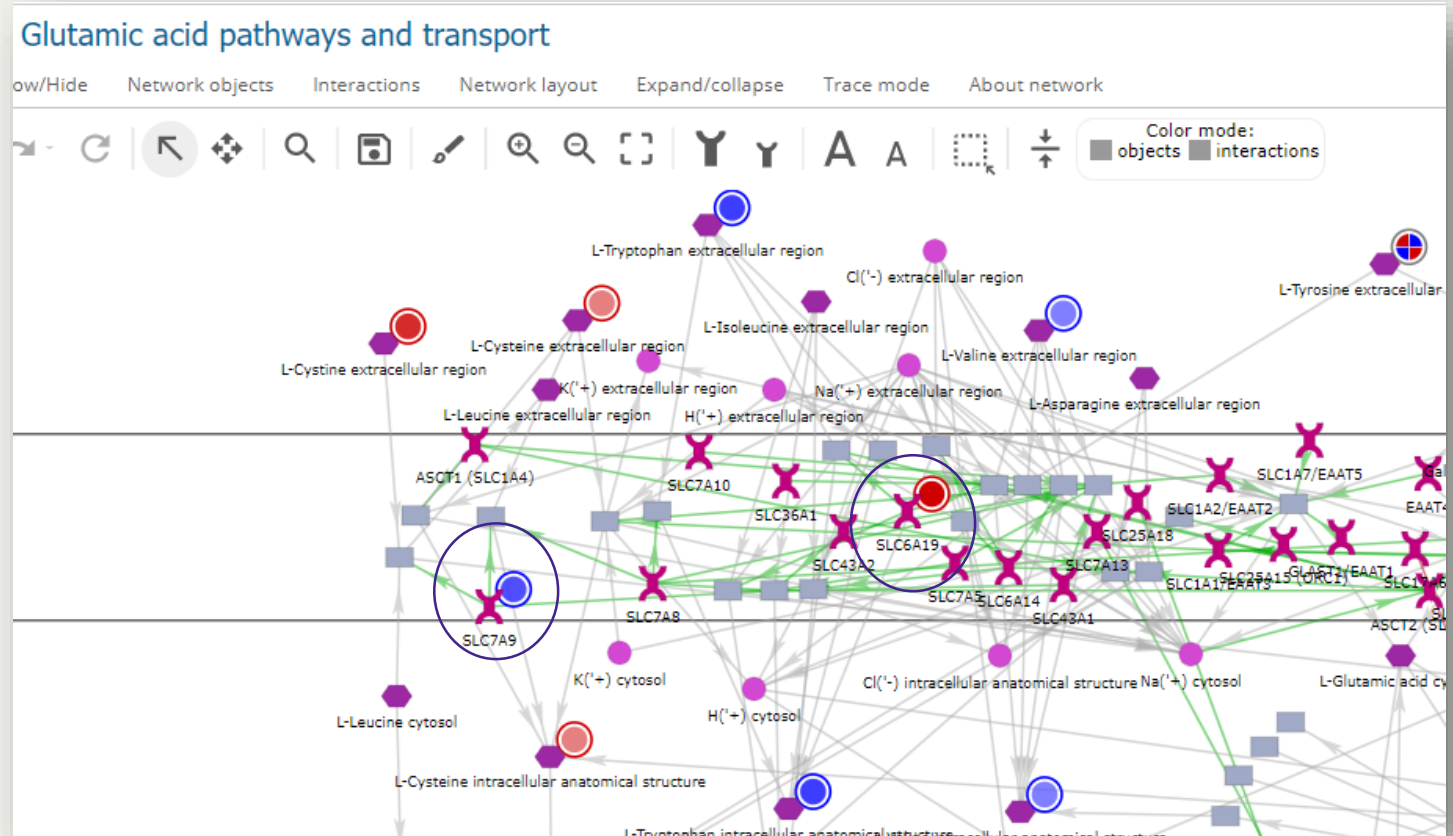
- ✓ Top 10 networks involved amino acid metabolism and glutamic acid processes.

#	Networks	0	1	2	3	4	5	-log(pValue)	pValue	min(pValue) ↑	FDR	Ratio
1	Glutamic acid pathways and transport							1.093e-7	1.093e-7	1.093e-7	7.214e-6	11/143
2	L-glutamate pathways and transport							4.290e-5	4.290e-5	4.290e-5	1.416e-3	8/132
3	Aminoacid metabolism Ala,Ser,Cys,Met,His,Pro,G... metabolism and transport							1.204e-4	1.204e-4	1.204e-4	1.987e-3	9/196
4	Lipid metabolism Glycosphingolipid metabolism							1.204e-4	1.204e-4	1.204e-4	1.987e-3	9/196

➤ What is the relationship between the metabolomic and expression data?

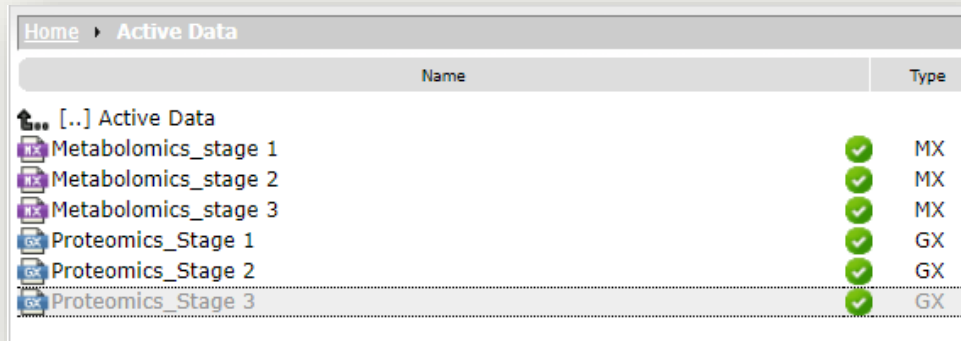
- ✓ Expression changes in SLC7A9 and SLC6A19 could be influencing the dysregulation of amino acid concentrations.

<input type="checkbox"/> Network Objects	# of Networks containing Network Object
<input type="checkbox"/> SLC6A19	18
<input type="checkbox"/> SLC7A9	16
<input type="checkbox"/> L-Tryptophan intracellular	15
<input type="checkbox"/> L-Tryptophan extracellular region	14
<input type="checkbox"/> L-Cysteine intracellular	10
<input type="checkbox"/> L-Alanine intracellular	8
<input type="checkbox"/> L-Cysteine extracellular region	8
<input type="checkbox"/> Glycogen phosphorylase	8
<input type="checkbox"/> L-Tyrosine intracellular	7
<input type="checkbox"/> L-Alanine extracellular region	7
<input type="checkbox"/> SHMT1	7
<input type="checkbox"/> PLC-beta	7
<input type="checkbox"/> Urea intracellular	6



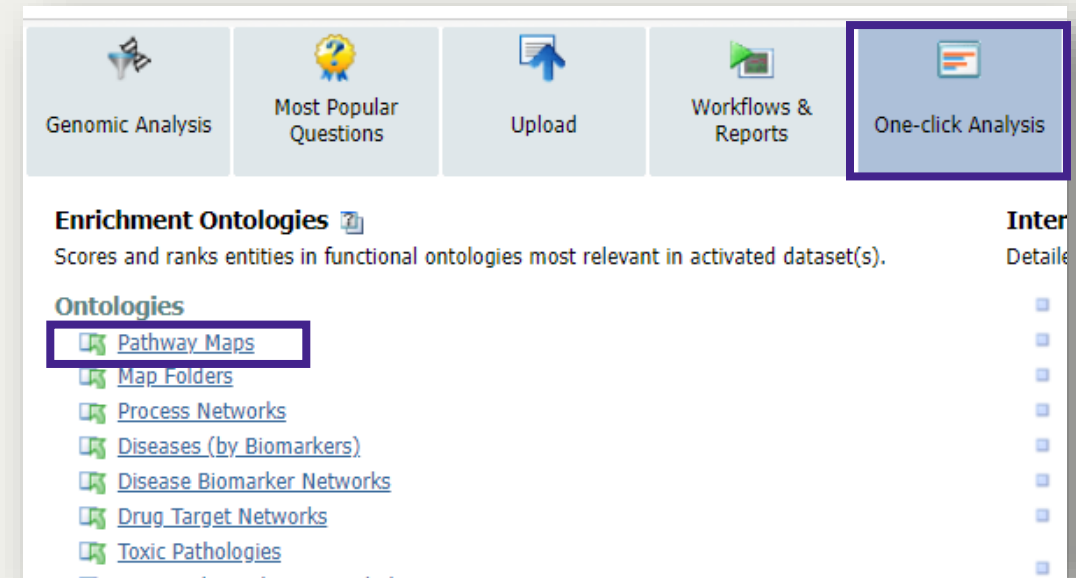
➤ What changes in metabolites and protein concentrations could be biomarkers for disrupted processes?

1. Activate metabolomic and proteomic data



Name	Type
[...] Active Data	
Metabolomics_stage 1	MX
Metabolomics_stage 2	MX
Metabolomics_stage 3	MX
Proteomics_Stage 1	GX
Proteomics_Stage 2	GX
Proteomics_Stage 3	GX

2. Find pathways where both data sets are involved



Genomic Analysis Most Popular Questions Upload Workflows & Reports **One-click Analysis**

Enrichment Ontologies
Scores and ranks entities in functional ontologies most relevant in activated dataset(s).

Ontologies

- Pathway Maps**
- Map Folders
- Process Networks
- Diseases (by Biomarkers)
- Disease Biomarker Networks
- Drug Target Networks
- Toxic Pathologies

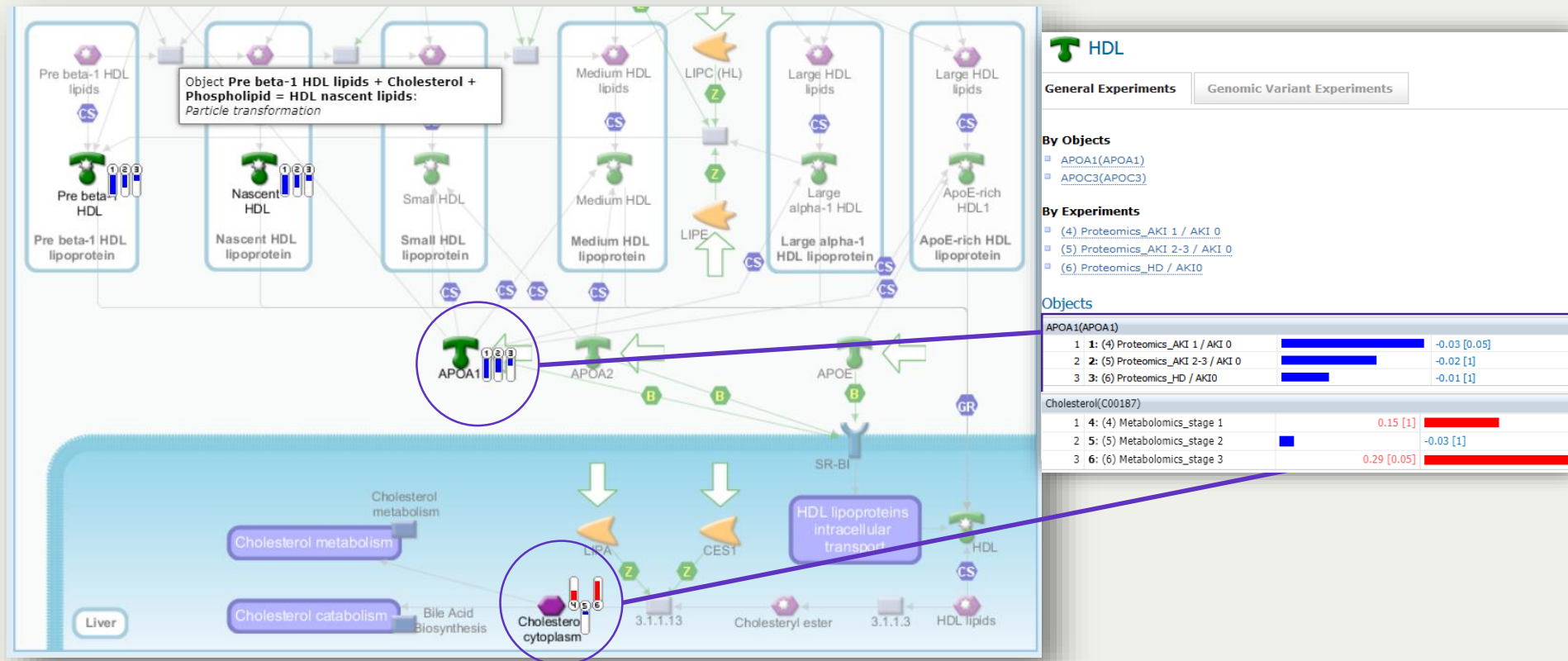
➤ What changes in metabolites and protein concentrations could be biomarkers for disrupted processes?

- ✓ Cholesterol related and complement pathways are both involved with the changes in these datasets

#	Maps	0	1	2	3	4	5	6	7	-log(pValue)	pValue	min(pValue) ↑	FDR	Ratio
1	Transport Intracellular cholesterol transport									1.279e-9	1.279e-9	1.279e-9	5.287e-8	9/83
										1.279e-9	1.279e-9		5.287e-8	9/83
										1.279e-9	1.279e-9		5.287e-8	9/83
										3.962e-2			1.657e-1	2/83
										5.015e-2			1.894e-1	2/83
										5.015e-2			1.894e-1	2/83
2	Immune response Alternative complement pathway									2.750e-1		1.514e-6	3.667e-1	1/53
										2.750e-1			3.667e-1	1/53
										2.750e-1			3.667e-1	1/53
										1.514e-6			6.966e-5	5/53
										2.947e-6			1.503e-4	5/53
										2.947e-6			1.503e-4	5/53
3	Transport HDL-mediated reverse cholesterol transport									2.315e-3		2.163e-5	2.609e-2	3/44
										2.315e-3			2.609e-2	3/44
										2.315e-3			2.609e-2	3/44
										2.163e-5			4.975e-4	4/44
										3.656e-5			9.324e-4	4/44
										3.656e-5			9.324e-4	4/44
4	Cholesterol and Sphingolipid transport / Recycling to plasma membrane in lung (normal and CF)									3.853e-4		3.853e-4	5.308e-3	3/24
										3.853e-4			5.308e-3	3/24

➤ What changes in metabolites and protein concentrations could be biomarkers for disrupted processes?

- ✓ APOA1 and Cholesterol levels change with kidney failure



➤ What changes in metabolites and protein concentrations could be biomarkers for disrupted processes?

- ✓ SR-B1 expression appears to decrease as kidney injury worsens and could be indicative of cholesterol metabolism dysregulation.

Thuahnai ST, Lund-Katz S, Williams DL, Phillips MC

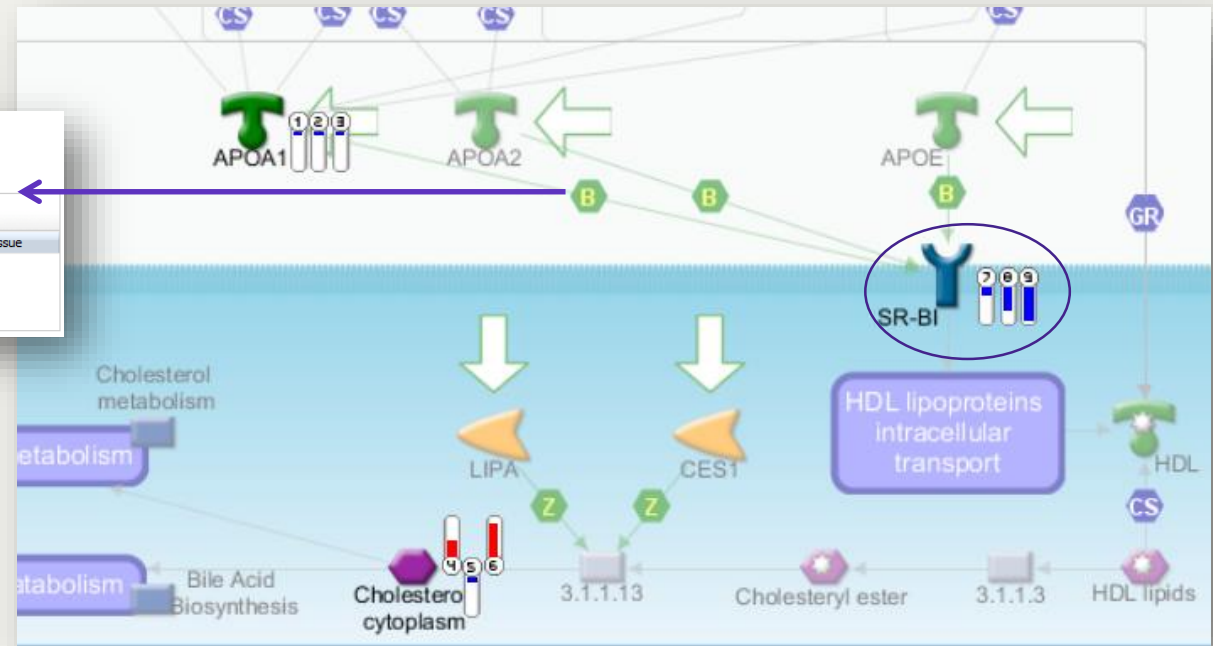
[Scavenger receptor class B, type I-mediated uptake of various lipids into cells. Influence of the nature of the donor particle interaction with the receptor.](#)

The Journal of biological chemistry 2001 Nov 23;276(47):43801-8

PMID: [11564739](#)

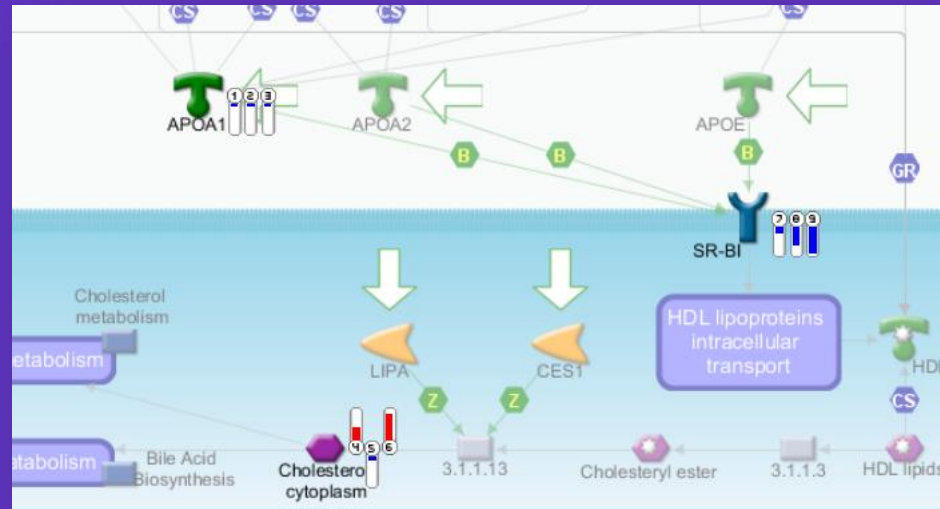
▼ Experiment Details

Note	APOA1 state	Mechanism	Effect	SR-BI state	Methods	Cell line/Tissue
APOA1 increases HDL binding to SRBI and selective uptake of Cholesterol ester.	APOA1 HUMAN	Binding	Activation	SCRB1 HUMAN	3h radiolabel, 125i radiolabel, transfection, binding assay, transport activity determination	COS7



SUMMARY

- ✓ Used metabolomic and RNA-seq analysis and identified channels such as SLC7A9 and SLC6A19 could be playing a role in the transport of amino acids in and out of cells.
- ✓ Used metabolomic and proteomic analysis to identify potential biomarkers for disrupted processes.
- ✓ Added the RNA-seq analysis to find that a decrease SR-B1 expression (associated to kidney injury) could be indicative of cholesterol metabolism dysregulation.



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SLC6A19	18
SLC7A9	16
L-Tryptophan intracellular	15
L-Tryptophan extracellular region	14
L-Cysteine intracellular	10
L-Alanine intracellular	8
L-Cysteine extracellular region	8
Glycogen phosphorylase	8
L-Tyrosine intracellular	7
SGK1	7
L-Alanine extracellular region	7
SHMT1	7
PLC-beta	7
Urea intracellular	6

Thank you

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