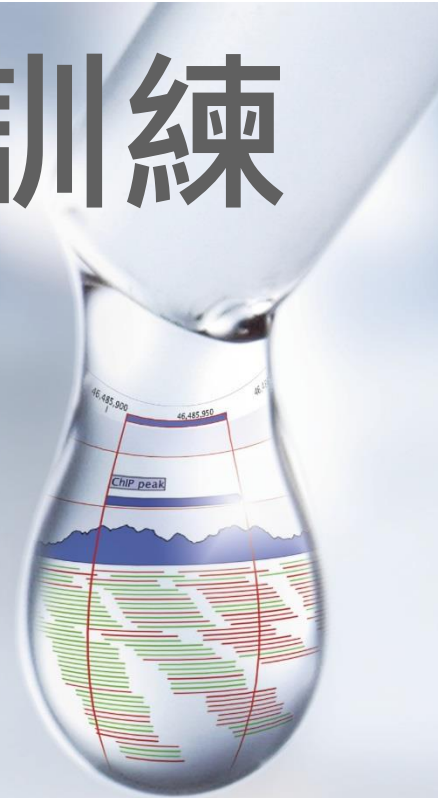


IPA進階模組教育訓練

多實驗組別等IPA分析方式及結果意義闡釋



Clair Tsai 蔡宜庭
創源生技 業務主任

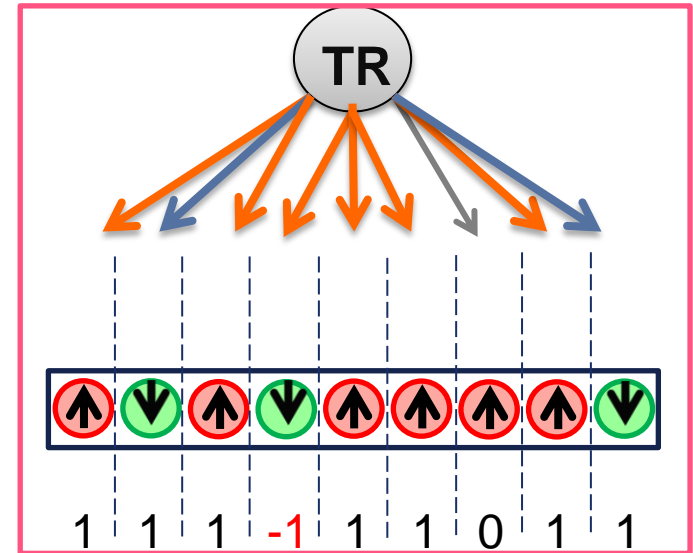
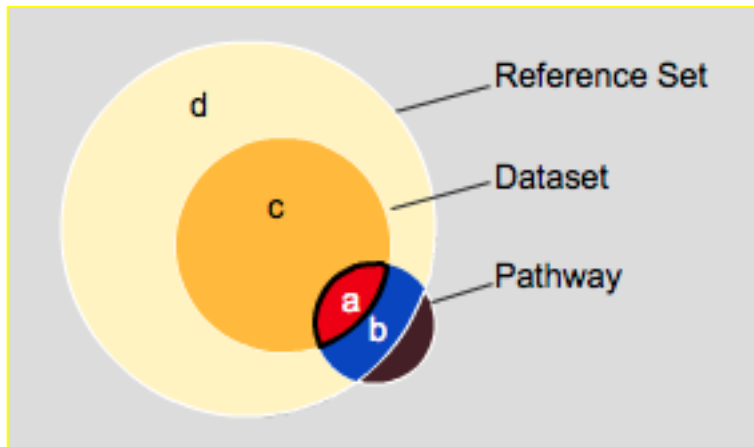
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p-value of overlap

- Null hypothesis: No overlap between molecules from dataset and disease/function/upstream regulator/pathway.
- Calculate using the right-tailed Fisher's Exact Test.
- Significant p-value ≤ 0.05

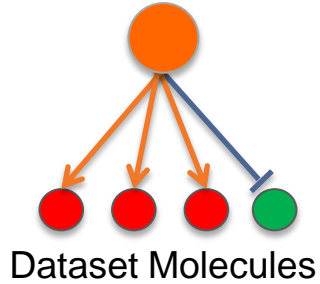
Note: Benjamini-Hochberg correction for multiple testing can be implemented in some cases



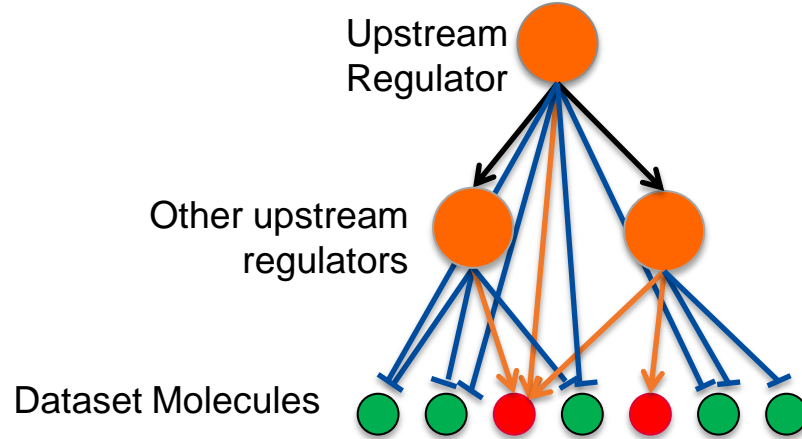
z-score

- Predicts Activation or Inhibition
- Correlation between what is known (IPA Knowledge Base) and your expression data

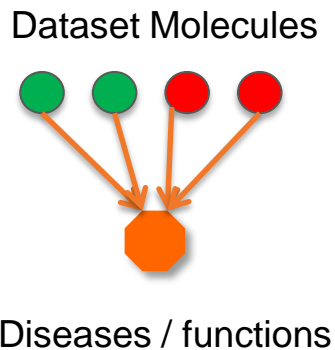
Upstream Analysis



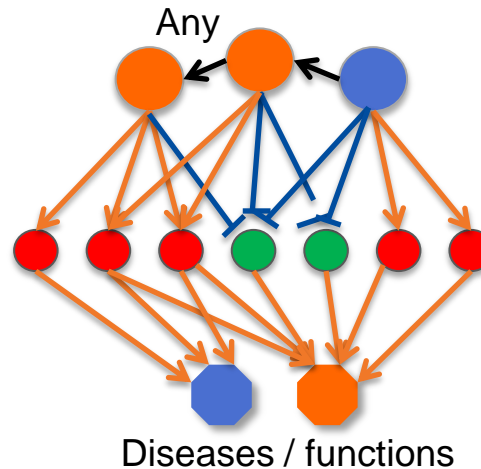
Mechanistic Network of Upstream Regulators



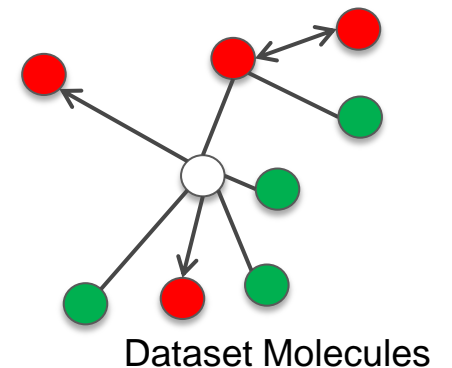
Function Analysis



Regulator Effect Network



Interaction Network



Summary: 將顯示前五名各頁籤之分析結果

Canonical Pathways : 列出受實驗影響的Signaling Pathway與Metabolic Pathway

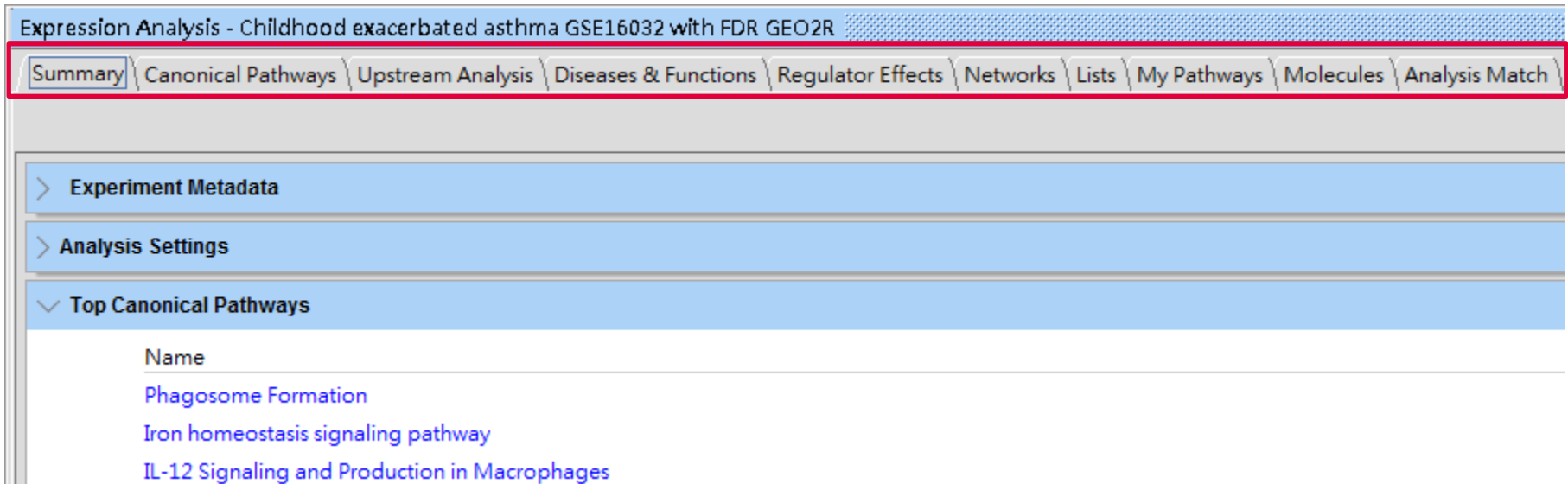
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Expression Analysis - Childhood exacerbated asthma GSE16032 with FDR GEO2R

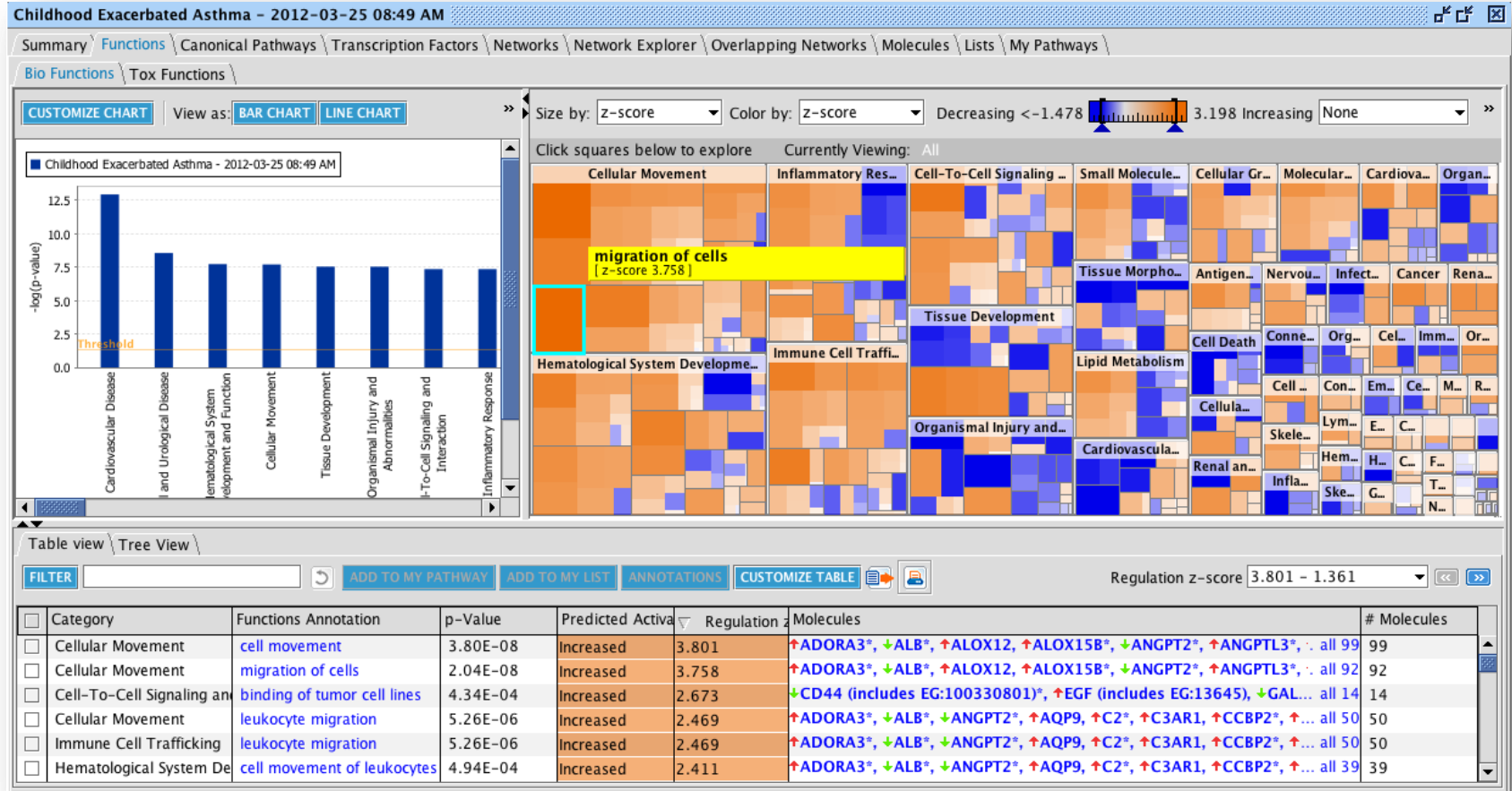
Summary | Canonical Pathways | Upstream Analysis | Diseases & Functions | Regulator Effects | Networks | Lists | My Pathways | Molecules | Analysis Match

> Experiment Metadata

> Analysis Settings

∨ Top Canonical Pathways

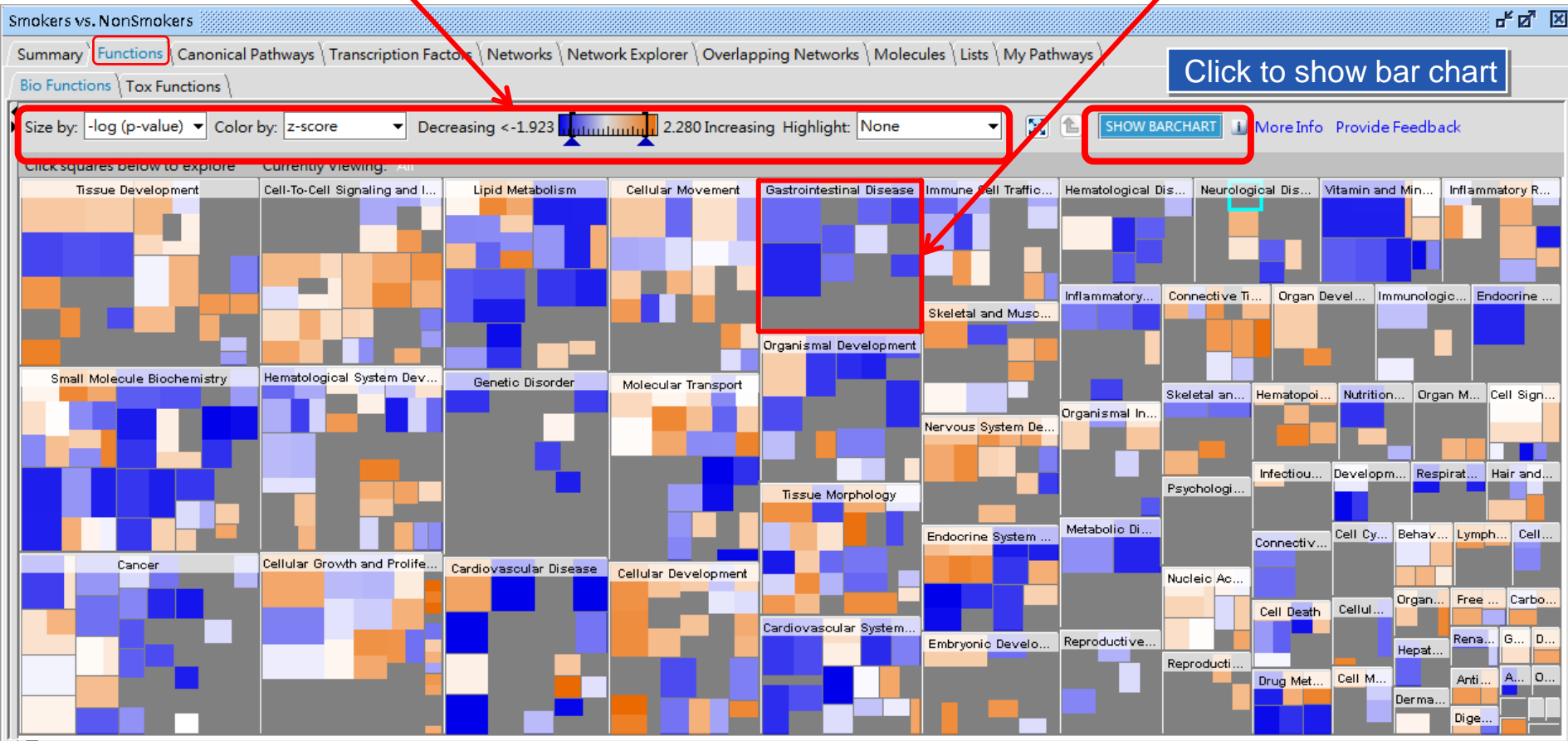
Name
Phagosome Formation
Iron homeostasis signaling pathway
IL-12 Signaling and Production in Macrophages



Identify over-represented biological functions and predict how those functions are increased or decreased in the experiment

方塊代表受實驗影響的生物功能與疾病，顏色可以用[Color by]指定是z-score, $-\log(p\text{-value})$, 或是 # of genes 上色。如果是用z-score 上色的話，藍色區塊是預測被減低的功能，橘色則是此功能會增加。是根據實驗資料做出的演算。

每個矩形可以經由點擊進入下一層分區: **Mid-level functional category (level 2)** 與 **Specific functions (level 3)**



Summary: 將顯示前五名各頁籤之分析結果

Canonical Pathways : 列出受實驗影響的Signaling Pathway與Metabolic Pathway

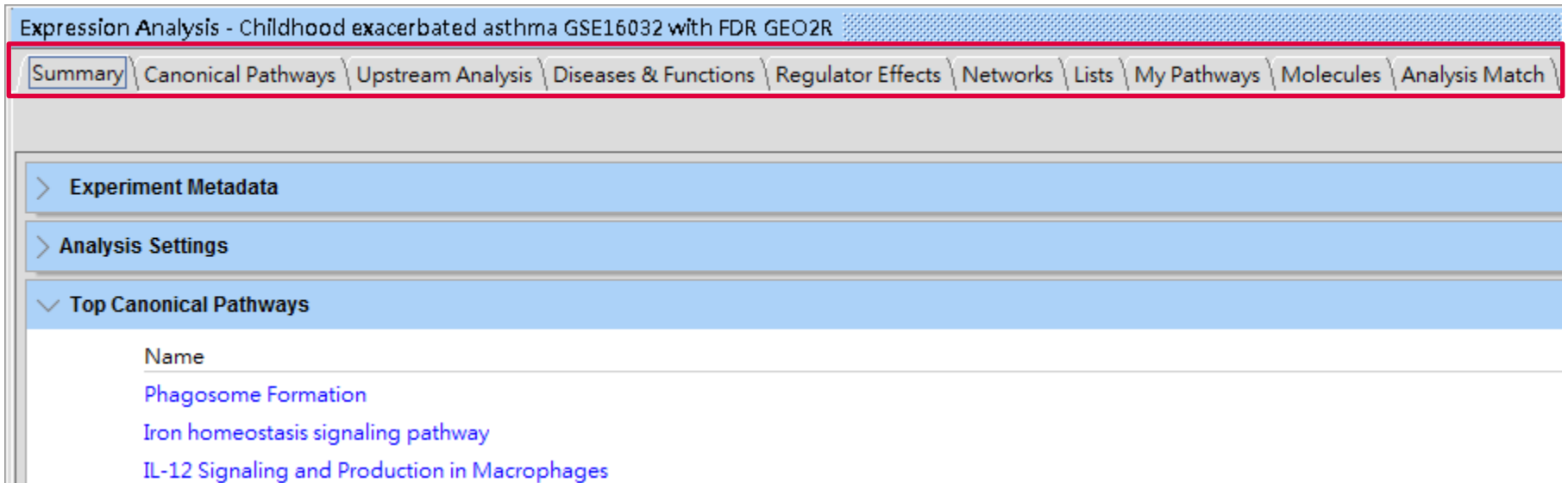
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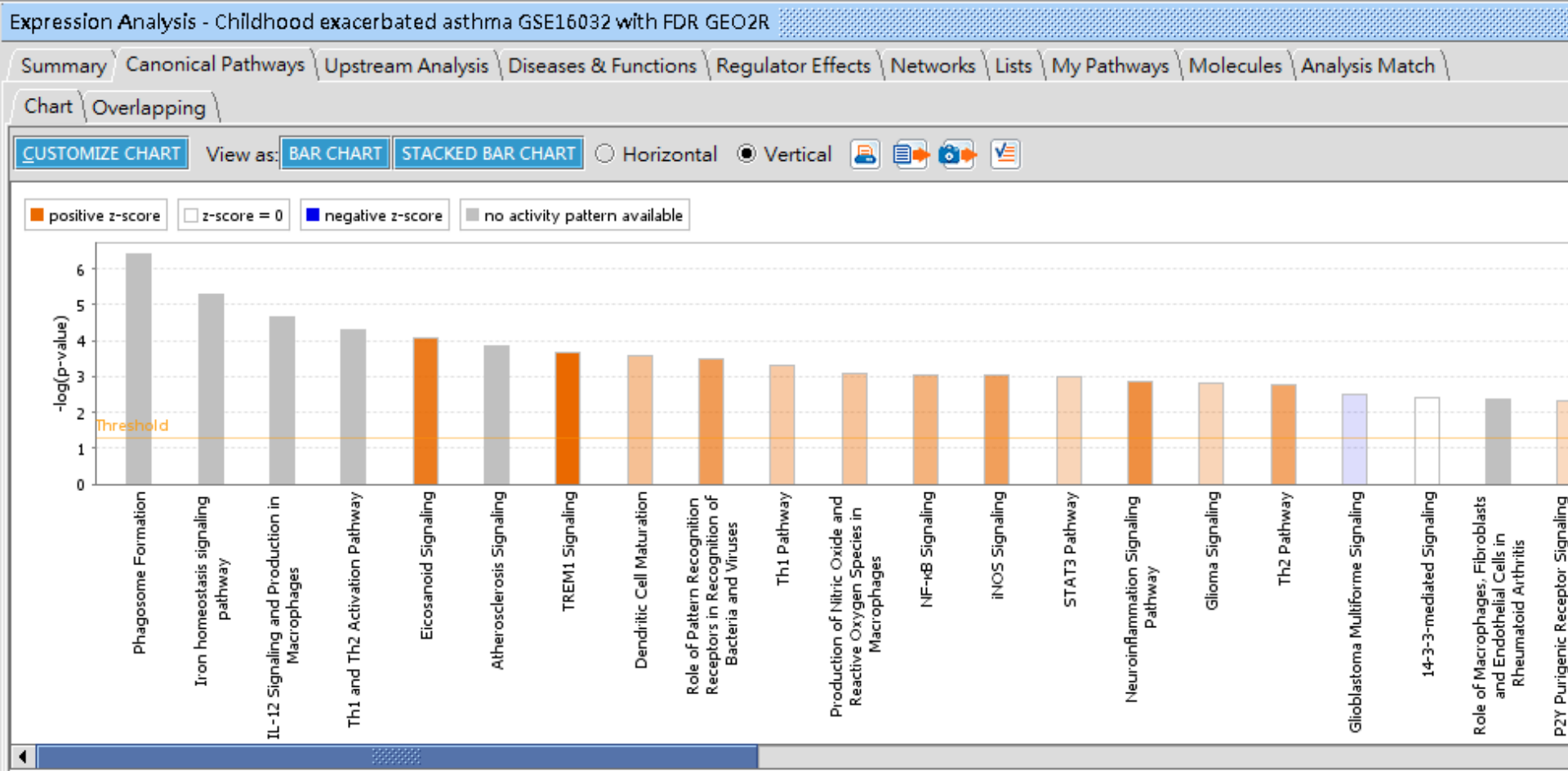
> Analysis Settings

∨ Top Canonical Pathways

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Canonical Pathways結果標籤:

受影響的Signaling Pathway與Metabolic Pathway 依照顯著性用條狀圖排列



10 molecule(s) associated with Eicosanoid Signaling at Childhood exacerbated asthma GSE16032 with FDR GEO2R [Ratio: 10/63 (0.159)] [z-score: 2.236] [p-value: 8.41E-05]

Sample to Insight

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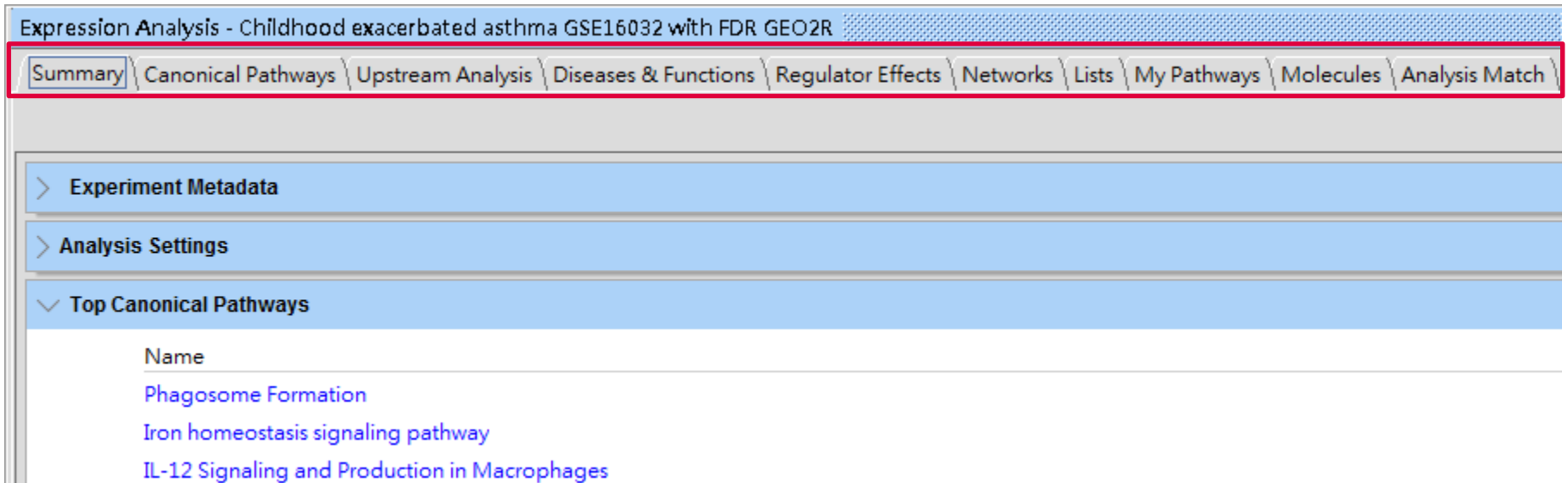
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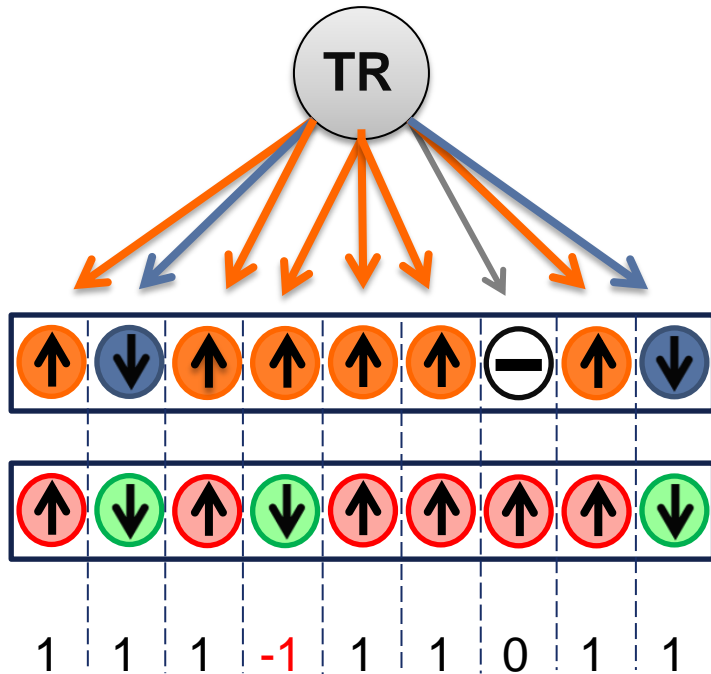
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∨ Top Canonical Pathways

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Statistical measure of correlation between the transcription regulator (TR) and resulting gene expression



N = 8 genes

TR effect on downstream genes
(Literature)

Differential gene expression
(Uploaded Data)

z-score > 2 or < -2 is considered significant

Actual z-score *can* be weighted by relationship types, relationship bias, data bias

Summary: 將顯示前五名各頁籤之分析結果

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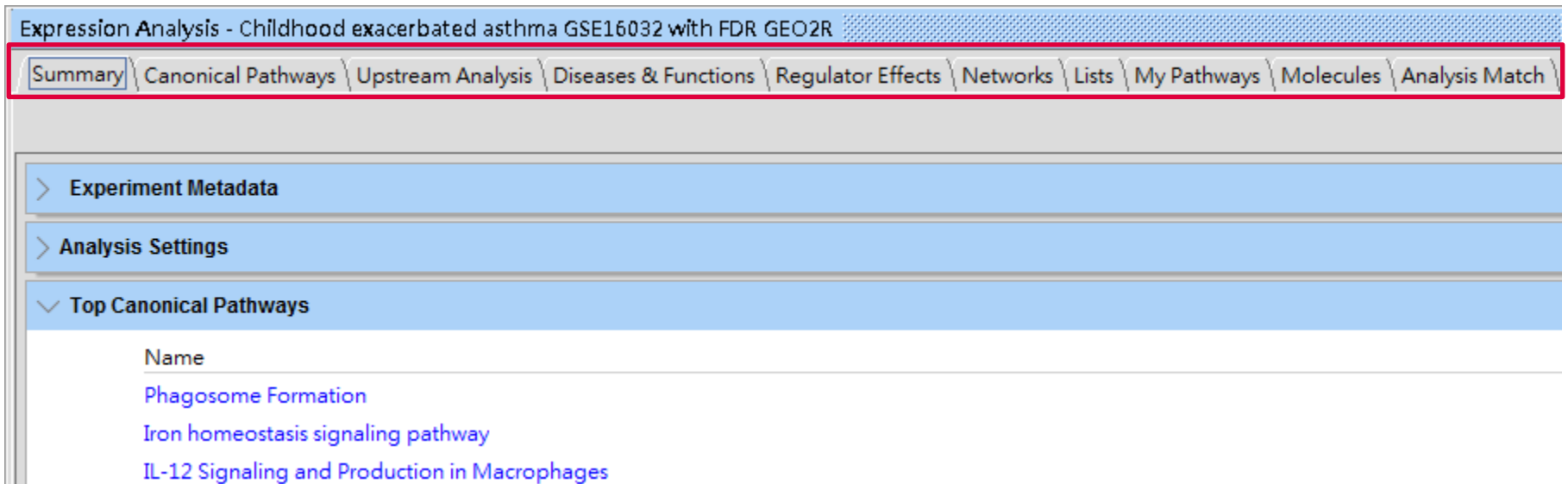
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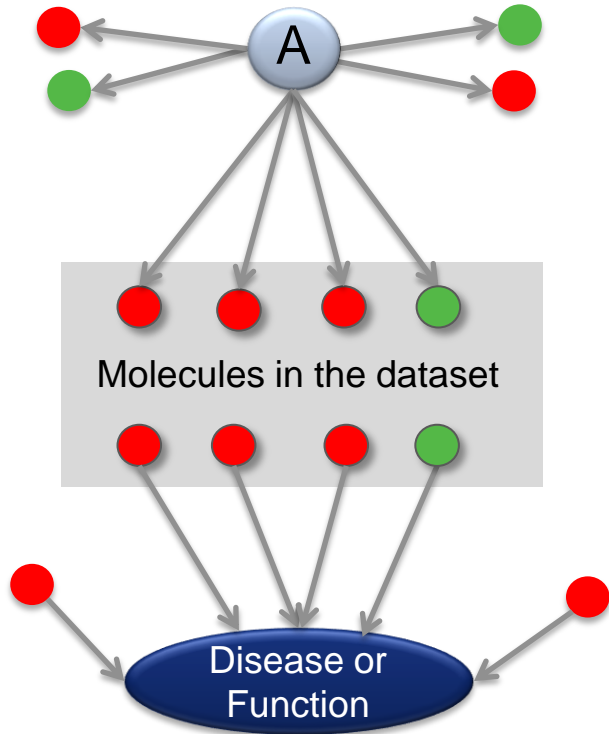
∨ Top Canonical Pathways

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IL-12 Signaling and Production in Macrophages

Concept of "Regulator Effects" - Spring 2014

Hypotheses for how activated or inhibited upstream regulators cause downstream effects on biology

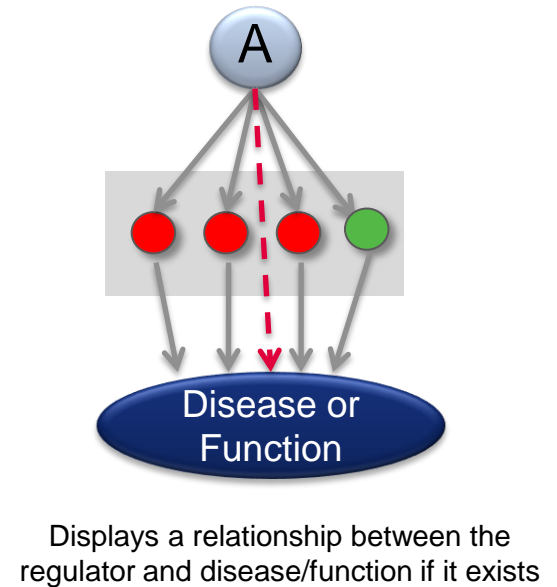
Upstream Regulators



Simplest Regulator Effects result

Algorithm

First iteration



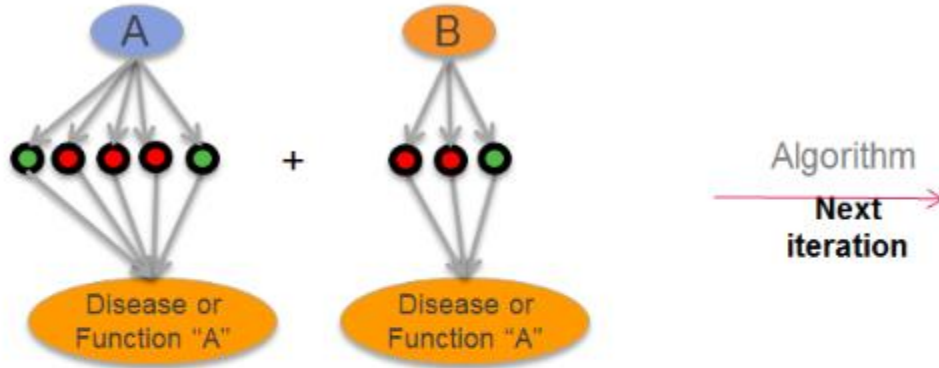
Downstream Effects Analysis

Causally consistent networks score higher

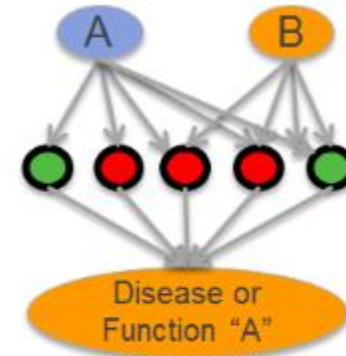
The algorithm runs iteratively to merge additional regulators with diseases and functions

Concept of "Regulator Effects"

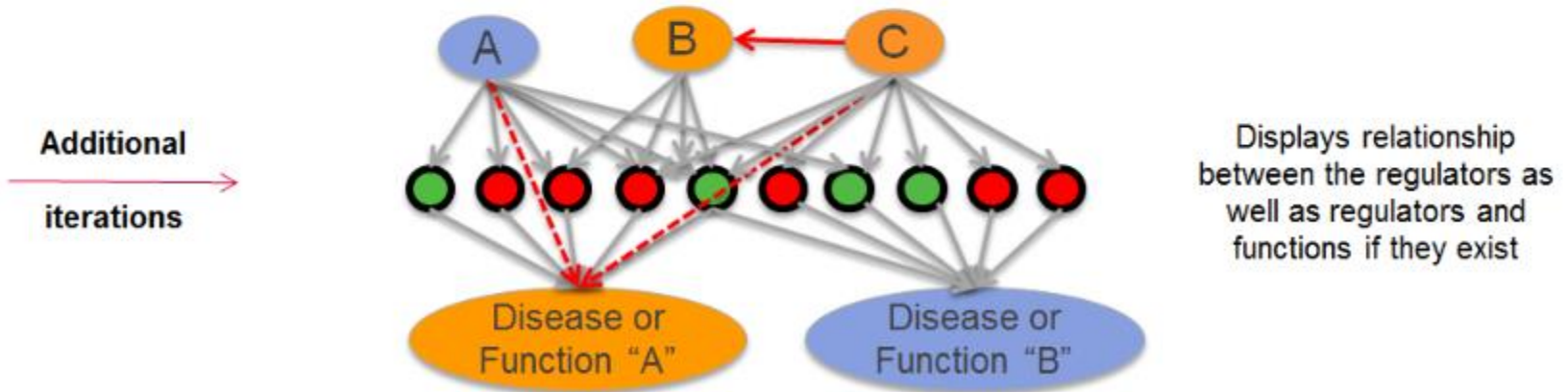
Upstream Regulator Analysis



Regulator Effects



Downstream Effects Analysis



$$\text{Consistency Score} = \frac{P_c \cdot W_c + P_i \cdot W_i + P_n \cdot W_n}{(S)^{W_s}}$$

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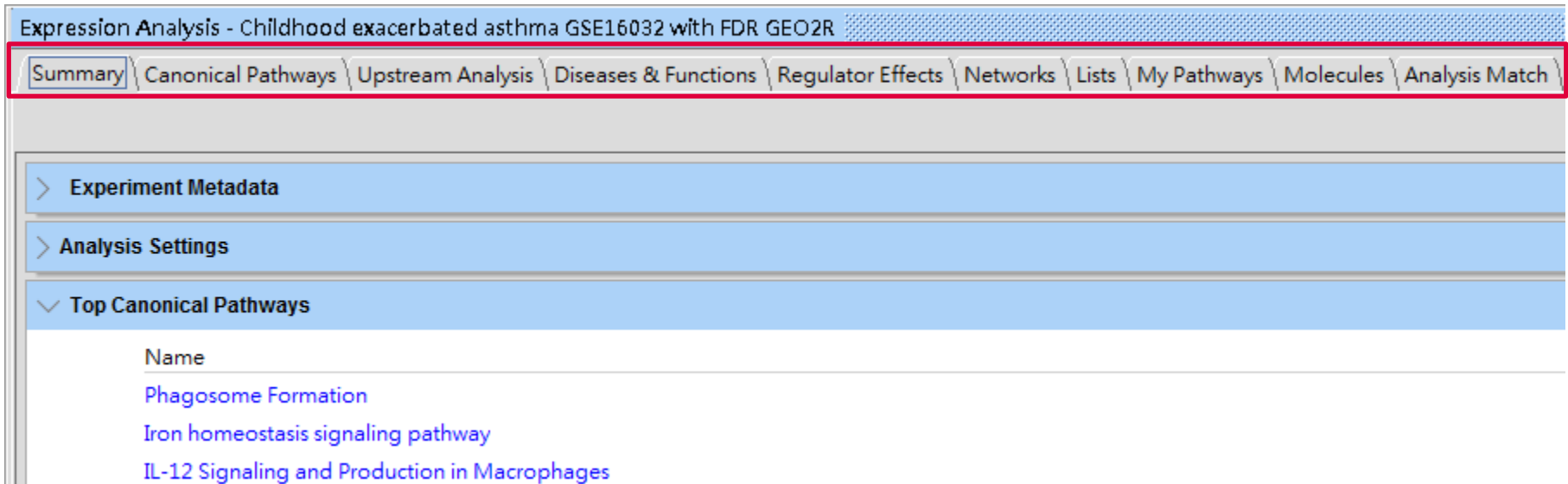
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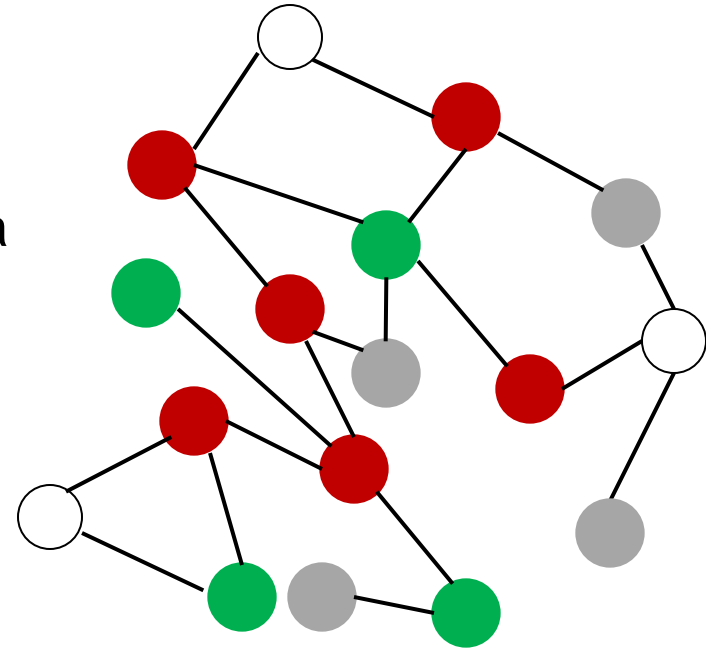
> Experiment Metadata

> Analysis Settings

∨ Top Canonical Pathways

Name
Phagosome Formation
Iron homeostasis signaling pathway
IL-12 Signaling and Production in Macrophages

1. **Focus molecules** are “seeds”
2. Focus molecules with the most interactions to other focus molecules are then connected together to form a network
3. Non-focus molecules from the dataset are then added
4. Molecules from the Ingenuity’s Knowledge Base are added
5. Resulting Networks are scored and then sorted based on the score



Molecules per Network	Networks per Analysis
35	25
35	10
70	25
140	50

Live Demo

A. Multi-Omics Analysis using IPA

Integrate and compare genomics, transcriptomics, proteomics and metabolomics data to see the big picture on your focus research

比較分析結果的差異

D. Q&A

Single Experiment

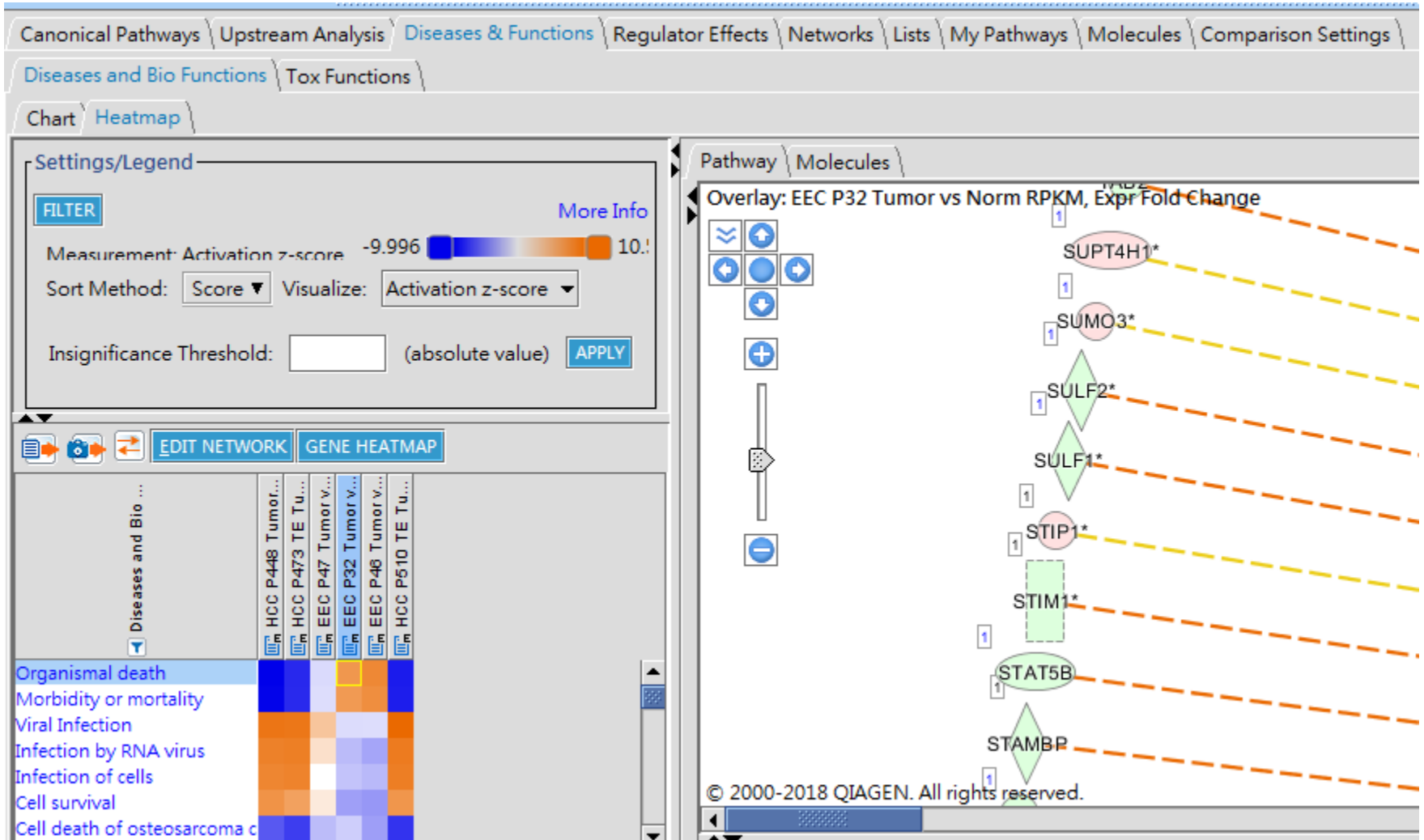
- Time Course
- Dose Response

Multi Experiment

- System biology
- Combining SNP, CNA, mRNA, microRNA, proteomics, etc

Set Analysis

- Exploring Common Molecules across one or more experiment (s)



Single Experiment

- Time Course
- Dose Response

Multi Experiment

- System biology
- Combining SNP, CNA, mRNA, microRNA, proteomics, etc

Set Analysis

- Exploring Common Molecules across one or more experiment (s)

Bringing together multiple types of genomic data

Research AIM:

- To attain a systems biology understanding of your research by bringing multiple types of genomic data together (SNP, CNA, mRNA, microRNA, proteomics, etc.).

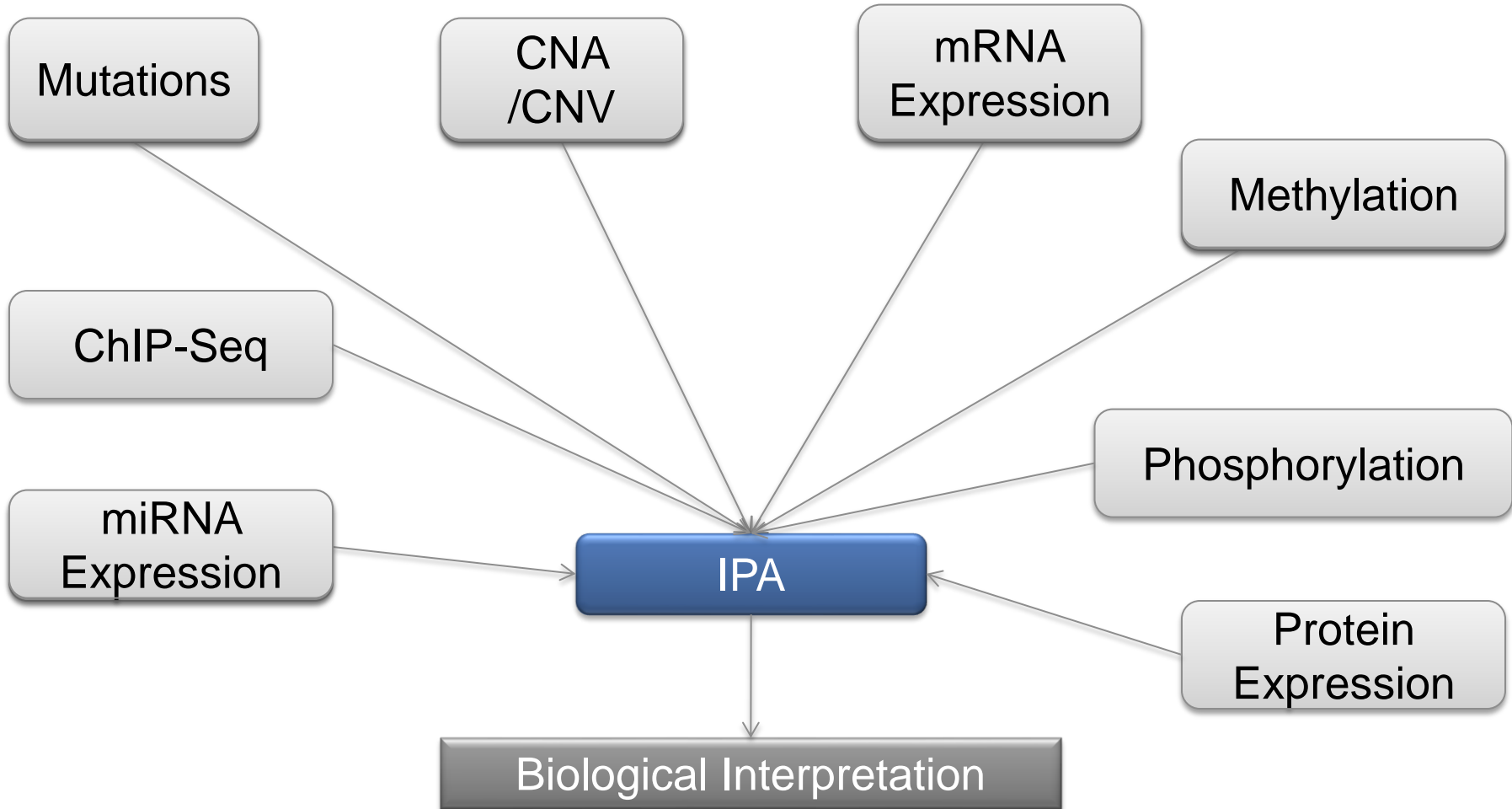
Challenge:

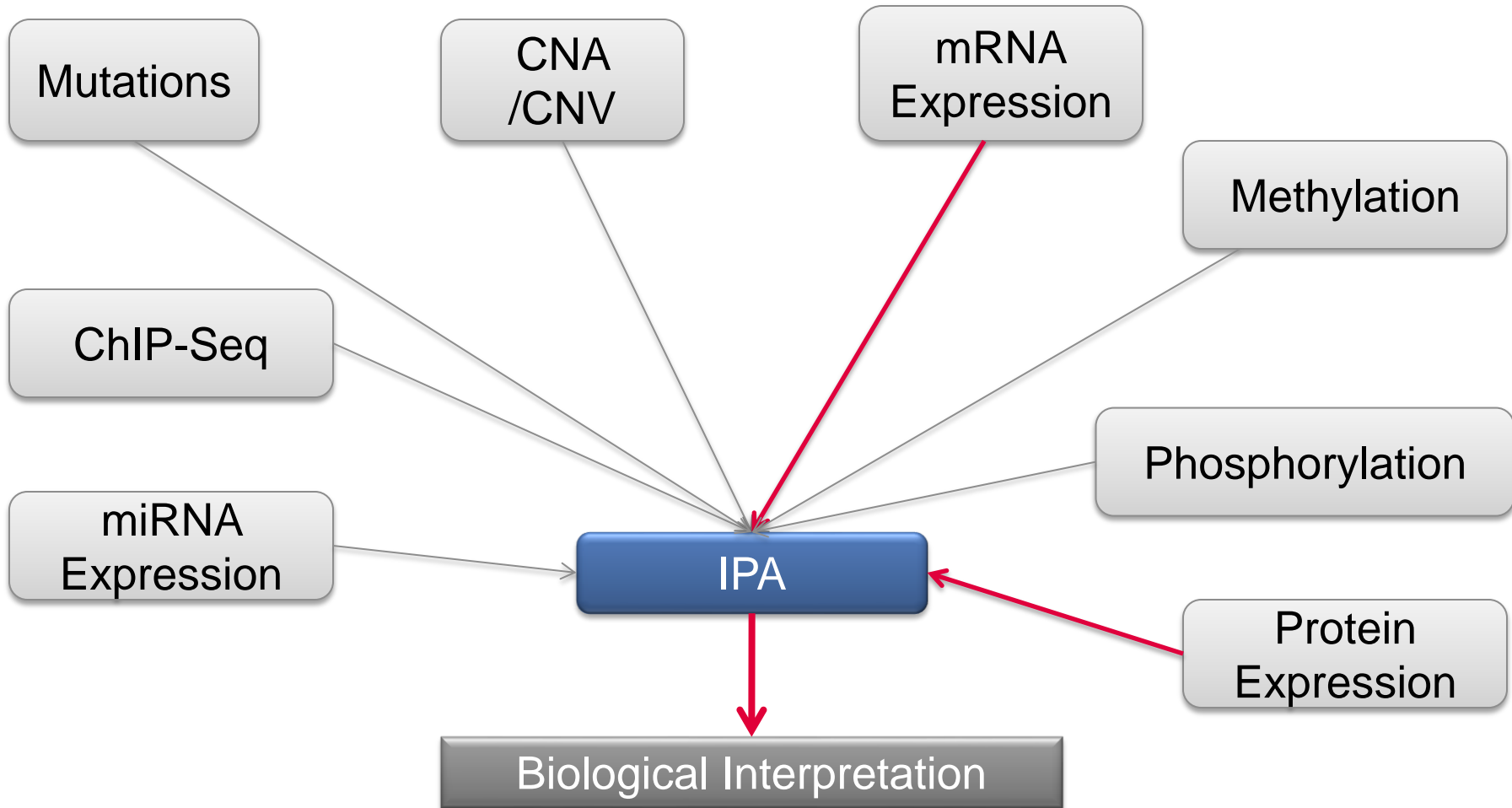
- Data types measured different molecular status in experiment
- Too much data, some data types may have extra 'noise'(i.e. arrays)
- Venn Diagram-type comparison excludes 'A affects B' information

Solution:

- Identify phenotypes, disease associations, and pathways that are common themes for multiple data types using Comparison Analysis
- Interactive pathways overlay multiple data types and find genes up or down-stream that change in the various data types.
- Pathway tools find regulatory connections between molecules of interest and the various data types
- microRNA Target Filter can link microRNAs and targets from miRNA and target data sets

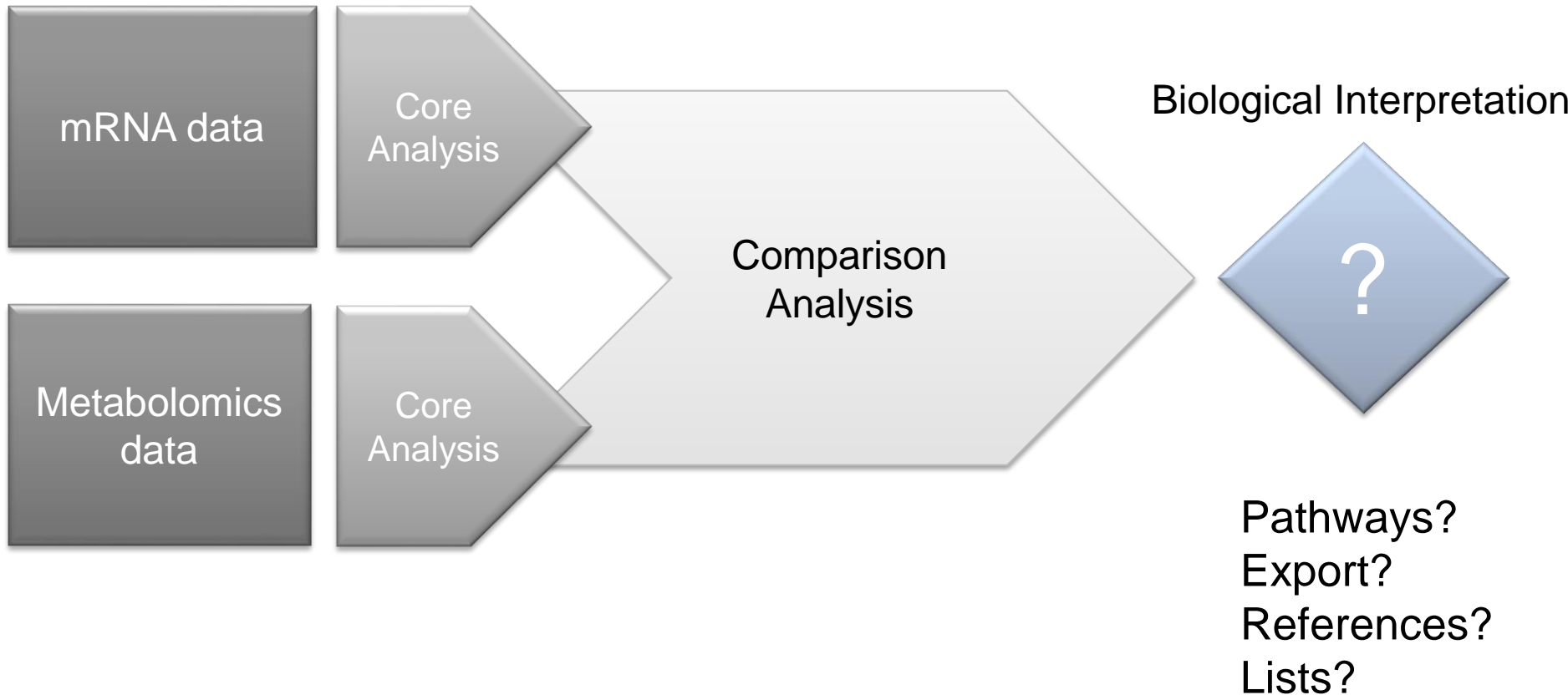
How do you integrate multiple data types now?





What do you want out of this comparison?

Review your workflow – What are your goals?



Single Experiment

- Time Course
- Dose Response

Multi Experiment

- System biology
- Combining SNP, CNA, mRNA, microRNA, proteomics, etc

Set Analysis

- Exploring Common Molecules across one or more experiment (s)

IPA Analysis of Metabolomics Data Including Cross-Platform Integration with Transcriptomics Data from a Diabetic Mouse Model

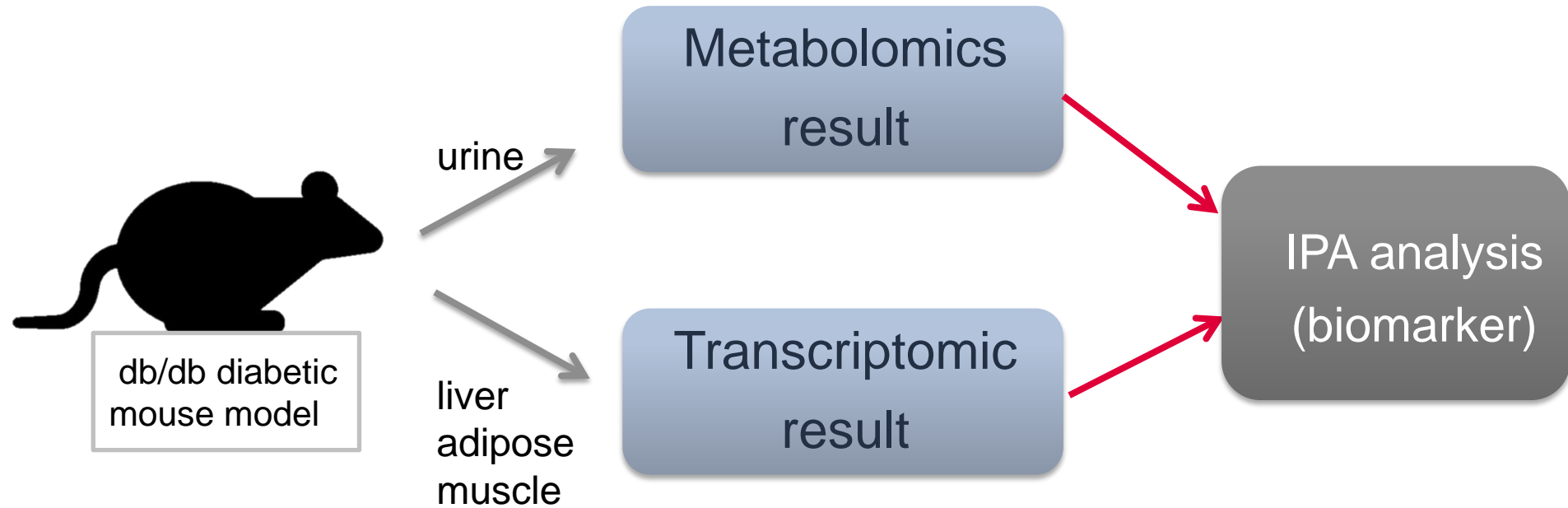
Integration of metabolomics and transcriptomics data to aid biomarker discovery in type 2 diabetes

Susan C. Connor,^{†*a} Michael K. Hansen,^{‡b} Adam Corner,^c Randall F. Smith^d and Terence E. Ryan^{‡b}

Received 15th July 2009, Accepted 4th December 2009

First published as an Advance Article on the web 23rd March 2010

DOI: 10.1039/b914182k



Input dataset

- Observation 1 : urinary NMR-based metabolomics data
- Observation 2 : liver transcriptomic data
- Observation 3 : adipose transcriptomic data
- Observation 4 : muscle transcriptomic data

metabolomics data



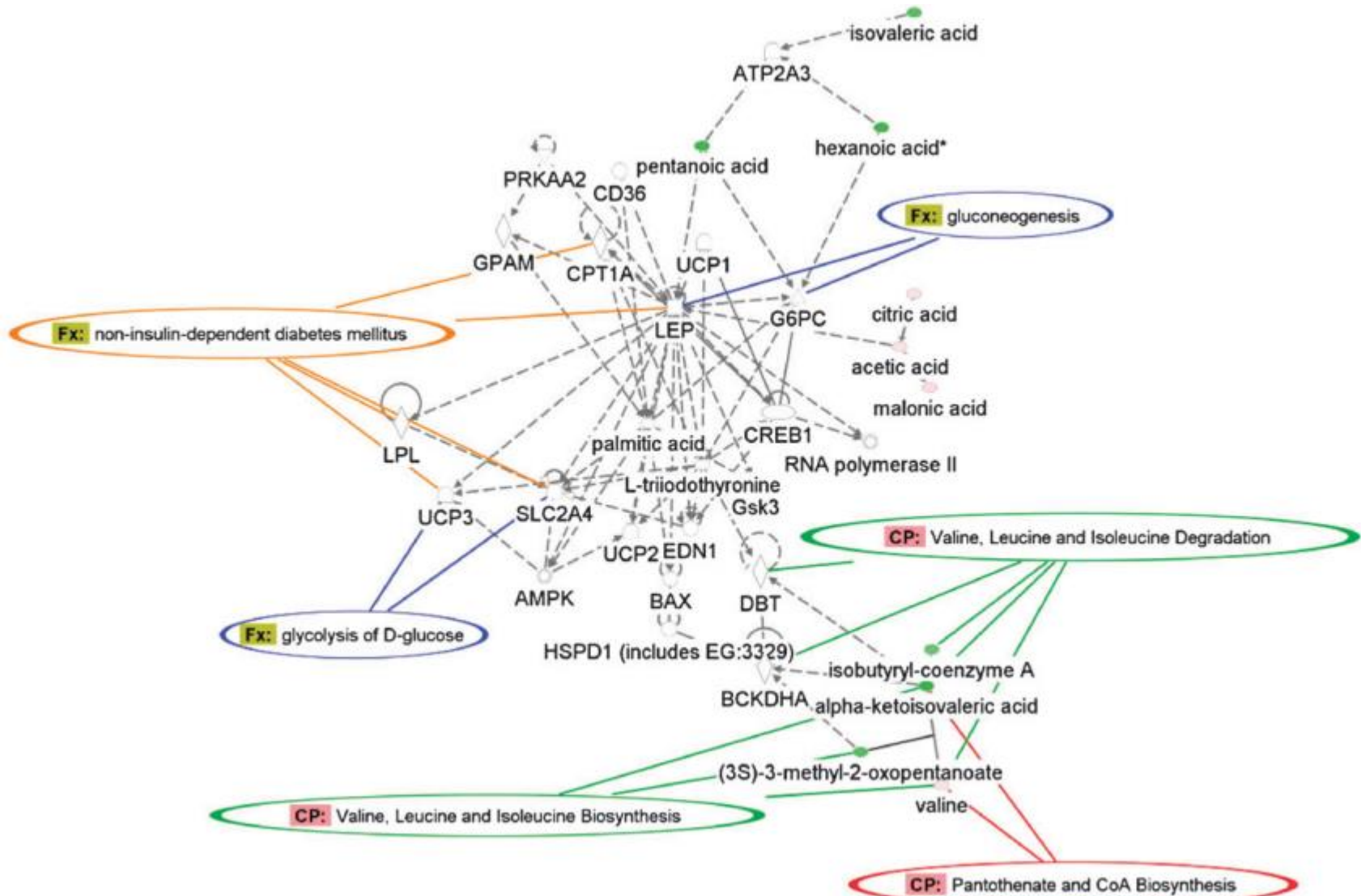
transcriptomic data

ID	Symbol	Fold Change	p-value
C00671	(3S)-3-methyl-2-oxopentanoate	-1.344	0.00E+00
C01089	(R)-3-hydroxybutyric acid	-1.311	0.00E+00
C05984	2-hydroxybutyric acid	-1.344	0.00E+00
C00322	2-oxoadipic acid	2	
C00026	2-oxoglutaric acid	2.031	0.00E+00
C01468	4-cresol	1.64	0.00E+00
C00642	4-hydroxyphenylacetic acid	1.002	0.00E+00
C00033	acetic acid	1.226	1.83E-02
C02571	acetyl-L-carnitine	-1.011	0.00E+00
C00212	adenosine	-1.066	0.00E+00
C01551	allantoin	1.081	0.00E+00
C00233	alpha-ketoisocaproic acid	-1.371	0.00E+00
C00141	alpha-ketoisovaleric acid	-1.559	0.00E+00
C00417	cis-aconitic acid	1.208	0.00E+00
C00158	citric acid	1.262	0.00E+00
C00327	citrulline	2	
C00300	creatine	-1.33	0.00E+00
C00791	creatinine	-1.281	6.00E-06
C00879	D-galactaric acid	2.896	0.00E+00
C00124	D-galactose	3.183	0.00E+00
C00031	D-glucose	10.945	0.00E+00

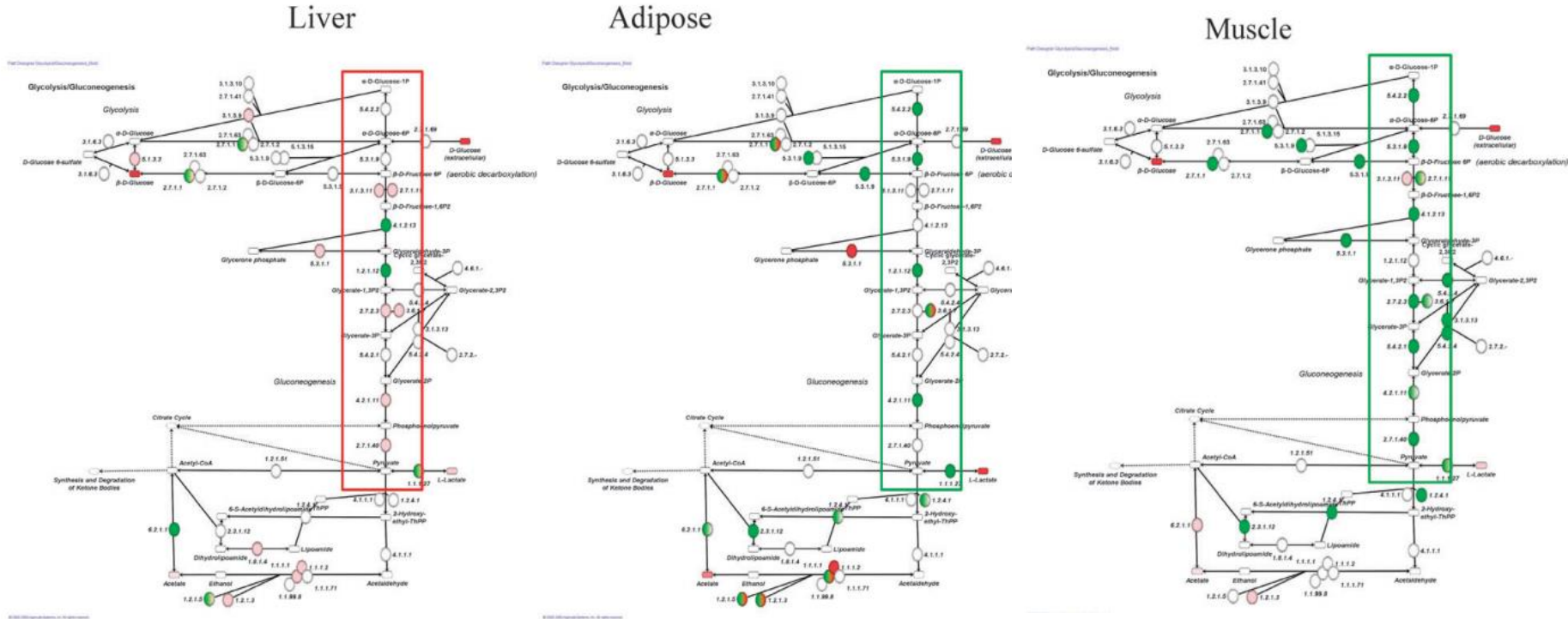
ID	Fold Change	p-value
C00671	-1.344	0.00E+00
C01089	-1.311	0.00E+00
1418083_at	-2	3.83E-02
1433936_at	-2	2.86E-03
1434484_at	2	1.86E-02
1453238_s_at	2	8.93E-05
1435137_s_at	2	3.06E-06
1427932_s_at	2	9.77E-08
1430989_a_at	-2	3.71E-02
1448038_at	-2	3.91E-02
1424365_at	-2	2.54E-07
C05984	-1.344	0.00E+00
C00322	2	0.00E+00
C00026	2.031	0.00E+00
1429115_at	-2	4.59E-02
1435522_a_at	-2	1.86E-08
1428083_at	-2	1.06E-09
1455207_at	-2	2.75E-04
1420269_at	2	5.55E-05
1423357_at	-2	2.68E-03
1453207_at	-2	4.41E-03

ID	Fold Change	p-value
C05270	-1.49	0.00E+00
C00888	-1.49	0.00E+00
C00026	2.031	0.00E+00
C00233	-1.371	0.00E+00
C00141	-1.559	0.00E+00
C01089	-1.311	0.00E+00
C11457	-1.838	0.00E+00
C02642	-1.072	0.00E+00
C02571	-1.011	0.00E+00
C00212	-1.066	0.00E+00
C00041	1.119	0.00E+00
C01551	1.081	0.00E+00
C05984	-1.344	0.00E+00
C01585	-1.49	0.00E+00
C00803	-1.49	0.00E+00
C00671	-1.344	0.00E+00
C00417	1.208	0.00E+00
C00158	1.262	0.00E+00
C00300	-1.33	0.00E+00
C00543	-1.12	0.00E+00
C00346	1.248	0.00E+00
C00671	-1.344	0.00E+00
C01089	-1.311	0.00E+00
1452730_at	2	2.60E-03
1436187_at	-2	2.94E-12
1424722_at	-2	3.67E-02
1456546_at	-2	1.13E-02
1455692_x	-2	1.11E-02
1448038_at	-2	4.14E-04
1451588_at	-2	6.20E-27
1424365_at	2	1.04E-04
1436339_at	2	2.61E-12
C05984	-1.344	0.00E+00
C00322	2	
C00026	2.031	0.00E+00
1435524_at	-2	7.42E-06
1452170_at	2	6.82E-08
1424968_at	-2	1.94E-06
1433530_at	-2	1.46E-03
1428500_at	-2	4.00E-05
1439962_at	-2	5.34E-05
1435522_a	2	2.54E-03

IPA analysis result



Network describing lipid metabolism, small molecule biochemistry and transport



Gluconeogenesis pathway mapping metabolomics and transcriptomics results

Result:

- Several biomarkers (e.g., BCAAs, nicotinamide metabolites, pantothenic acid) have not previously been suggested as possible biomarkers for diabetes.
- metabolomics highlighted at least 24 distinct pathways that distinguish diabetic and control mice. The pathways most affected were amino acid, amino group metabolism and the urea cycle. Also affected were fatty acid biosynthesis, degradation and transport, DNA and protein synthesis changes in urinary protein, MUP and NAG, energy metabolism, and steroid hormone synthesis.

Live Demo

Compare
🔍 📄 🗑️

Select Entities to compare and click Add

REFRESH

- 📁 My Projects
 - 📁 Data integration training
 - 📁 Dataset Files
 - 📁 Analyses
 - 📄 GBM vs Norm Expression - 1.5LR-p0.05
 - 📄 GBM paper CNA_q0.05
 - 📄 GBM paper Mutation Data_Freq>2%
 - 📁 My Pathways
 - 📁 My Lists
 - 📁 GBM
 - 📁 Charite -- Cellular study
 - 📁 Charite--Human Study
 - 📁 Melanoma Case Study
 - 📁 UPMC
 - 📁 Project 1
 - 📁 Endothelial Genes
 - 📁 COPD
 - 📁 Tubulin binders heart Effect
 - 📁 ENS 211111
 - 📁 Biblio1
 - 📁 Erasmus Wednesday
 - 📁 Erasmus training
 - 📁 Certification Exam

Show All ▼

Entities to Compare

- 📄 GBM vs Norm Expression - 1.5LR-p0.05
- 📄 GBM paper CNA_q0.05
- 📄 GBM paper Mutation Data_Freq>2%

ADD >>
<< REMOVE
CLEAR ALL

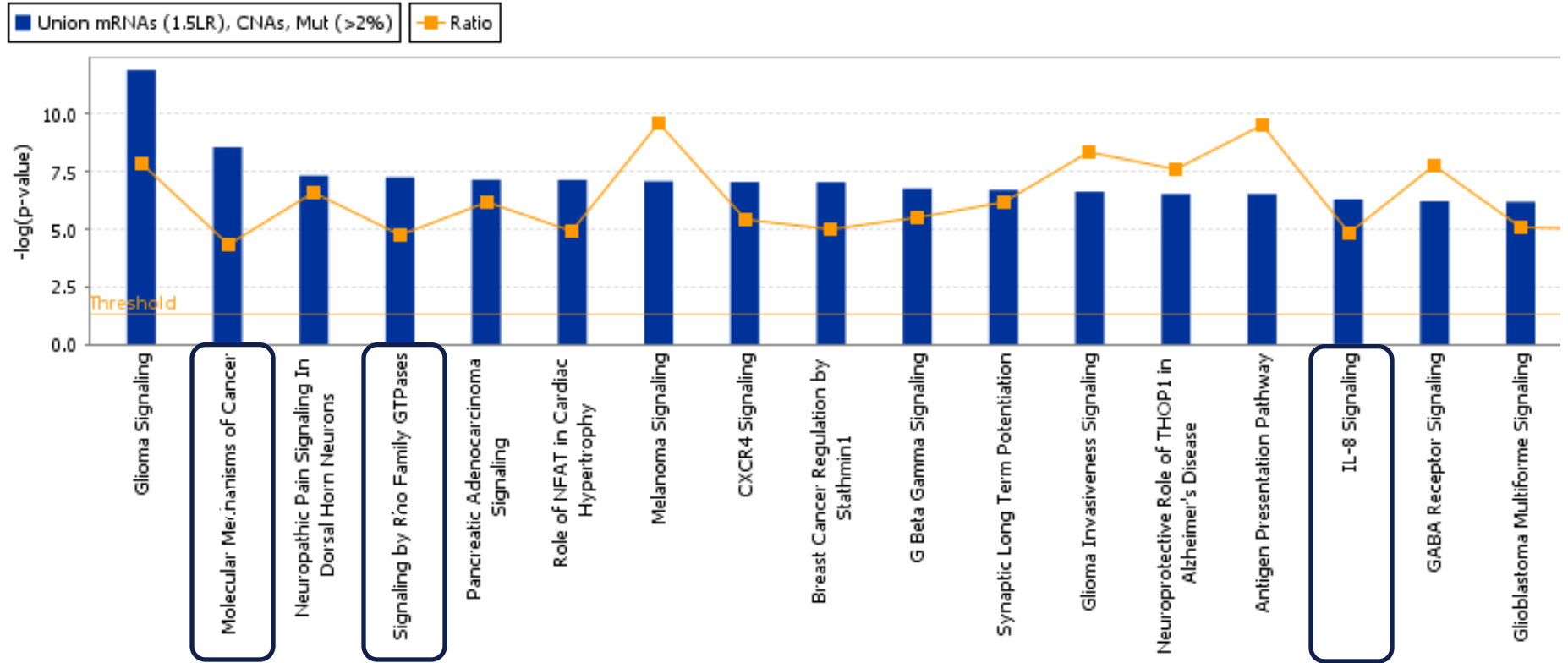
UNION
COMMON
UNIQUE

Entities Comparison Results

Union of all nodes in Entity (1305)

- AACS
- ABCA1
- ABCC3
- ABHD3
- ABR
- ACCN1
- ACOT7
- ACP6
- ACSBG1

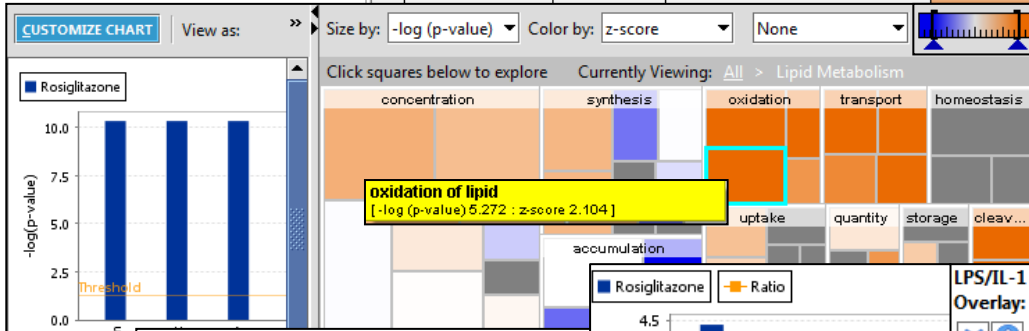
ADD TO MY PATHWAY
ADD TO MY LIST
ANNOTATIONS



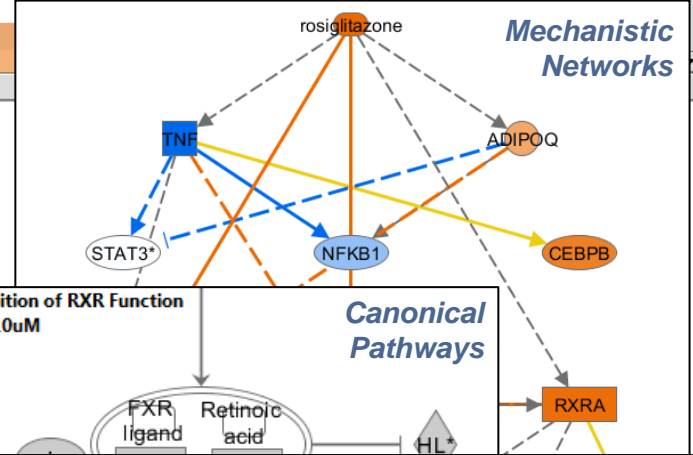
Upstream Analysis

Upstream Regulator	Log Ratio	Molecule Type	Predicted Activation State	Activation z-score	p-value of overlap	Target molecules in dataset	Mechanistic Network
rosiglitazone	↑0.706	chemical drug	Activated	3.746	1.68E-11	↑ACAA2, ↑ACADVL, ... all 59	240 (15)
PPARG	↑0.706	ligand-dependent nuclear receptor	Activated	4.793	2.22E-09	↑ACAA2, ↑ACOX1, ... all 53	185 (18)
TNF	↑5.150	cytokine	Inhibited	-3.414	2.62E-09	↓ABCC2, ↓ABR, ↑A... all 147	244 (18)
9-cis-retinoic acid		chemical drug		1.201			

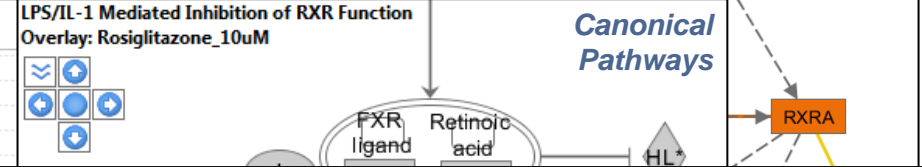
Functions



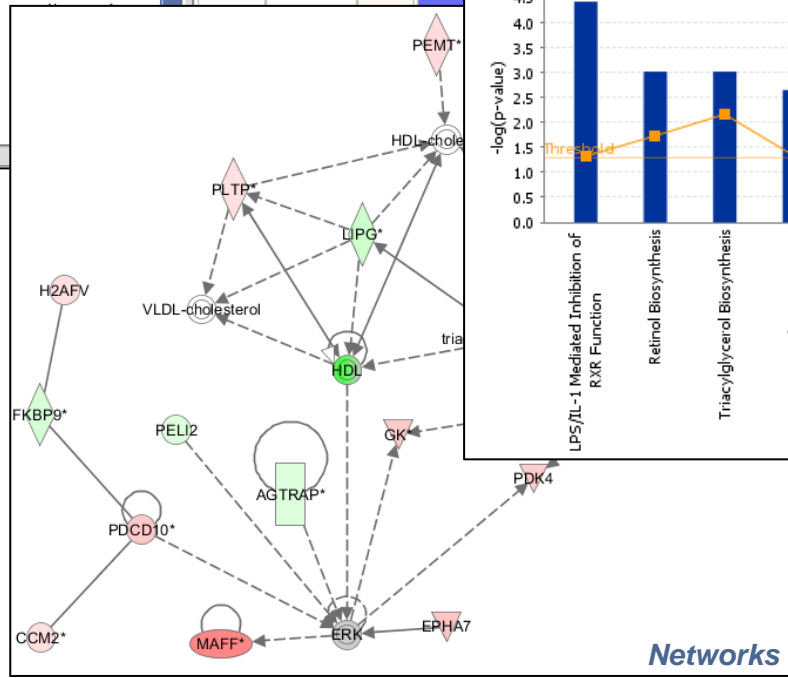
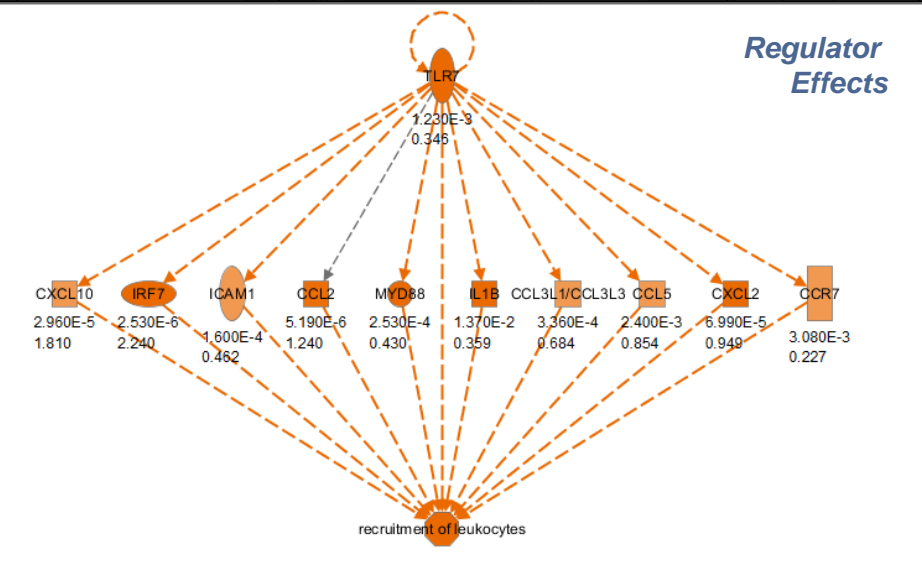
Mechanistic Networks



Canonical Pathways



Regulator Effects



Networks

Live Demo

microRNA Target Filter

68 microRNA families have targeting information available.
Filtered to 51 microRNAs targeting 32 mRNAs.

ADD/REPLACE MRNA DATASET EXPRESSION PAIRING

Details \ Summary

ADD TO MY PATHWAY ADD TO MY LIST

Rows: 1 - 131

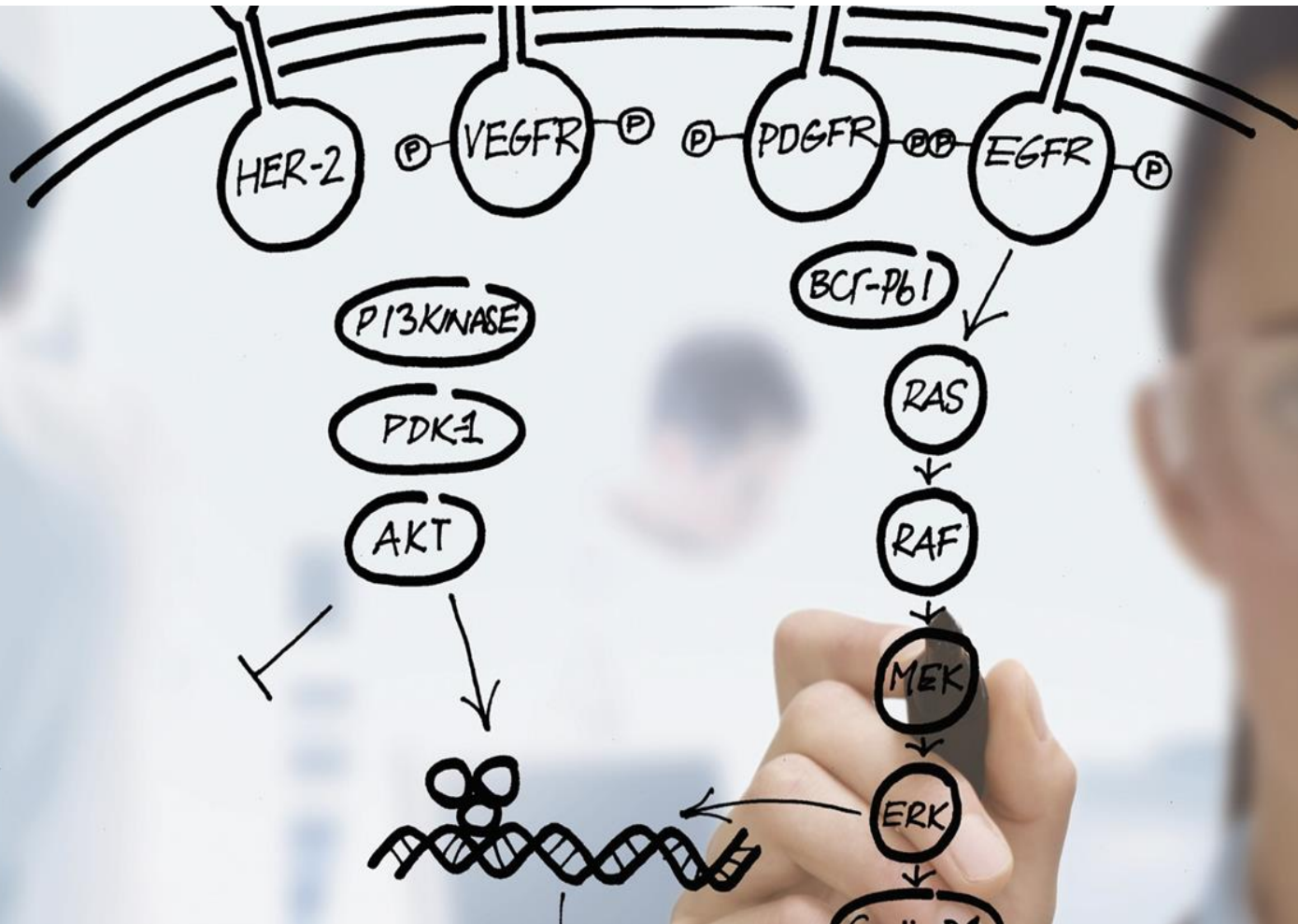
Use [v] to filter a column. Add data or more columns using 'Add column(s) [+]'.

microRNA dataset: melanoma_microRNA_data						mRNA dataset: mRNA Metastasis vs Normal - 2FC,0.05PV				
ID	Symbol	metastatic melanoma (Fold C...)	Relationship	Confidence	Expression Pairing	ID	Symbol	Fold Change	Molecular Type	Pathway
hsa-let-7c	let-7	↓-3.120	TargetScan Human	High (predicted)	↕	8072015	ADRBK2	↑3.394	kinase	Colorectal Cancer Met
hsa-let-7c	let-7	↓-3.120	TargetScan Human	Moderate (predicted)	↕	8067167	AURKA	↑2.136	kinase	Molecular Mechanisms
hsa-let-7c	let-7	↓-3.120	TargetScan Human	High (predicted)	↕	8105121	GHR	↑2.052	transmembrane receptor	Growth Hormone Signa
hsa-let-7c	let-7	↓-3.120	TargetScan Human	Moderate (predicted)	↕	7994131	PRKCB	↑4.995	kinase	Breast Cancer Regulat
hsa-miR-206	mir-1	↑1.880	TargetScan Human	Moderate (predicted)	↕	7956301	LRP1	↓-3.463	transmembrane receptor	Colorectal Cancer Met
hsa-miR-206	mir-1	↑1.880	TargetScan Human	High (predicted)	↕	8008201	NGFR	↓-2.917	transmembrane receptor	PTEN Signaling
hsa-miR-122	mir-122	↑1.970	TargetScan Human	High (predicted)	↕	7963670	MAP3K12	↓-3.119	kinase	Germ Cell-Sertoli Cell J
hsa-miR-122	mir-122	↑1.970	TargetScan Human	Moderate (predicted)	↕	8157524	TLR4	↓-6.290	transmembrane receptor	Colorectal Cancer Met
hsa-miR-125a-5p	mir-125	↓-1.450	TargetScan Human	Moderate (predicted)	↕	7985213	CHRNA5	↑2.965	transmembrane receptor	AMPK Signaling



Use Pathway tools to build hypothesis for microRNA to mRNA target association

- **Goal:** Utilize newly discovered microRNAs to better understand biology around potential mRNA targets/disease
- **Challenge:** New and rapidly evolving field with different measurement techniques and prediction algorithms leading to variability in data
- **Need:** Identify mRNA targets to microRNAs using biological and experimental information, correlate microRNA and mRNA target expression, specify easy to use confidence levels of interaction predictions, annotate mRNA targets with biological context, pathways, species, etc., all within a single workflow
- **Outcome:** Reduce time of identification of relevant mRNA targets from months to minutes



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