

Mechanistic Interpretation of the Ovarian Cancer Tumor Microenvironment Using Single-Cell and Spatial Transcriptomics with IPA



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Minimum Software Requirements

Windows OS	Windows 11 Windows 10 Windows 8
Browser	Microsoft Edge 94 or later Chrome 110 or later Firefox 91 or later Safari 16 or later
macOS	Sequoia Sonoma Ventura
Java (JRE)	JRE 1.8.0_xx or later

Minimum Hardware Requirements

- PC - 1.25GHz, 2GB RAM (for lightweight usage of IPA)*
- PC - 2GHz, 4GB RAM (Recommended)
- Mac - 1.25GHz, 2GB RAM (for lightweight usage of IPA)*
- Mac - 2GHz, 4GB RAM (Recommended)

Minimum Screen Resolution of 1280 x 800

*Lightweight usage of IPA includes Search, Build/Overlay operations and small dataset upload and analysis creation. For larger analyses and Comparison Analyses, IPA requires more memory.

For Causal Network Analysis, BioProfiler, IsoProfiler, Phosphorylation Analysis, Relationship Export, and Analysis Match-related features:

Core™ i5 processor or equivalent running at 2 GHz or higher with 64-bit OS and Java, and at least 3 GB RAM free for Java. Screen resolution of at least 1280 x 800.

Notes:

1. We recommend that you install the IPA client on your computer with this installer: <https://analysis.ingenuity.com/pa/installer/select>. The installed IPA client still requires you to have internet access to launch but does *not require* you to install Java (a JRE) or to launch IPA from a web browser.
2. Alternatively, you can launch IPA using Java Web Start, which requires a recent version of Java installed on your computer. Oracle has changed its licensing terms for Java: <https://www.java.com/en/download/>. Therefore, please ensure you are following Oracle's terms and conditions for the Java version on your computer should you choose to launch IPA via Web Start, which is available at this link: <https://analysis.ingenuity.com>. Help on installing and/or launching IPA can be found at the following links:
 - i. Mac: https://qiagen.my.salesforce-sites.com/KnowledgeBase/articles/Basic_Technical_Q_A/Running-IPA-on-Mac
 - ii. Windows: https://qiagen.my.salesforce-sites.com/KnowledgeBase/articles/Basic_Technical_Q_A/Running-IPA-on-Windows

[IPA Installer Download \(ingenuity.com\)](https://analysis.ingenuity.com)

Introduction to pathway analysis

What is QIAGEN Ingenuity Pathway Analysis

- Introduction of Ingenuity Pathway Analysis
- What's new in Ingenuity Pathway Analysis

Create networks from scratch

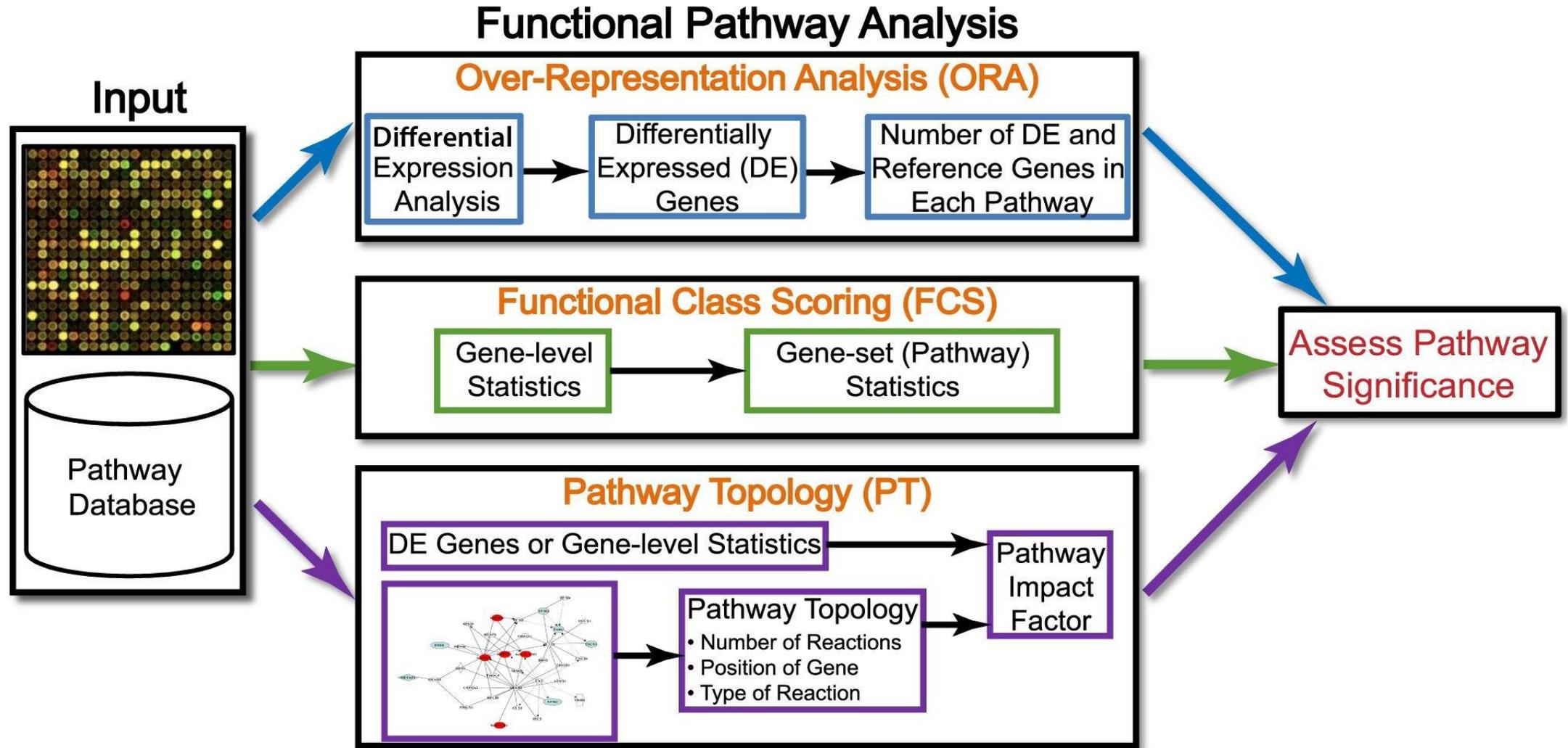
Machine Learning pathway

Interpreting your 'omics data using IPA

- Data upload and analysis setup
- Canonical pathways and upstream regulators
- Comparison analysis
- Diseases and functions/Tox analysis

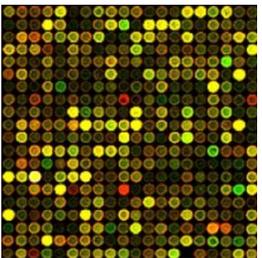
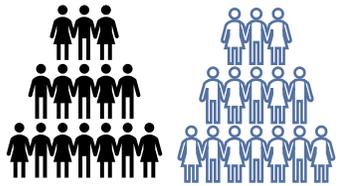
Comparison analysis

Summary



Khatri, Sirota, and Butte. *PLoS Comp Bio.* 2012.

Your dataset



- PDE6A
- SLC6A14
- LPCAT1
- C2
- CFB
- REG4
- CD55
- TIMP1
- DPP10
- PDIA4
- PRKG2
- NAT8B
- SHISA5
- LCN2
- CDH3
- ACAT1
- NAALADL1
- APOBEC3B
- NMT2
- KYNU
- TMEM63C
- S100A11
- PI3
- CDC25B
- CNNM2
- CHRNA1
- LRRN2
- RMDN2
- CNTFR
- CDC14A
- C7orf31
- BACE2
- CXCL1
- SLC36A1
- WDR78
- PKM

Drugs and chemicals

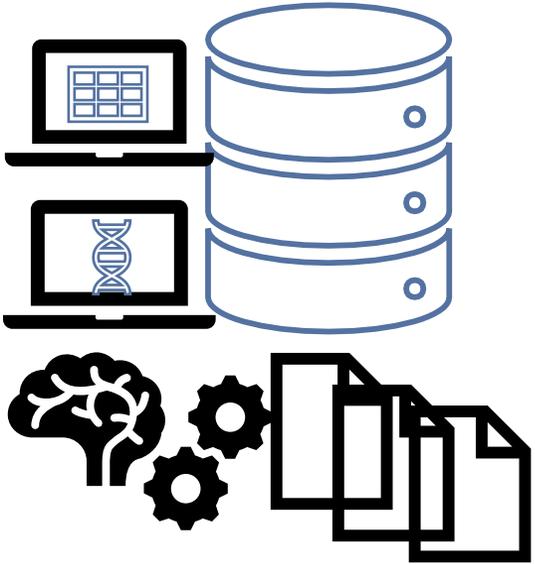
Pathway

Disease

Function

Network

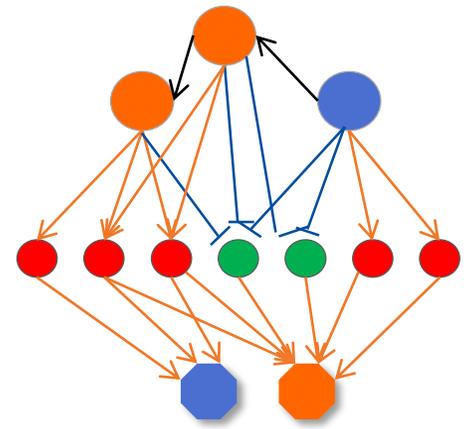
Public /commercial database



ORA/FCS/Topology Pathway Analysis

Machine learning

What do they relate to each other?



What are the relationship between each molecules?

> *Hepatology Commun.* 2020 Mar 15;4(5):724-738. doi: 10.1002/hep4.1497. eCollection 2020 May.
Integrated GWAS and mRNA Microarray Analysis Identified IFNG and CD40L as the Central Upstream Regulators in Primary Biliary Cholangitis

GWAS

> *J Neuroinflammation.* 2024 Mar 20;21(1):69. doi: 10.1186/s12974-024-03065-z.
Deletion of Slc9a1 in Cx3cr1⁺ cells stimulated microglial subcluster CREB1 signaling and microglia-oligodendrocyte crosstalk

transcriptomic

> *J Allergy Clin Immunol.* 2024 May;153(5):1268-1281. doi: 10.1016/j.jaci.2023.12.030. Epub 2024 Mar 29.
Galectin-10 in serum extracellular vesicles reflects asthma pathophysiology

proteomics

> *Chin Med.* 2022 Jun 15;17(1):71. doi: 10.1186/s13020-022-00632-5.
Serum metabolomics analysis of deficiency pattern and excess pattern in patients with rheumatoid arthritis

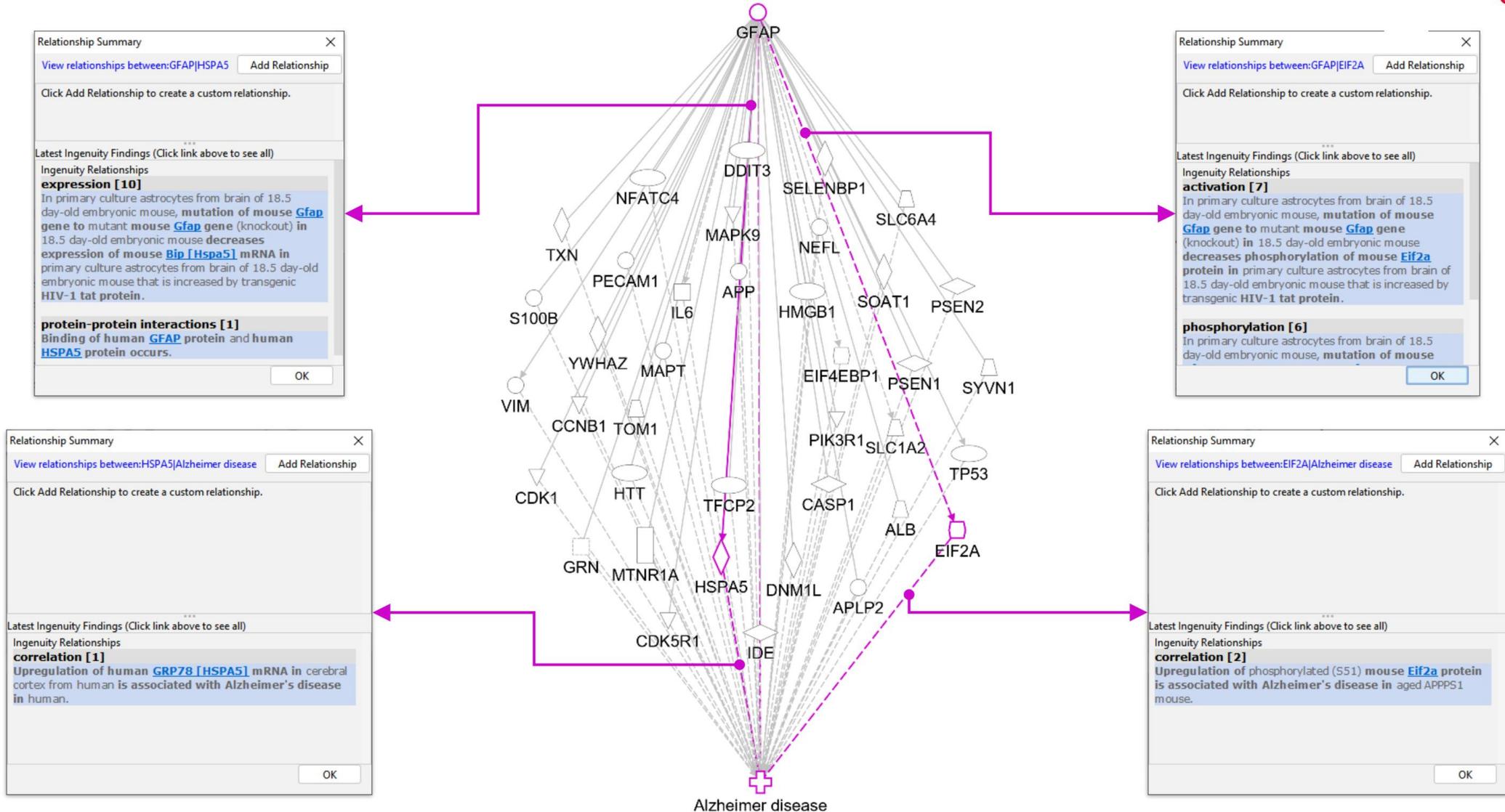
metabolomics

The screenshot shows a PubMed search for 'ingenuity pathway analysis'. The search results page displays 1,573 results. The first result is titled 'Ingenuity pathway analysis of gingival epithelial cells stimulated with estradiol and progesterone' by Sugiyama N, Uehara O, Kawano Y, Paudel D, Morikawa T, Nakamoto N, Kato S, Takayama T, Nagasawa T, Miura H, Abiko Y, Furuichi Y. The second result is 'Ingenuity pathway analysis of alpha-synuclein predicts potential signaling pathways, network molecules, biological functions, and its role in neurological diseases' by Suthar SK, Lee SY. The third result is 'Gene set enrichment analysis and ingenuity pathway analysis to verify the...'. The search interface includes a search bar, filters, and a 'RESULTS BY YEAR' bar chart.

From 2020-2026
1,537 literatures

> *Stem Cells Transl Med.* 2024 Mar 15;13(3):293-308. doi: 10.1093/stcltm/szad090.
Histone Trimethylations and HDAC5 Regulate Spheroid Subpopulation and Differentiation Signaling of Human Adipose-Derived Stem Cells

Single-cell RNA-seq



Fully supported:

What species identifiers are accepted for analysis by IPA?



Human

- ✓ Atlantic Salmon (*Salmo salar*)
- ✓ Thale cress (*Arabidopsis thaliana*)
- ✓ Bat (Greater horseshoe bat, *Rhinolophus ferrumequinum*)
- ✓ Brewer's yeast (*Saccharomyces cerevisiae*)
- ✓ Cat (domestic, *Felis catus*)
- ✓ Chicken (*Gallus gallus*)
- ✓ Chimpanzee (*Pan troglodytes*)
- ✓ Chinese hamster (*Cricetulus griseus*)
- ✓ Cow (*Bos taurus*)
- ✓ Crab-eating macaque (*Macaca fascicularis*)
- ✓ Dog (*Canis lupus familiaris*)
- ✓ Fission yeast (*Schizosaccharomyces pombe*)
- ✓ Fruit fly (*Drosophila melanogaster*)
- ✓ Golden hamster (*Mesocricetus auratus*)

- ✓ Guinea pig, domestic (*Cavia porcellus*)
- ✓ Horse (*Equus caballus*)
- ✓ Human (*Homo sapiens*)
- ✓ Mouse (*Mus musculus*)
- ✓ Pig (*Sus scrofa*)
- ✓ Rabbit (*Oryctolagus cuniculus*)
- ✓ Rainbow trout (*Oncorhynchus mykiss*)
- ✓ Rat (*Rattus norvegicus*)
- ✓ Rhesus Monkey (*Macaca mulatta*)
- ✓ Roundworm (*Caenorhabditis elegans*)
- ✓ Sheep (*Ovis aries*)
- ✓ Western clawed frog (*Xenopus tropicalis*)
- ✓ Zebrafish (*Danio rerio*)
- ✓ Domestic goat
- ✓ three-spined stickleback



Mouse



Rat

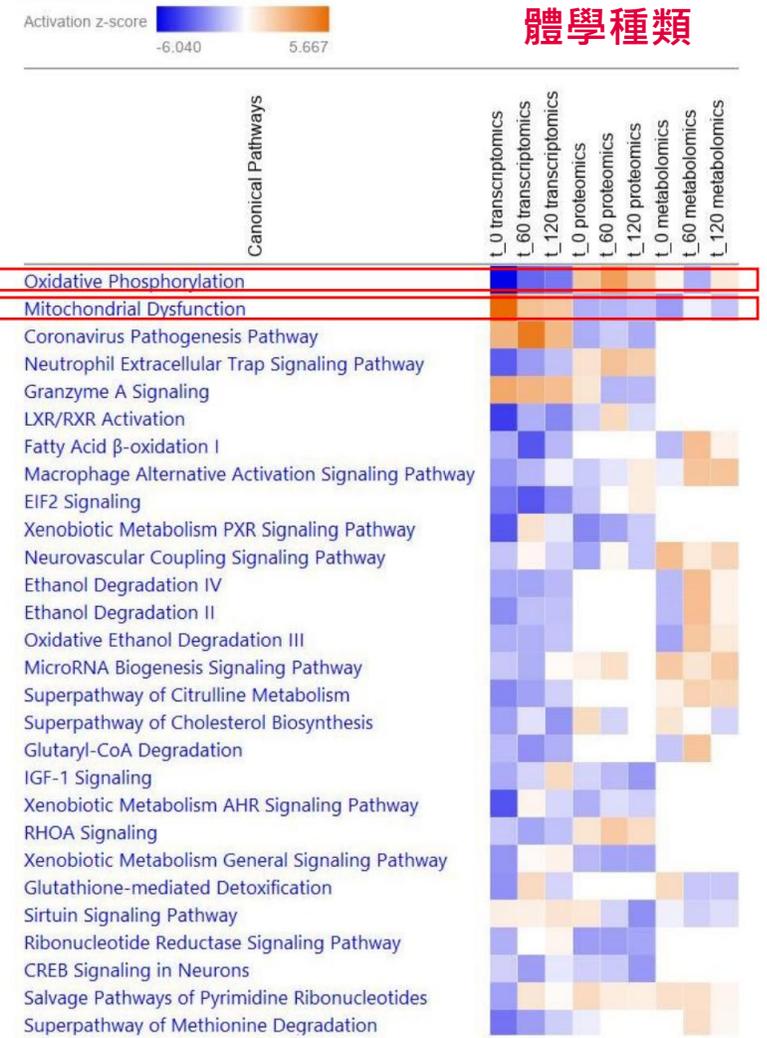
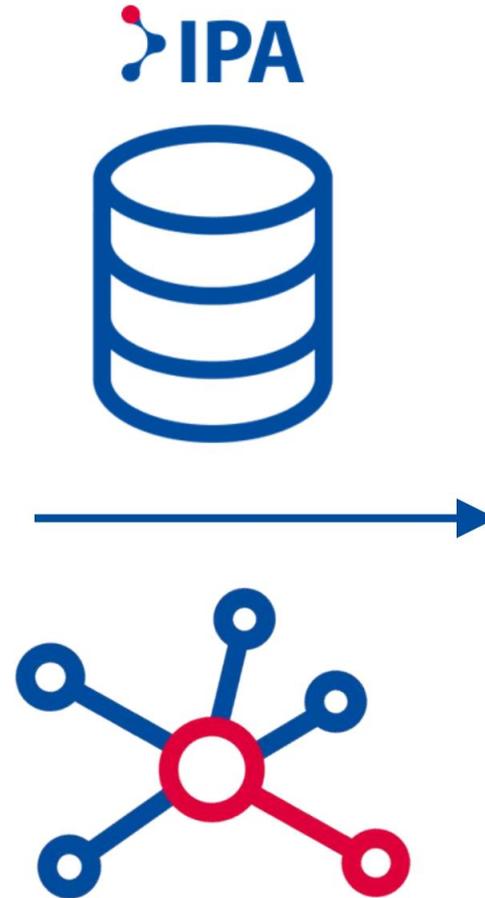
Orthologs Gene from NCBI Eukaryotic Genome Annotation Pipeline

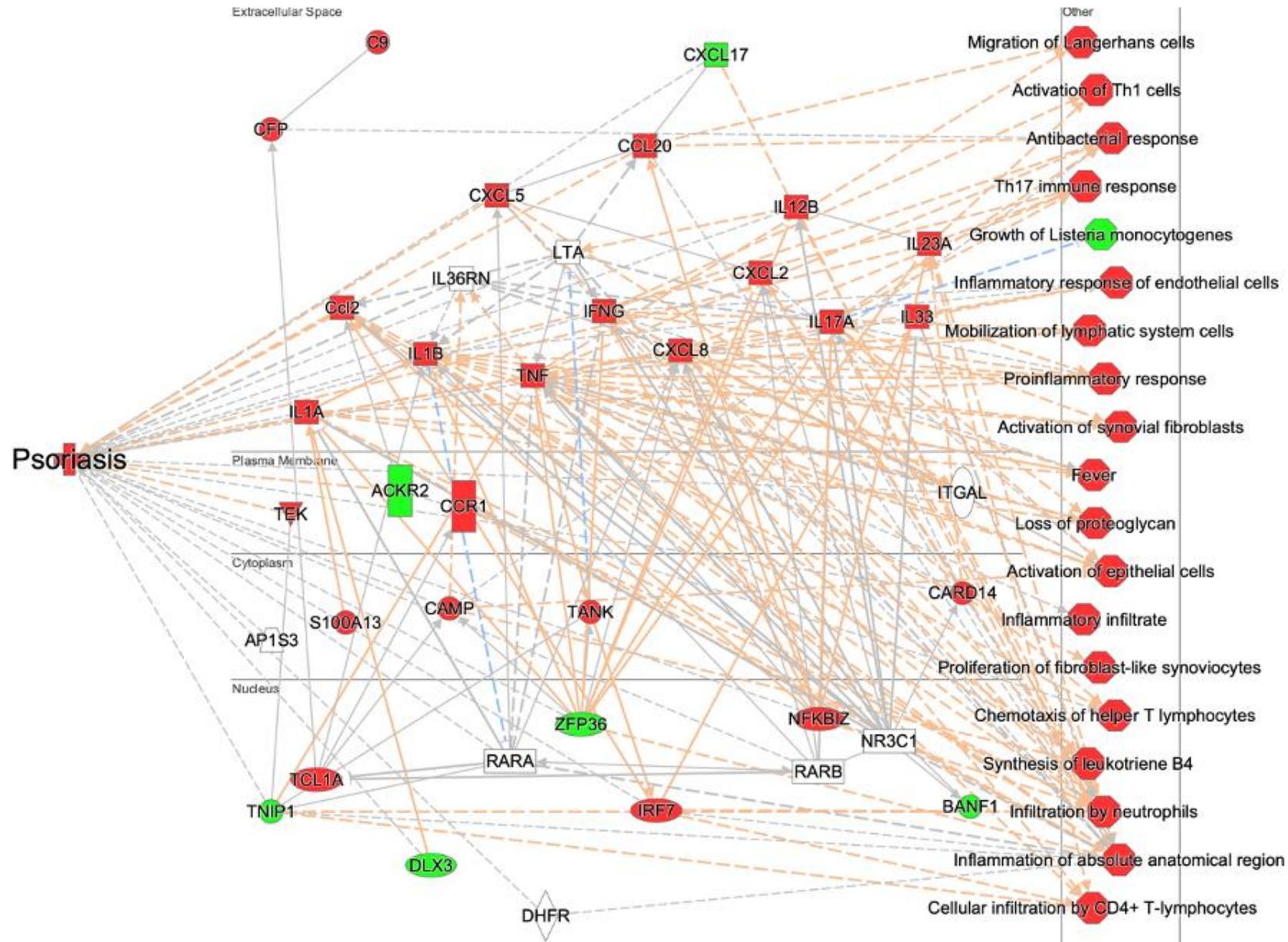
Get more complete mapping during dataset upload!

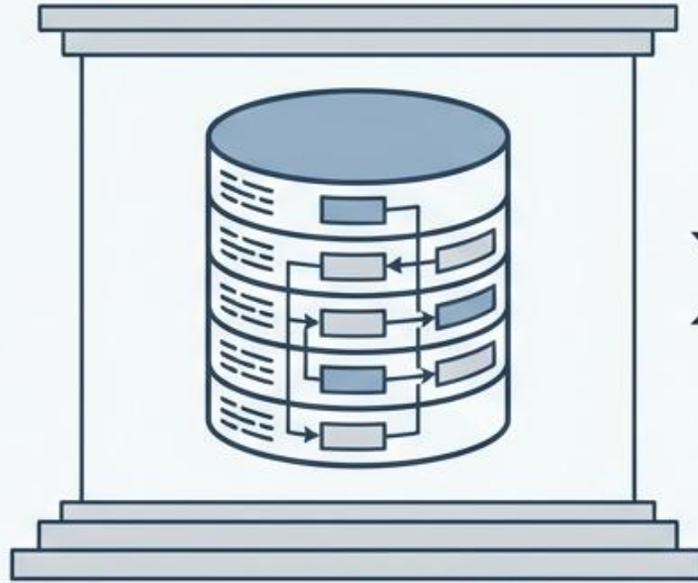
Vendor IDs	Gene	Protein	Transcript	microRNA	SNP	Chemical
Affymetrix (na36)	Entrez Gene (2023/8)	GenPept	Ensembl (110)	miRbase (mature)	Affy SNP IDs	CAS Registry Number
Agilent	GenBank (257)	International Protein Index (IPI)	RefSeq (human, mouse)	miRBase (stemloop)	dbSNP	HMDB
Life Tech (ABI)	Symbol-human (HUGO/ HGNC, EG)	UniProt/ Swiss-Prot Accession (2022_02)	UCSC (hg18)			KEGG
Codelink	Symbol- mouse (EG)		UCSC (hg19)			PubChem CID
Illumina	Symbol- rat (EG)		UCSC (hg38)			
Ingenuity	GI Number					
	UniGene					

Omics data type

- RNA-seq
- scRNA-seq
- Microarray
- Nanostring
- qPCR
- ChIP-seq
- Proteomics
- Metabolomics
- RNAi
- CRISPR
- WGS/WES etc.

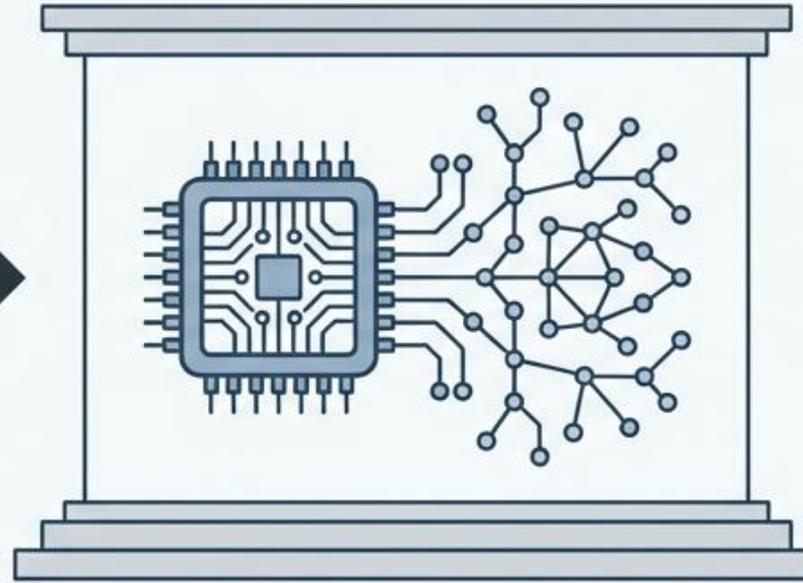






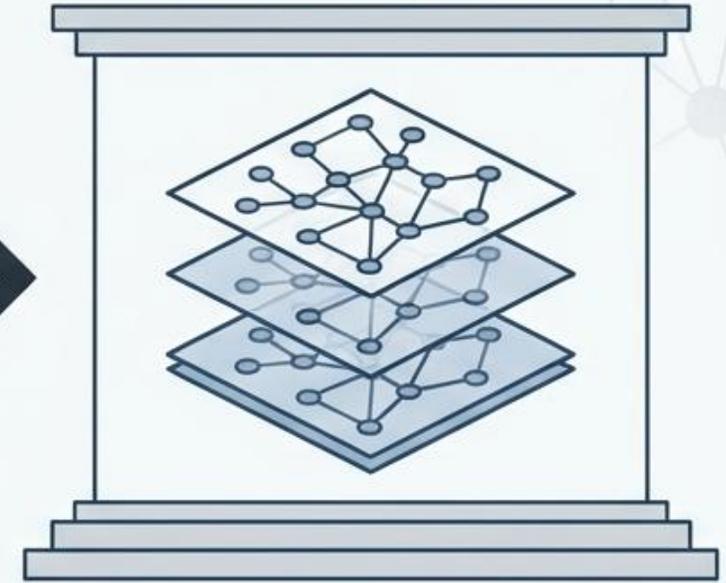
The Source: QIAGEN Knowledge Base

Mining decades of **causal findings**.



The Engine: Machine Learning Generation

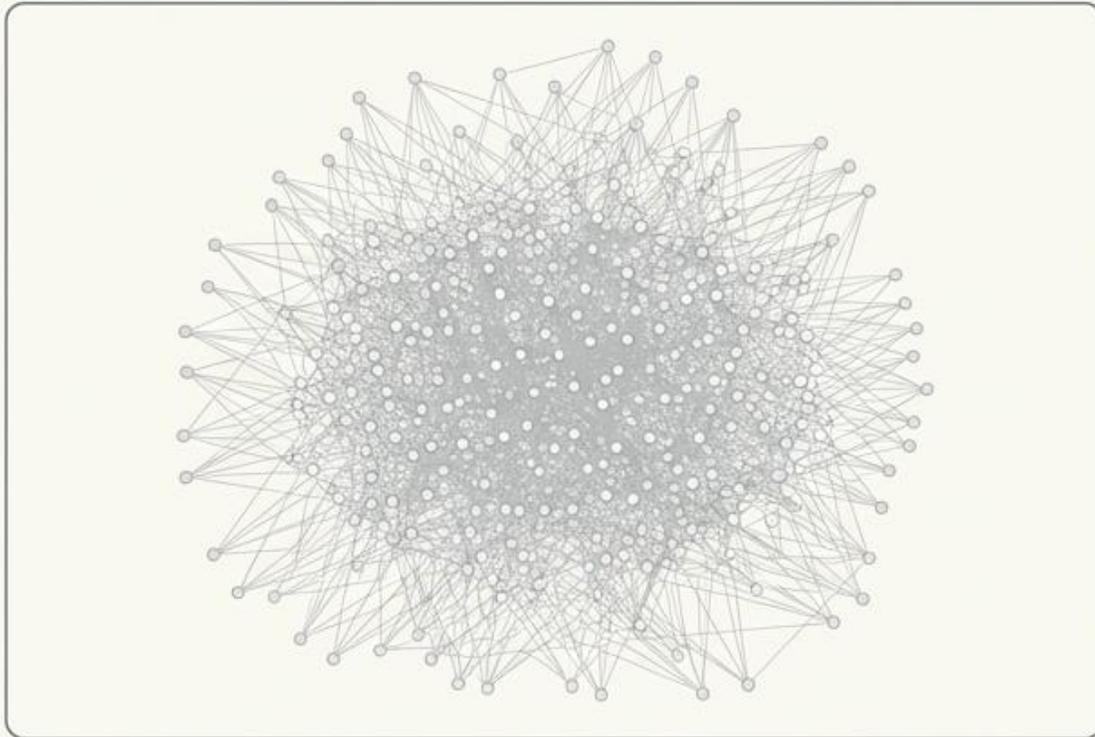
Automated creation of **~1500 disease, phenotype, and function pathways** to prioritize **key causal genes**.



The Application: Data Overlay

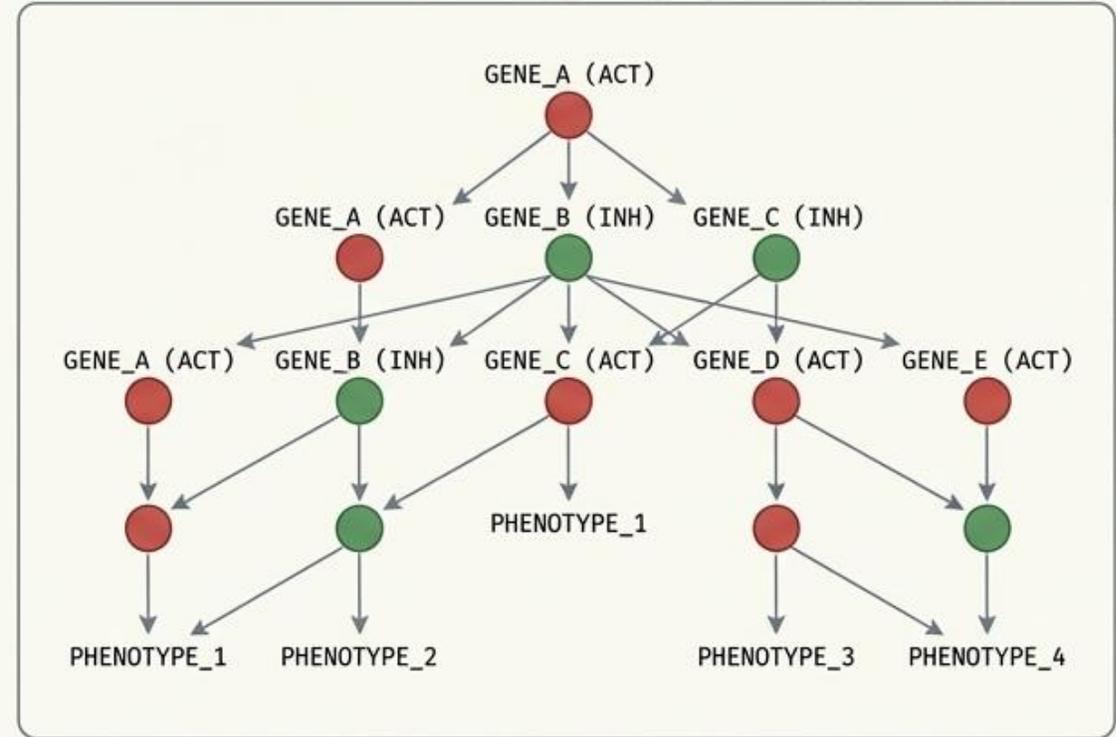
Mapping **custom expression datasets** onto **predictive networks** to uncover **novel etiology**.

ML Disease Pathways visualize a **human-readable set** of the most important **causally connected genes**—revealing **known players** and inferring **novel participants**.



What it is NOT

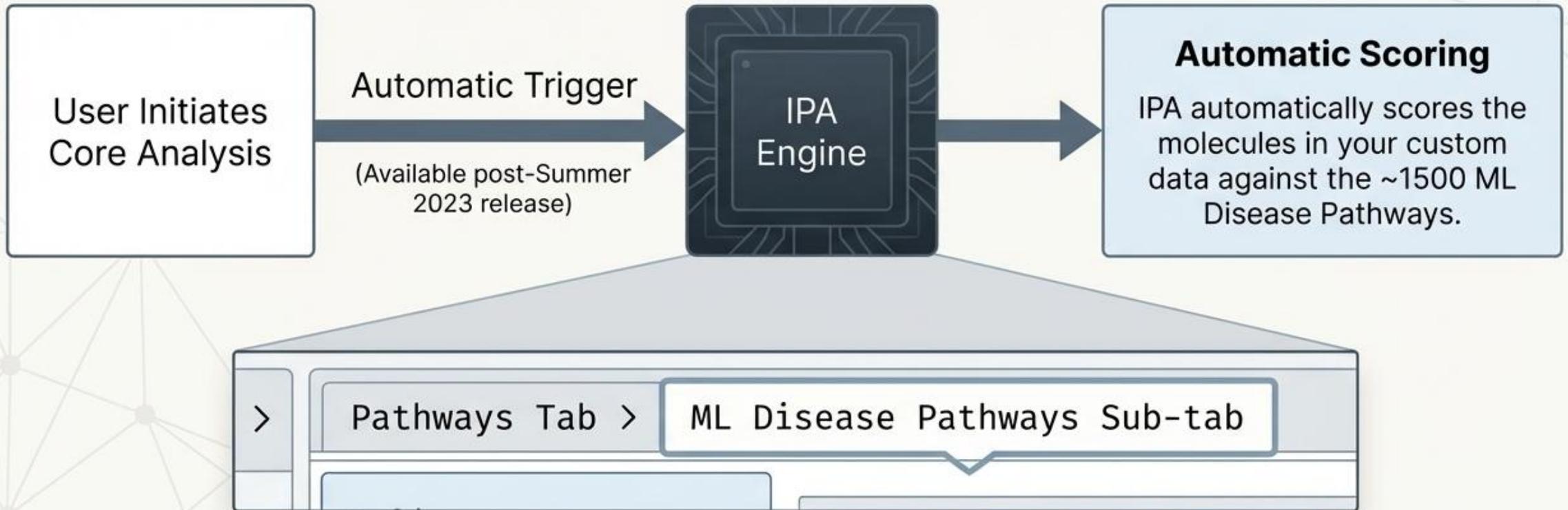
Comprehensive Catalogs: Overwhelming, unprioritized mapping of every single associated gene.



What it IS

ML Disease Pathways: A human-readable prioritization of the most critical causally connected genes and phenotypes.

Objective: Suggest genes with similar regulatory patterns to implicate them as potentially important in the disease, utilizing inferred implicit associations.





Prioritized Causal Focus

~1500 pathways built purely on automated KB mining, independent of expression data.



Predictive Power

Red/Green activity nodes hypothesize novel participants through shared regulatory patterns.



Seamless Overlay

Instantly map custom datasets to validate hypotheses and discover matching global expression patterns.

Help shape the algorithm. Please use the link at the top of the main IPA window.

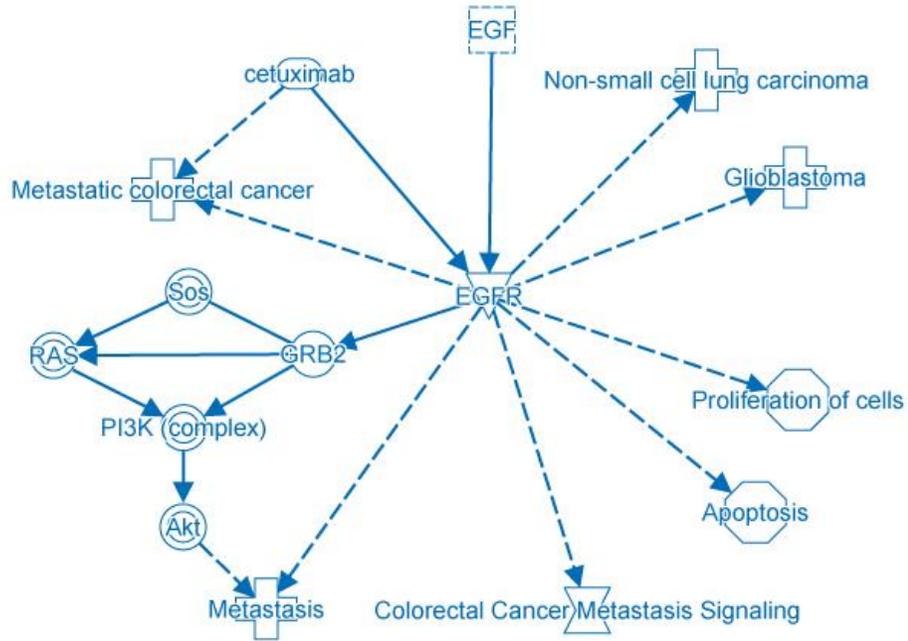
With dataset

- Find connections in your data
- Identify novel biomarkers
- Uncover key targets and regulators
- Discover novel disease mechanisms
- Compare across experiments

Without dataset

- Search and explore the QIAGEN Knowledge Base
- Test hypothesis in silico
- Identify degree of novelty in a hypothesis

Selected biomedical relationships between different types of Attributes for selected biomedical relationships entities



Cetuximab is a metastatic colorectal cancer drug. EGFR is a target of cetuximab. Molecular interactions enable you to reconstruct a pathway between EGF, EGFR and the pathological process metastasis. EGFR is a known member of the canonical pathway Colorectal Cancer Metastasis Signaling. In addition to metastatic colorectal cancer, EGFR is involved in other diseases, for example non-small cell lung carcinoma and glioblastoma. Activation of cell proliferation and inhibition of apoptosis by EGFR are known oncology mechanisms.

EGF – EGFR

[one of many]

Type: activation
 Direction: directional
 Effect: increases
 Directness: direct
 Tissue or primary cell: epithelial cells
 Subcellular location: plasma membrane
 Source: PubMed PMID: 17909010

cetuximab – EGFR

[one of many]

Type: phosphorylation
 Direction: directional
 Effect: decreases
 Cell line: CaR1 cells
 Organism: human
 Experiment: anti-phosphoresidue immunoblot
 Source: PubMed PMID: 23213241

EGFR – Proliferation of cells

[one of many]

Type: causation
 Direction: directional
 Effect: increases
 Tissue or primary cell: epithelial cells
 Subcellular location: plasma membrane
 Source: PubMed PMID: 22674072

EGFR – Glioblastoma

[one of many]

Type: causation
 Direction: directional
 Effect: increases
 Organism: human
 Source: PubMed PMID: 24782454



Human Molecular Genetics, 2024, Vol. 33, 15, 1367–1377
<https://doi.org/10.1093/hmg/ddae076>
 Advance access publication date 4 May 2024
 Original Article

From data to discovery: AI-guided analysis of disease-relevant molecules in spinal muscular atrophy (SMA)

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²Center for Systems Neuroscience (ZSN), Bunteweg 2, Hannover 30559, Germany
³Hannover Medical School, Department of Conservative Dentistry, Periodontology and Preventive Dentistry, Carl-Neuberg-Str. 1, Hannover 30625, Germany
⁴QIAGEN Digital Insights, 1001 Marshall Street, Redwood City, CA 94063, United States
 *Corresponding author. SMATHERIA gGmbH – Non-Profit Biomedical Research Institute, Feodor-Lynen-Str. 31, Hannover 30625, Germany
 E-mail: peter.claus@smatheria.org

Abstract

Spinal Muscular Atrophy is caused by partial loss of survival of motoneuron (SMN) protein expression. The numerous interaction partners and mechanisms influenced by SMN loss result in a complex disease. Current treatments restore SMN protein levels to a certain extent, but do not cure all symptoms. The prolonged survival of patients creates an increasing need for a better understanding of SMA. Although many SMN-protein interactions, dysregulated pathways, and organ phenotypes are known, the connections among them remain largely unexplored. Monogenic diseases are ideal examples for the exploration of cause-and-effect relationships to create a network describing the disease-context. Machine learning tools can utilize such knowledge to analyze similarities between disease-relevant molecules and molecules not described in the disease so far. We used an artificial intelligence-based algorithm to predict new genes of interest. The transcriptional regulation of 8 out of 13 molecules selected from the predicted set were successfully validated in an SMA mouse model. This bioinformatic approach, using the given experimental knowledge for relevance predictions, enhances efficient targeted research in SMA and potentially in other disease settings.

Keywords: spinal muscular atrophy; SMA; network biology; artificial intelligence; motoneuron disease

Introduction

Spinal Muscular Atrophy (SMA) is a rare monogenic disease caused by mutations or deletions of the Survival of Motoneuron 1 (SMN1) gene [1]. Ubiquitous reduction of the SMN protein results primarily in the degeneration of alpha-motoneurons in the brain stem and spinal cord followed by muscular atrophy [2, 3]. Untreated patients with the most common subtype, SMA type 1, die within the first two years of life [4]. Current treatments enhance SMN protein levels in the central nervous system (CNS) or systemically, respectively, prolonging survival of patients [5–10].

Although SMA is monogenic, it is a disease involving several molecular, cellular, and systemic networks: On the genetic level (I), SMN1 is encoded by a second gene, SMN2, which differs from SMN1 by a crucial base transition resulting in about 20% residual functional full-length SMN [1, 11]. The SMN2 copy number varies (CNV) from 0–8 copies leading to an inverse correlation of copy number and disease severity, formerly clinically classified in types 0–IV [4, 12]. At the protein level (II), SMN1 interacts with proteins via several binding domains and forms complexes in different cellular compartments [13]. It has multiple functions involved in basal cellular processes, e.g. snRNP assembly [14–16], translation [17, 18], transcription [19, 20], R-loop resolution [21], and cytoskeleton regulation [22–26]. On a systemic level (III), SMA affects peripheral

organs resulting in a multi-organ disease [27–29]. At phenotypic or clinical level (IV) the complexity increases since patients differ in disease severity, disease onset, development, and genetic modifiers [4, 12, 30–32]. Unfortunately, no available treatments cure SMA, due to limitations in timing, dosage, and response [32, 33].

The pathological mechanisms after SMN loss are still elusive. Although several dysregulated pathways in SMA are known, the molecular network behind this cause-and-effect relationship remains largely unexplored. The integration and interpretation of single experimental observations in a network of molecular disease mechanisms is challenging. Bioinformatic tools enable integration of scattered observations into a network. Prime examples for this conceptual approach are rare diseases such as SMA caused by a single gene defect, which enables the analysis of the relationship between the genetic cause, molecular alterations, and phenotypic outcome. Disease-specific molecular networks can represent the current knowledge of the disease. We hypothesize that we could use a machine-learning based algorithm to assemble new molecular networks that identify novel disease-specific molecules and molecular relationships. This approach could help explain the pathogenesis and help identify new potential targets of interest. In this study, an artificial intelligence (AI)-based approach was used to analyze causal relationships in SMA

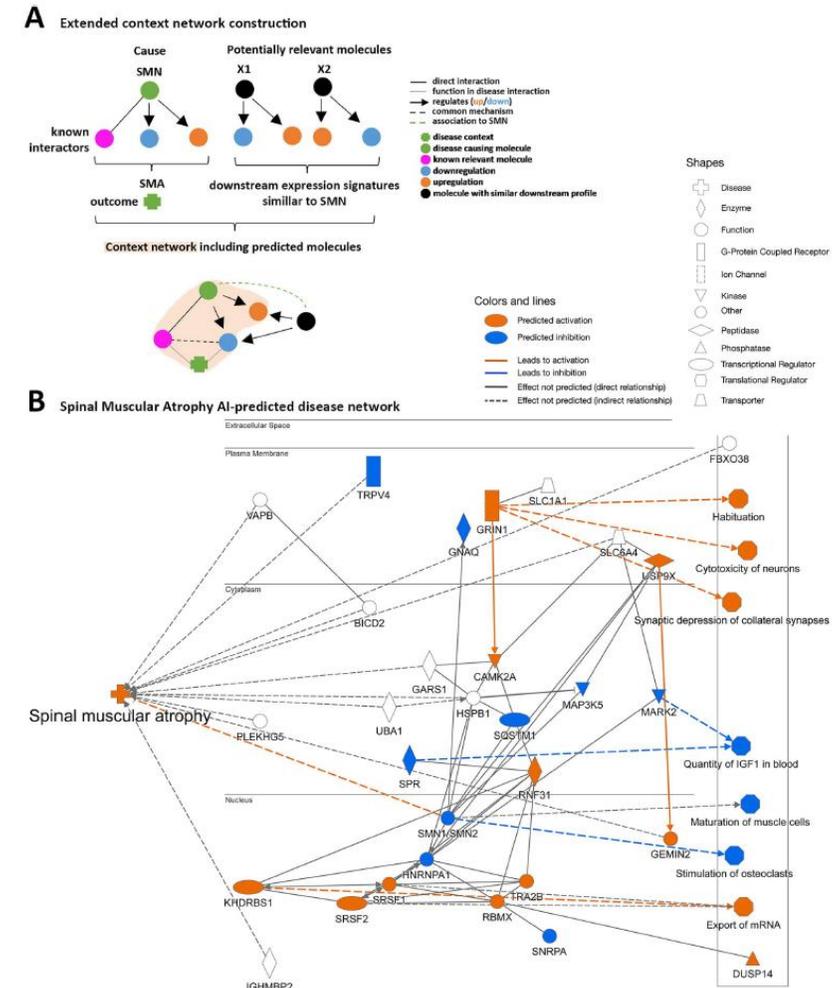


Figure 1. Artificial intelligence-predicted context network for spinal muscular atrophy. (A) Schematic representation of the AI-prediction algorithm and network construction. SMN (green circle) is the genetic cause and SMA (green cross) the disease outcome. In the QIAGEN Knowledge Base (QKB), interactors (pink circle) and causal relationships (black line: protein-protein interaction (PPI), grey line: Function), and dependency keywords (arrow: Direction; orange circle: increases; blue circle: Decreases) are curated. The downstream profile of the disease-causing molecule is compared to other molecules (X) and similarities are ranked for potential relevance in the disease context. A context network is displayed including known and predicted disease-relevant molecules. Those were selected based on their connectivity to present a network to a size that could be reasonably interpreted. (B) IPA context network for SMA. The network includes known disease relevant molecules (connected to SMA) and predicted potentially relevant molecules with their direction of regulation (orange, blue). Functional outcomes are displayed on the right. Prediction activation (orange)/inhibition (blue). Regulation is predicted from interacting molecule measurements. Color codes for lines are based on the same concept. Molecule shapes represent their type.

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Analytical Biochemistry

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¹H NMR serum metabolomics and its endogenous network pharmacological analysis of Gushudan on kidney-yang-deficiency-syndrome rats

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ARTICLE INFO

Keywords:
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 Gushudan
 Pharmacodynamics
¹H NMR metabolomics
 Endogenous network pharmacology strategy

ABSTRACT

The pharmacodynamics, ¹H NMR metabolomics and endogenous network pharmacology strategy approaches were integrated to investigate the preventive mechanism of Gushudan (GSD) on kidney-yang-deficiency-syndrome (KYDS) rats in this study. Firstly, the KYDS rat model was achieved by hydrocortisone induction, and the efficacy of GSD on KYDS model rats was assessed by the pharmacodynamic indicators. Next, the comprehensive untargeted serum metabolic profile of rats was obtained in ¹H NMR metabolomics study, 29 potential biomarkers closely associated with KYDS were identified, which were mainly involved in carbohydrate metabolism, amino acid metabolism and intestinal flora metabolism. In addition, the potential biomarkers-targets-pathways-disease metabolic network was further investigated for deeper understanding the preventive effects of GSD on KYDS rats and its mechanism, which was further obtained for the important targets related to biomarkers and diseases such as NOS3, PTGS2 and CXCL6, and important metabolic pathways such as glyoxylate and dicarboxylate metabolism, arginine and proline metabolism, and microbial metabolism in diverse environments. Finally, compared with our previous anti-osteoporosis study of GSD, it suggested that some similar metabolic pathways, which would provide some scientific reference of the existence of the kidney-bone axis under the traditional Chinese medicine (TCM) theory of “kidney dominates bone”.

1. Introduction

Gushudan (GSD) was a traditional Chinese compound prescription based on the “kidney dominates bone” theory in traditional Chinese medicine (TCM) and clinical practices, which was carefully formulated by the technical platform of the “A basic concept of establishing platforms for operational techniques in systems of elaborately selecting small prescriptions of traditional Chinese medicine” [1]. It consists of *Epimedium brevicornu* Maxim, *Drynaria fortunei* (Kunze) J. Sm, *Cnidium monnieri* (L.) Cuss and *Salvia miltiorrhiza* Bge, which had the effect of strengthening tendons and bones and benefiting kidneys. In the Pharmacopoeia of the People’s Republic of China (2020 edition), these four Chinese herbs of GSD were included. The preclinical pharmacodynamic research showed that GSD could prevent and treat osteoporosis by increasing bone mineral density, serum calcium and bone gla protein levels, etc [2,3]. The high performance liquid chromatography (HPLC) chemical fingerprints of GSD had been studied in our previous research [4,5]. Subsequently, the main active ingredients of GSD include icariin, osthole, naringin and tanshinone, and pharmacokinetic studies of the

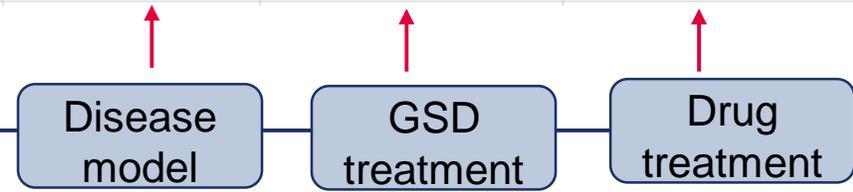
related active ingredients were performed based on ultra performance liquid chromatography-mass spectrometry (UPLC-MS) [6,7]. In addition, metabolomics studies had been further conducted from the perspective of the bone strengthening effects of GSD, and it was found to have a preventive effect on glucocorticoid osteoporosis (GIOP) by call-backing metabolite levels and adjusting metabolic pathways [8,9]. According to the “kidney dominates bone” theory of TCM, it proved that the kidney-bone axis existed [10]. However, the effects of GSD in tonifying the kidney are still unclear, and how does GSD play the roles in tonifying the kidney and strengthening the bones? Further researcher on the effects of GSD as a whole on “kidney deficiency syndrome” in TCM theory are of great significance, which would help to reveal the comprehensive mechanism of GSD *in vivo* and provide a scientific basis of its clinical application.

Kidney-yang-deficiency-syndrome (KYDS) was firstly recorded in the traditional Chinese medical classics “Nei jing”, which was a kind of deficiency cold syndrome with clinical manifestations of cold extremities, fear of cold, and metabolic disorders of the body [11]. The modern pharmacological studies showed that the function of the

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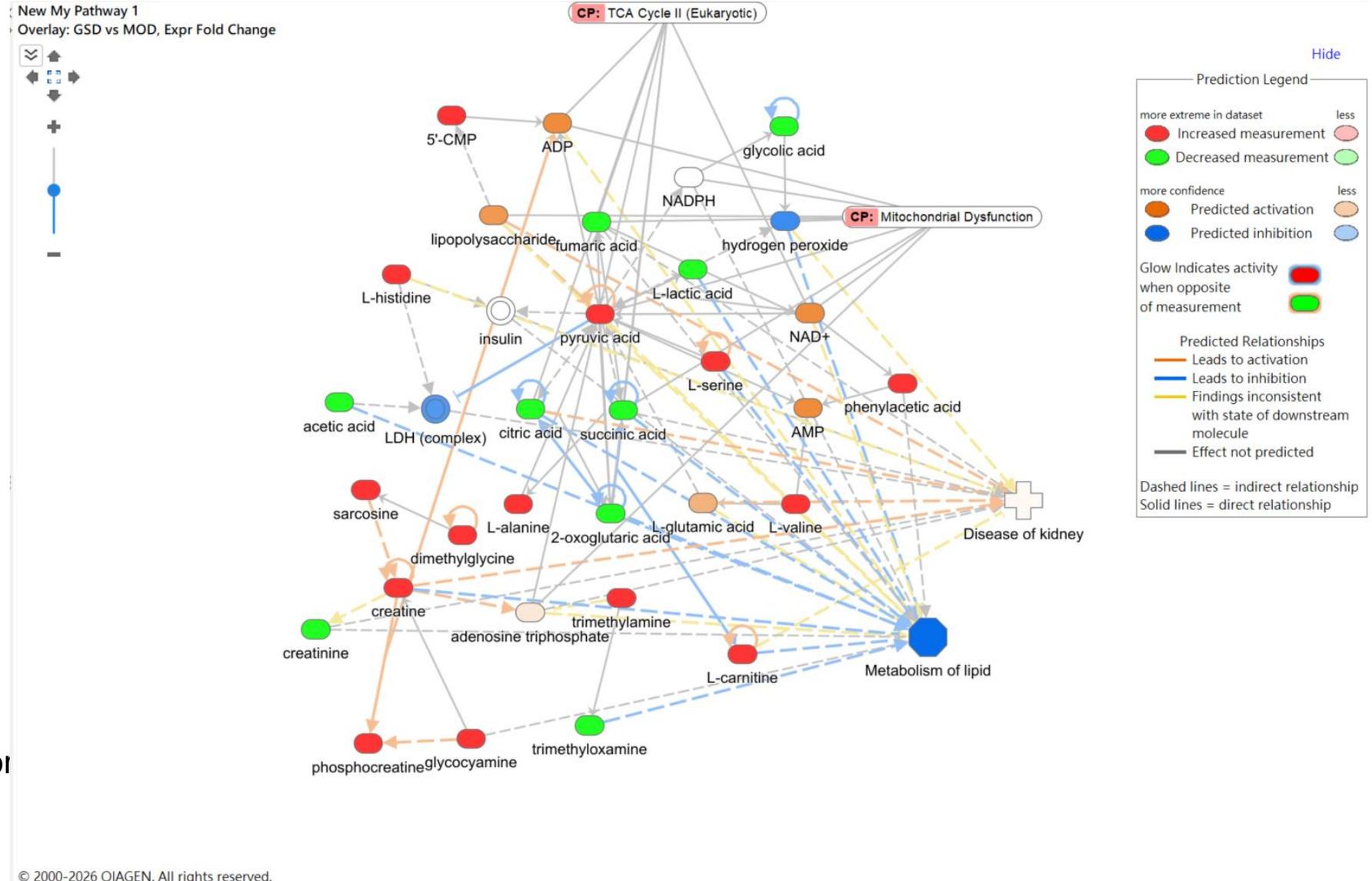
E-mail address: beary200@126.com (Z. Xiong).

	A	B	C	D
1	HMDB ID	MOD vs CON	GSD vs MOD	POS vs MOD
2	HMDB0000172	0.8	1.5	1.5
3	HMDB0000883	0.8	1.5	1.5
4	HMDB0000190	1.5	0.8	0.8
5	HMDB0000161	0.8	1.5	1.5
6	HMDB0000042	1.5	0.8	0.8
7	HMDB0000243	0.8	1.5	1.5
8	HMDB0000254	1.5	0.8	0.8
9	HMDB0000208	1.5	0.8	0.8
10	HMDB0000094	1.5	0.8	0.8
11	HMDB0000095	0.8	1.5	1.5
12	HMDB0000906	0.8	1.5	1.5
13	HMDB00001511	0.8	1.5	1.5
14	HMDB0000062	0.8	1.5	1.5
15	HMDB0000925	1.5	0.8	0.8
16	HMDB0000209	0.8	1.5	1.5
17	HMDB0000167	0.8	1.5	1.5
18	HMDB0000271	0.8	1.5	1.5
19	HMDB0000711	0.8	1.5	1.5
20	HMDB0000092	0.8	1.5	1.5
21	HMDB0000714	0.8	1.5	1.5
22	HMDB0000128	0.8	1.5	1.5
23	HMDB0000187	0.8	1.5	1.5
24	HMDB0000064	0.8	1.5	1.5
25	HMDB0000115	1.5	0.8	0.8
26	HMDB0000562	1.5	0.8	0.8
27	HMDB0000462	0.8	1.5	1.5
28	HMDB0000134	1.5	0.8	0.8
29	HMDB0000177	0.8	1.5	1.5
30	HMDB0000142	0.8	1.5	1.5



**New feature:
Cells and Tissues overlay**

Predict cell types associated with the genes on your network or pathway using data from The Human Protein Atlas



- Upload list
- Build: grow/network/ path-explore (molecular or disease a function)
- Search for disease
- Path explore
- Overlay: Molecule activity predictor datasets, Drug, Cells & Tissues
- Drug: IPA Chem View

ArrayExpress, GEO, TCGA, SRA, LINCS, etc.



Processing, curation and QA

QIAGEN OmicSoft Studio

OmicSoft datasets

246,776 total datasets from OmicSoft with 15,001 datasets newly added. A new source called NCI Patient-Derived Models has been added in this release derived from this source: <https://pdmr.cancer.gov/>.

Land	Repository	Datasets Q1 2025	Datasets Q2 2025	Increase
DiseaseLand	HumanDisease	38,710	39,036	326
	MouseDisease	28,784	29,355	571
	RatDisease	10,264	10,269	5
	LINCS	25,880	25,880	
OncoLand	OncoHuman	24,972	25,262	290
	OncoMouse	1,516	1,516	
	TCGA	4,854	4,854	
	ENCODE RNA Binding	486	486	
	ClinicalProteomicTumor	2,978	2,978	
	NCBI Patient-Derived Models		552	552
Single Cell Land	SingleCellHuman	194	194	
	SingleCellHumanUmi	77,140	81,140	4,000
	SingleCellHumanHCL	1,469	1,469	
	SingleCellMouse	81	81	
	SingleCellMouseUmi	13,135	22,392	9,257
Normal Cells and Tissues	Human Tissues (GTEx)	1,312	1,312	

Journal articles and databases such as Clinical Trials, COSMIC, MGD, OMIM, etc.



Curated Findings

Ingenuity Pathway Analysis



- Explore biological findings in public datasets
- Build confidence in your analysis results
- Make unexpected insights into shared mechanisms between studies
- “Anti-matches” may provide insights



- Explore gene expression levels
- Determine where a target is differentially expressed
- Understand how ‘omics data influences survival
- Identify mutation status of a target

IPA

File Edit View Window Help

Provide Feedback | Support Gene Chen Close IPA

Genes and Chemicals **Diseases and Functions** Pathways and Lists Datasets and Analyses

Create New...

Spinal muscular atrophy [spinal muscle degeneration,spinal muscle wasting] Search

Advanced Search

Process RNA-seq data QIAGEN Land Explorer

Project Manager Search Results

Molecule Annotations

Add To My Pathway Add To My List Create Dataset Customize Table

Symbol AARS1 - NEFL (1/2)

Symbol	Entrez Gene Name	Location	Type(s)	Biomarker Application(s)	Drug(s)
<input type="checkbox"/> AARS1	alanyl-tRNA synthetase 1	Cytoplasm	enzyme		
<input type="checkbox"/> acetaminophen	--	Other	chemical drug		
<input type="checkbox"/> ALT (family)	--	Other	group	efficacy, safety	
<input type="checkbox"/> amantadine	--	Other	chemical drug		
<input type="checkbox"/> apitegromab	--	Other	biologic drug		
<input type="checkbox"/> AR	androgen receptor	Nucleus	ligand-dependent nuclear receptor	diagnosis, disease progression, unspecified application	clascoterone, nandrolone phenpro...
<input type="checkbox"/> ASAH1	N-acylsphingosine amidohydrolase 1	Cytoplasm	enzyme		
<input type="checkbox"/> ASCC1	activating signal cointegrator 1 complex s...	Nucleus	transcription regulator		
<input type="checkbox"/> ATP2A1	ATPase sarcoplasmic/endoplasmic reticul...	Cytoplasm	transporter	unspecified application	
<input type="checkbox"/> ATP7A	ATPase copper transporting alpha	Plasma Membrane	transporter		
<input type="checkbox"/> BAG3	BAG cochaperone 3	Cytoplasm	other		
<input type="checkbox"/> BCL2L1	BCL2 like 1	Cytoplasm	other	efficacy, prognosis	LP-118, AZD0466
<input type="checkbox"/> BICD2	BICD cargo adaptor 2	Cytoplasm	other		
<input type="checkbox"/> BSCL2	BSCL2 lipid droplet biogenesis associated,...	Cytoplasm	other		
<input type="checkbox"/> butyric acid	--	Other	chemical - endogenous mammalian		
<input type="checkbox"/> C1QB	complement C1q B chain	Extracellular Space	other		
<input type="checkbox"/> CASQ1	calsequestrin 1	Cytoplasm	other	unspecified application	
<input type="checkbox"/> ceramide	--	Other	chemical - endogenous mammalian		
<input type="checkbox"/> CHCHD10	coiled-coil-helix-coiled-coil-helix domain c...	Cytoplasm	other		
<input type="checkbox"/> CHMP1A	charged multivesicular body protein 1A	Extracellular Space	peptidase		
<input type="checkbox"/> creatine	--	Other	chemical - endogenous mammalian	efficacy, safety	
<input type="checkbox"/> CREATINE KINASE (family)	--	Other	group	efficacy, safety	

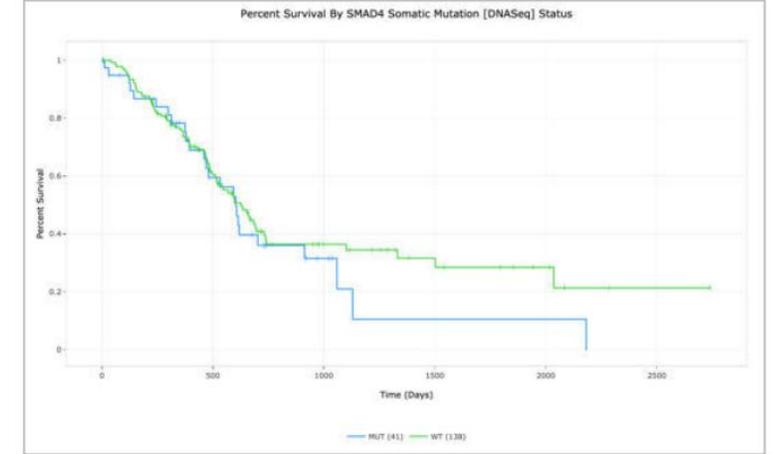
Selected/Total molecules: 0/144



Expression in Rat, Mouse, and Human Disease



Mutation frequency



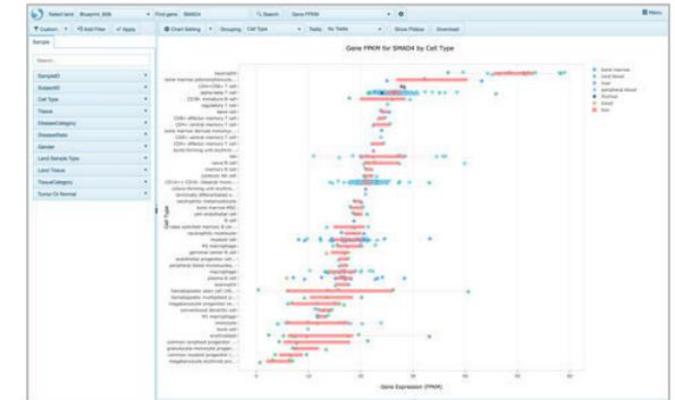
Survival plots



Cell line expression



Tumor expression



Hematopoietic expression (BluePrint)

The screenshot shows the OmicSoft Land Explorer interface. At the top, the 'Genes and Chemicals' tab is selected, and a search for 'EGFR' has been performed. The search results show 158 items, with the first result being EGFR. A blue arrow points from the 'EGFR' result in the search results to the 'OmicSoft Land Explorer: Sample-level experimental data' table below. A red arrow points from the text 'Choose which you want' to the 'Oncology Consortia' column in the table.

Data Type / Data Source	Normal Tissue	Cell Lines	Oncology Consortia	Oncology Studies	Disease Studies
RNA-seq expression:	Solid tissue (GTEx), Solid tissue (HPA), Blueprint	Cancer cell lines (CCLE)	TCGA, TARGET, BeatAML, ICGC, CGCI, CCLE+GTEx+TCGA, ENCODE RNA-associated gene knockdown	General oncology, Mouse studies	Human disease, Mouse disease, Rat disease
Microarray expression:	Solid tissue (GTEx)	Cancer cell lines (CCLE), Cell lines (Other)	TARGET, expO, METABRIC, CCLE+GTEx	General oncology, Metastasis, Mouse studies	Human disease, Mouse disease, Rat disease
Differential regulation:	Solid tissue (GTEx)	Treated cells (LINCS)	TCGA, TARGET, ENCODE RNA-associated gene knockdown	General oncology, Metastasis, Mouse studies	Human disease, Mouse disease, Rat disease
Alteration frequency:		Cancer cell lines (CCLE), Cell lines (Other)	TCGA, TRACERx, BeatAML, ICGC, TARGET, METABRIC	General oncology, Metastasis	
Survival by expression:			TCGA, BeatAML, TARGET, CGCI	General oncology, Clinical outcomes	
Single Cell differential regulation:	Human Cell Landscape (HCL), Tabula Sapiens			Human Disease (UMI), Human Disease (non-UMI), Mouse Disease (UMI), Mouse Disease (non-UMI)	Human Disease (UMI), Human Disease (non-UMI), Mouse Disease (UMI), Mouse Disease (non-UMI)
Protein expression:	Solid tissue (GTEx)	Cancer cell lines (CCLE)		General oncology	

IPA Gene View :OmicSoft Land Explorer

- TCGA-B38-G33

Land selection
Search bar
View selection

Download data for current view

View controller

Metadata filtering

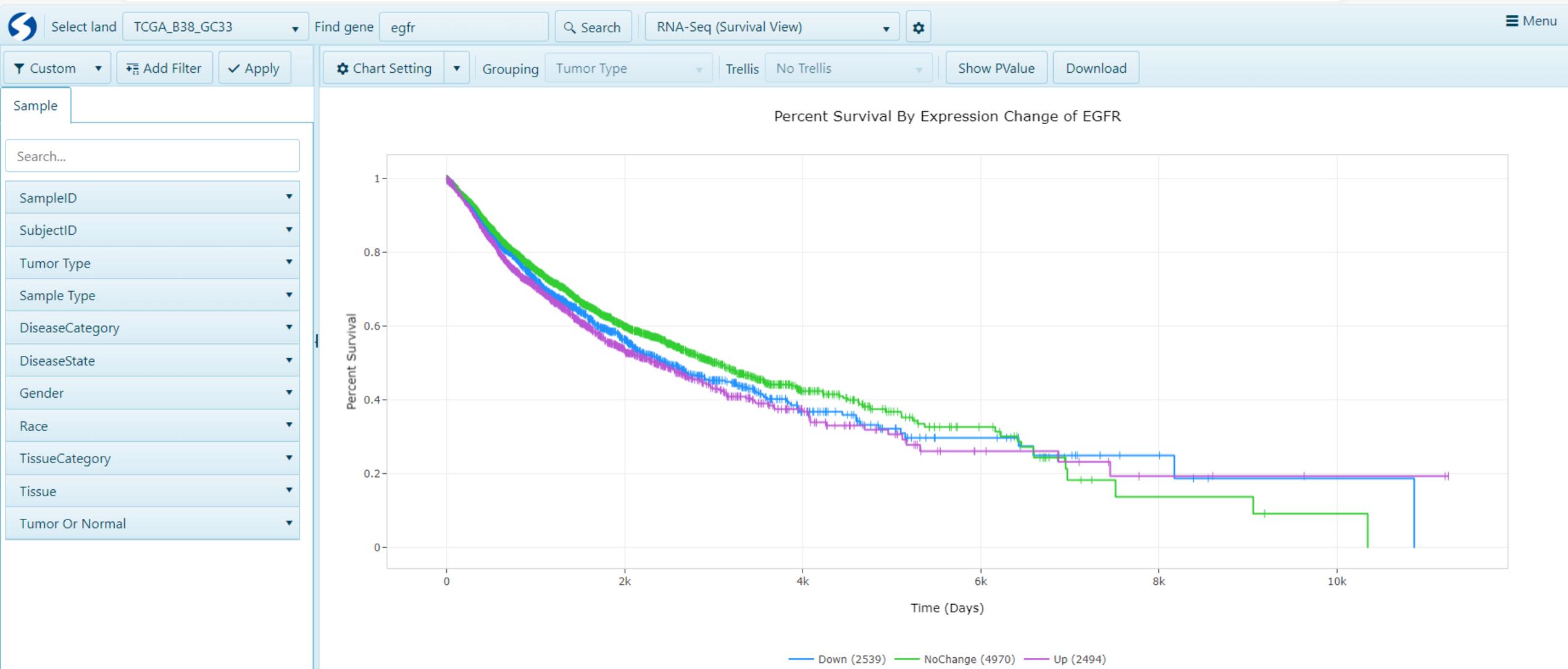
https://explorer.omicsoft.com/OPA/Home/MainPage?landName=TCGA_B38_GC33&qeneID=EGFR&viewID=RnaSeq_Transcript.GeneVariable&grouping=Tumor.Type&trellis=No.Trellis

- Through DiseaseState filter, to observe the expression difference of EGFR gene in cancer type in TCGA
- Select a specific experimental group to view more detailed information.

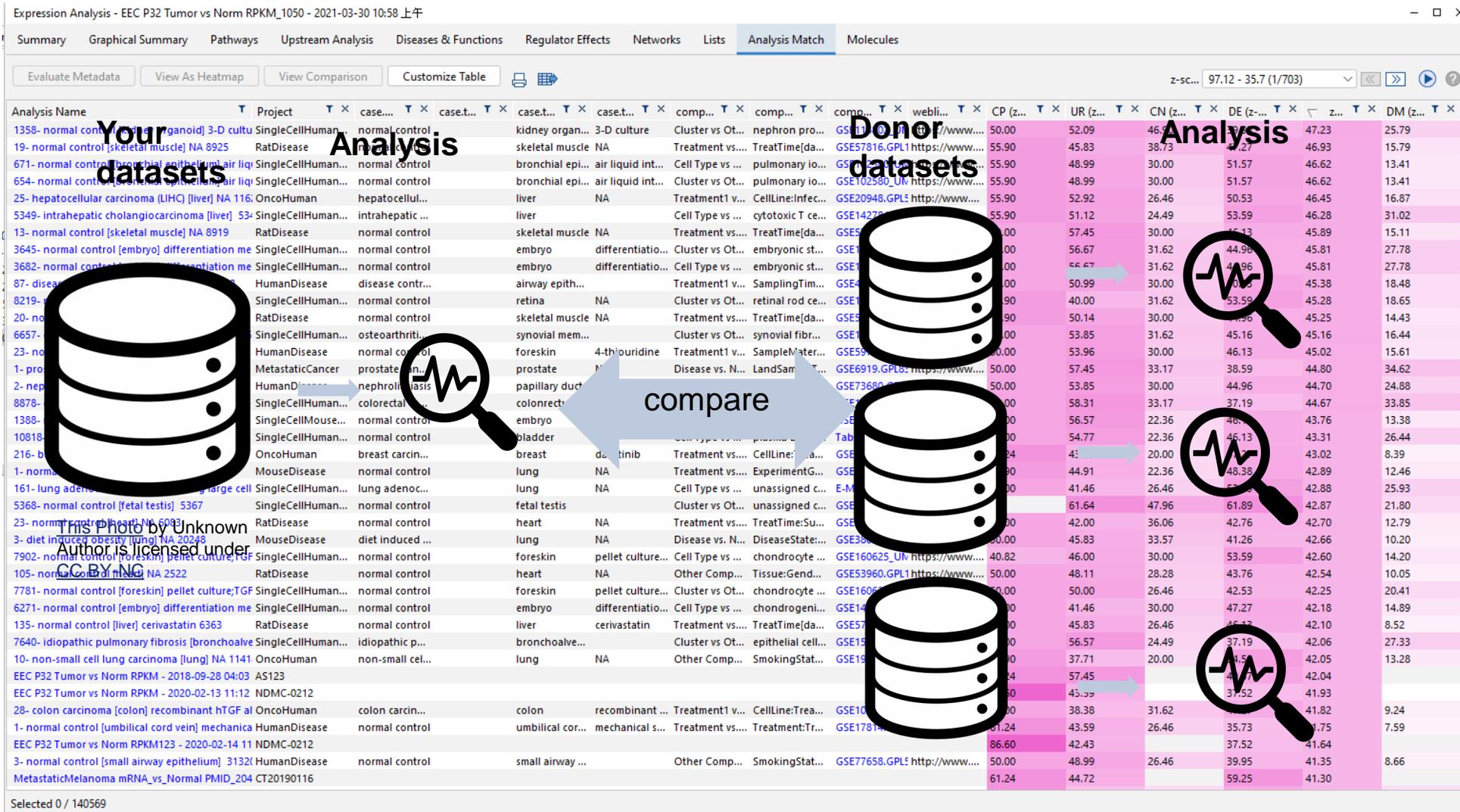
The screenshot shows the OmicSoft Land Explorer interface. The top navigation bar includes 'Select land' (TCGA_B38_GC33), 'Find gene' (egfr), and 'Gene FPKM'. The left sidebar shows a filter menu with 'DiseaseState' selected. The main chart area displays a dot plot for EGFR expression, with data points colored by tumor type (Metastatic, Primary Tumor, Recurrent Tumor, Solid Tissue Normal) and grouped by disease state (LUAD, BRCA). A red box highlights a specific data point in the BRCA group, which is linked to a data table below.

SampleID	SubjectID	Tumor Type	Sample Type	CNV Call	GeneID	GeneName	Expression
TCGA-A2-A0D1-01A	TCGA-A2-A0D1	BRCA	Primary Tumor	Amplification	ENSG00000146648.18	EGFR	439.373199462891
TCGA-AC-A2QH-01B	TCGA-AC-A2QH	BRCA	Primary Tumor	Diploid	ENSG00000146648.18	EGFR	1703.68493652344
TCGA-D8-A143-01A	TCGA-D8-A143	BRCA	Primary Tumor	Amplification	ENSG00000146648.18	EGFR	1030.41870117188
TCGA-E2-A150-01A	TCGA-E2-A150	BRCA	Primary Tumor	Amplification	ENSG00000146648.18	EGFR	518.170043945313

TCGA_B38_GC33



Automatically discover other IPA Core Analyses with similar (or opposite) biological results as compared to yours, to help confirm your interpretation of the results or to provide unexpected insights into underlying shared biological mechanisms



Mapping Your Results to OmicSoft Datasets by IPA Analysis Match

Project

Cell & Tissue

Datasets information

similar

opposite

Analysis Name	Project	Cell & Tissue	Datasets information	z-scores
127- breast carcinoma [breast] human marrow strom HumanDisease	breast	breast	human marro... Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	23.33
67- breast carcinoma [breast] human marrow strom HumanDisease	breast	breast	human marro... Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	55.90
129- breast carcinoma [breast] IL-6;siltuximab 27511 HumanDisease	breast	breast	IL-6;siltuximab Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	20.00
101- breast carcinoma [breast] IL-6;siltuximab 27481 HumanDisease	breast	breast	IL-6;siltuximab Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	41.23
east carcino...	breast	breast	IL-6;siltuximab Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-20.00
east carcino...	breast	breast	TRE28786.GPL93 Dosage:Experi... GSE28786.GPL93 https://www.n...	43.59
east carcino...	breast	breast	none CellType1 vs. C... SamplingTime... GSE54329.GPL18 https://www.n...	10.00
east cancer	breast	breast	ethanol Treatment1 vs. ... Treatment:Tra... GSE64536.GPL57 https://www.n...	47.96
east carcino...	breast	breast	IL-6 Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-18.86
east carcino...	breast	breast	IL-6 Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-11.34
east cancer	breast	breast	ethanol Treatment1 vs. ... Treatment:Tra... GSE64536.GPL57 https://www.n...	42.43
east carcino...	breast	breast	IL-6;siltuximab Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	20.00
east carcino...	breast	breast	IL-6;siltuximab Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-28.40
east carcino...	breast	breast	human marro... Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-38.38
east carcino...	breast	breast	none Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-37.42
east carcino...	breast	breast	human marro... Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-38.73
east carcino...	breast	breast	none Treatment1 vs. ... CellLine:Sampli... GSE54329.GPL18 https://www.n...	-42.43

Project

- Select Projects
- Shared Projects
- Libraries
 - OmicSoft
 - OncoLand
 - DiseaseLand
 - SingleCellLand
 - Normal Cells and Tissues

Or filter using wild card search

include: (use * for wildcard)

[comma-separated list]

exclude:

[comma-separated list]

Apply Cancel

atasets
ta

z-scores

Match Analyses Heatmap: treat2_vs_untreat

Settings/Legend

Filter

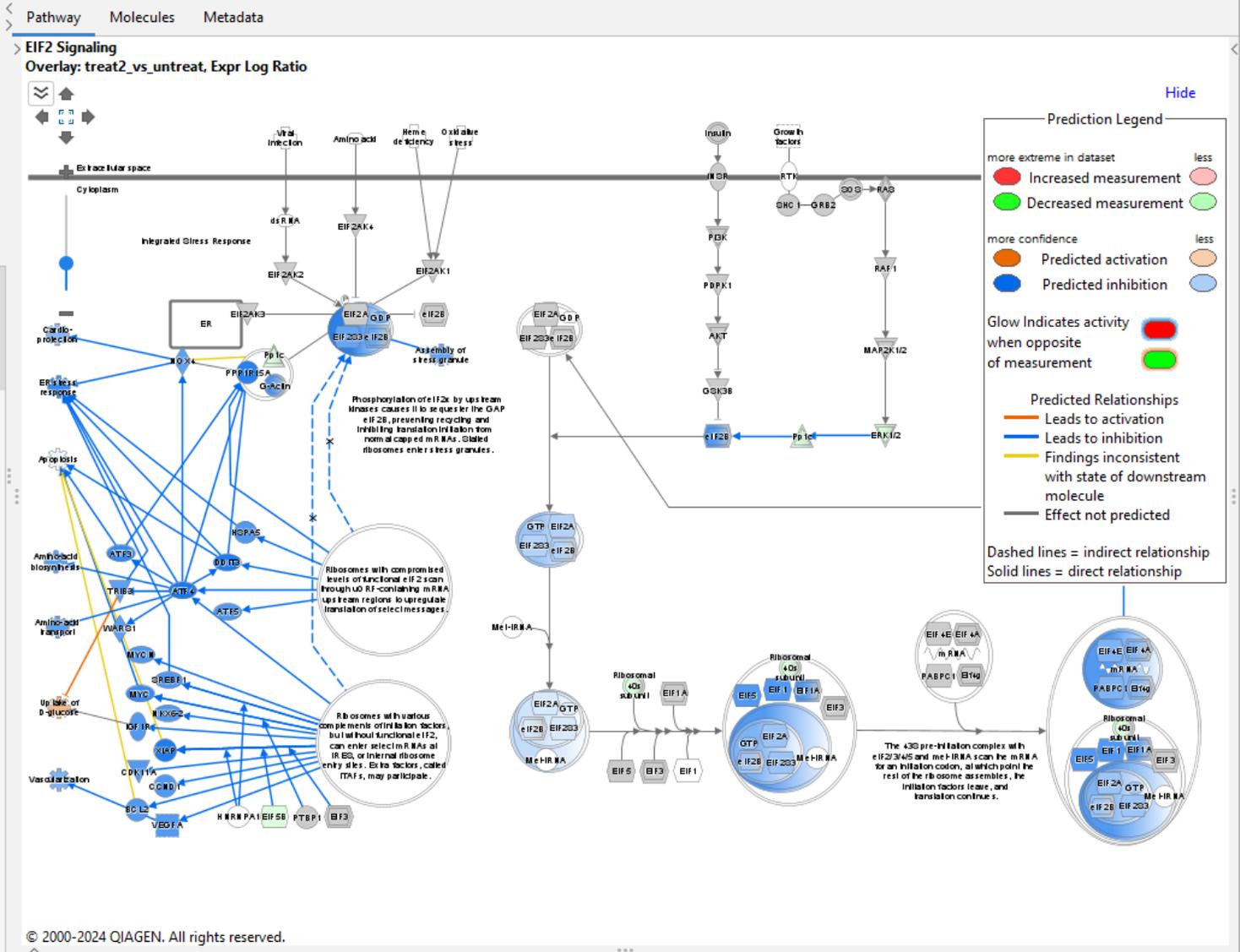
Measurement: Activation z-score -9.075 34.771

Sort Method: Hierarchical Clustering Visualize: z-score

Insignificance Threshold: (absolute value)

View Report Open Network Expand Header

Entity Type	Entity Name	treat2_vs_untreat	treat2_vs_untreat
DM	Analysis-ready genes		
UR	RICTOR		
CN	RICTOR		
CN	SIGLEC8		
CP	Oxidative Phosphorylation		
UR	EIF2 Signaling		
UR	MYC		
CN	MYC		
CN	MLXIPL		
UR	MLXIPL		
CP	Eukaryotic Translation Initi...		
CP	Response of EIF2AK4 (GCN...		
CP	Major pathway of rRNA pro...		
CP	Nonsense-Mediated Decay ...		
CP	Selenoamino acid metaboli...		
CP	SRP-dependent cotranslati...		
CP	Eukaryotic Translation Elon...		
DE	Organismal death		
UR	NPC1		
CN	NPC1		
DE	Necrosis of tumor		
DE	Cell death of cancer cells		
DE	Cell death of tumor cells		
DE	Cell death of osteosarcoma...		
CP	Coronavirus Pathogenesis ...		



File Edit View Window Help

Genes and Chemicals Diseases and Functions Pathways and Lists **Datasets and Analyses**

Create New... Search [Advanced Search](#)

Search Results QIAGEN Land Explorer

Diseases and Functions **Datasets and Analyses**

Search Results

Showing first 5000 results out of 33129 in 18888ms for query [lung cancer]

Folder Types

- dataset (17090)
- analysis (16031)
- VariantLossGain (8)

4

Open **Add to Comparison** Customize Table Crea... 2024/... - 2024/... (1/125) << >>

Name	Type	Creation Date	case.diseasestate
colon cancer-association - 2024-03-05 03:36 下午	analysis	2024/03/04 23:36:43	
colon cancer-association	dataset	2024/03/04 23:33:24	
1294- breast cancer [breast] 1293	analysis	2024/01/12 09:20:15	breast cancer
263- normal control [bladder;bone;bone marrow;brain;embryo...	analysis	2024/01/12 09:19:07	normal control
4631- breast cancer [peripheral blood] 4630	analysis	2024/01/12 09:17:53	breast cancer
4938- breast cancer [breast] 4937	analysis	2024/01/12 09:17:39	breast cancer
5223- breast cancer [breast] 5222	analysis	2024/01/12 09:17:22	breast cancer
1870- lung adenocarcinoma (LUAD);lung squamous cell carcino...	analysis	2024/01/12 09:17:15	lung adenocarci
2446- normal control;pulmonary fibrosis [lung] 2445	analysis	2024/01/12 09:16:59	normal control;p
6615- hepatocellular carcinoma (LIHC);intrahepatic cholangiocar...	analysis	2024/01/12 09:16:30	hepatocellular ca
314- normal control [testis] 313	analysis	2024/01/12 09:16:24	normal control
1240- normal control [fetal lung] 1239	analysis	2024/01/12 09:16:13	normal control
3918- breast cancer [breast] 3917	analysis	2024/01/12 09:15:24	breast cancer
4042- chronic obstructive pulmonary disease (COPD);disease co...	analysis	2024/01/12 09:14:00	chronic obstruct
8970- colorectal cancer [colonrectum] 8969	analysis	2024/01/12 08:40:25	colorectal cancer
8975- colorectal cancer [colonrectum] 8974	analysis	2024/01/12 08:40:15	colorectal cancer
1- acute myeloid leukemia (LAML) [bone marrow] NA 168	analysis	2024/01/09 02:17:06	acute myeloid le
1- acute myeloid leukemia (LAML) [bone marrow] NA 213	analysis	2024/01/09 02:16:46	acute myeloid le
1- breast cancer [breast;lymph node;peripheral blood] 0	analysis	2024/01/09 02:13:03	breast cancer
1- breast cancer [breast] 68	analysis	2024/01/09 02:12:49	breast cancer
1- breast cancer [peripheral blood] NA 8	analysis	2024/01/09 02:12:37	breast cancer
1- breast carcinoma [breast] estradiol;ethanol 0	analysis	2024/01/09 02:12:21	breast carcinoma
1- breast carcinoma [breast] estradiol;ethanol 4	analysis	2024/01/09 02:12:05	breast carcinoma
1- germ cell cancer [ovary] NA 4	analysis	2024/01/09 02:09:17	germ cell cancer
1- kidney clear cell sarcoma (CCSK) [kidney] NA 14	analysis	2024/01/09 02:07:58	kidney clear cell
1- kidney rhabdoid cancer [kidney] Transfection_BAF47 442	analysis	2024/01/09 02:07:40	kidney rhabdoid
1- childhood acute lymphocytic leukemia [hematopoietic tissue]...	analysis	2024/01/09 02:02:21	childhood acute
1- endometrial cancer;endometrial squamous cell carcinoma;ova...	analysis	2024/01/09 02:01:04	endometrial can

Libraries > OmicSoft > SingleCellLand > SingleCellHumanUmi > Analyses

[1870- lung adenocarcinoma \(LUAD\);lung squamous cell carcinoma \(LUSC\) \[lung\] 1869](#)

Case/Control Differences

Key	Case	Control
cluster	1	0;10;11;12;13;14;15;16;17;18;19;2;20;3;4;5;6;7;8;9
clustercelltype	T cell	alveolar epithelial cell;B cell;cytotoxic T cell;endothelial cell;epithelial cell;fibroblast;macrophage;mast cell;monocyte;myeloid cell;NK cell;T cell;unassigned cell

Comparison Context

cellmarkers CD235A-
 celltype lung cell
 comparisoncategory Cluster vs Others
 comparisoncontrast T cell (cluster) vs others
 diseasestate lung adenocarcinoma (LUAD);lung squamous cell carcinoma (LUSC)
 ethnicity Caucasian
 gender female;male
 organism human
 platformname NGS.Illumina.NextSeq500
 smokingstatus ex-smoker;NA
 tissue lung
 tmstage pN0;pT1a;pN0;pT2a;pN1;pT1b;pNX;pT2a

All Experiment Metadata

case.cellmarkers CD235A-
 case.celltype lung cell
 case.cluster 1
 case.clustercelltype T cell
 case.diseasestate lung adenocarcinoma (LUAD);lung squamous cell carcinoma (LUSC)
 case.ethnicity Caucasian
 case.gender female;male
 case.samplematerial cryopreserved cells;MACS depleted cells;surgical resection
 case.smokingstatus ex-smoker;NA

3

You can also use the repository without your own analysis, just by searching for available analyses of interest.

The Project Manager window displays a hierarchical view of projects and libraries. Under 'My Projects', there is a 'Shared Projects' folder and a 'Libraries' folder containing 'OmicSoft', 'OncoLand', 'DiseaseLand', 'SingleCellLand', and 'Normal Cells and Tissues'. Below these, there are several 'Ingen' project folders. A secondary window shows a list of projects with columns for project name and a numerical value. The selected project is '1- breast cancer [breast] 10214'.

Graphical summary

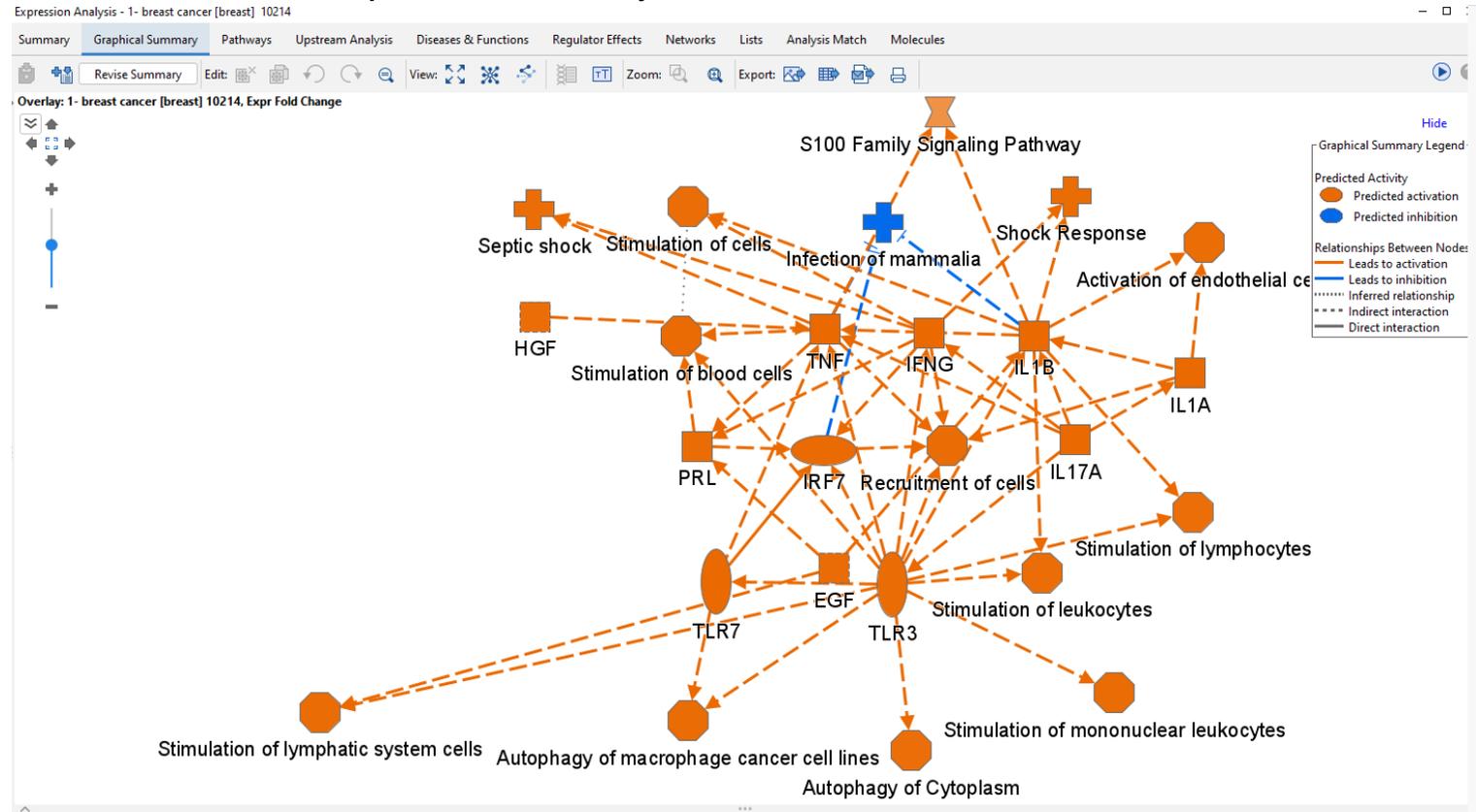


Table **Bar Chart**

X-axis: Activation z-score

Sort by: **Negative Z** -log[P-value] Data Display: **Positive Z** Select Range... More filters

Z-Score: ■ Positive ■ Negative ■ Zero ■ Neutral or No Prediction

Figure Legend ON

Number next to the bar: -log[P-value]

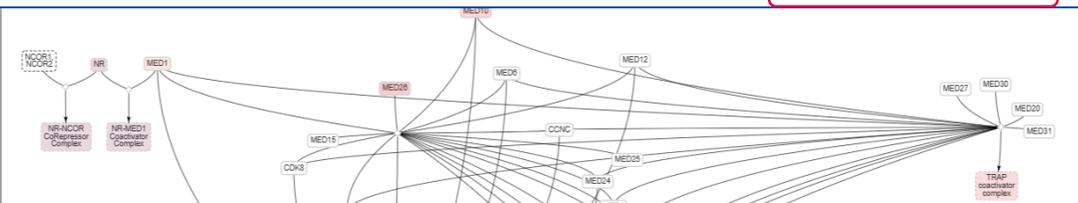
RNA.24h / Canonical Pathways

Canonical Pathways

Signaling and metabolic pathways that are potentially activated or inhibited in the dataset

Table **Bar Chart**

Pathway	P-value ▲	BH P-value	Activation z-score	Percentage overlap	Overlapping molecules	Total pathway size
Filter	Filter ≤	Filter ≤	Filter abs. ≥	Filter ≥	Filter ≥	Filter ≥
Generic Transcription Pathway	1.60e-39	1.95e-36	12.93	41.82	179	428
Chromatin organization	7.17e-22	4.38e-19	8.91	40.39	103	255
Oxidative Phosphorylation	3.77e-13	1.54e-10	-3.43	45.28	48	106
rRNA processing	1.61e-12	4.29e-10	4.38	71.88	23	32
Pulmonary Fibrosis Idiopathic Signaling Pathway	1.76e-12	4.29e-10	1.86	31.06	100	322
Histone Modification Signaling Pathway	5.99e-12	1.22e-9	6.93	31.6	91	288



protein-encoding genes. Figure 1 shows a diagram of the various components involved in cell-specific regulation of Pol-II gene transcription. Core Promoter: Pol II-regulated genes typically have a Core Promoter where Pol II and a variety of general factors bind to specific DNA motifs: i: the TATA box (TATA DNA sequence), which is bound by the 'TATA-binding protein' (TBP). ii: the Initiator motif (INR), where Pol II and certain other core factors bind, is present in many Pol II-regulated genes. iii: the Downstream

Highlight nodes of interest in a canonical pathway or network

Want to analyze your own data? [Stuart Tugendreich](#) [Logout](#)

channels on the cardiac sarcolemma membrane are generally triggered by an influx of Na⁺ during phase 0 of the action potential. Cardiac muscle cells are so tightly bound that when one of these cells is excited the action potential spreads to all of them. The standard model used to understand the cardiac action potential is the action potential of the ventricular myocyte (Park and Fishman 2011, Grant 2009). The action potential has 5 phases (numbered 0-4). Phase 4 describes the membrane potential when a cell is not being stimulated. The normal resting potential in the ventricular myocardium is between -85 to -95 mV. The K⁺ gradient across the cell membrane is the key determinant of the resting potential. Phase 0 is the rapid depolarisation phase in which electrical stimulation opens the closed, fast Na⁺ channels, causing a large influx of Na⁺ creating a Na⁺ current (I_{Na}). This causes depolarisation of the cell. The slope of phase 0 represents the maximum rate of potential change and differs in contractile and pacemaker cells. Phase 1 is the inactivation of the fast Na⁺ channels. The transient net outward current causing the small downward deflection (the 'notch' of the action potential) is due to the movement of K⁺ and Cl⁻ ions. In pacemaker cells, this phase is due to rapid K⁺ efflux and closure of L-type Ca²⁺ channels. Phase 2 is the plateau phase which is sustained by a balance of Ca²⁺ influx and K⁺ efflux. This phase sustains muscle contraction. Phase 3 of the action potential is where a concerted action of two outward delayed currents brings about repolarisation back down to the resting potential (Bartos et al. 2015). (Imported from Reactome as R.HSA-5576891, 06/2023)

Dataset molecules

Name ▲	Entrez Gene	Identifier	Expr p-value	Expr p-value	Expr False Discovery Rate (q-value)	Expr Fold Change	Expr Log Ratio	Expr Other	Molecule Type	Location
Filter	Filter	Filter	Filter <	Filter <	Filter <	Filter abs. >	Filter abs. >	Filter <	Select items ▼	Filter
CASQ2	calyculin 2	ENSG00000118729	6.05e-12	1.86e-7	5.42e-11	68.11	6.09	3	other	Cytoplasm
CORIN	corin, serine peptidase	ENSG00000145244	7.18e-29	2.20e-24	2.30e-27	1096.05	10.10	3	peptidase	Plasma Membrane
GATA4	GATA binding protein 4	ENSG00000136574	6.48e-72	1.99e-67	1.52e-69	679.09	9.41	3	transcription regulator	Nucleus

2) Highlights the corresponding node(s) even if inside a group or complex

1) Clicking row(s) here

IPA interpret

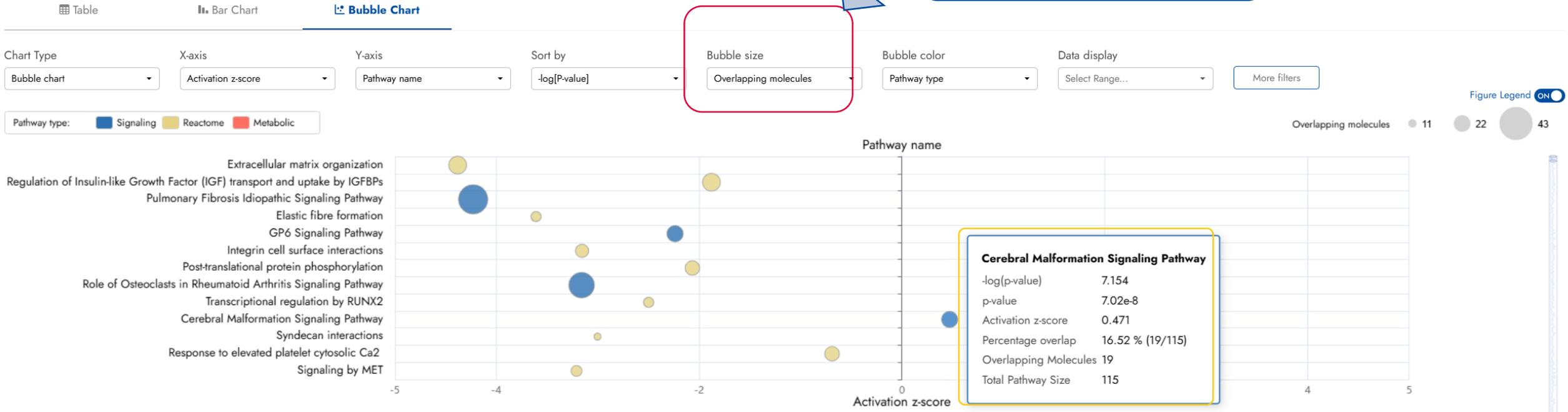
In canonical pathway, could show volcano bubble plot

1. Z-score
2. P-value
3. Overlay molecules
4. Percentage overlap
5. Pathway type
6. Total pathway size

protein.24 / Canonical Pathways

Canonical Pathways

Signaling and metabolic pathways that are potentially activated or inhibited in the dataset



IPA interpret

In canonical pathway, could show each molecules overlap in this pathway

Dataset molecules for Cerebral Malformation Signaling Pathway

Showing all 19 molecules



Name ▲	Entrez Gene	Identifier	Expr p-value	Expr Log Ratio	Expected	Molecule Type	Location
<input type="text" value="Filter"/>	<input type="text" value="Filter"/>	<input type="text" value="Filter"/>	<input type="text" value="Filter ≤"/>	<input type="text" value="Filter abs. ≥"/>	<input type="text" value="Select"/>	<input type="text" value="Select"/>	<input type="text" value="Select"/>
AKT1	AKT serine/threonine kinase 1	AKT1	1.44e-4	-0.63	Up	kinase	Cytoplasm
AKT2	AKT serine/threonine kinase 2	AKT2	7.32e-12	-4.42	Up	kinase	Cytoplasm
AKT3	AKT serine/threonine kinase 3	AKT3	3.05e-3	-0.82	Up	kinase	Cytoplasm
CCM2	CCM2 scaffold protein	CCM2	6.84e-3	-4.77	Down	other	Cytoplasm
CDKN1A	cyclin dependent kinase inhibitor 1A	CDKN1A	0.05	-4.64	Up	kinase	Nucleus
CKS1B	CDC28 protein kinase regulatory subunit 1B	CKS1B	2.95e-4	-5.17	Down	kinase	Unknown
CTNNA1	catenin alpha 1	CTNNA1	1.40e-21	-0.62	Down	other	Plasma Membrane
CTNNB1	catenin beta 1	CTNNB1	1.30e-25	-1.25	Down	other	Nucleus
F2	coagulation factor II, thrombin	F2	2.15e-19	0.87	Up	peptidase	Extracellular Space
F5	coagulation factor V	F5	6.71e-4	0.86	Down	other	Extracellular Space

Canonical_Pathways_Dataset_Molecules

IPA interpret in Upstream Regulator

We can change the X-axis Y-axis

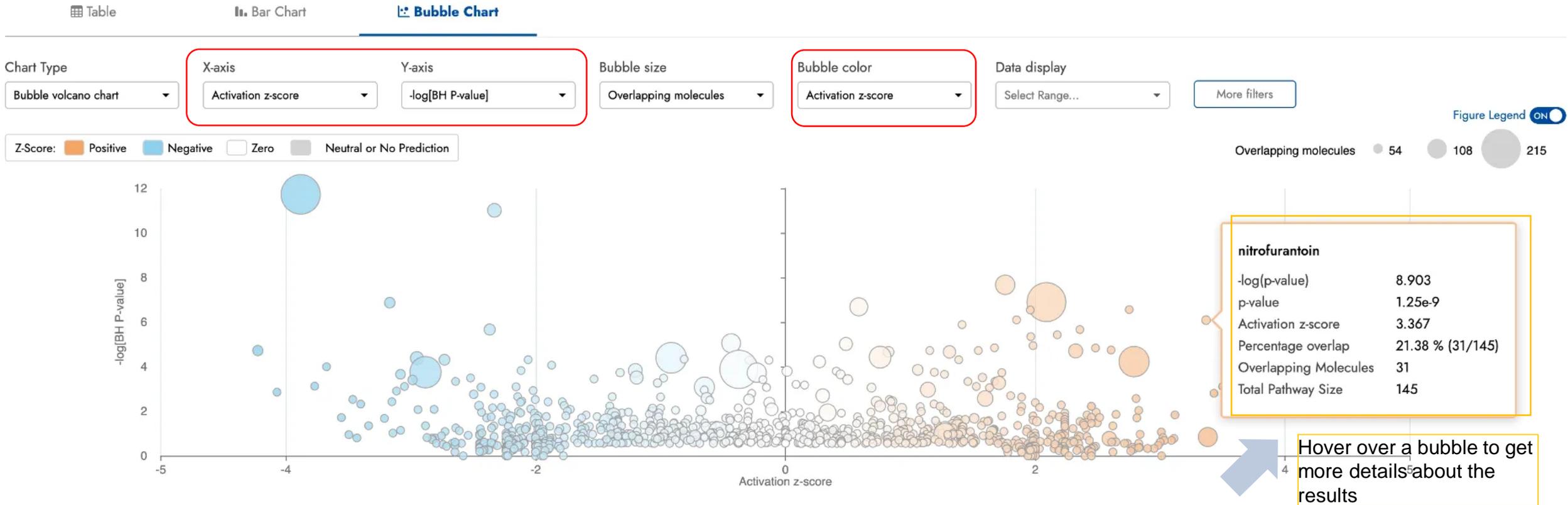
Color showed the Z-score

Upstream Regulators

Potentially activated or inhibited upstream molecules driving differential changes in the dataset

Upstream Regulators

Potentially activated or inhibited upstream molecules driving differential changes in the dataset

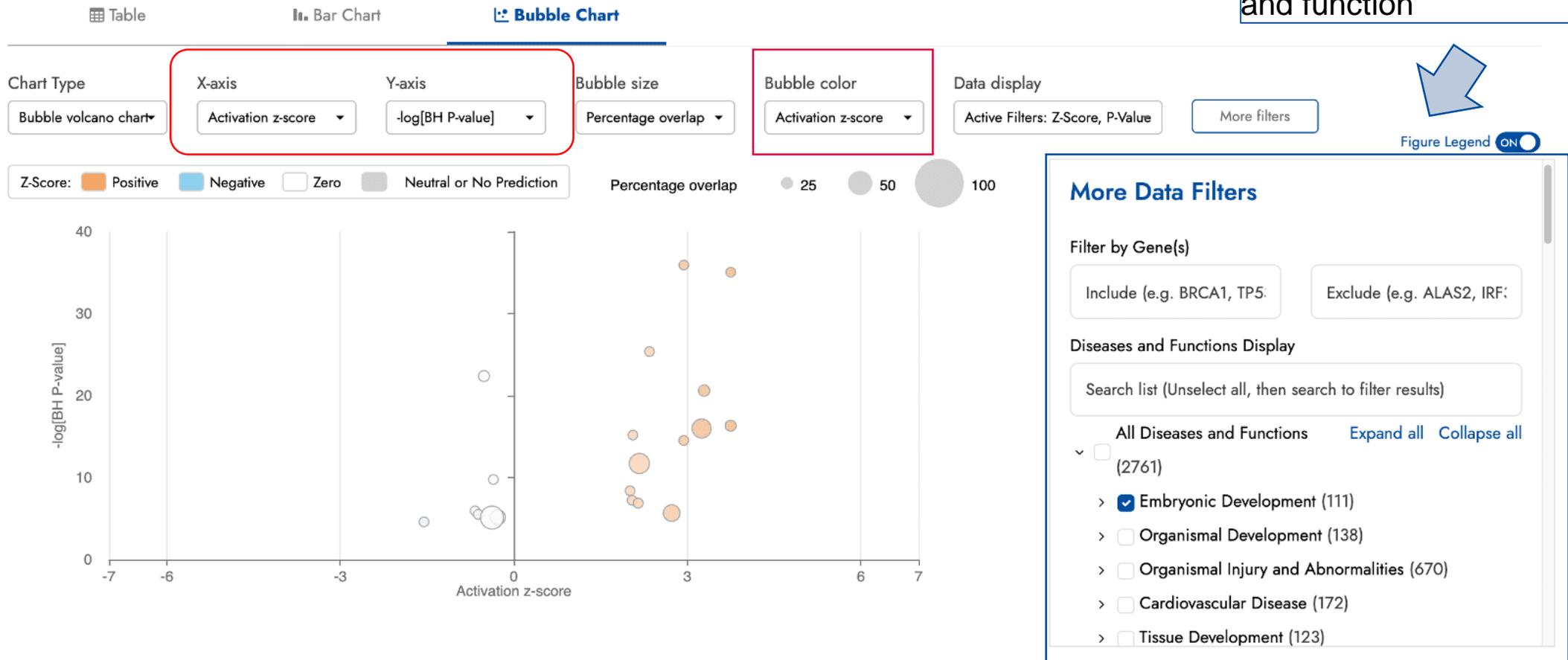


IPA interpret in Disease and Function

In disease and functional, It also could show Bubble Chart

Diseases and Functions

Diseases and biological processes predicted to be impacted in the dataset



For Disease and Function
We could use more filter to
select our interested disease
and function

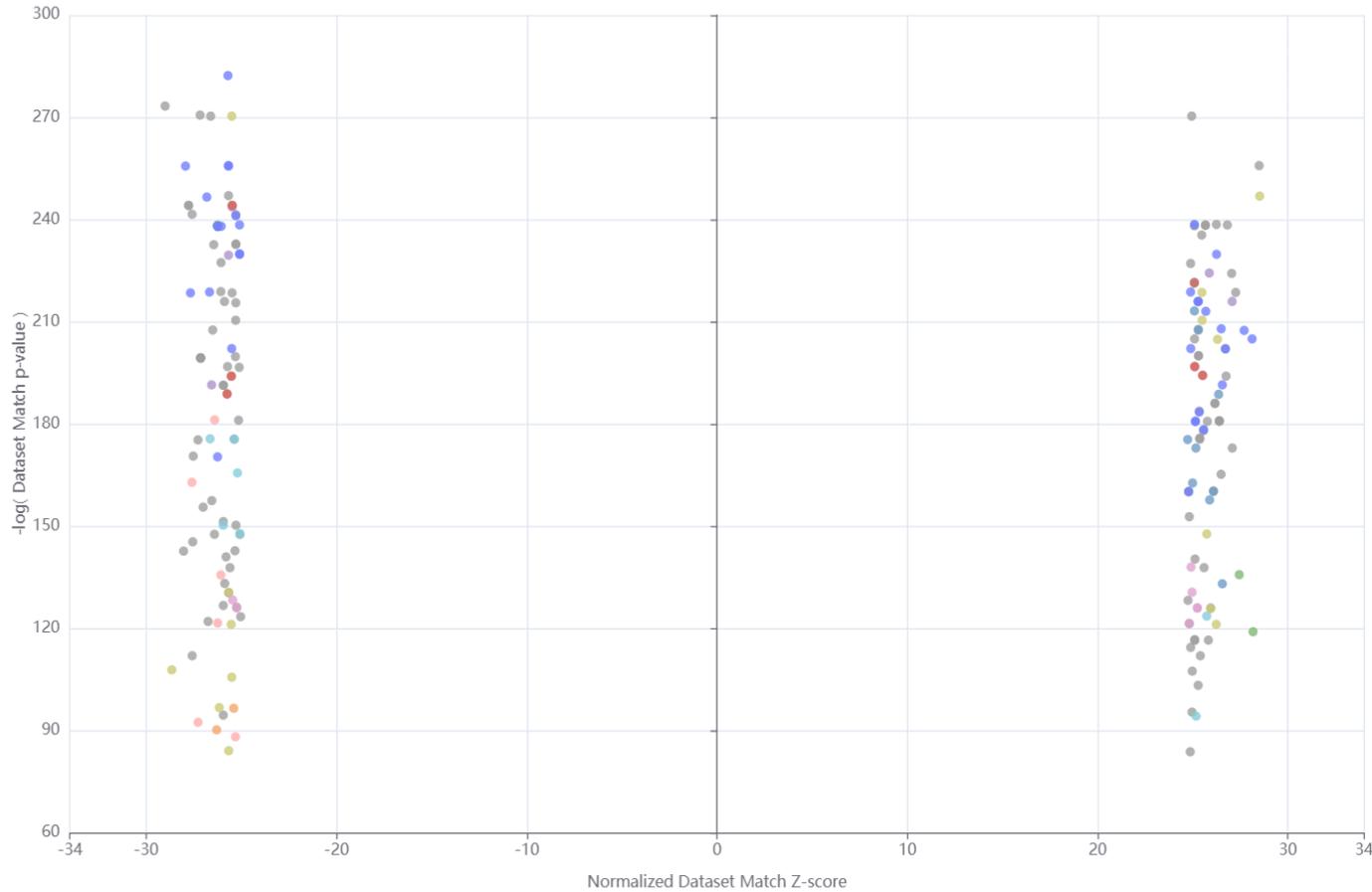
Analysis match of Omicsoft analysis

protein.24 / Similarities and Differences to OmicSoft Analyses

Similarities and Differences to OmicSoft Analyses



Analyses with the most significant matching (similarities, on the right) or anti-matching (differences, on the left) to your dataset. The table shows metadata statistically over-represented among the analyses in the plot.



Color the analyses (dots) by Metadata field

Cell types ▼

Term	P-value ▲
colon cell	6.93e-30
pancreatic cell	8.57e-8
mesenchymal stem cell (MSC)	5.28e-7
lymphoid cell	2.42e-6
vascular cell	3.05e-6
lymph node cell	1.19e-5
CD45- cell;CD45+ cell	1.28e-5
trachea cell	1.36e-4
common monocyte progenitor (cMoP)	1.96e-4
aortic smooth muscle cell	1.03e-3

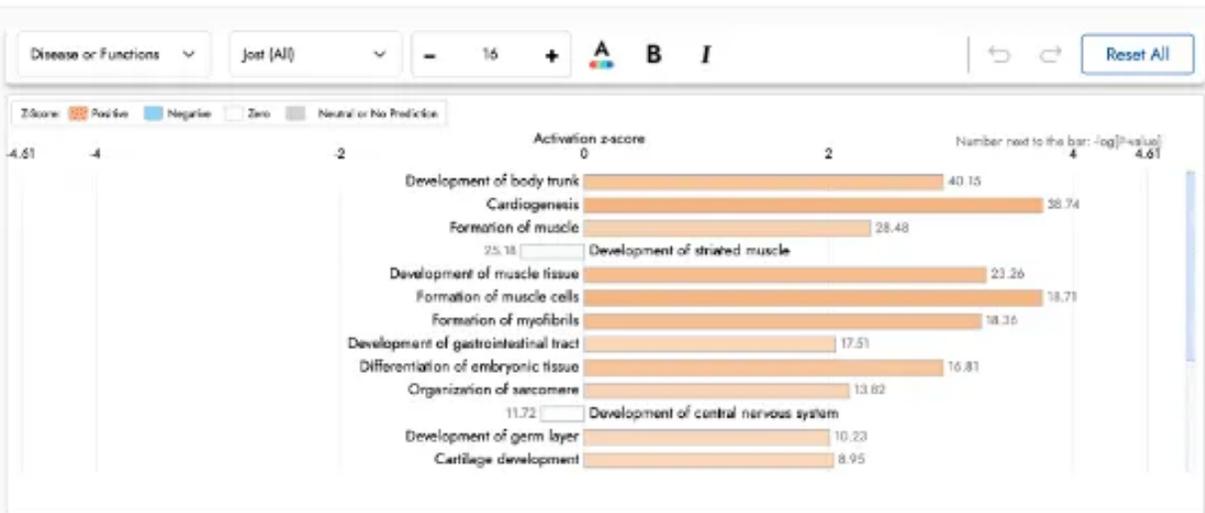
Customize bar charts for image export

protein.24 / Canonical Pathways

Canonical Pathways

Signaling and metabolic pathways that are potentially activated or inhibited in the dataset

Customize Chart & Download



Please select how to export the bar chart

Full Data (maximum 1000 bars) Preview Only - Displays up to 13 bars

Please select one of the following resolutions for download (all PNG format)

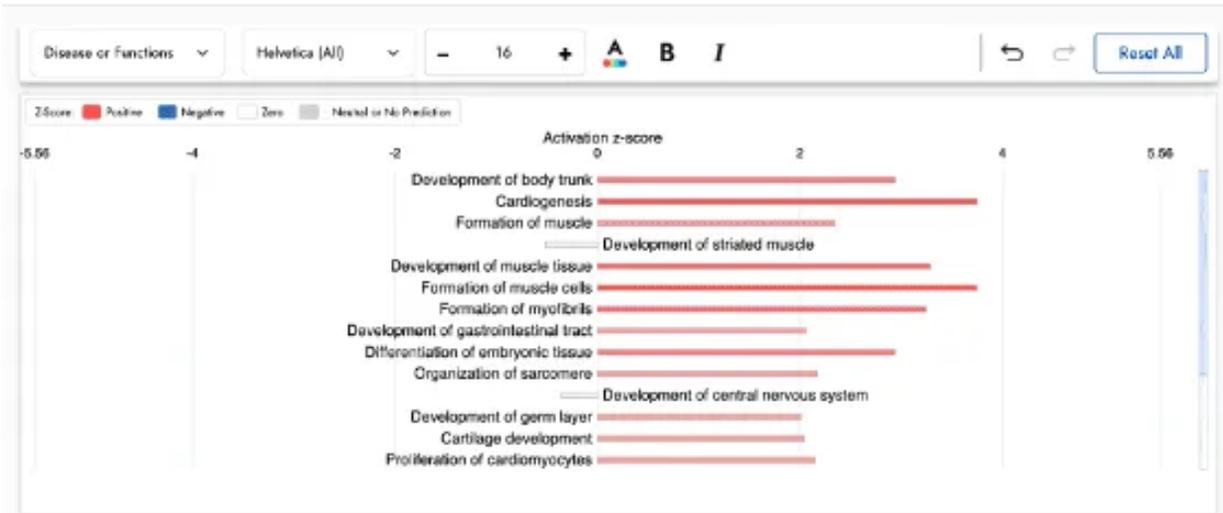
1x 2x 3x

Save for Future Download Use (Use this custom style by default next time)

Cancel

Download

Customize Chart & Download



Please select how to export the bar chart

Full Data (maximum 1000 bars) Preview Only - Displays up to 13 bars

Please select one of the following resolutions for download (all PNG format)

1x 2x 3x

Save for Future Download Use (Use this custom style by default next time)

Cancel

Download

Grow function

Build
Overlay
Path Designer
Pattern Search
View: [Icons]
Zoom: [Icons]
Export: [Icons]

Tool: Grow

Choose what type of node(s) you would like to add to the pathway

Canonical Pathways

Grow from selected molecules to selected canonical pathways

Indicate canonical pathways related to **Any** of the selected molecules

Recalculate

Canonical pathways	p-value	B-H ...	z-score	Mole...
NRF2-mediated Oxidative Stress Response	5.12E-37	2.00E-34	3.606	ABCC2,all 26
Xenobiotic Metabolism Signaling	7.17E-26	1.40E-23		ABCC2,all 21
LPS/IL-1 Mediated Inhibition of RXR Function	3.01E-20	3.92E-18		ABCC2,all 17
Xenobiotic Metabolism General Signaling Pathway	3.49E-19	3.41E-17	1.890	FTL, G... ..all 14
Xenobiotic Metabolism CAR Signaling Pathway	7.82E-19	6.11E-17	2.121	ABCC2,all 15
NFE2L2 regulating anti-oxidant/detoxification enzymes	1.82E-18	1.19E-16	3.000	GCLC, G... ..all 9
FXR/RXR Activation	3.38E-16	1.89E-14	2.121	ABCC2,all 13
Xenobiotic Metabolism PXR Signaling Pathway	5.81E-16	2.84E-14	1.633	ABCC2,all 13
Xenobiotic Metabolism AHR Signaling Pathway	2.30E-14	9.99E-13		CYP1A1,all 10
Glutathione-mediated Detoxification	7.06E-13	2.76E-11		Gsta1 (in... ..all 8
Glutathione Redox Reactions I	8.36E-13	2.97E-11	2.000	GPX2, G... ..all 7
Aryl Hydrocarbon Receptor Signaling	5.30E-12	1.73E-10		CYP1A1,all 10
Nicotine Degradation II	2.03E-09	6.09E-08	0.447	AOX1, C... ..all 7
NFE2L2 regulates pentose phosphate pathway genes	4.44E-09	1.24E-07	2.000	G6PD, N... ..all 4
Apelin Adipocyte Signaling Pathway	3.32E-08	8.65E-07		GPX2, G... ..all 6
Warburg Effect Signaling Pathway	4.93E-08	1.20E-06	1.134	FASN, G... ..all 7
Ferroptosis Signaling Pathway	7.84E-08	1.80E-06	-1.633	FTH1, FTL, ...all 7
Phase II - Conjugation of compounds	3.38E-07	6.67E-06	1.890	ESD, GC... ..all 7
Regulation of lipid metabolism by PPARalpha	3.41E-07	6.67E-06	1.633	ALAS1,all 6
LXR/RXR Activation	3.41E-07	6.67E-06		C3, CD36, ...all 6
PXR/RXR Activation	7.36E-07	1.37E-05	2.000	ABCC2,all 5

NFE2L2 1

Overlay: CDDO-me vs vehicle 2024-10-22 145429 - 2025-06-05, Expr Log Ratio

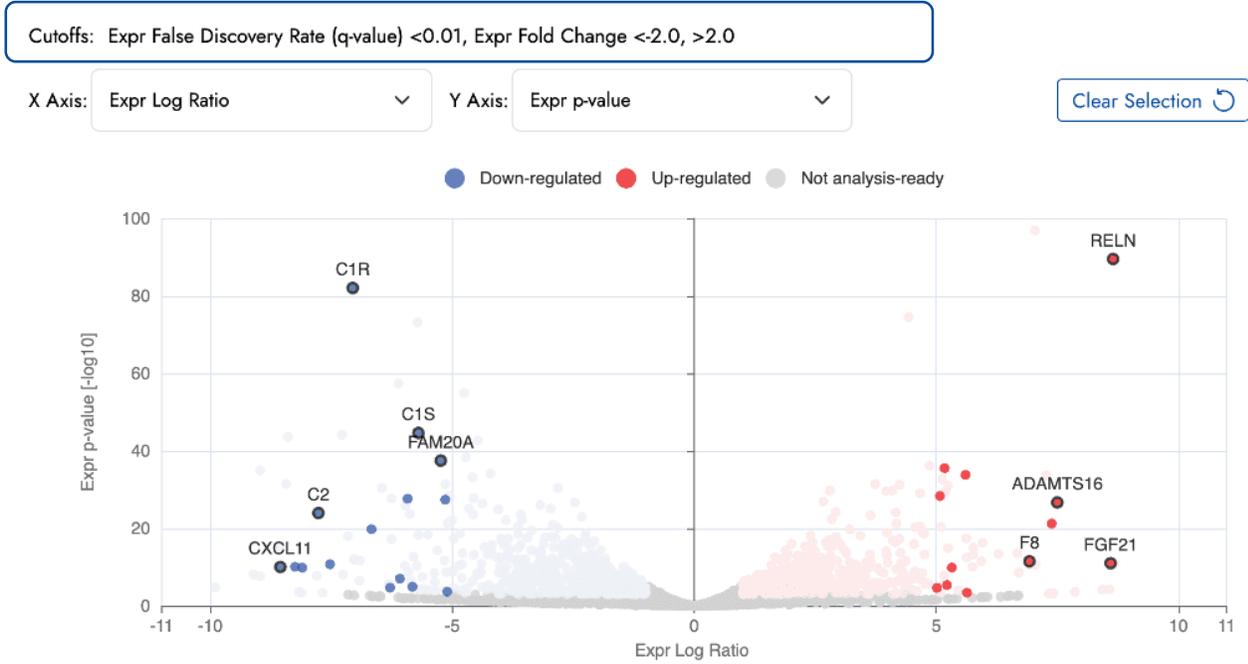
Show Legend

NRF2-mediated Oxidative Stress Response

0/391
Reset
Apply

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If we use this cut off and threshold, the plot highlights genes of interest by fading away those that do not meet your criteria.



ADAMTS16 [↗](#)

Entrez Gene Summary:

This gene encodes a member of the ADAMTS (a disintegrin and metalloproteinase with thrombospondin motifs) protein family. ADAMTS family members share several distinct protein modules, including a propeptide region, a metalloproteinase domain, a disintegrin-like domain, and a thrombospondin type 1 (TS) motif. Individual members of this family differ in the number of C-terminal TS motifs, and some have unique C-terminal domains. The encoded preproprotein is proteolytically processed to generate the mature protein, which may inhibit chondrosarcoma cell proliferation and migration. This gene may regulate blood pressure. [provided by RefSeq, May 2016]

Entrez Gene Name:

ADAM metalloproteinase with thrombospondin type 1 motif 16

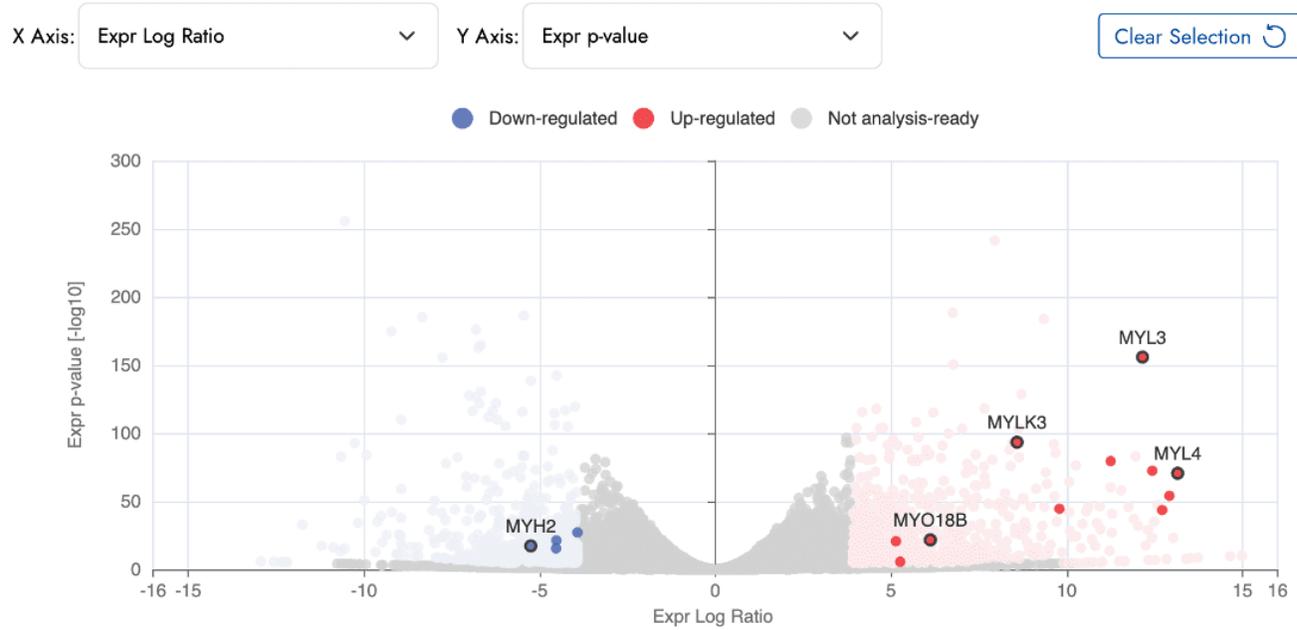
Dataset molecules

Showing 32 of 13406 molecules

Set filter

Name ▲	Entrez Gene	Identifier	Expr p-value	Expr p-value	Expr False Discovery Rate (q-value)	Expr Fold Change	Expr Log Ratio	Expr Other	Molecule Type	Location	Analyzed
APOL6	apolipoprotein L6	ENSECAG00000018752	8.01e-11	1.43e-6	4.02e-9	-303.79	-8.25	3	transporter	Extracellular Space	Yes
BPIFB4	BPI fold containing family B member 4	ENSECAG00000017316	4.29e-6	0.08	8.50e-5	37.24	5.22	3	other	Extracellular Space	Yes

Sample to



MYL3 [↗](#)

Entrez Gene Summary:

MYL3 encodes myosin light chain 3, an alkali light chain also referred to in the literature as both the ventricular isoform and the slow skeletal muscle isoform. Mutations in MYL3 have been identified as a cause of mid-left ventricular chamber type hypertrophic cardiomyopathy. [provided by RefSeq, Jul 2008]

Entrez Gene Name:

myosin light chain 3

Synonyms:

Alkali Myosin Light Chain 1, CMH8, Cmlc1, ELC, Elc1v, Elcv1, MLC1s, MLC1SB, MLC1V, MLCIV, MLC-IV/sb, Mylc, Mylc1v, myosin light chain 3, myosin, light polypeptide 3, rVMLC1, VELC, Ventricular Myosin Essential Light Chain, VLC1, VLCI

Member of:

Dataset molecules



We can filter the gene names

Showing **73** of 27087 molecules

Name ▲	Entrez Gene	Identifier	Expr p-value	Expr p-value	Expr False Discovery Rate (q-value)	Expr Fold Change	Expr Log Ratio	Expr Other	Molecule Type	Location	Analyzed
Filter	<input type="text" value="myosin"/>	Filter	Filter ≤	Filter ≤	Filter ≤	Filter abs. ≥	Filter abs. ≥	Filter ≤	Select ▼	Select ▼	Select ▼
	protein C3	1									
MYBPH	myosin binding protein H	ENSG00000133055	3.53e-3	1.00	9.24e-3	115.20	6.85 ■	1 ■	other	Cytoplasm	No
MYBPHL	myosin binding protein H like	ENSG00000221986	2.06e-3	1.00	5.69e-3	9.46	3.24 ■	1 ■	other	Cytoplasm	No

Reduced learning curve with accessible definitions for statistics in IPA Interpret

M-B / Canonical Pathways / Table View

Canonical Pathways

Signaling and metabolic pathways that are potentially activated or inhibited in the dataset

Table | Bar Chart | Bubble Chart

Showing all 780 canonical pathways

Pathway	P-value ⓘ	BH P-value ▲ ⓘ	Activation z-score ⓘ	Percentage overlap ⓘ	Overlapping molecules ⓘ	Total pathway size ⓘ
Filter	Filter ≤	Filter ≤	Filter abs. ≥	Filter ≥	Filter ≥	Filter ≥
Extracellular matrix organization	1.64e-30	1.29e-27	-5.49	31.78%	34	107
Complement cascade	7.48e-27	2.93e-24	-5.49	25.37%	34	134
Acute Phase Response Signaling	3.82e-24	9.98e-22	-0.30	19.57%	36	184
LXR/RXR Activation	4.22e-22	8.27e-20	-4.08	23.58%	29	123
DHCR24 Signaling Pathway	1.34e-20	2.10e-18	-3.80	21.01%	29	138
Binding and Uptake of Ligands by Scavenger Receptors	1.49e-19	1.94e-17	-5.10	22.81%	26	114
Intercellular surface interactions	9.22e-17	9.22e-15	4.15	24.71%	21	85

The **BH P-value** (or Benjamini-Hochberg corrected p-value) adjusts (reduces the significance of) the standard p-value when performing multiple hypothesis tests. The corrected p-value can be interpreted as an upper bound for the expected fraction of false positives. For example, if the BH p-value significance threshold is 0.01, you can expect that the fraction of false positives among the significant results is less than 1%. [Learn More](#)

ID not on the left

	A	B	C	D	E	F	G	H	I
1	Metabolite	HMDB	KEGG	Log2FC_M-B	Log2FC_M-D	Log2FC_B-D	Pval_M-B	Pval_M-D	Pval_B-D
2	Uracil	HMDB00	C00106	0.063778306	0.054996167	NA	0	0.0057048	NA
3	Fumaric acid	HMDB00	C00122	-0.015374258	NA	NA	0	NA	NA
4	p-Cresol sulfate	HMDB00	-	-0.110212803	NA	NA	0	NA	NA
5	2-Methylhippuric acid	HMDB00	C01586	0.079419552	NA	NA	0	NA	NA
6	(黃)-Anisoxide	HMDB00	-	-0.020309069	-0.074907841	NA	0	0.01090889	NA
7	Indoxyl sulfate	HMDB00	-	-0.082471626	-0.005070156	NA	0	0.01866236	NA
8	Varenicline	HMDB00	-	0.061591798	NA	NA	0	NA	NA
9	1-Isopropyl citrate	HMDB00	-	-0.266587082	NA	0.20588052	0	NA	0.045405
10	Asparaginy1-Hydroxyproline	HMDB00	-	0.035167221	NA	NA	0	NA	NA
11	Prenyl glucoside	HMDB00	C09808	-0.001194566	NA	NA	0	NA	NA
12	2'-Deoxyadenosine	HMDB00	C00559	0.052776526	0.127315183	0.07453866	0	0.00295749	0.046854
13	modafinil acid	-	-	0.143163905	NA	NA	0	NA	NA
14	Aspartylphenylalanine	HMDB00	-	-0.024029247	NA	NA	0	NA	NA
15	N1-Methyladenosine	HMDB00	C02494	-0.012577063	NA	NA	0	NA	NA
16	Fosthiazate	-	-	0.18631347	NA	NA	0	NA	NA
17	Estradiol-17beta 3-sulfate	HMDB00	C08357	-0.087844827	NA	NA	0	NA	NA
18	N-([4-(AMINOSULFONYL)PHENYL]AMINO)CARBONYL)-4-METHYLBENZENESULFONAMIDE	-	-	0.098155449	0.097618308	NA	0	0.02067507	NA
19	Rivoglitazone	-	-	-0.086180769	NA	NA	0	NA	NA
20	Flecainide	HMDB00	C07001	0.217340677	0.19207361	NA	0	0.00433429	NA
21	{2-hydroxy-5-[3-(5-methoxy-2,2-dimethyl-2H-chromen-6-yl)prop-2-enoyl]phenyl}oxidanesulfonic acid	-	-	-0.00309481	-0.070693348	NA	0	0.01031109	NA

Multi observation

Raw Data (487) Dataset Summary (274) Metadata

Edit Observation Names Infer Observations ?

ID/Observation Name	Ignore	ID	ID	Ignore	Ignore	Ignore	Ignore
Measurement/Annotation		Human Met...	KEGG				
49	1-Methylhypoxanthi...	HMDB0013141	-	151.0614_1.6	8.852885000000000...	1.59866E-3	M-D
50	1,5-Dihydroxy-3-me...	HMDB0030605	-	325.1073_6.2	0.16434707800000001	1.703099999999999...	M-D
51	12-Oxo-2,3-dinor-1...	HMDB0032090	-	263.1648_8.7	-0.182096564999999...	5.067939999999999...	M-D
52	17-hydroxy-11,15-di...	-	-	353.067_3.9	-0.261518497999999...	1.94006E-3	M-D
53	2-(4-Hydroxyphenyl)...	-	-	289.0497_8.8	0.20510102499999999	3.726257999999999...	M-D
54	2-(Methylthiomethyl...	-	-	193.0677_1.5	0.23968714799999999	4.495472999999999...	M-D
55	2-[[hydroxy(1-oxo-1...	-	-	246.0415_9.7	-0.169499689000000...	7.225800000000000...	M-D
56	2-[[hydroxy(5-hydrox...	-	-	233.0564_5.1	-0.775961921000000...	3.961799999999999...	M-D
57	2-Decylfuran	HMDB0032215	-	209.1896_9.7	-4.756241900000000...	2.428599999999999...	M-D
58	2-Deoxy-2-Amino Gl...	HMDB0001504	C06605	260.0533_3.1	-0.193207566	5.902499999999999...	M-D
59	2-Methoxyxanthone	HMDB0032998	-	225.055_7.9	0.29050186300000003	3.906299999999999...	M-D
60	2-oxo-3-(3,4,5-trihy...	-	-	211.0247_8.9	-0.127978258000000...	3.038522000000000...	M-D
61	2-Pyrrolidinone	HMDB0002039	C11118	86.06_1.8	-0.134968731000000...	1.376500000000000...	M-D
62	2,4-Diamino-6-[N-(2...	-	-	340.177_6.6	-0.192521124999999...	2.596532999999999...	M-D
63	2,4,6-Triethyl-1,3,5-...	-	-	207.0877_1.2	-0.130454037999999...	3.546219999999999...	M-D

AI can help parse and map automatically

		Observation 1		Observation 2	
	A	B	C	D	E
1	geneid	UCvsNormal.Log2FoldChange	UCvsNormal.pval	52wksVedolizumabvsBaseline.Log2FoldChange	52wksVedolizumabvsBaseline.pval
2	DDX11L1	-0.1067	0.2878	0.1183	0.1624
3	WASH7P	-0.1883	0.0097	0.3063	0.0006
4	FAM138F	-0.0761	0.4699	0.2466	0.0191
5	OR4F5	0.1474	0.5311	0.1713	0.2913
6	LOC729737	0.4789	0.0017	0.029	0.8331
7	LOC100133331	0.4789	0.0017	0.029	0.8331
8	LOC100132062	0.4789	0.0017	0.029	0.8331
9	OR4F29	0.2495	0.2389	0.2181	0.1887
10	JA429831	0.1215	0.3338	0.2556	0.0004

Analyte identifier **REQUIRED** to explore enrichment

RNA examples: Gene symbols, array identifiers from Affymetrix, Ensembl, etc.

Protein examples: UniProt, GenPept, Gene symbols, Ensembl. etc.

Metabolite examples: KEGG, CAS registry number, etc. **add multiple columns of ids to ensure best mapping*

Change values needed to calculate activity predictions

Change value examples: fold changes, ratios, etc.

Significance values: P-values **optional but recommended to enable filtering for significance*

Accepted file formats:

- ✓ .txt (tab-delimited text files)
- ✓ .xls, .xlsx, .csv (Excel tables)
- ✓ .diff (Cuffdiff output)

Multiple comparisons or observations may be uploaded in one file

IDs (required)

	A	B	C	D
	Proteins	Fold change	P_value	P_value_adjust
1				
2	P00738	0.592740341	0.000671209	0.016736513
3	P01008	0.25826353	0.000155027	0.006454004
4	P01011	0.47378079	0.000628734	0.016577608
5	P04003	0.312321917	2.2507E-05	0.001618456
6	P06681	0.272046102	0.001374078	0.027869114
7	P05155	0.429462469	4.19294E-05	0.002551241
8	P02748	0.580232999	0.002252137	0.038734209
9	P02763	0.555940063	0.00014192	0.006236575
10	Q14520	0.368464274	9.75518E-05	0.004786156
11	Q08380	0.536007179	0.000258392	0.009290371
12	Q9BXR6	0.332814513	0.00075662	0.01813594
13	P03951	0.306633696	0.000594476	0.016236342
14	P08185	0.304349939	1.12204E-05	0.000914984
15	P05090	0.302847519	0.000817844	0.018730825

Ratio, fold change, etc. (recommended)

Significance (optional)

Common protein IDs

- Ensembl
- Gene symbols (Entrez or HUGO)
- GenPept and GenBank
- International Protein Index
- UniProt and SwissProt

UniProt ID conversion tool:

- <https://www.uniprot.org/mapping/>

IDs (required)

	A	B	C	D	E
1	ID	Symbol	Phospho Fold Change	Phospho p-value	Phospho Site
2	IPI00137139	1700003H04Rik	-1.271	0.221	_M(ox)ET(ph)LGEK_
3	IPI00224491	2900026A02Rik	-1.244	0.25	_RQS(ph)LYENQA_
4	IPI00224491	2900026A02Rik	-1.404	0.156	_SEECs(ph)PQWLK_
5	IPI00652957	4930594M22Rik	-5.729	5.47E-09	_MFKSS(ph)PR_
6	IPI00137111	4933402E13Rik	2.196	0.000423	_AWALNDS(ph)ANT(ph)SPNAWFVER_
7	IPI00137111	4933402E13Rik	2.196	0.000423	_AWALNDS(ph)ANT(ph)SPNAWFVER_
8	IPI00137111	4933402E13Rik	2.196	0.000423	_AWALNDS(ph)ANT(ph)SPNAWFVER_
9	IPI00654190	4933431E20Rik	-1.184	0.304	_VGGLS(ph)PR_
10	IPI00654176	4933439C10Rik	-1.097	0.431	_SPHLSGS(ph)LPR_
11	IPI00225598	A430057M04Rik	1.079	0.299	_ALPT(ph)EPR_
12	IPI00227449	A730008H23Rik	-1.448	0.133	_GM(ox)TLQWLIS(ph)PVK_
13	IPI00311509	AAAS	-1.085	0.37	_ITHIPLYFVNAQFPRFS(ph)PVLGR_
14	IPI00458612	AAK1	1.07	0.311	_VGSLT(ph)PPSS(ph)PKTQR_
15	IPI00458612	AAK1	1.07	0.311	_VGSLT(ph)PPSS(ph)PKTQR_
16	IPI00458612	AAK1	1.057	0.332	_AGQTQPNPILPIQPALT(ph)PR_

Observation 1

Ratio, fold change, etc. (recommended)

Significance (optional)

Common protein IDs

- Ensembl
- Gene symbols (Entrez or HUGO)
- GenPept and GenBank
- International Protein Index
- UniProt and SwissProt

UniProt ID conversion tool:

- <https://www.uniprot.org/mapping/>

Multiple ID columns

Ratio, fold change, etc. (recommended)

	A	B	C	D	E	F	G	H
	Pubchem	Kegg	HMDB	CAS	Metabolites	Fold change	P_value	P_value_adjust
1								
2					(2 or 3)-decenoate (10:1n7 or n8)	1.212936133	4.44028E-05	0.000585189
3	6443013	C14762	HMDB0004667	29623-28-7	13-HODE + 9-HODE	0.584109411	0.003698077	0.016919182
4	10111	C02294	HMDB01522	471-29-4	1-methylguanidine	1.219937764	0.015399637	0.049446834
5	5462190	C15606	HMDB0012134	746507-19-7	2,3-dihydroxy-5-methylthio-4-pentenoate (DMTPA)*	1.566518315	0.002802172	0.013670263
6	80283	C02356	HMDB00452	1492-24-6	2-aminobutyrate	0.633800292	0.011016709	0.038805594
7	10796774		HMDB00317	488-15-3	2-hydroxy-3-methylvalerate	0.997343835	0.006172648	0.024774766
8	11427		HMDB37115	120-91-2	2-hydroxy-4-(methylthio)butanoic acid	1.294720456	0.000305912	0.002622524

Observation 1

Common metabolite IDs

- CAS registry number
- Human Metabolome Database
- KEGG
- PubChem CID

Metabolite ID conversion tools:

- <https://biodbnet-abcc.ncifcrf.gov/db/db2db.php>
- <https://cts.fiehnlab.ucdavis.edu/batch>
- <http://csbg.cnb.csic.es/mbrole2/conversion.php>

nature communications



Article

<https://doi.org/10.1038/s41467-024-47271-y>

Spatial transcriptomics reveals discrete tumour microenvironments and autocrine loops within ovarian cancer subclones

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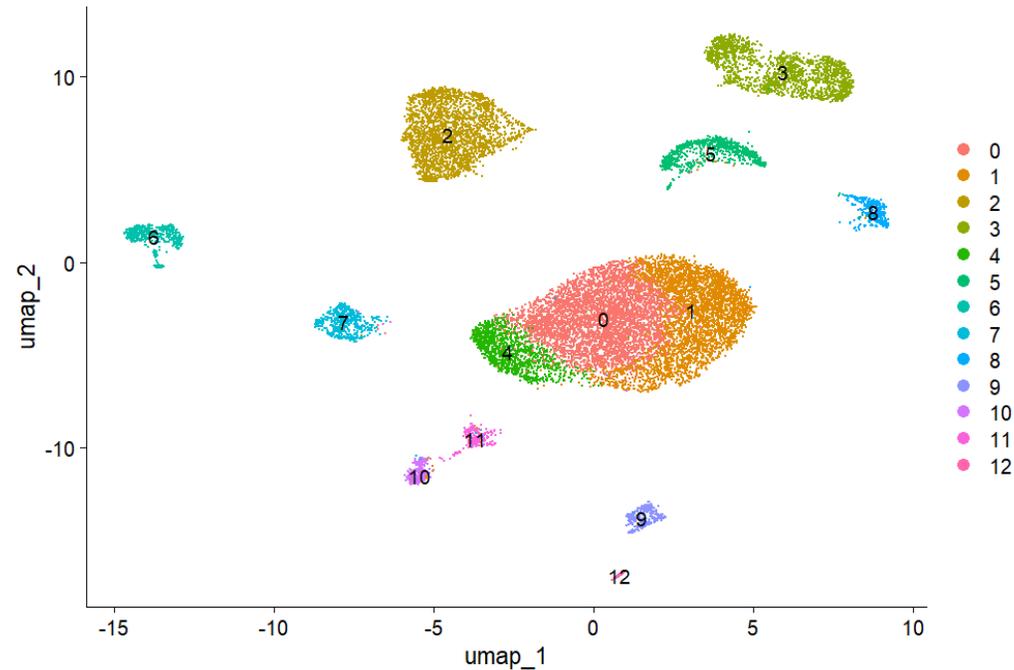
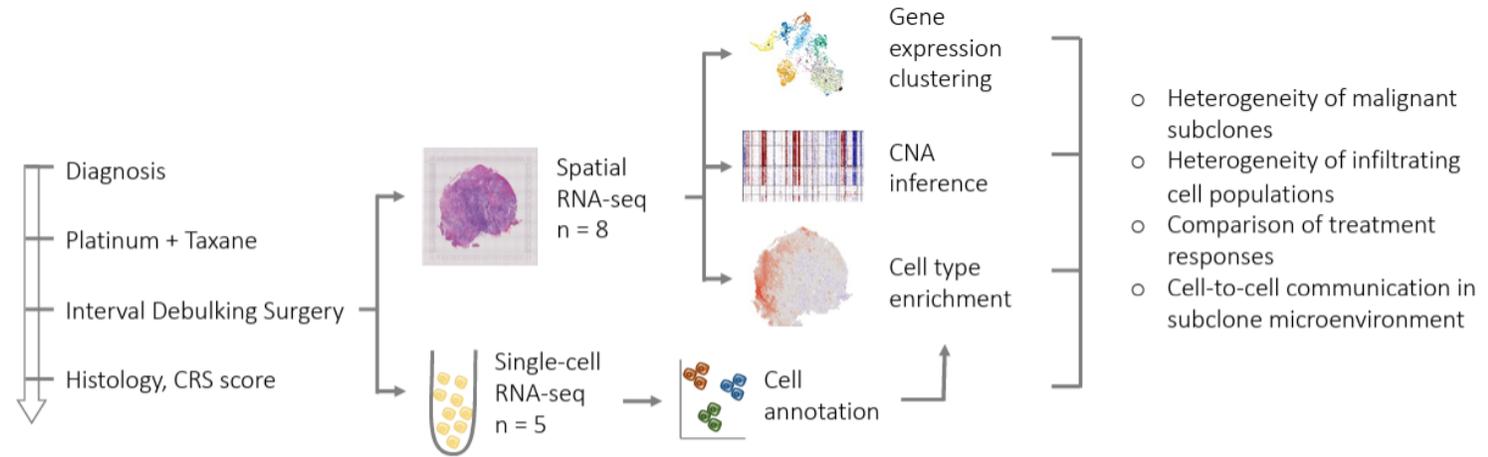
Elena Denisenko¹, Leanne de Kock^{1,2}, Adeline Tan², Aaron B. Beasley³, Maria Beilin⁴, Matthew E. Jones¹, Rui Hou¹, Dáithí Ó Muiri¹, Sanela Bitic⁴, G. Raj K. A. Mohan^{4,5}, Stuart Salfinger⁶, Simon Fox¹, Khaing P. W. Hmon¹, Yen Yeow¹, Youngmi Kim⁷, Rhea John⁷, Tami S. Gilderman⁷, Emily Killingbeck⁷, Elin S. Gray³, Paul A. Cohen^{8,9}, Yu Yu^{8,10,11} & Alistair R. R. Forrest¹

High-grade serous ovarian carcinoma (HGSOC) is genetically unstable and characterised by the presence of subclones with distinct genotypes. Intratumoural heterogeneity is linked to recurrence, chemotherapy resistance, and poor prognosis. Here, we use spatial transcriptomics to identify HGSOC subclones and study their association with infiltrating cell populations. Visium spatial transcriptomics reveals multiple tumour subclones with different copy number alterations present within individual tumour sections. These subclones differentially express various ligands and receptors and are predicted to differentially associate with different stromal and immune cell populations. In one sample, CosMx single molecule imaging reveals subclones differentially associating with immune cell populations, fibroblasts, and endothelial cells. Cell-to-cell communication analysis identifies subclone-specific signalling to stromal and immune cells and multiple subclone-specific autocrine loops. Our study highlights the high degree of subclonal heterogeneity in HGSOC and suggests that subclone-specific ligand and receptor expression patterns likely modulate how HGSOC cells interact with their local microenvironment.

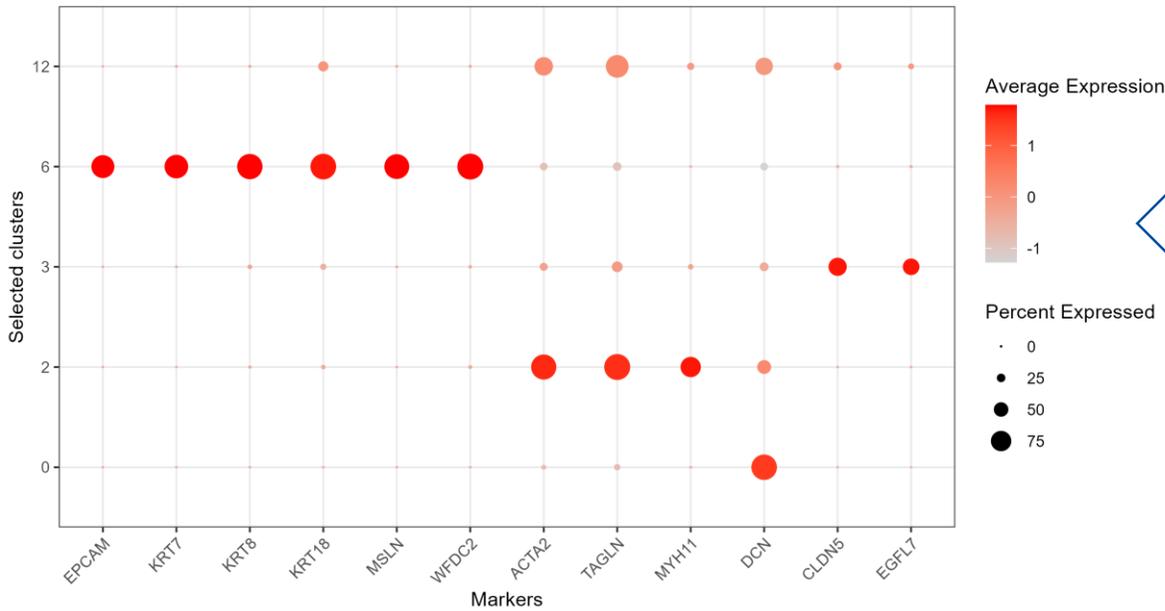
Ovarian cancer is the eighth leading cause of cancer deaths in women worldwide¹. High-grade serous ovarian carcinoma (HGSOC) is the most common and lethal histologic subtype, accounting for 70–80% of ovarian cancer deaths². HGSOC is thought to be derived from both

fallopian tube and ovarian surface epithelium^{3,4} and genomically is characterised by almost universal *TP53* mutations and copy number alterations (CNAs)^{5–8}. Notably, although several chromosomal regions are recurrently altered⁹, and multiple genes (*FAT3*, *CSMD3*, *BRCA1*,

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Marker-based annotation supporting cluster 6 vs cluster 2 comparison



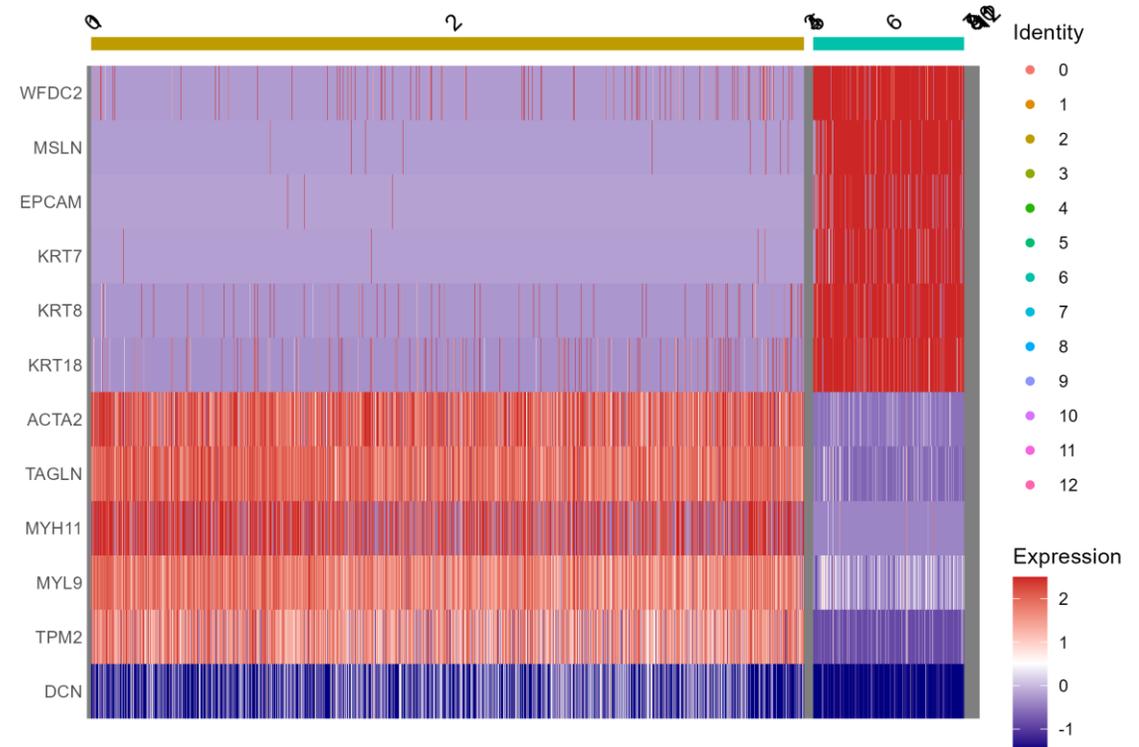
Dot plot

Cluster 6 shows epithelial/tumor markers, whereas cluster 2 shows CAF/myofibroblast markers, supporting their annotation as tumor epithelial cells and CAFs.

Heatmap

The heatmap highlights distinct transcriptional programs between cluster 6 and cluster 2, supporting their use for downstream DEG analysis.

Marker Heatmap: Tumor epithelial (6) vs CAF (2)



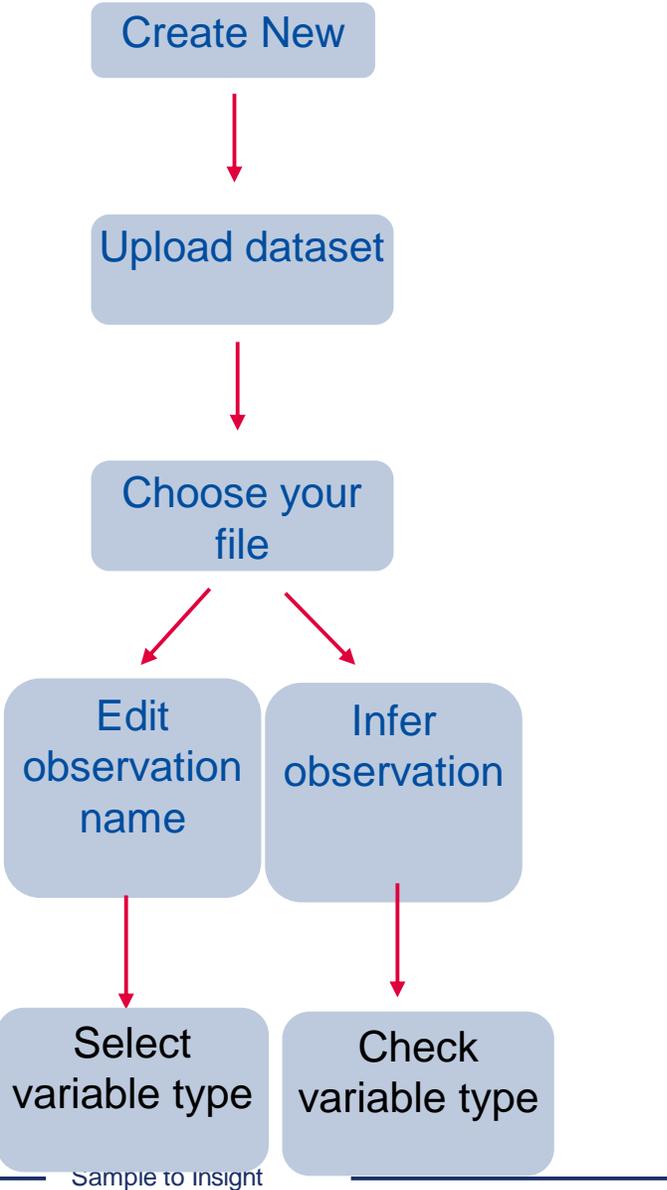
Cluster 6
tumor epithelial program

VS

Cluster 2
stromal / CAF program

A	B	C	D
GeneSymbol	log2FC	P.Value	FDR
CRISP3	10.32897	0	0
FOLR1	9.887196	0	0
MAL2	9.84615	0	0
SMIM22	9.816256	0	0
CLDN4	9.679122	0	0
C19orf33	9.656416	0	0
ELF3	9.444942	0	0
MMP7	9.263814	0	0
CLDN3	9.181715	0	0
LCN2	9.077388	0	0
MSLN	8.996525	0	0
EPCAM	8.784433	0	0
KRT7	8.734719	0	0
MPZL2	8.543441	0	0
FXYD3	8.495489	0	0
LYPD1	8.482665	0	0
KLK6	8.471744	0	0
TSPAN1	8.343217	0	0
TACSTD2	8.249799	0	0
SLPI	8.163842	0	0
CLDN7	8.136355	0	0
S100A1	8.057301	0	0
CD24	7.689896	0	0
ASRGL1	7.522038	0	0
S100A14	7.426849	0	0
CLDN1	7.35181	0	0
MUC1	7.070337	0	0
PART1	6.881187	0	0
SOX17	6.83132	0	0

Upload dataset



1. Select File Format: ?

2. Contains Column Header: Yes No

3. Select Identifier Type: Please assign at least one column below as "ID", and assign the identifier type(s). Assign additional columns as ID to improve mapping coverage if desired.

4. Array platform used for experiments: Select relevant array platform as a reference set for c

5. Use the dropdown menus to specify the column names that contain identifiers and observations. For observations, select the appro

Raw Data (5699) Dataset Summary (5635) Metadata

?

ID/Observation Name	ID	GeneSymb...	GeneSymb...
Measurement/Annotation	Gene Symb...	Expr Log Ra...	Expr p-value
1	GeneSymbol	log2FC	P.Value
2	CRISP3	10.3289664830995	0
3	FOLR1	9.88719584748606	0
4	MAL2	9.8461501409304	0
5	SMIM22	9.8162558096731	0
6	CLDN4	9.67912247200801	0
7	C19orf33	9.65641614146133	0
8	ELF3	9.44494172636148	0
9	MMP7	9.26381398549865	0
10	CLDN3	9.18171478859272	0
11	LCN2	9.07738795271416	0
12	MSLN	8.99652482126691	0
13	EPCAM	8.78443250855201	0
14	KRT7	8.7347187250338	0
15	MPZL2	8.54344129810654	0
16	FXD3	8.49548858871906	0
17	LYPD1	8.48266506085511	0
18	KLK6	8.47174366416617	0
19	TSPAN1	8.34321684333466	0
20	TACSTD2	8.24979880861286	0
21	SLPI	8.16384177560933	0
22	CLDN7	8.1363548506867	0
23	S100A1	8.05730092469511	0
24	CD24	7.68989567092128	0
25	ASRGL1	7.5220381516916	0
26	S100A14	7.42684900746169	0
27	CLDN1	7.35180960052029	0
28	MUC1	7.07033707717086	0

Edit Observation Names [X]

To label each observation, select an existing name from the pull-down lists, or create a new label by typing directly into the Observation Name field. Then click OK.

Edit Observation Names

Observation Name

1.

Core analysis

Analyze filter dataset



Core analysis



Set cut off

Annotated Dataset: IPA_scRNA_cluster6_vs_cluster2
 Preview Dataset IPA_scRNA_cluster6_vs_cluster2

Mapped IDs (5635) Unmapped IDs (63) All IDs (5698) Metadata

Add To My Pathway Add To My List Create Dataset Customize Table

Symbol A2M - AFDN-DT (1/57)

Expr Log Ratio	Expr p-value	Expr False Discovery Rate (q-...)	ID	Flags	Symbol	Entrez Gene Name	Location	Type(s)	Drug(s)
-4.665	3.53E-38	6.90E-34	A2M		A2M	alpha-2-macroglobulin	Extracellular Space	other	
1.169	1.67E-33	3.25E-29	AACS		AACS	acetoacetyl-CoA synthetase	Cytoplasm	enzyme	
1.346	1.91E-108	3.74E-104	AAK1		AAK1	AP2 associated kinase 1	Cytoplasm	kinase	LP-935509, SM1-71
0.459	2.36E-61	4.61E-57	AAMDC		AAMDC	adipogenesis associated Mth938 do...	Cytoplasm	other	
0.362	3.51E-18	6.86E-14	AASDH		AASDH	aminoadipate-semialdehyde dehydr...	Other	enzyme	
-0.294	4.57E-25	8.93E-21	AASDHPPPT		AASDHPPPT	aminoadipate-semialdehyde dehydr...	Cytoplasm	enzyme	
-0.697	1.45E-05	2.82E-01	AASS		AASS	aminoadipate-semialdehyde synthase	Cytoplasm	enzyme	
2.832	8.70E-52	1.70E-47	ABCA2		ABCA2	ATP binding cassette subfamily A m...	Plasma Membrane	transporter	
0.410	7.19E-12	1.40E-07	ABCA5		ABCA5	ATP binding cassette subfamily A m...	Plasma Membrane	transporter	
3.304	2.86E-55	5.58E-51	ABCC4		ABCC4	ATP binding cassette subfamily C m...	Plasma Membrane	transporter	
0.539	4.18E-25	8.17E-21	ABCD3		ABCD3	ATP binding cassette subfamily D m...	Cytoplasm	transporter	
0.641	5.08E-64	9.93E-60	ABCF1		ABCF1	ATP binding cassette subfamily F me...	Cytoplasm	transporter	
1.477	8.37E-40	1.63E-35	ABCF3		ABCF3	ATP binding cassette subfamily F me...	Other	transporter	
2.632	2.31E-150	4.51E-146	ABHD11		ABHD11	abhydrolase domain containing 11	Cytoplasm	enzyme	
0.397	2.11E-40	4.13E-36	ABHD12		ABHD12	abhydrolase domain containing 12, ...	Plasma Membrane	enzyme	
0.474	1.37E-32	2.67E-28	ABHD13		ABHD13	abhydrolase domain containing 13	Other	peptidase	
1.498	3.78E-128	7.38E-124	ABHD14A		ABHD14A	abhydrolase domain containing 14A	Cytoplasm	enzyme	
0.352	9.62E-56	1.88E-51	ABHD14B		ABHD14B	abhydrolase domain containing 14B	Cytoplasm	enzyme	
-0.597	1.31E-09	2.55E-05	ABHD2		ABHD2	abhydrolase domain containing 2, a...	Cytoplasm	enzyme	
-0.568	5.81E-11	1.14E-06	ABHD3		ABHD3	abhydrolase domain containing 3, p...	Plasma Membrane	enzyme	
0.534	1.26E-52	2.46E-48	ABI2		ABI2	abl interactor 2	Cytoplasm	other	
-0.375	3.29E-13	6.43E-09	ABI3BP		ABI3BP	ABI family member 3 binding protein	Extracellular Space	other	
1.039	6.63E-40	1.29E-35	ABL2		ABL2	ABL proto-oncogene 2, non-recepto...	Cytoplasm	kinase	nilotinib, dasatinib
1.665	3.95E-103	7.71E-99	ABLIM1		ABLIM1	actin binding LIM protein 1	Cytoplasm	other	
4.676	3.64E-223	7.10E-219	ABO		ABO	ABO, alpha 1-3-N-acetylgalactosami...	Other	enzyme	
3.361	2.34E-126	4.57E-122	ABRACL		ABRACL	ABRA C-terminal like	Nucleus	other	
-1.247	5.83E-04	1.00E00	ABRAXAS1		ABRAXAS1	abraxas 1, BRCA1 A complex subunit	Nucleus	other	
0.527	1.84E-47	3.58E-43	ABT1		ABT1	activator of basal transcription 1	Nucleus	transcription regulator	
-1.987	3.53E-02	1.00E00	ABTB1		ABTB1	ankyrin repeat and BTB domain con...	Cytoplasm	translation regulator	
-0.252	5.09E-32	9.93E-28	ACAA1		ACAA1	acetyl-CoA acyltransferase 1	Cytoplasm	enzyme	trimetazidine
-0.573	2.31E-17	4.51E-13	ACAA2		ACAA2	acetyl-CoA acyltransferase 2	Cytoplasm	enzyme	
0.773	1.87E-30	3.65E-26	ACADB		ACADB	acyl-CoA dehydrogenase family me...	Cytoplasm	enzyme	
-0.538	1.16E-12	2.26E-08	ACAD9		ACAD9	acyl-CoA dehydrogenase family me...	Cytoplasm	enzyme	
0.365	5.71E-38	1.12E-33	ACAP2		ACAP2	ArfGAP with coiled-coil, ankyrin repe...	Nucleus	other	

0 / 5635

Flags:
 "D" - Duplicates. Gene/Protein/Chemical identifiers marked with an asterisk indicate that multiple identifiers in the dataset file map to a single gene/chemical in the Global Molecular Network.
 "O" - Override molecules. Gene/Protein/Chemical identifiers marked as "Override" are displayed with italic text.
 "A" - Gene/Protein/Chemical ID marked as Absent. The gene/protein/chemical will not be used as a focus molecule or appear in networks unless you also explicitly override this flag with the Override column.

Edit Dataset Settings Analyze/Filter Dataset Close

Core Analysis

- Biomarker Filter
- Filter Dataset
- microRNA Target Filter
- BioProfiler
- IsoProfiler

Choose which analysis do you want

Analyze filter
dataset



Core analysis



Choose which
analysis

Set cut off

Create Core Analysis

Selected Dataset: IPA_scRNA_cluster6_vs_cluster2

Based on this dataset, which Core Analysis type would you like to run?

Expression Analysis

On which measurement type would you like to base the analysis?

Expr Log Ratio

This measurement will be used to calculate directionality (z-scores) in the analysis and will be displayed in color on pathways and networks. If you choose a non-directional measurement (e.g. p-value) then z-scores will not be calculated.

Back

Next

Set Cutoff

Analyze filter dataset



Core analysis



Set cut off

Set Cutoffs Biological Filters

Use cutoffs to select a set of molecules from your dataset to analyze. Ideally choose between 100 and 3000 significantly regulated molecules, and not more than 8000. Include *both* up-regulated and down-regulated, if possible, to obtain causal predictions.

Volcano plot

Create Expression Analysis - [analysis: IPA_scrRNA_cluster6_vs_cluster2]

Set Cutoffs Biological Filters

Use cutoffs to select a set of molecules from your dataset to analyze. Ideally choose between 100 and 3000 significantly regulated molecules, and not more than 8000. Include *both* up-regulated and down-regulated, if possible, to obtain causal predictions.

Set Cutoffs

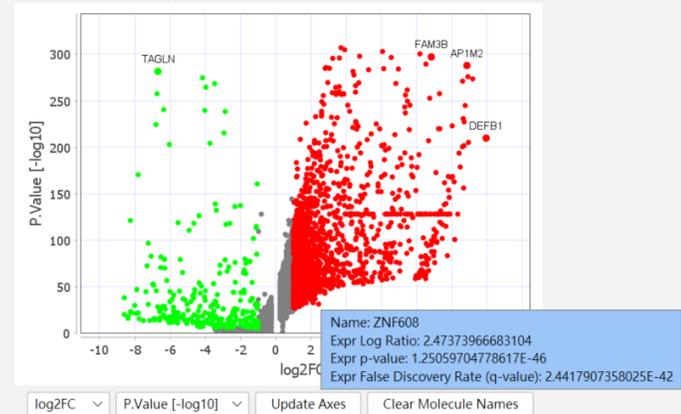
Dataset Column	Measurement Value Type	Range	Cutoff
log2FC	Expr Log Ratio	-8.5933 to 11.9397	-1 Down 1 Up
P.Value	Expr p-value	0.0 to 0.9737	
FDR	Expr False Discovery Rate (q-value)	0.0 to 1.0	0.05

Recalculate

Advanced

Recalculate 2017 analysis-ready molecules (334 Down and 1683 Up)

Select molecules by clicking or dragging to label them with their names. Note that fold changes are converted to log2 for charting purposes.



- General Settings ?
- > Networks Interaction & Ca... ?
- Node Types biologic drug... ?
- Data Sources All ?
- miRNA Confidence Experi... ?
- Species Human ?
- Tissues & Cell Lines All ?
- Mutation All ?

Save As Default

Generate the following Networks (increases analysis time)

Interaction networks

Include endogenous chemicals Molecules per network Networks per analysis
Genes are always included

Causal networks

Score master regulators for relationships to diseases, functions, genes, or chemicals (max 50)

Score using causal paths only

TGFB1

Add...

Remove

3.304	2.86E-55	5.58E-51	ABCC4	ABCC4	ATP binding cassette subfamily C m...	Plasma Membrane	transporter
1.477	8.37E-40	1.63E-35	ABCF3	ABCF3	ATP binding cassette subfamily F m...	Other	transporter
2.632	2.31E-150	4.51E-146	ABHD11	ABHD11	abhydrolase domain containing 11	Cytoplasm	enzyme

Pathway or gene activity predicted by IPA



Actual measurement of gene expression in your dataset



What do z-scores mean in IPA?

Actual dataset measurement

VS.

What IPA expects if pathway is activated

Symbol	Measurement Expr Log Ratio	Expected
CCL2	↓ -2.030	↑ Up
CD44	↓ -1.634	↑ Up
CD274	↓ -2.218	↑ Up
COL1A1	↓ -2.040	↑ Up
COL1A2	↓ -1.920	↑ Up

Pathway inhibited

- Z score

Symbol	Measurement Expr Log Ratio	Expected
CCL2	↓ -2.030	↑ Up
CD44	↑ 1.634	↑ Up
CD274	↓ -2.218	↑ Up
COL1A1	↑ 2.040	↑ Up
COL1A2	↓ -1.920	↑ Up

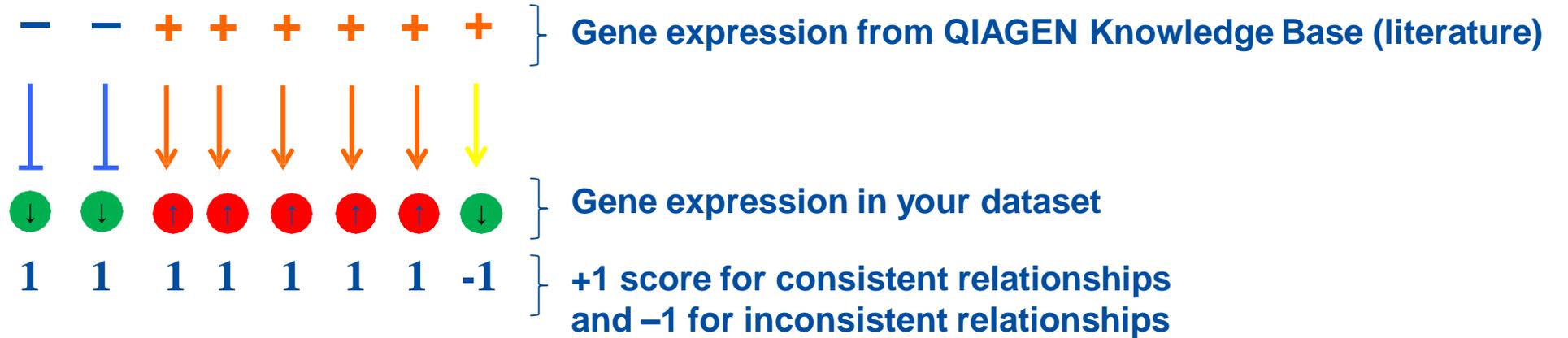
No clear signal for prediction
Z score = 0

Symbol	Measurement Expr Log Ratio	Expected
CCL2	↑ 2.030	↑ Up
CD44	↑ 1.634	↑ Up
CD274	↑ 2.218	↑ Up
COL1A1	↑ 2.040	↑ Up
COL1A2	↑ 1.920	↑ Up

Pathway activated

+ Z score

How well do the actual measurements match the expected measurements?



$$z = \frac{x}{\sigma_x} = \frac{\sum_i x_i}{\sqrt{N}} = \frac{N_+ - N_-}{\sqrt{N}} = (7-1)/\sqrt{8} = 2.12 (= \text{predicted activation})$$

- z-score is a statistical measure of the match between expected relationship direction and observed gene expression
- z-score greater than 2 or less than -2 is considered significant
- Note that the actual z-score is weighted by the underlying findings, the relationship bias and dataset bias

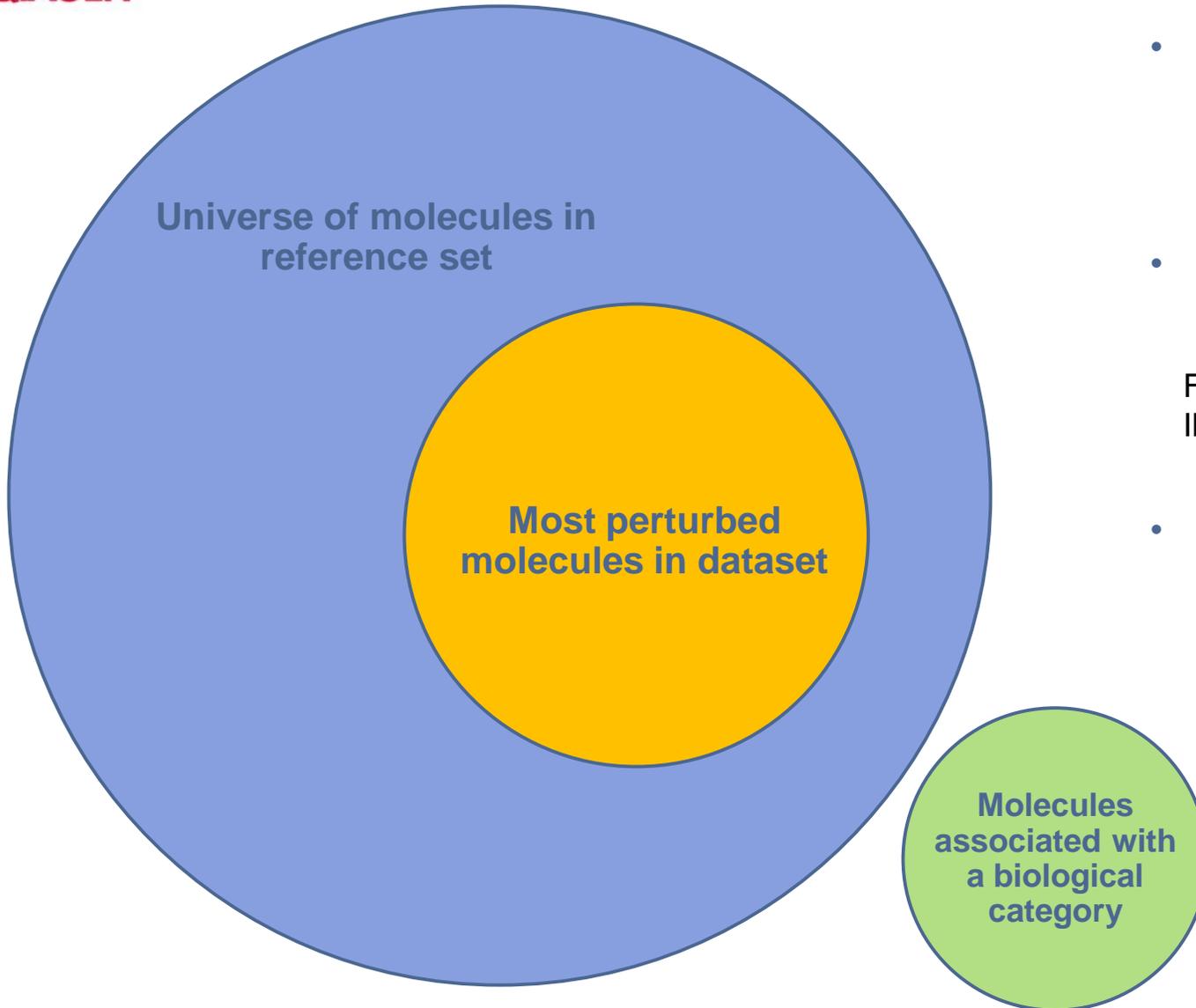
Symbol	Measurement Expr Log Ratio	+ △ ×	Expected
NRSA2	↓ -1.002	↓	Down
ABCB11	↓ -1.056	↓	Down
CYP2B6	↓ -3.063	↓	Down
PPARGC1A	↓ -2.495	↓	Down
ACOX1	↓ -1.727	↓	Down
SLCO1B3	↑ 3.223	↓	Down
TLR4	↑ 1.213	↑	Up
LY96	↑ 1.189	↑	Up
IL1R1	↑ 1.634	↑	Up
IL1RAP	↑ 1.046	↑	Up
IL1B	↑ 3.890	↑	Up
LIPC	↓ -1.375	↑	Up

Symbol	Measurement Expr Log Ratio	+ △ ×	Expected
CREB3L3	↓ -1.536	↑	Up
IHH	↓ -1.173	↑	Up
PBX1	↓ -1.037	↑	Up
CD86	↑ 1.016	↓	Down
IL1RAP	↑ 1.046	↓	Down
PKM	↑ 1.082	↑	Up
HLA-DMB	↑ 1.106	↓	Down
IL18RAP	↑ 1.124	↓	Down
CREB5	↑ 1.148	↑	Up
CREB3L2	↑ 1.179	↑	Up
CCN4	↑ 1.204	↑	Up
TLR4	↑ 1.213	↓	Down

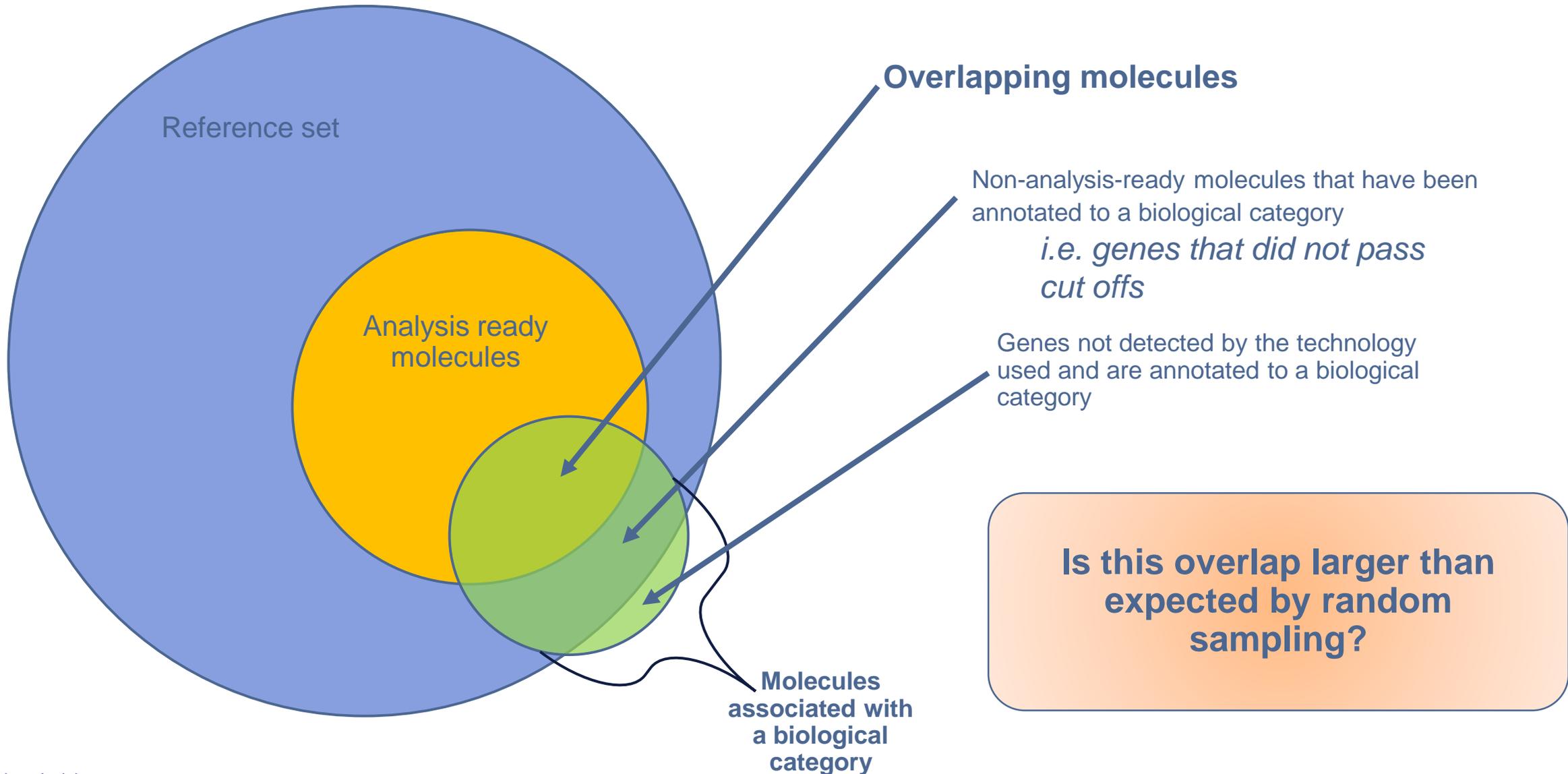
Z-score = 2.4
10/12 measurements match expected
Mostly matching
Signal predominantly points to predicted activation

Z-score = -2.236
4/12 measurements match expected
Mostly anti-matching
Signal predominantly points to predicted inhibition

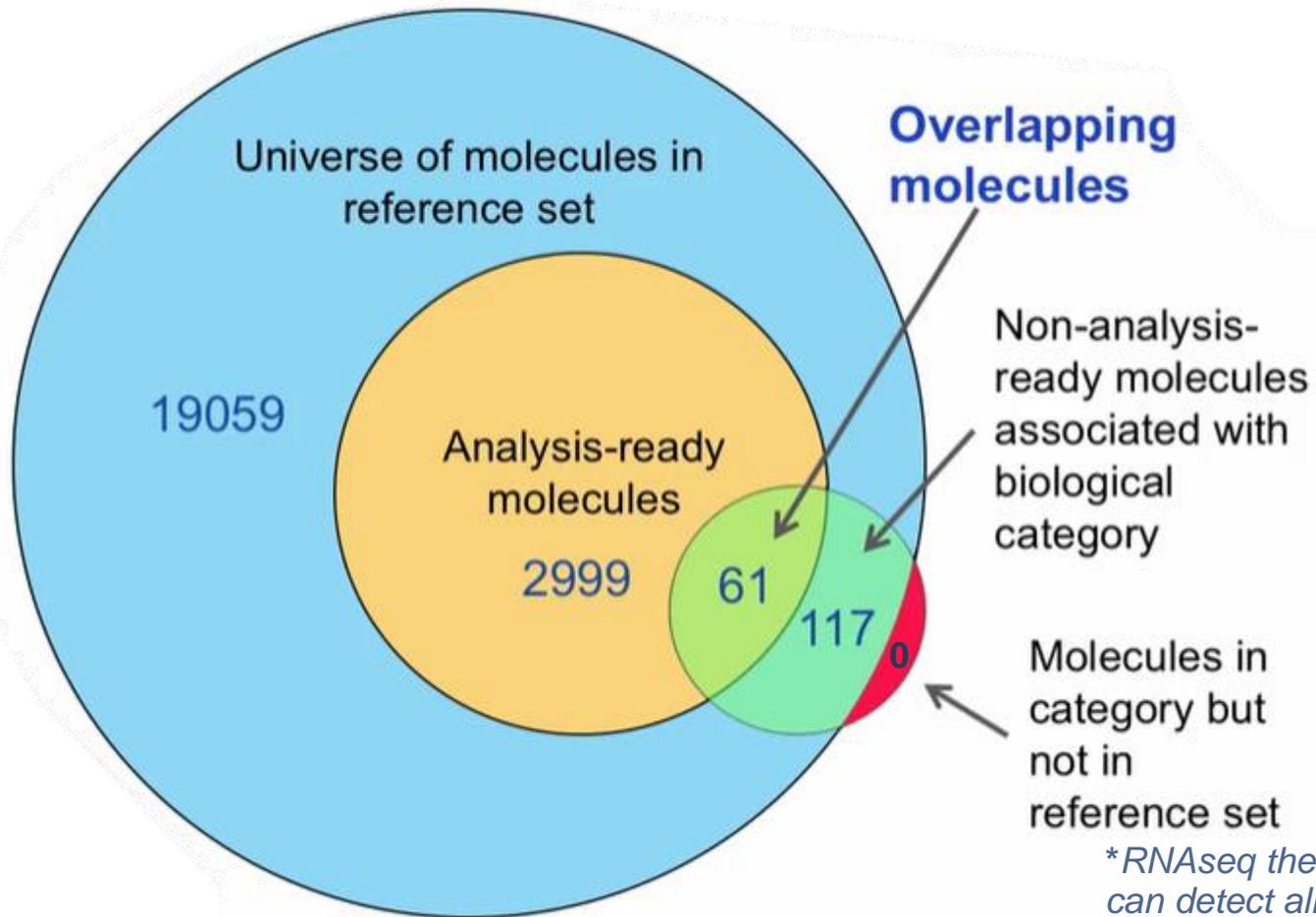
IPA Analysis Tabs



- Reference set is typically all genes or proteins that can be reliably detected by the ‘omics technology used
- Most perturbed is a subset of measured genes/proteins that were significantly different between experimental groups
Fold change cut offs and p-value cut offs used
IPA calls these “Analysis-ready molecules”
- Molecules associated with a biological category are a set of genes/proteins that the IPA knowledgebase has annotated to be important for a biological pathway, function, or disease.



p-value: the probability of observing a result as extreme or more extreme, if the null hypothesis is true



**RNAseq theoretically can detect all molecules*

H_0 = Overlap of molecules for a particular biological category is due to chance

α (significance level) = 0.05

		Category 1		Total
		Group 1	Group 2	
Category 2	Group 1	a	b	a+b
	Group 2	c	d	c+d
Total		a+c	b+d	a+b+c+d = n

$$p\text{-value} = \frac{(a+b)!(c+d)!(a+c)!(b+d)!}{n!a!b!c!d!}$$

P-value = 2.08×10^{-12}

We can reject the null hypothesis

Summary Tab

QIAGEN IPA Interpret ← View your analysis with AI-enhanced interpretation and dynamic visualizations

Export:

> Experiment Metadata

> Analysis Settings

∨ Top Canonical Pathways

Name	p-value	Overlap
Signaling by Rho Family GTPases	1.91E-14	23.5 % 63/268
RHO GTPase cycle	5.41E-14	19.3 % 87/450
Smooth Muscle Contraction	2.91E-12	48.8 % 21/43
Sertoli Cell-Germ Cell Junction Signaling Pathway (Enhanced)	2.44E-11	22.4 % 52/232
Cell junction organization	2.47E-11	32.6 % 30/92

∨ Top Upstream Regulators

∨ Upstream Regulators

Name	p-value	Predicted Activation
TNF	6.16E-30	Activated
ARID1A	1.03E-26	
TP63	2.17E-24	
GLI1	2.87E-24	Inhibited
ERBB2	4.36E-21	

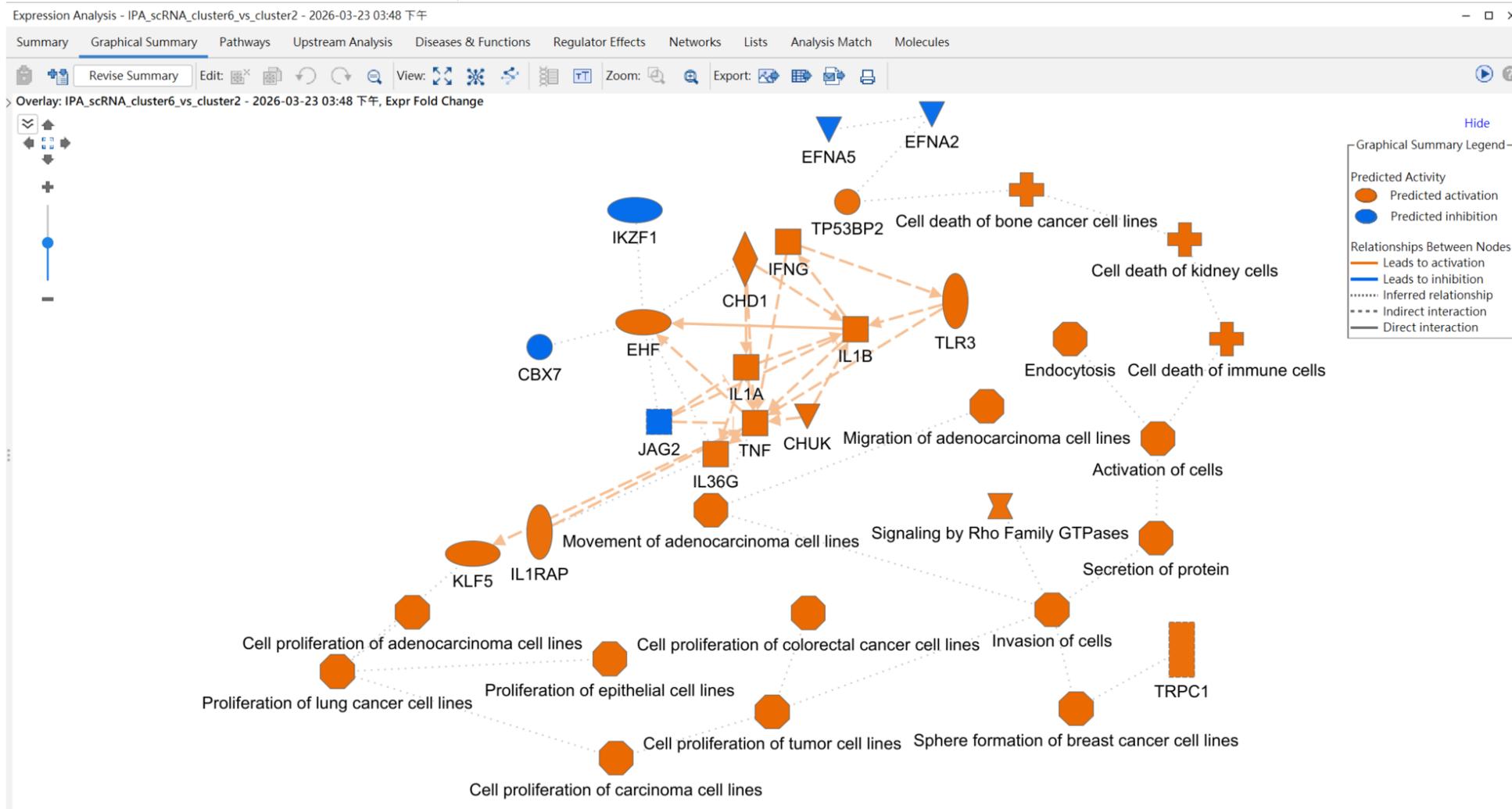
∨ Causal Network

Name	p-value	Predicted Activation
OLR1	1.53E-52	
ESR1	5.90E-51	
MYD88	4.77E-50	
ST6GAL1	3.26E-48	Activated
HSPA1A	3.52E-48	Activated

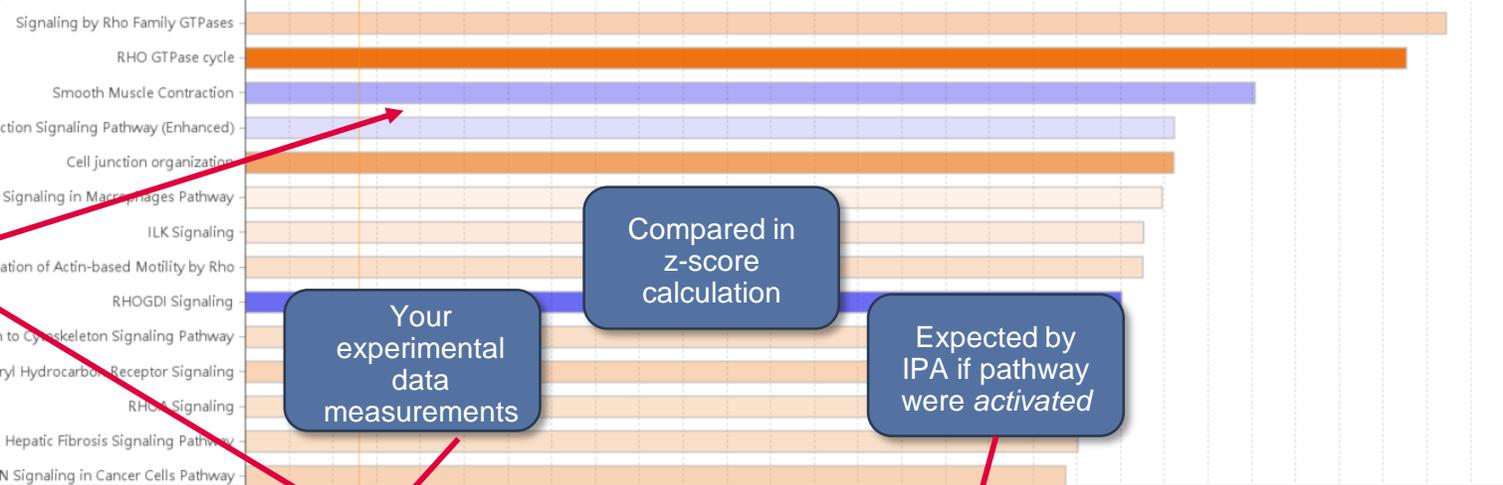
∨ To

Top 5 for all analysis modules and a quick high-level look at your data

Cluster 6 vs Cluster2



Graphical display of the top biological themes and features within your data with added AI inferences (dotted lines)



Change chart characteristics

Change chart view

Export data or picture

Click on bar to display chart below

Genes in data set annotated to selected pathway

View network map of pathway

Your experimental data measurements

Compared in z-score calculation

Expected by IPA if pathway were activated

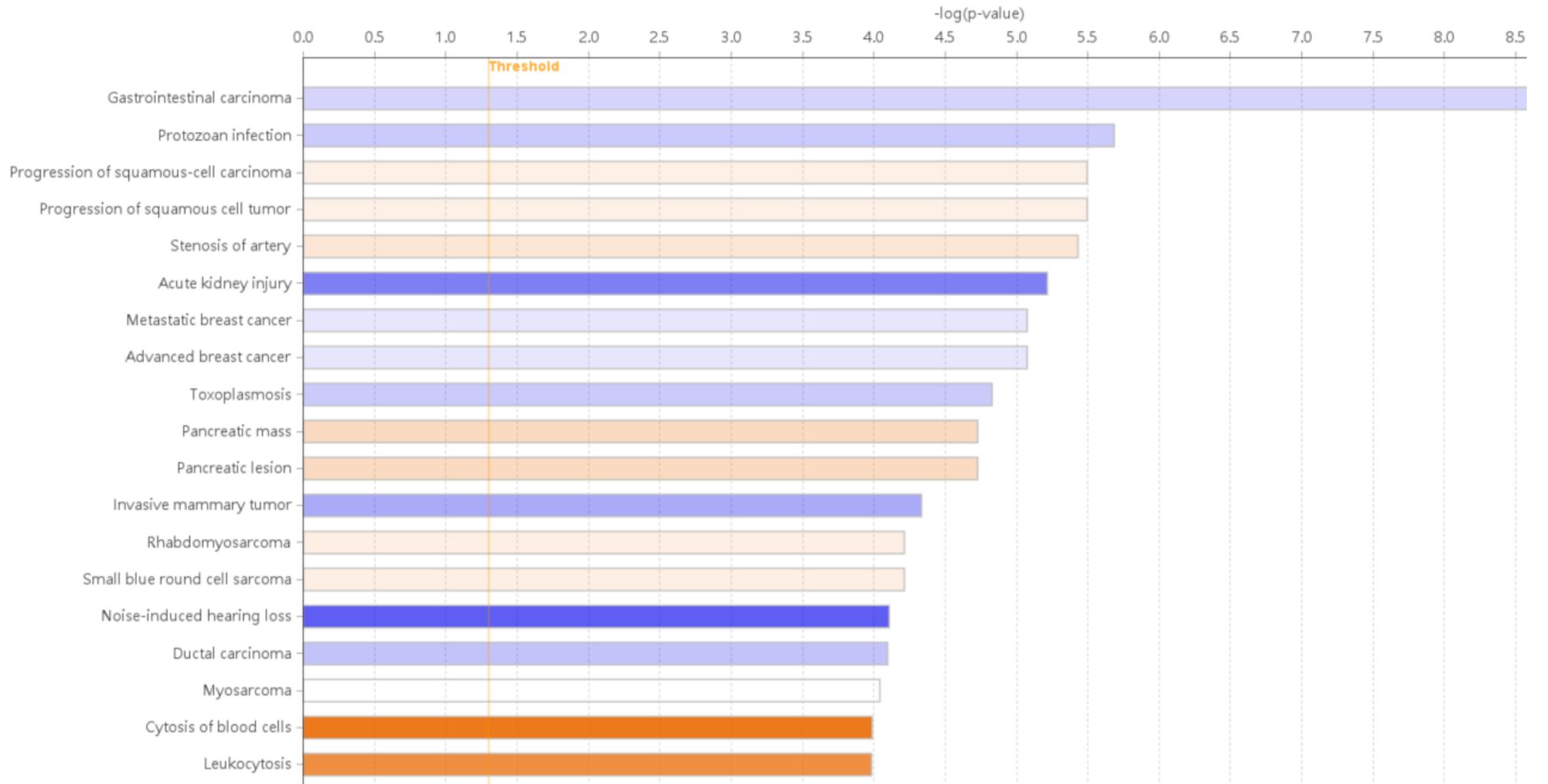
molecule(s) associated with **RHO GTPase cycle** [Ratio: 87/450 (0.193)] [z-score: 6.174] [p-value: 5.41E-14]

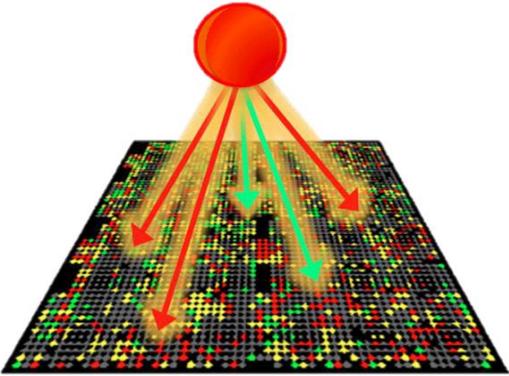
Add To My Pathway Add To My List Create Dataset Customize Table Expand

Symbol	Entrez Gene Name	Identifier	Measurement	Add/Remove column(s)	Expected	Location	Type(s)	Biomarker Applicat...	Drug(s)
		Gene Symbol - hum...	Expr Log Ratio	Expr p-value	Expr False Discover...				
ABL2	ABL proto-oncogene 2, nor	ABL2	↑1.039	6.63E-40	1.29E-35	↑ Up	Cytoplasm	kinase	dasatinib, nilotinib ...all 2
ADD3	adducin 3	ADD3	↑1.920	6.59E-121	1.29E-116	↑ Up	Cytoplasm	other	
AKAP13	A-kinase anchoring proteir	AKAP13	↓-1.054	5.78E-07	1.13E-02	↑ Up	Cytoplasm	other	
ARAP1	ArfGAP with RhoGAP dome	ARAP1	↑1.889	5.63E-49	1.10E-44	↑ Up	Cytoplasm	other	
ARAP2	ArfGAP with RhoGAP dome	ARAP2	↑2.914	5.38E-74	1.05E-69	↑ Up	Cytoplasm	other	

Metabolic and cell signaling pathways that are enriched in your data with activity prediction

■ positive z-score
 ■ z-score = 0
 ■ negative z-score
 ■ no activity pattern available





- Use experimentally observed relationships (vs. Predicted event) between Upstream Regulators and genes to predict potential regulator and activation
- Predict activation or inhibition of regulator to explain the changes in gene expression in your dataset
- Calculates two complementary statistical measures:
 - Activation z-score
 - Overlap p-value

Upstream Regulator	Expr Log Ratio	Molecule Type	Predicted Activation S...	Activation z-score	Flags	p-value of overlap	Target Molecules in D...
TNF	↑5.257	cytokine	Activated	6.325	bias	6.16E-30	ACTA2, ADAMTS4, ...all 160
ARID1A		transcription regulator		-1.799		1.83E-26	ACTA2, AGRN, ALD...all 98
TP63		transcription regulator		0.806		2.17E-24	ADA2, ADAMTS1, ...all 192
GLI1		transcription regulator	Inhibited	-4.301		2.87E-24	AKR1C3, AKT1, AL...all 142
ERBB2	↑1.439	kinase		0.231	bias	4.36E-21	ACP2, AKT1, ANGP...all 98
ESTROGEN RECEPTOR (family)		group		3.251		7.34E-20	ANXA1, BMP7, C3...all 63
PDGF-BB (complex)		compl		-0.279	bias	1.63E-19	AHR, ATF3, ATP2B1, ...all 41
TP53	↑1.826	transc		1.563		5.50E-18	ACLY, ACTA2, AKT1, ...all 157
FTO		enzym		-1.680		1.02E-16	ALDH1A1, ALKBH5, ...all 48
SMARCA4	↑0.940	transc		0.937	bias	2.03E-16	A2M, ABRACL, AC...all 106
GPER1		G-protein coupled receptor		-0.451	bias	2.83E-16	ATF3, CCN1, CCN2, ...all 27
EZH2	↑0.758	transcription regulator	Activated	3.703	bias	3.54E-16	ATAD2, CALD1, C...all 76
FOXA1		transcription regulator		-1.307	bias	1.83E-15	AGR2, ALDOA, ANX...all 50
IFNG		cytokine	Activated	4.320	bias	4.97E-15	ADA2, ADAM17, AGT...all 88
SRF	↑1.354	transcription regulator	Inhibited				ACTG2, AP...all 41
YAP1	↑0.823	transcription regulator	Activated				ADAMTS4, ...all 86
TGFB1		growth factor					ANGPTL4, ...all 102
SSTR2		G-protein coupled receptor					ATF3, BST2, ...all 35
AHR	↑1.816	ligand-dependent nuclear rece...					ACTA2, ADA...all 51
PRKCD	↑1.187	kinase	Activated				P32, BIRC1, ...all 41
EHMT1	↑0.788	enzyme	Activated				BCR, C3, ...all 38
TEAD4	↑0.986	transcription regulator					2, CALD1, C...all 28
OGA	↓-0.488	enzyme					ADAP1, AL...all 56
IGG (complex)		complex	Inhibited				ATP1B1, ...all 43
JUN	↓-1.747	transcription regulator	Activated				AR, ATF3, ...all 52
RRAS2	↑1.445	enzyme	Activated				ATP2B1, CASP4...all 41
PGR		ligand-dependent nuclear rece...	Activated				AKR1C3, A...all 46
FOXO3	↓-0.401	transcription regulator					AR, ASS1, ...all 22
LH (complex)		complex					ACTA2, ACT...all 54
EPHA2	↑3.518	kinase					ATF3, CDKN1A...all 16
CG (complex)		complex					S1, ALDH1A1, r...all 67
CST5		other					ACAT2, A...all 62
CDKN1A	↓-2.661	other	Activated				AP1M2, BAX, ...all 42
FSH (complex)		complex					ACTA2, ACT...all 61
ESR2		ligand-dependent nuclear rece...					ADAMTS1, ...all 50

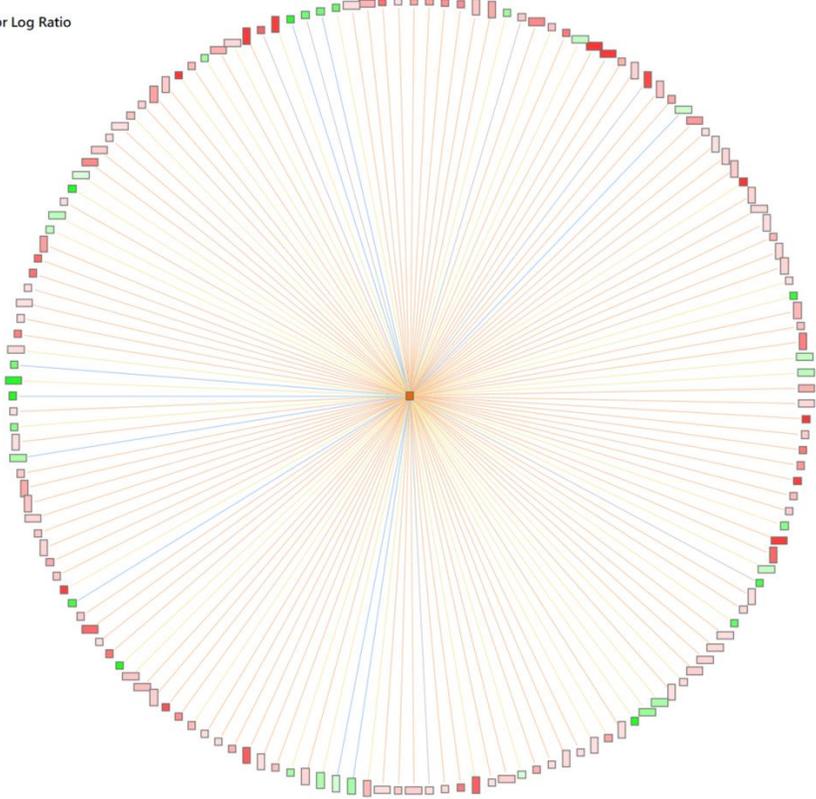
Immediately upstream of dataset genes regulators

One additional level upstream of regulatory networks

Measurement from your dataset for this regulator

Regulator predicted by IPA using patterns seen in your data (no measurement)

Highlight row and click to display at network map



Export

Filter icons

Activity prediction

Genes that this regulator targets present in your filtered dataset

P-value of significance

Regulators that may be contributing to the signal observed in your dataset have been highlighted in orange. ** ALL COLUMN

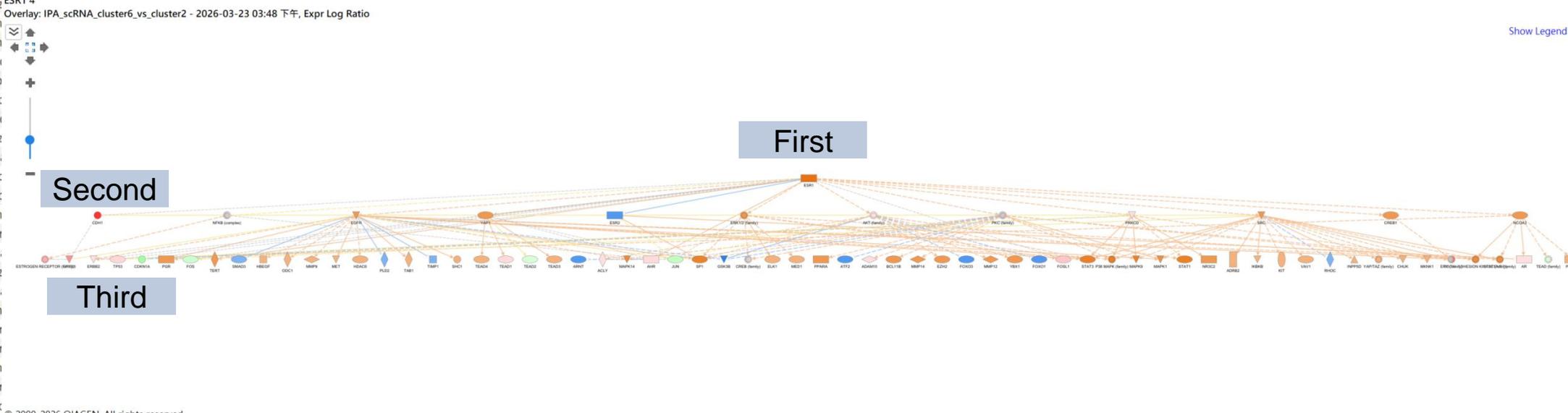
dataset and some have

Upstream Regulators Causal Networks

Add To My Pathway Add To My List Display as Network Activity Plot Customize Table p-val... 1.53E-52 - 5.87E-39 (1/9)

Master Re...	Expr Lo...	Molecu...	Partici...	Depth	Predict...	Notes	Activat...	p-v...	Netwo...	Target ...	Causal ...	Target...	TGFB1 ...	TGFB1 ...	Increas...	Decrea...
OLR1		transmembran...	↑ADAM, ...all 42	3			1.933	1.53E-52	1.00E-04	↑A2M, ...all 407	407 (42)	42	1 1	AU(1)	ARID1A, ...all 2	↑CBX5, P...all 4
ESR1	↑3.710	ligand-depend...	↑ACLY, ...all 77	3			1.871	5.90E-51	3.00E-04	↑ABCC4, ...all 504	504 (77)	77	2 159	AB(75), AD(6), ARID1A, ...all 13	↑KLF9, ...all 2	
MYD88	↑1.305	other	↑ADAM, ...all 54	3			0.506	4.77E-50	1.00E-04	↑A2M, ...all 390	390 (54)	52	2 29	AB(7), DB(10), ↑ARIH2, ...all 3	↑HIVEP1, ...all 5	
ST6GAL1		enzyme	↑ACLY, ...all 76	3	Activated	biased	4.843	3.26E-48	1.10E-03	↑ABL2, ...all 435	435 (76)	74	2 34	AB(5), DB(4),	↑ERBB2, ...all 2	
HSPA1A	↓-1.471	enzyme	↑ADAM, ...all 66	3	Activated		5.118	3.52E-48	1.00E-04	↑ABCC4, ...all 462	462 (66)	66	2 21	AB(7), AD(3), ↑ING1, T...all 2	APP, EST...all 2	
CYBB		enz	ESR1 4													
POSTN		oth														
PYHIN1		oth														
PRL		cyt														
SRC (family)		gro														
S1PR2		G-γ														
SPP1		cyt														
TGM2		enz														
PAK4	↑1.459	kin.														
F2RL1	↑8.627	G-γ														
USP21		pep														
VIRMA		oth														
HIF1A	↑0.719	tra														
JAK3		kin.														
STUB1		enz														
PDPK1	↓-0.773	kin.														
NCAPG		oth														
ITGB4	↑5.408	tra														
TLR4		tra														
IGFBP2	↑1.232	oth														
YAP1	↑0.823	tra														
PPP5C		phc														
MAZ		transcription re...	↑ACLY, ...all 32	3	Activated	biased	5.871	2.46E-45	5.60E-03	↑A2M, ...all 326	326 (32)	32	2 10	AB(1), DB(3),		
NFE2L2		transcription re...	265 PR, ...all 43	3			0.157	4.08E-43	5.00E-04	↑ABCC4, ...all 365	365 (43)	43	1 1	DD(1)	↑ESR1, ...all 9	↑CFB, SP...all 2
NCL	↑0.257	other	AKT (fa... all 32	3			0.266	4.63E-43	1.20E-03	↑ABCC4, ...all 353	353 (32)	31	2 35	AB(18), AD(3), CMAS, C...all 2	CST5, PI3...all 2	
KLRK1		transmembran...	↑ACLY, ...all 57	3	Activated		4.538	8.16E-43	5.00E-04	↑ABCC4, ...all 376	376 (57)	55	2 18	AB(3), DB(5),	↑IL18, ...all 2	GLI1 ...all 1
AR	↑1.455	ligand-depend...	265 PR, ...all 88	3	Activated		2.778	9.14E-43	7.90E-03	↑A2M, ...all 498	498 (88)	87	2 142	AB(56), AD(4),	CBL, ↑C...all 13	CG (co...all 11
AXCL8	↑5.333	cytokine	↑ACLY, ...all 92	3	Activated	biased	4.270	1.43E-42	2.91E-02	↑A2M, ...all 495	495 (92)	88	1 1	DD(1)	ADORA3, ...all 79	ARID1A, ...all 29
IP6K2	↑1.015	kinase	AKT (fa... all 39	3			-0.157	2.36E-42	5.30E-03	↑ACP2, ...all 367	367 (39)	38	2 4	AB(2), DB(2)		CDK19 ...all 1
TNFSF12	↓-2.935	cytokine	↑ADAM, ...all 42	3	Activated	biased	2.372	2.42E-42	4.00E-03	↑ABLI, ...all 344	344 (42)	42	2 25	AB(8), DB(2),	↑ATG5 ...all 1	
RPS6KA3	↑1.404	kinase	↑AR, AT...all 72	3	Activated		3.463	2.97E-42	6.50E-03	↑A2M, ...all 469	469 (72)	69	2 28	AB(8), AU(2),	CSF2, FHL2...all 3	GLI1, ↑O...all 3
CD44	↓-0.957	other	↑ACLY, ...all 105	3			1.466	4.05E-42	1.57E-02	↑A2M, ...all 507	507 (105)	102	1 1	ID(1)	ALK, ↑C...all 36	BCOR, ...all 9

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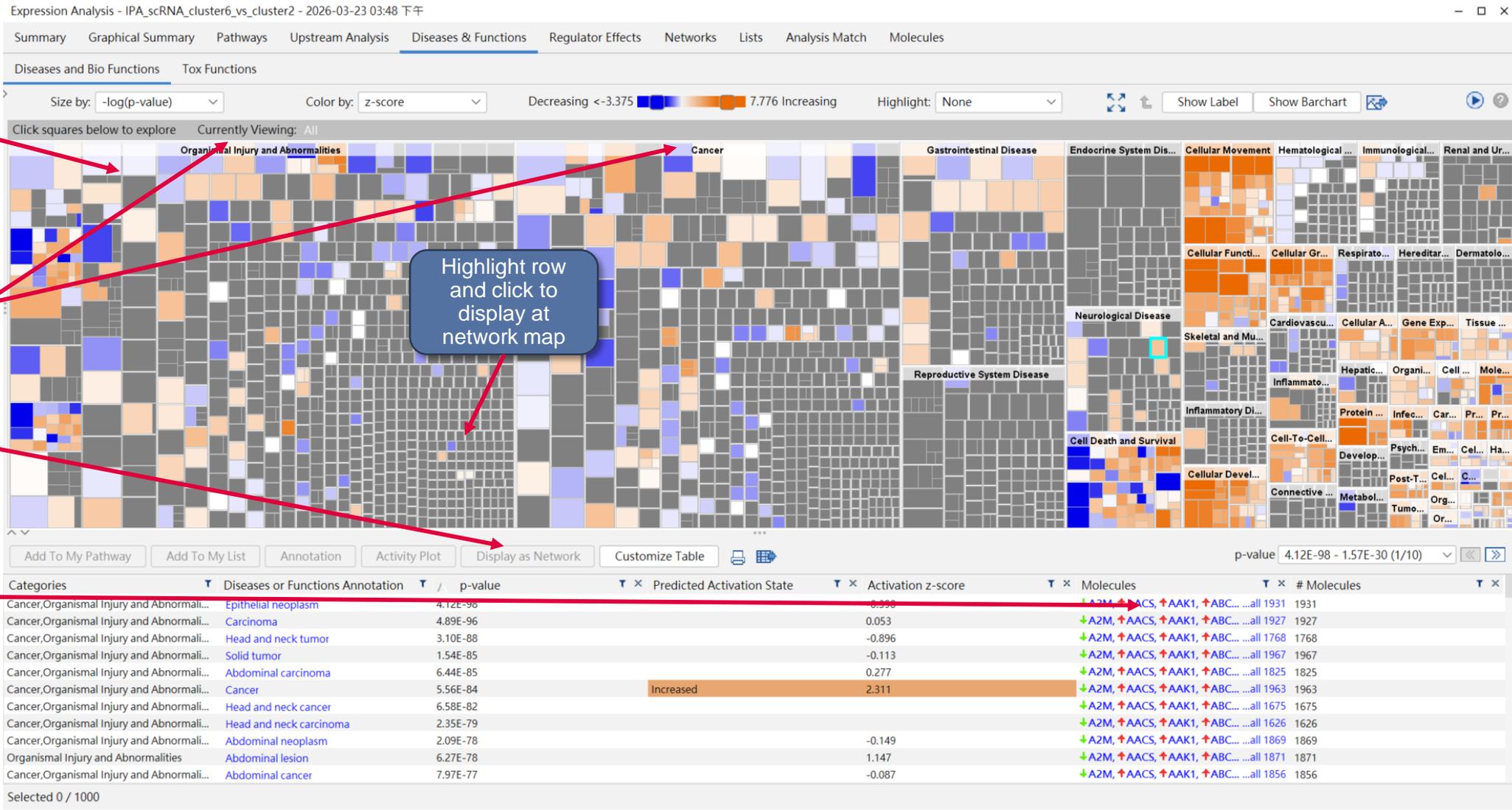


Color is activity prediction; size of square is p-value but can be changed

Organized by biological themes

Significance of enrichment

Genes from dataset involved in disease or function



Diseases and functions that may be key to the biology in your experimental data based on patterns of expression observed

ID	Consistency Score	Node Total	Regulator Total	Regulators	Target Total	Target Molecules	Disease & Function
1	37.593	34	6	IL1RL2, JAG2, MARCHF3, ...all 6	17	↑BCL10, ↑BIRC3, ↑C3, ...all 17	Activation of gene, Bi...all 11 36
2	33.724	39	7	↑IL1RAP, IL1RL2, JAG2, ...all 7	19	↑AHR, ↑BCL10, ↑C3, ...all 19	Activation of gene, A...all 13 37
3	32.163	48	12	↑CXADR, F13B, ↑GN...all 12	26	↑AREG, ↑BCL10, ↑C3, ...all 26	Activation of gene, A...all 10 23
4	31.500	30	5	JAG2, MARCHF3, mir-...all 5	16	↑BCL10, ↑C3, ↑CXCL1 ...all 16	Biosynthesis of mac...all 9 5
5	28.001	29	7	↑CXADR, ↑GNA13, ↑...all 7	12	↑BCL10, ↑C3, ↑CXCL1 ...all 12	Activation of respons...all 10 41
6	25.019	44	9	↑CXADR, F13B, ↑GNA...all 9	27	↑BCL10, ↑C3, ↑CFB, ...all 27	Cell movement of tum...all 8 33
7	20.960	18	2	↑CIC, ↑RPS6KB1 ...all 2	8	↑CCND1, ↑DHCR24, ↑...all 8	Biosynthesis of macro...all 8 50
8	19.645	29	6	↑IL1RAP, IL1RL2, ↑MA...all 6	17	↑BCL10, ↑CCN1, ↑C...all 17	Activation of gene, Infl...all 6 39%
9	17.898	23	4	↑ATP8B1, F13B, ↑GN...all 4	12	↑AREG, ↑CCN1, ↑C...all 12	Cell death of ovaria...all 7 21%
10	17.463	28	6	CES1, ↑IKBKG, ↑METT...all 6	17	↑BAX, ↑BIRC3, ↑CA...all 17	Cell death of stomach...all 5 33%
11	16.227	47	7	↑IL1RAP, IL1RL2, IL1RN...all 7	35	↓AGT, ↑APOL1, ↑BC...all 35	Inflammatory response...all 5 34
12	16.148	35	4	CSF (family), ↓ERN1, IF...all 4	21	↓B2M, ↑BAX, ↑BIRC3...all 21	Apoptosis of bone c...all 10 19
13	15.250	55	6	CHUK, IFNA2, NFKB (c...all 6	43	↑AHR, ↑BAX, ↑BBC3...all 43	Apoptosis of bone c...all 6 17
14	15.057	31	3	INTERFERON ALPHA (f...all 3	21	↓AGT, ↑APOL1, ↑BAX...all 21	Apoptosis of kidney c...all 7 19
15	14.378	26	4	INTERFERON ALPHA (f...all 4	18	↓AGT, ↑APOL1, ↑BAX...all 18	Apoptosis of kidney c...all 4 69
16	13.914	18	3	F13B, ↑GNA13, OSCAR...all 3	10	↑CXCL1, ↑CXCL2, ↑...all 10	Chemotaxis, Inflamma...all 5 33%
17	13.650	43	7	↑IL1RAP, IL1RL2, IL1RN...all 7	31	↑BCL10, ↓BST2, ↑C3...all 31	Adhesion of tumor cel...all 5 29%
18	13.193	30	5	↓ERN1, ↑IKBKG, ↑PP...all 5	20	↓ATF3, ↑BIRC3, ↑CD...all 20	Cell proliferation of br...all 5 32%
19	13.039	80	11	↑ATP8B1, CES1, ↑CX...all 11	60	↑AREG, ↑ATF5, ↑B2M...all 60	Cell movement of ova...all 9 16%
20	12.810	56	9	↑ATP8B1, CES1, CHUK...all 9	43	↑AR, ↑BIRC3, ↑C3, ...all 43	Chemotaxis, Inflamma...all 4 19%
21	12.780	40	6	↑CARM1, CHUK, ↑CU...all 6	30	↑ADAM17, ↓AGT, ↑...all 30	Assembly of protein-p...all 4 4%
22	12.728	25	4	CD28, CD3 (complex), ...all 4	18	↑BAX, ↑CCND2, ↑C...all 18	Invasion of carcinoma...all 3 33%
23	12.612	25	4	↑IKBKG, ↑MYD88, ↓S...all 4	17	↑BCL10, ↑BIRC3, ↓B...all 17	Activation of gene, Act...all 4 63%
24	12.492	27	2	↑DCAF13, WNT3A ...all 2	18	↑AHR, ↑AQP3, ↑BAX...all 18	Activation of protein ...all 7 43%
25	12.366	31	4	CD28, CD3 (complex), ...all 4	22	↓AGT, ↑APOL1, ↑BAX...all 22	Apoptosis of kidney c...all 5 20%
26	10.936	39	6	↑IL1RAP, IL1RL2, ↑MY...all 6	29	↓AGT, ↑BCL10, ↓BST2...all 29	Adhesion of tumor cel...all 4 13%
27	10.752	18	3	↑HOXB3, HOXBLINEC, ...all 3	10	↑BIRC3, ↑CCND1, ↓...all 10	Activation of gene, Ap...all 5 40%
28	10.510	27	3	CHUK, ↓ECSIT, ↓STIN...all 3	20	↑CASP1, ↑CCND1, ↑...all 20	Distribution of protein...all 4 0%
29	10.171	80	8	↑CARM1, ↓CHD1, CH...all 8	65	↓AGT, ↑APOL1, ↑BAX...all 65	Assembly of protein-p...all 7 16%
30	9.800	32	4	↑EFNA5, IL1RN, NONO...all 4	25	↑ADAM17, ↑BAX, ↑...all 25	Cell death of immune ...all 3 25%
31	9.553	21	2	↑EFNA5, ↑RC3H1 ...all 2	15	↑CCN2, ↑CLDN1, ↑...all 15	Invasion of tumor cell ...all 4 38%
32	9.449	12	2	↑METTL3, ↑MYD88 ...all 2	7	↑BAX, ↑CCND1, ↑CD...all 7	Inhibition of mRNA, Tr...all 3 33%
33	9.167	44	5	CES1, ↓ETV3, IFNL1, I...all 5	36	↑AREG, ↑BIRC3, ↑C...all 36	Activation of cells, Che...all 3 7%
34	9.071	37	5	↑IL1RAP, IL1RL2, ↑MY...all 5	28	↓B2M, ↑CASP4, ↑CC...all 28	Endocytosis, Inflamma...all 4 30%
35	9.000	34	5	IGG (complex), ↑IL1RAP...all 5	25	↑ADGRG1, ↑CCN2, ↓...all 25	Engulfment of cells, In...all 4 20%
36	8.928	64	7	CD28, ↑IL1RAP, IL1RL2...all 7	53	↑AR, ↑BIRC3, ↑BTG2...all 53	Cell movement of squ...all 4 25%
37	8.372	19	3	↑IKBKG, ↑MYD88, ↓S...all 3	12	↑BIRC3, ↑CASP1, ↑...all 12	Activation of gene, Re...all 4 75%
38	7.826	28	3	↓FLNA, SMARCAL1, W...all 3	20	↑ACLY, ↑AHR, ↑AP...all 20	Cell proliferation of h...all 5 20%

Network of molecules and regulators that are predicted to be involved in diseases & functions

How matching your data is with the expected directions in IPA for the diseases & functions they're predicted to effect

Regulators involved in network

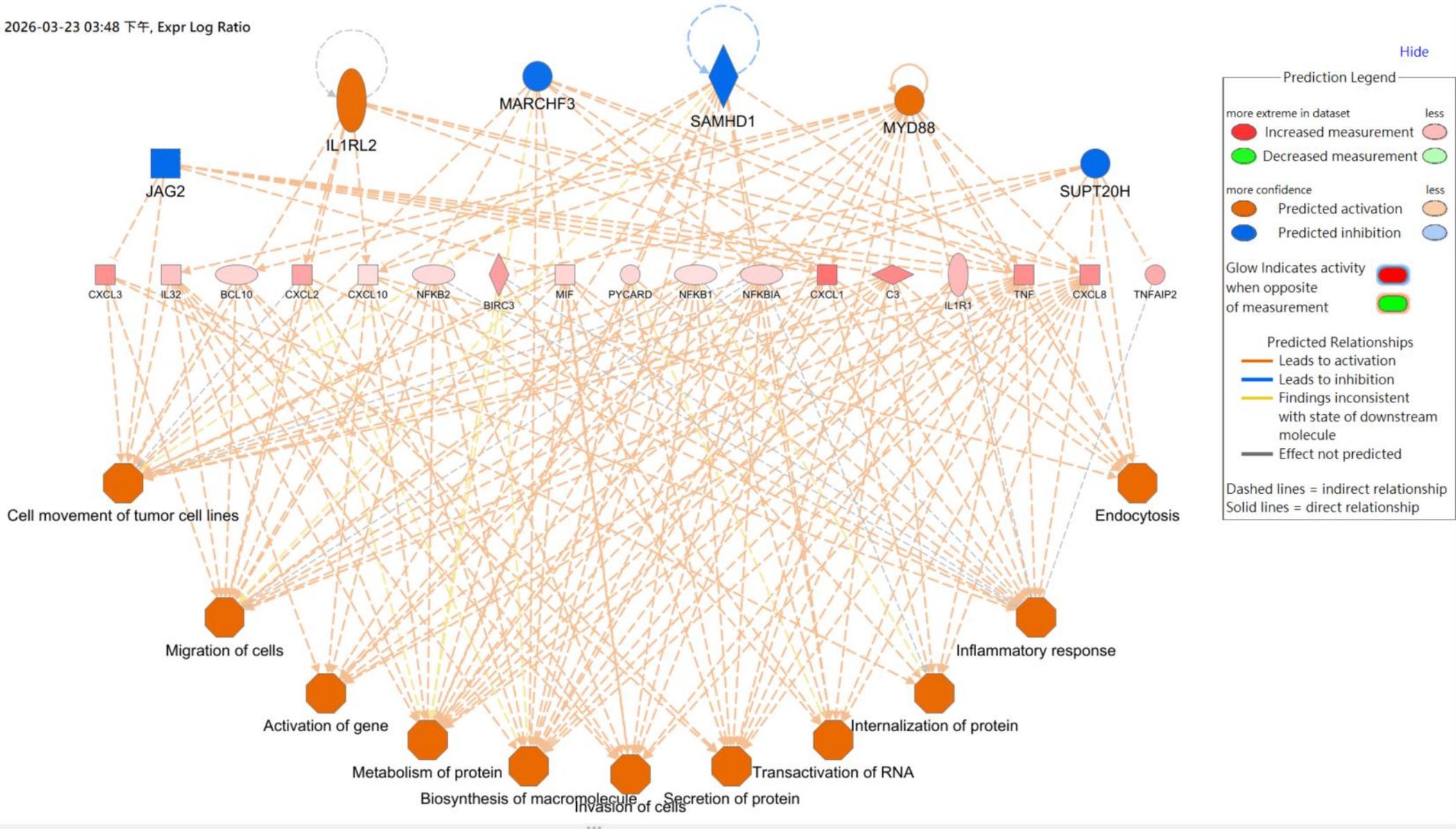
Genes from dataset involved in disease or function

Disease or function

Known connections in IPA between regulator and disease & function-discover novel relationships

Ties dataset molecules and regulators to a predicted phenotypic outcome

15
 Overlay: IPA_scRNA_cluster6_vs_cluster2 - 2026-03-23 03:48 下午, Expr Log Ratio



Network of highly connected molecules, click to open network map

Molecule in bold is in your dataset; unbolded have been added to maximize connectivity

Based on a p-value calculation how likely molecules exist as part of a network than chance alone

Expression Analysis - IPA_scRNA_cluster6_vs_cluster2 - 2026-03-23 03:48 下午

Summary Graphical Summary Pathways Upstream Analysis Diseases & Functions Regulator Effects **Networks** Lists Analysis Match Molecules

Networks Overlapping Networks

View Networks Add To My Pathway Add To My List Merge Networks Functions Annotation Customize Table Expand

The analysis is composed of 25 networks. To view a network, select the appropriate network(s) and click View Networks. To merge selected networks, click Merge Networks. Total selected molecules: 0

ID	Molecules in Network	Score	Focus Molecules	Top Diseases and Functions
1	↑ACBD3 , ↑ALDH5A1 , ↑ALG8 , ↑B3GNT5 , ↑BOK , ↑BRI3BP , ↑C19orf33 , ↑CDK6 , ↑CEP170B , ↑CNDP2	34	35	Cell Cycle, Endocrine System Disorders, Gastrointestinal Disease
2	↑ACP2 , ↑AHS1 , ↑B3GALT6 , ↑BCAM , ↑BPNT2 , ↑C1GALT1 , ↑CDC42EP3 , ↑CHD7 , ↑CKS2 , ↑CLDN4	32	34	Embryonic Development, Organismal Development, Tissue Developm...
3	↑ANK3 , APC (complex), ↑APH1A , ↑CDC42EP2 , ↑CDH1 , ↑CLDN1 , ↑CLDN16 , ↑CRB2 , ↑CYTOR , ↑EPCAM	29	33	Cellular Movement, Dermatological Diseases and Conditions, Heredita...
4	↑ADGRA3 , ↑AR , ↑ASS1 , ↑CHPT1 , ↑CNKSR1 , ↑CTSC , ↑DEFB1 , ↑DHCR24 , ↑DHRS11 , ↑DHRS3	29	33	Cellular Movement, Hereditary Disorder, Organismal Injury and Abno...
5	↑ABLIM1 , ↑AIMP2 , ↑AKR1C3 , ↑CDK16 , ↑CSNK2A2 , ↓EDNRA , ↑FILIP1L , ↓HEXIM1 , HSP90 (family), ↑IP6K2	29	33	Cellular Assembly and Organization, Developmental Disorder, Heredit...
6	↑AGTRAP , ↑APRT , ↑AQP3 , ↑CHCHD5 , ↑CTSH , ↓DCN , ↑ENO1 , ↑ERBB4 , ↑GNG11 , ↓ITGA7	29	33	Carbohydrate Metabolism, Organismal Injury and Abnormalities, Sma...
7	↑AKT , ↑B4GALT5 , ↑BAIAP2L1 , ↑BASP1 , ↓CALM1 , Collagen type I (complex), ↑DPP3 , ↑EEA1 , ↑ERO1A , ↑FOLH1	28	32	Cellular Assembly and Organization, Neurological Disease, Organisma...
8	↓AKTIP , ↓ARMCX1 , ↓C7 , ↑CAMSAP3 , ↑CCND1 , CDK4/6 , ↑COPG1 , ↑CPED1 , ↑DDX52 , ↑FAM204A	28	32	Cancer, Organismal Injury and Abnormalities, Reproductive System Di...
9	↑ARK2N , ↑ARPC5L , ↓CAV1 , ↓CAV2 , ↑CAVIN1 , ↓CAVIN3 , ↑CCHCR1 , ↑CELSR2 , ↑CIMAP1B , ↑COBL	28	32	Cellular Assembly and Organization, Cellular Function and Maintenance...
10	↑ANKRD28 , ↑APOO , ↑ATAD3A , ↓B2M , ↑CARD16 , ↑CD83 , ↓CD99 , CSF, ↑EMP1 , ↓FOSB	28	32	Hematological System Development and Function, Humoral Immune ...
11	↑ACSL5 , ↑AGRN , ↓ANGPTL4 , AP1 (family), ↑ARHGAP18 , ↑BARX2 , ↑CDH2 , ↑CDH3 , ↑CEBPG , ↑CNFN	28	32	Cell-To-Cell Signaling and Interaction, Cellular Function and Mainten...
12	↑ADGRG2 , ↑ALDH1A1 , ↓ALKBH5 , ↓BCAS2 , ↓BST2 , ↑CRB3 , ↑CTBP1 , ↑DDAH1 , ↑EML4 , ↑FAM83H	28	32	Cell Death and Survival, Organismal Injury and Abnormalities, Tissue ...
13	↑APOBEC3C , ↑ATIC , AURK, ↑CASP2 , ↑CC2D1A , ↑CDK7 , CERS, ↓COXFA12 , ↑CRACR2B , ↑DLGAP1	26	31	Cell Death and Survival, Nucleic Acid Metabolism, Small Molecule Bio...
14	↑ADD3 , ↑ARAP1 , ↑ATP5MF , ↓CARMN , ↓COX7A1 , ↑CYP3A5 , ↑DENND4A , ↑DMAC2L , ↑EIF3B , ↑GATD3	26	31	Embryonic Development, Organismal Development, Organismal Injury and Abno...
15	↑ABO , ↑ANXA2 , ↑BTG2 , ↑CASP1 , ↑CHD1 , ↑CHD3 , Collagen type II, ↑CXCL1 , ↑CXCL2 , ↑CXCL5	26	31	Cellular Movement, Infectious Diseases, Skeletal and Cartilage Develo...
16	↑ACAT1 , ↑ACTA2 , ADCY, ↑AMOTL2 , ↑ARHGAP32 , ASC/CASP1/NALP3, ↑CLU , ↑COL3A1 , Complement component 1, ↑CP	26	31	Cardiovascular Disease, Infectious Diseases, Organismal Injury and Abno...
17	↓A2M , ↑ADGRG1 , ↑BBLN , ↑CBX3 , ↑CFI , ↓COL1A2 , ↑COQ9 , ↑EPCAM3 , ↑HDGF , ↑HSPA1A	26	31	Cancer, Lipid Metabolism, Small Molecule Biochemistry, Organismal Injury and Abno...
18	↓ARPC1A , ↑ATP13A3 , ↑ATP2B1 , ↑ATP2C1 , ↑BIK , ↑CARM1 , ↑C2 , ↑CCN1 , ↑CD24 , CG	26	31	Cancer, Dental Disease, Gastrointestinal Disease
19	↑ABCC4 , ↑ALDH18A1 , ↑ATAD3B , ↑ATM19A2 , CDK (family), ↑CIAO2A , cyclin D, ↑EXOSC5 , ↓H2AZ1 , ↑KCTD1	24	30	Cancer, Cell Death and Survival, Organismal Injury and Abnormalities ...
20	↑AGPAT2 , ↑AP1M2 , ↑CDKN1A , ↑CDS1 , ↑CLIC3 , ↑DAPL1 , ENT, ↑EPS8L1 , ↑FBXW9 , ↑FHIT	24	30	Cell Cycle, Gastrointestinal Disease, Organismal Injury and Abnormalities ...
21	↓ACTG2 , ↑ACAD7 , ALP, ↓APOLD1 , BET, ↑C3 , ↑CFB , ↑FGFR2 , ↑FOS , ↑LIMS2	24	30	Cellular Movement, Glomerular Injury, Immunological Disease, Organismal Injury and Abno...
22	↑BRCE1 , ↑BCAT1 , ↑BCR , ↑CDKN2A , ↑CDKN2B , DNA methyltransferase, E2F, ↓EDIL3 , ↑EDN1 , ↑EFHC1	24	30	Cell-To-Cell Signaling and Interaction, Organismal Injury and Abnor...
23	↑ADAP1 , ↓AKIP1 , Ap1, ↑CASP4 , ↓CBLC , ↑CCN5 , collagenase, Complement, ↑DNAJC15 , ↑GALNT1	22	29	Cell Cycle, Cell Death and Survival, Organismal Injury and Abnormalities ...
24	↑AKT1 , alpha tubulin, ↑ATP9A , ↑BMP7 , ↑BMPR1B , ↑CLNS1A , ↑CYBA , ↑DCDC2 , ↑DIAPH1 , FCGR2	22	29	Cardiovascular System Development and Function, Cellular Movement, ...
25	↓AGT , ↑CAPG , ↑CASP8 , caspase 3/7, ↓COL6A1 , ↓COL6A2 , ↑COL9A2 , estrogen receptor, ↑KRT17 , ↑KRT18	22	29	Cancer, Cell Death and Survival, Organismal Injury and Abnormalities ...

Disease or function predicted to be an outcome

Networks constructed from your dataset with level of connectivity prioritized

Analysis Name	Project	Case	Case	Com	Com	Com	Land	Proje	Webli	CP (z...)	UR (z...)	CN (z...)	DE (z...)	z-sco...	DM (...)
5- Alzheimer's disease (AD);disease control [superi	SingleCellHuman	Alzheimer's ...	superior pari...	Cluster vs Ot...	microglial ce...	CMP:4pf9UK3c	SingleCellHu...	GSE146639_no	https://www....		26.46			6.61	0.42
1- Alzheimer's disease (AD);disease control;mild c	SingleCellHuman	Alzheimer's ...	superior pari...	Cluster vs Ot...	microglial ce...	CMP:6Yqxw6	SingleCellHu...	GSE146639_no	https://www....						4.62
2- Alzheimer's disease (AD);disease control;mild c	SingleCellHuman	Alzheimer's ...	superior pari...	Cluster vs Ot...	microglial ce...	CMP:7YTePVjn	SingleCellHu...	GSE146639_no	https://www....						3.53
3- Alzheimer's disease (AD);disease control;norma	SingleCellHuman	Alzheimer's ...	superior pari...	Cluster vs Ot...	microglial ce...	CMP:CMQ2XYI	SingleCellHu...	GSE146639_no	https://www....						-5.40
3- breast adenocarcinoma;breast cancer [periphei	SingleCellHuman	breast aden...	peripheral bl...	Cluster vs Ot...	circulating t...	CMP:GBfxWYrc	SingleCellHu...	GSE111065_no	https://www....	52.70	3.33		55.90	27.98	-11.48
4- breast cancer [peripheral blood] digitoxin;none	SingleCellHuman	breast cancer	peripheral bl...	Cluster vs Ot...	circulating t...	CMP:OwDj39X	SingleCellHu...	GSE111065_no	https://www....						9.40
1- breast cancer [peripheral blood] CMP_ONYmK	SingleCellHuman	breast cancer	peripheral bl...	Cluster vs Ot...	circulating t...	CMP:ONYmK4	SingleCellHu...	GSE111065_no	https://www....		18.90		64.95	20.96	20.40
2- breast cancer [peripheral blood] digitoxin;NA;n	SingleCellHuman	breast cancer	peripheral bl...	Cluster vs Ot...	circulating t...	CMP:uAl8cRcQ	SingleCellHu...	GSE111065_no	https://www....						3.57
4- breast carcinoma [breast] estradiol;ethanol CM	SingleCellHuman	breast carcin...	breast	Cluster vs Ot...	mammary gl...	CMP:zXLQWwl	SingleCellHu...	GSE107858_no	https://www....		36.06			9.01	2.79
1- breast carcinoma [breast] monolayer culture;sp	SingleCellHuman	breast carcin...	breast	Cluster vs Ot...	mammary gl...	CMP:W1Gp7St	SingleCellHu...	GSE124989_no	https://www....				-68.47	-17.12	
1- breast carcinoma [breast] estradiol;ethanol CM	SingleCellHuman	breast carcin...	breast	Cluster vs Ot...	mammary gl...	CMP:t1KdQ29c	SingleCellHu...	GSE107858_no	https://www....		4.47		-70.71	-16.56	
3- breast carcinoma [breast] monolayer culture C	SingleCellHuman	breast carcin...	breast	Cluster vs Ot...	mammary gl...	CMP:OEIpMsC	SingleCellHu...	GSE124989_no	https://www....						4.07
2- breast carcinoma [breast] estradiol;ethanol CM	SingleCellHuman	breast carcin...	breast	Cluster vs Ot...	mammary gl...	CMP:cJogjs1kg	SingleCellHu...	GSE107863_no	https://www....		-4.47		68.47	16.00	2.23
2- breast carcinoma [breast] sphere forming cultu	SingleCellHuman	breast carcin...	breast	Cluster vs Ot...	mammary gl...	CMP:LyJ0xLAh	SingleCellHu...	GSE124989_no	https://www....		-8.16		68.47	15.08	0.84
7- disease control [superior parietal cortex] CMP_	SingleCellHuman	disease control	superior pari...	Cluster vs Ot...	microglial ce...	CMP:g5sf6AEV	SingleCellHu...	GSE146639_no	https://www....						2.16
4- disease control [superior parietal cortex] CMP_	SingleCellHuman	disease control	superior pari...	Cluster vs Ot...	microglial ce...	CMP:V4ZvBJXc	SingleCellHu...	GSE146639_no	https://www....		28.87			7.22	-4.26
4- endometrial cancer (fallopian tube) none CMP_	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	fallopian tub...	CMP:nMxq2Wv	SingleCellHu...	GSE132149_no	https://www....		21.38		-58.63	-9.31	-1.16
3- endometrial cancer;endometrial squamous cell	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	ciliated epith...	CMP:GmOyJUt	SingleCellHu...	GSE132149_no	https://www....		-30.00	-24.49		-13.62	-6.26
5- endometrial cancer;endometrial squamous cell	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	stromal cell (...)	CMP:5gZtQK	SingleCellHu...	GSE132149_no	https://www....		-36.06			-9.01	-39.46
1- endometrial cancer;endometrial squamous cell	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	fallopian tub...	CMP:1UR4C0b	SingleCellHu...	GSE132149_no	https://www....		-28.87		-53.03	-20.48	10.10
2- endometrial cancer;endometrial squamous cell	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	fallopian tub...	CMP:l1Y0XPJ6	SingleCellHu...	GSE132149_no	https://www....						-0.70
7- endometrial cancer;ovary serous adenocarcino	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	leukocyte (cl...	CMP:2pY8mK3	SingleCellHu...	GSE132149_no	https://www....		-18.90		-59.95	-19.71	-34.34
6- endometrial squamous cell carcinoma;ovary se	SingleCellHuman	endometrial ...	fallopian tube	Cluster vs Ot...	fallopian tub...	CMP:Sim3ergq	SingleCellHu...	GSE132149_no	https://www....		-8.16		59.95	12.95	0.42
9- glioblastoma (GBM) [temporal lobe] CMP_i05C	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	astrocyte (clu...	CMP:i05Om8p	SingleCellHu...	PRJNA579593_	https://www....				30.62	7.65	3.09
5- glioblastoma (GBM) [temporal lobe] CMP_9yce	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	astrocyte (clu...	CMP:9ycejLbrV	SingleCellHu...	PRJNA579593_	https://www....						-1.72
4- glioblastoma (GBM) [temporal lobe] CMP_qVzI	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	radial glial c...	CMP:qVzBH2W	SingleCellHu...	PRJNA579593_	https://www....		16.33		45.07	15.35	-0.81
10- glioblastoma (GBM) [temporal lobe] CMP_MiI	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	microglial ce...	CMP:MiNRrDy	SingleCellHu...	PRJNA579593_	https://www....		30.51	20.00	25.00	18.88	5.56
1- glioblastoma (GBM) [temporal lobe] CMP_xrUc	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	oligodendro...	CMP:xrUgMo2	SingleCellHu...	PRJNA579593_	https://www....						-3.57
3- glioblastoma (GBM) [temporal lobe] CMP_aQK	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	astrocyte (clu...	CMP:aQK3oqV	SingleCellHu...	PRJNA579593_	https://www....						5.78
13- glioblastoma (GBM) [temporal lobe] CMP_YLZ	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	astrocyte;per...	CMP:YLZFFkMI	SingleCellHu...	PRJNA579593_	https://www....				70.71	17.68	
14- glioblastoma (GBM) [temporal lobe] CMP_jfCI	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	neural cell (cl...	CMP:jfCImeoly	SingleCellHu...	PRJNA579593_	https://www....		-4.47		69.60	16.28	2.23
11- glioblastoma (GBM) [temporal lobe] CMP_Qh	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	microglial ce...	CMP:QhOxGq	SingleCellHu...	PRJNA579593_	https://www....						6.04
2- glioblastoma (GBM) [temporal lobe] CMP_XEHt	SingleCellHuman	glioblastom...	temporal lobe	Cluster vs Ot...	astrocyte (clu...	CMP:XEHtK2dk	SingleCellHu...	PRJNA579593_	https://www....		24.49		33.07	14.39	1.31
4- lung adenocarcinoma (LUAD) [lung] CMP_I5D2	SingleCellHuman	lung adenoc...	lung	Cluster vs Ot...	CD8+ tissue...	CMP:I5D2HRBc	SingleCellHu...	GSE111894_no	https://www....			-22.36		-5.59	-9.46
3- lung adenocarcinoma (LUAD);lung squamous c	SingleCellHuman	lung adenoc...	lung	Cluster vs Ot...	cytotoxic T c...	CMP:WLWni68	SingleCellHu...	GSE111894_no	https://www....			22.36		5.59	9.46
6- melanoma [skin] CMP_Dg2w7W7z3iKe	SingleCellHuman	melanoma	skin	Cluster vs Ot...	melanoma c...	CMP:Dg2w7W	SingleCellHu...	GSE81383_non	https://www....				67.31	16.83	5.94
5- melanoma [skin] CMP_bKrEvTh94Fzx	SingleCellHuman	melanoma	skin	Cluster vs Ot...	melanoma c...	CMP:bKrEvTh9	SingleCellHu...	GSE81383_non	https://www....		8.16		59.95	17.03	12.94
7- melanoma [skin] CMP_ZMp0SQEfUV9	SingleCellHuman	melanoma	skin	Cluster vs Ot...	melanoma c...	CMP:ZMp0SQf	SingleCellHu...	GSE81383_non	https://www....		38.73		63.74	25.62	6.96
4- melanoma [skin] CMP_eE2PBgkEkuIW	SingleCellHuman	melanoma	skin	Cluster vs Ot...	melanoma c...	CMP:eE2PBgkI	SingleCellHu...	GSE81383_non	https://www....		8.16			2.04	1.87

nature communications



Article <https://doi.org/10.1038/s41467-024-47271-y>

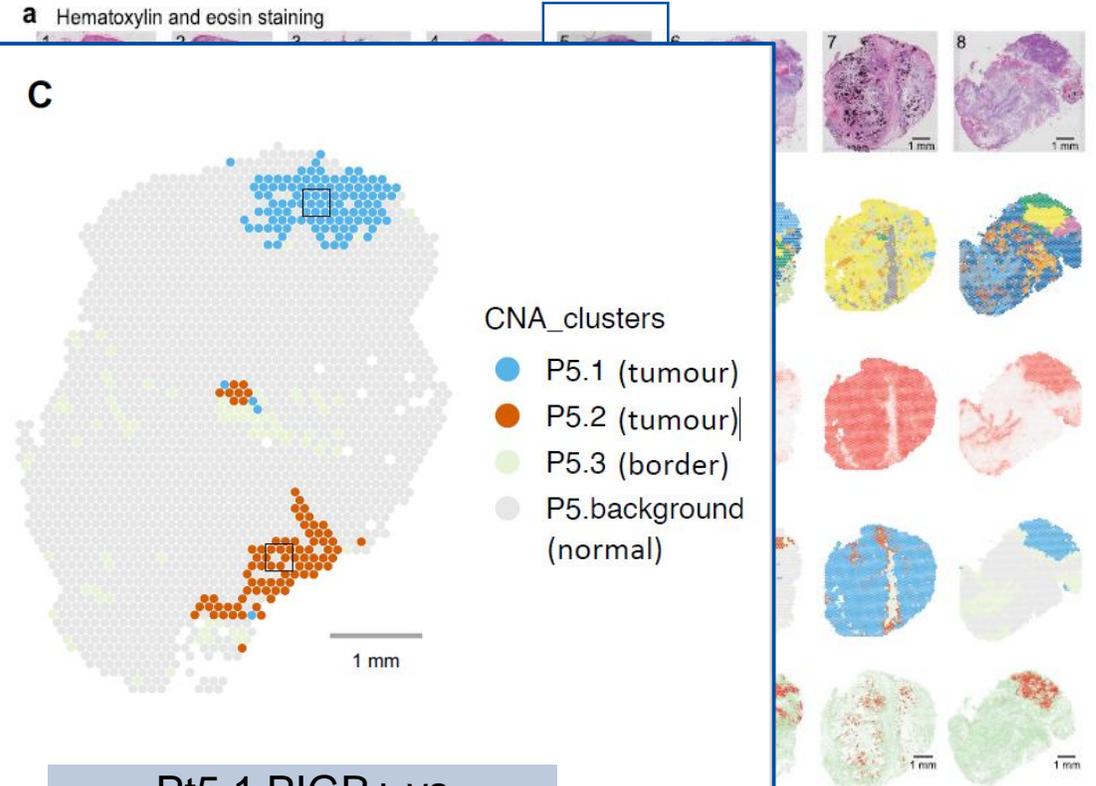
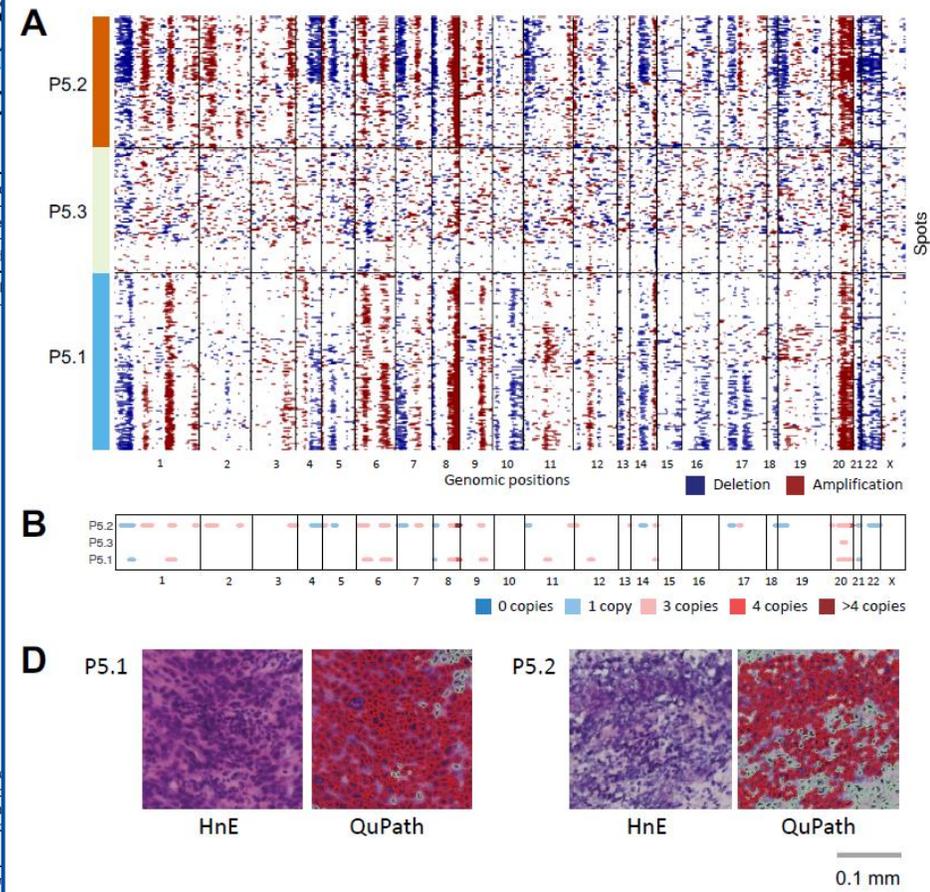
Spatial
 tumour
 local

Received
 Accepted
 Published
 Check

Ovarian
 worldwide
 common
 ovarian

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 6009, Au

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Pt5.1 PIGR+ vs
 Pt5.2 PTGS1+

tumour scores <0.15, green and pink correspond to border regions.

notation of the tissue sections using QuPath⁷⁷. Red, green corresponds to stroma. Scale bar = 1 mm. **a** and **b** are arbitrary but highlight that unsupervised data using Seurat (b), and clustering of inferCNV with spatial patterns that largely reflected the morphology shown in e. Supplementary Fig. S19 shows summarising the relationship between the clusters

PIGR+ 腫瘤亞群

PTGS1+ 腫瘤亞群

	A	B	C	D	E	F
1	Gene	avg_logF	pct.1	pct.2	p_val_adj	pair of malignant subclones
2	IGHM	1.31	0.952	0.737	1.11E-09	P5.2_vs_P5.1
3	PTGS1	1.17	0.917	0.544	3.97E-18	P5.2_vs_P5.1
4	ALPG	1.05	0.774	0.14	5.42E-18	P5.2_vs_P5.1
5	MMP7	0.92	0.857	0.456	8.76E-09	P5.2_vs_P5.1
6	ADIRF	0.88	0.917	0.763	4.73E-12	P5.2_vs_P5.1
7	THY1	0.86	0.893	0.447	1.77E-15	P5.2_vs_P5.1
8	INHBB	0.84	0.631	0.14	8.73E-11	P5.2_vs_P5.1
9	PAX8	0.79	0.702	0.158	1.38E-12	P5.2_vs_P5.1
10	TAGLN	0.79	0.988	0.675	1.45E-13	P5.2_vs_P5.1
11	MFG8	0.76	0.786	0.404	1.39E-08	P5.2_vs_P5.1
12	IGFBP2	0.75	0.929	0.693	1.12E-08	P5.2_vs_P5.1
13	KRT17	0.75	0.655	0.202	1.56E-08	P5.2_vs_P5.1
14	MROH6	0.71	0.786	0.447	4.40E-09	P5.2_vs_P5.1
15	EPS8L1	0.7	0.75	0.316	7.34E-09	P5.2_vs_P5.1
16	KLK10	0.68	0.821	0.623	5.65E-06	P5.2_vs_P5.1
17	NRBP2	0.68	0.726	0.368	1.71E-08	P5.2_vs_P5.1
18	L1CAM	0.67	0.714	0.184	8.25E-12	P5.2_vs_P5.1
19	SNCG	0.67	0.821	0.456	1.03E-07	P5.2_vs_P5.1
20	KLK5	0.66	0.548	0.018	1.90E-13	P5.2_vs_P5.1
21	S100A1	0.64	0.548	0.158	5.66E-06	P5.2_vs_P5.1
22	C20orf204	0.63	0.571	0.088	4.83E-10	P5.2_vs_P5.1
23	MLLT6	0.62	0.774	0.544	6.45E-07	P5.2_vs_P5.1
24	PCGF2	0.62	0.607	0.114	2.64E-10	P5.2_vs_P5.1
25	TPM2	0.62	0.75	0.368	3.71E-07	P5.2_vs_P5.1
26	AFDN	0.61	0.702	0.36	1.55E-06	P5.2_vs_P5.1
27	SCD	0.61	1	0.588	8.46E-09	P5.2_vs_P5.1
28	LSM8	0.6	0.893	0.711	5.88E-07	P5.2_vs_P5.1
29	SCRIB	0.6	0.845	0.596	5.55E-07	P5.2_vs_P5.1
30	FLOT1	0.59	0.75	0.518	1.70E-04	P5.2 vs P5.1

To find the Root nodes

create Expression Analysis - [analysis : naturecomm_pt5.sp.cluster1vs2]

Set Cutoffs **Biological Filters**

General Settings

Generate the following Networks (increases analysis time)

Interaction networks

Include endogenous chemicals Molecules per network: Networks per analysis:

Genes are always included

Causal networks

Score master regulators for relationships to diseases, functions, genes, or chemicals (max 50)

Score using causal paths only

FGF9

WNT7A

Add most important regulator ←

Analysis Filter Summary

Consider only molecules and/or relationships where
 (species = Human) AND
 (confidence = Experimentally Observed) AND
 (mol. types = biologic drug OR canonical pathway OR chemical - endogenous mammalian OR chemical - endogenous non-mammalian OR chemical - kinase inhibitor OR chemical - other OR chemical - protease inhibitor OR chemical drug OR chemical reagent OR chemical toxicant OR complex OR cytokine OR disease OR enzyme OR function OR G-protein coupled receptor OR group OR growth factor OR ion channel OR kinase OR ligand-dependent nuclear receptor OR mature microRNA OR microRNA OR other OR peptidase OR phosphatase OR related pathway node OR transcription regulator OR translation regulator OR transmembrane receptor OR transporter)

 113 analysis-ready molecules (58 Down and 55 Up)

Preview Dataset naturecomm_pt5.sp.cluster1vs2

Analysis-Ready (113) Mapped IDs (114) Unmapped IDs (0) All IDs (114) Metadata

PTGS+ activate FGF9/FGF18 -> FGFR1/2/3
 FGF18 and FGFR1/2 poorly survival and implicated in
 cisplatin resistant

Expression Analysis - naturecomm_pt5.sp.cluster1vs2 - 2026-03-23 04:12 下午

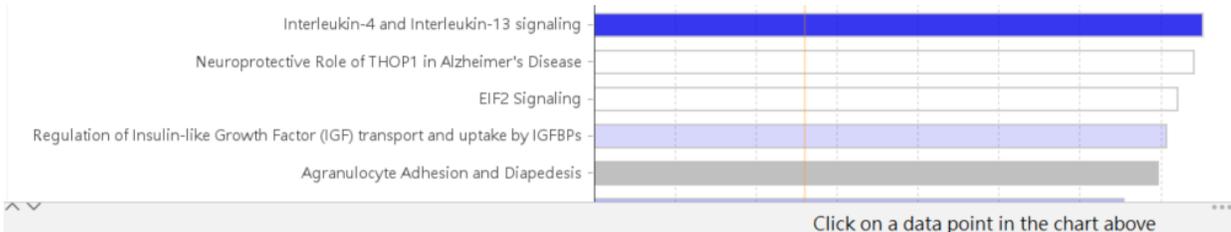
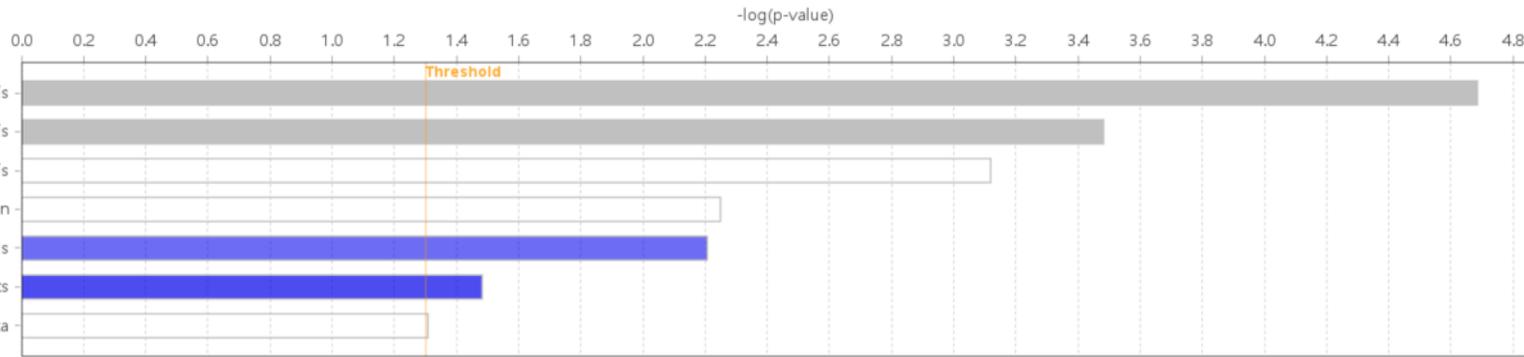
Summary Graphical Summary **Pathways** Upstream Analysis Diseases & Functions Regulator Effects Networks Lists Analysis Match Molecules

Canonical Pathways My Pathways ML Disease Pathways

Chart Overlapping

positive z-score
 z-score = 0
 negative z-score
 no activity pattern available

CXCL9

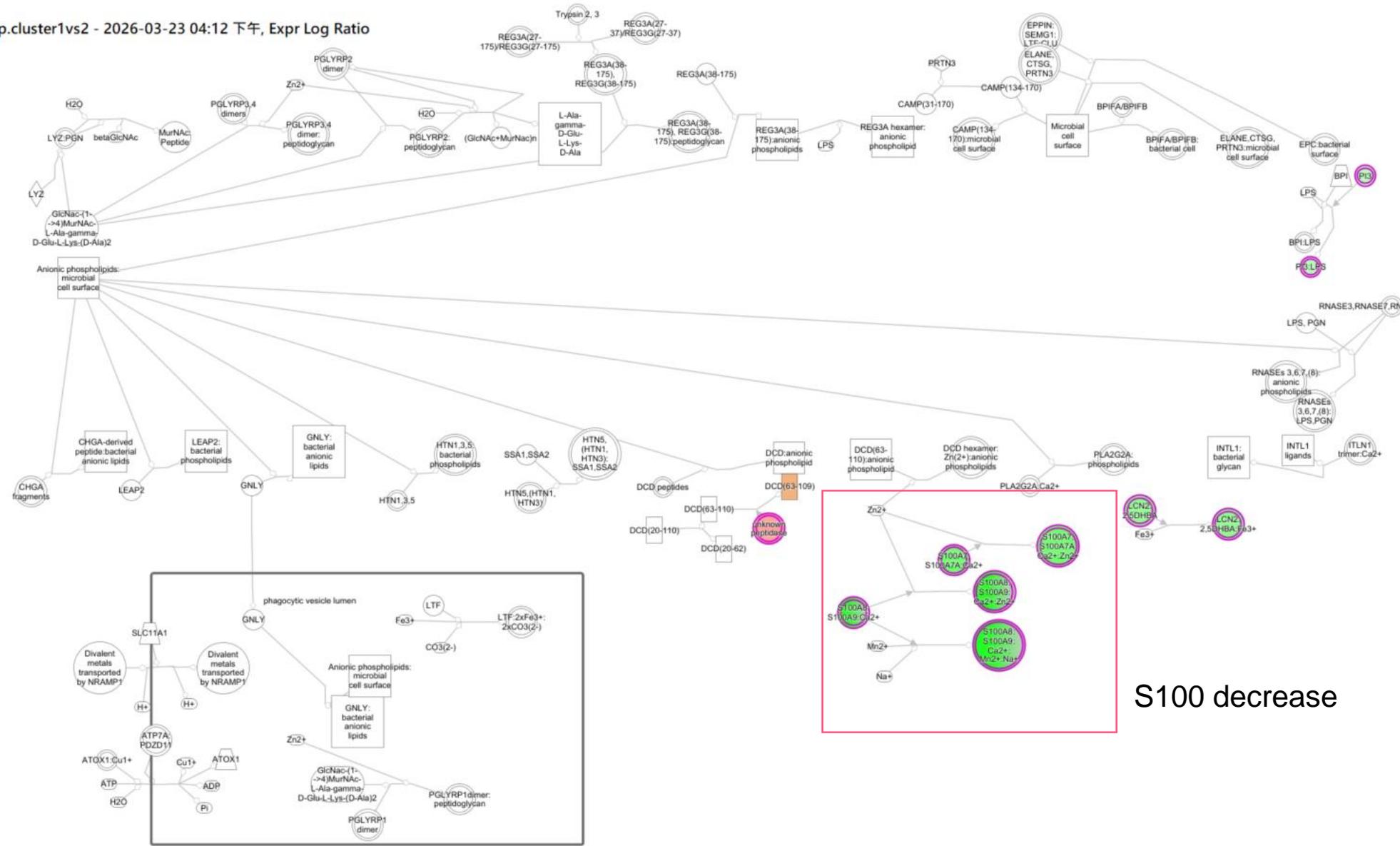


This is driven by its unique autocrine loops, including **FGF and WNT signaling**, which actively recruit COL3A1+ fibroblasts and promote profound stromal remodeling



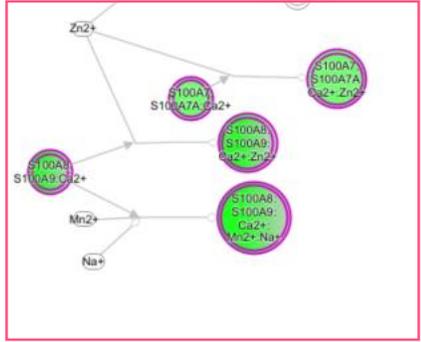
Antimicrobial peptides

Overlay: naturecomm_pt5.sp.cluster1vs2 - 2026-03-23 04:12 下午, Expr Log Ratio



Prediction Legend

- more extreme in dataset
- Increased measurement (Red circle)
- Decreased measurement (Green circle)
- more confidence
- Predicted activation (Orange circle)
- Predicted inhibition (Blue circle)
- Glow Indicates activity when opposite of measurement (Glowing red/green circles)
- Predicted Relationship
- Leads to activation (Orange line)
- Leads to inhibition (Blue line)
- Findings inconsistent with state of downstream molecule (Yellow line)
- Effect not predicted (Grey line)
- Dashed lines = indirect relationship
- Solid lines = direct relationship



S100 decrease

Upstream Regulators
Causal Networks

Add To My Pathway
Add To My List
Display as Network
Activity Plot
Customize Table
Mechanistic Networks

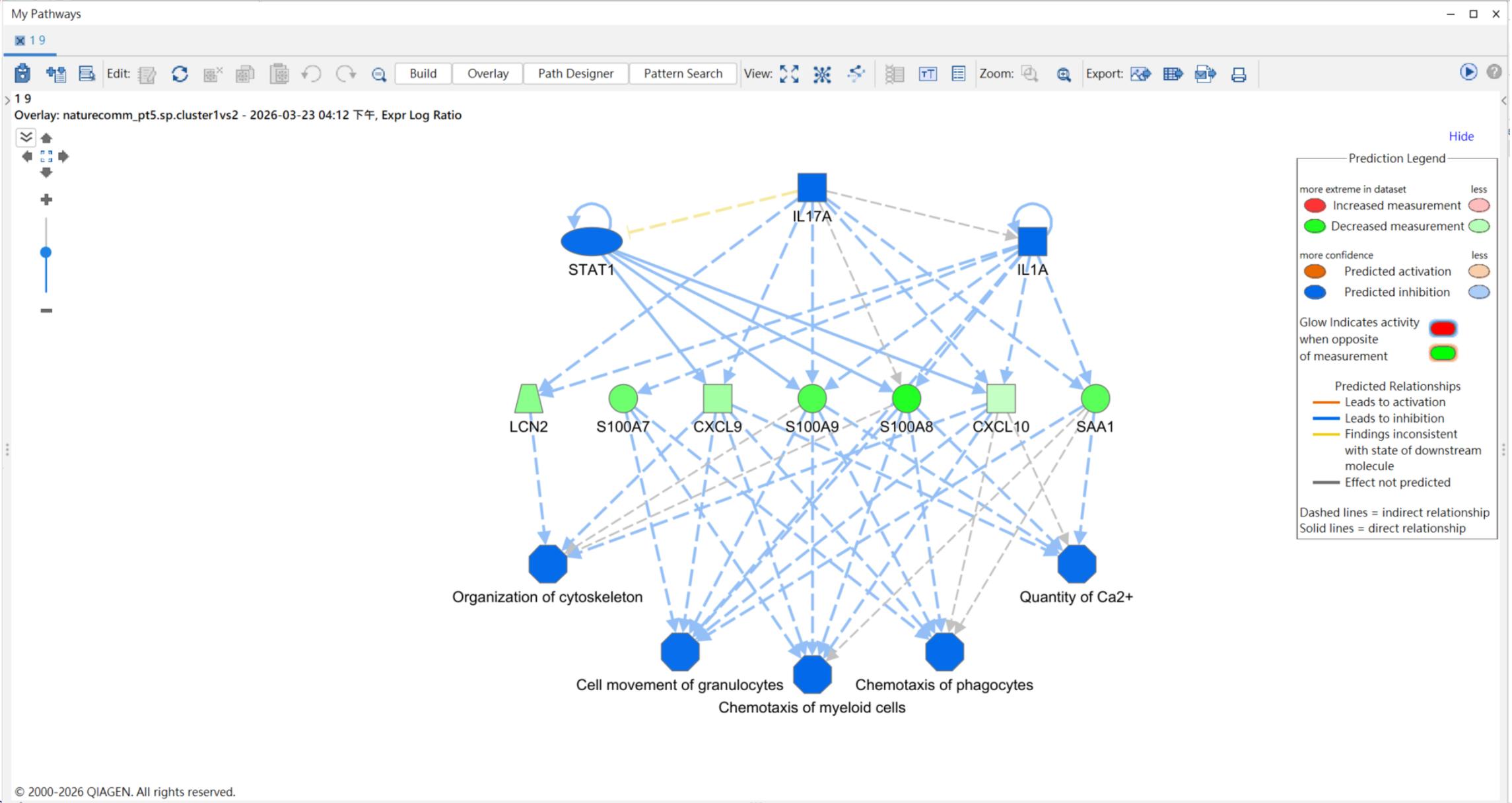
p-va... 6.02E-14 - 4.89E-04 (1/8)

Upstream Regulator	Expr Log Ratio	Molecule Type	Predicted Activation State	Activation z-score	p-value of overlap	Target Molecules in Datas...	Mechanistic Network
TNF		cytokine	Inhibited	-3.844	6.02E-14	↓ C3, ↑ CA12, ↓ CFB, ↑ CLDN3, ...all 24	30 (9)
EHF		transcription regulator		-1.667	1.77E-10	↓ CRABP2, ↑ KLK5, ↑ KLK6, ...all 9	
TP63		transcription regulator		-0.662	8.96E-10	↑ GAPDH, ↑ IGFBP2, ↑ KRT17, ...all 15	
IL17A		cytokine	Inhibited	-3.070	3.00E-09	↓ CFB, ↓ CXCL10, ↓ CXCL9, ...all 11	26 (8)
IL17F		cytokine	Inhibited	-2.923	6.10E-09	↓ CFB, ↓ CXCL10, ↓ CXCL9, ...all 9	
PELP1		other			1.17E-08	↓ ASS1, ↓ PI3, ↑ PSAT1, ↑ RBP1, ...all 9	
IL1A		cytokine	Inhibited	-2.800	2.34E-08	↓ CXCL10, ↓ LCN2, ↓ PDZK11P1, ...all 8	18 (2)
KRT14		other			2.45E-08	↑ KLK10, ↑ KLK5, ↑ KLK6, ↑ KRT... all 6	
LARP1		translation regulator			1.00E-07	↑ EEF1D, ↓ RABPC1, ↑ RPL32, ...all 7	
NFKBIZ		transcription regulator					
ARID1A		transcription regulator					
S100A8	↓ -2.460	other					
SMARCA4		transcription regulator					
IL37		cytokine					
IL22		cytokine					
SAFB		other					
FTO		enzyme					
TGM2		enzyme					
ATP2A2		transporter					
IL1B		cytokine					
KEAP1		other					
IRF2		transcription regulator					
AHR		ligand-dependent nuclear recept					
FGF8		growth factor					
SREBF1		transcription regulator					
S100A9	↓ -1.950	other					
ZIC2		transcription regulator					
HIF1A		transcription regulator					
RELA		transcription regulator					
CBX5		transcription regulator					
ESR1		ligand-dependent nuclear recept					
IFNG		cytokine					
ANG		enzyme					
SFTPA1		other					
S100A5		other					
ACOD1		enzyme					

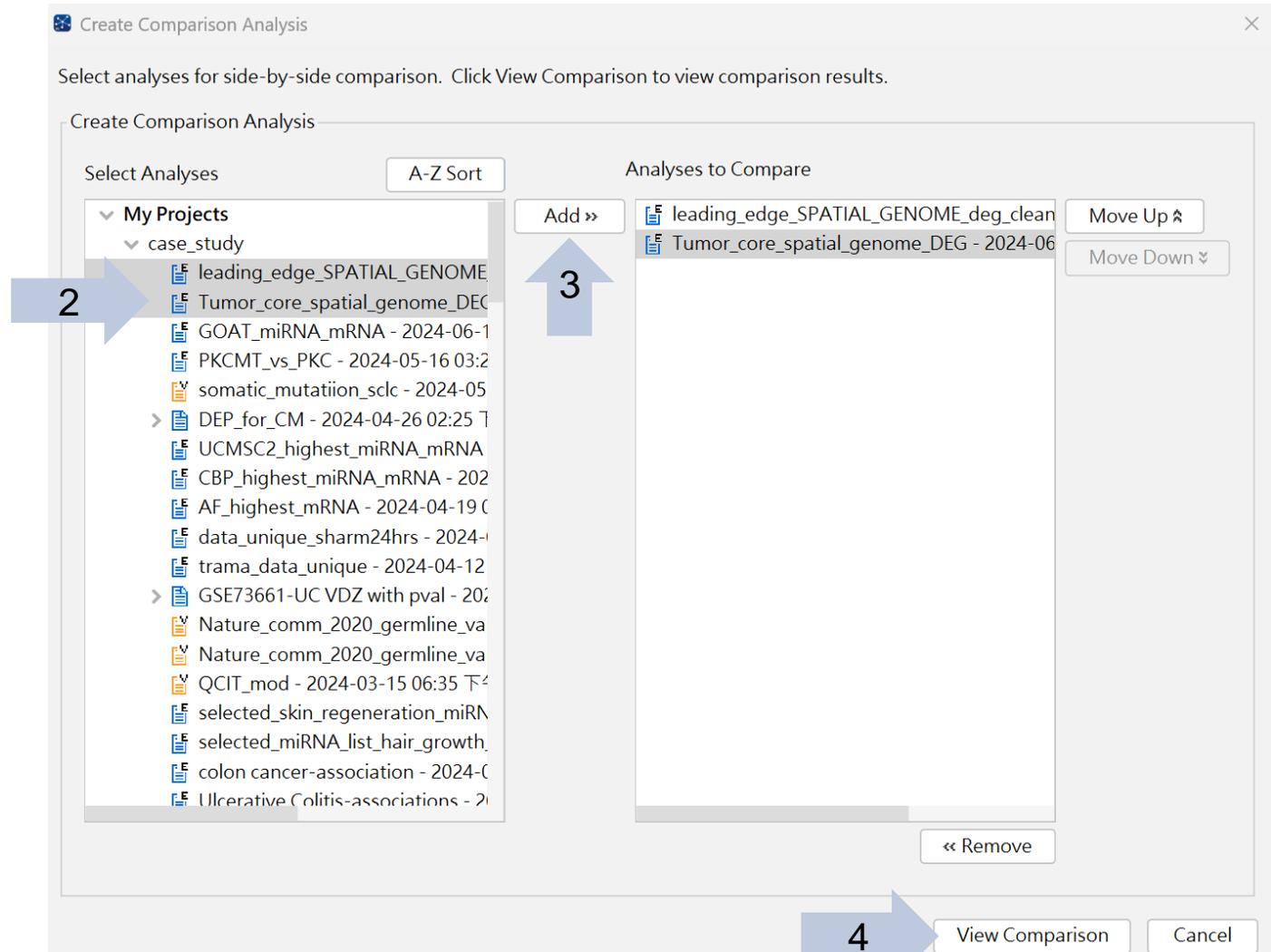
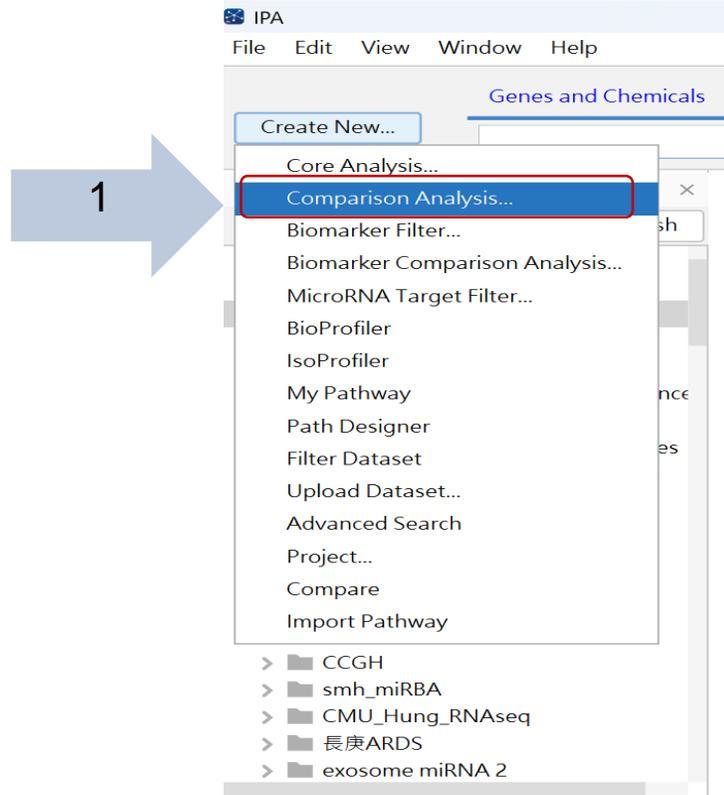
TNF 7
Overlay: naturecomm_pt5.sp.cluster1vs2 - 2026-03-23 04:12 下午, Expr Log Ratio

Prediction Legend

- more extreme in dataset: Increased measurement (red circle), Decreased measurement (green circle)
- more confidence: Predicted activation (orange circle), Predicted inhibition (blue circle)
- Glow Indicates activity when opposite of measurement: Red glow (increased), Green glow (decreased)
- Predicted Relationships: Leads to activation (orange dashed line), Leads to inhibition (blue dashed line), Findings inconsistent with state of downstream molecule (yellow dashed line), Effect not predicted (black dashed line)
- Dashed lines = indirect relationship, Solid lines = direct relationship



Step for You to do your compared analysis



Canonical Pathways Upstream Analysis Diseases & Functions Regulator Effects Lists My Pathways Molecules

Canonical pathway

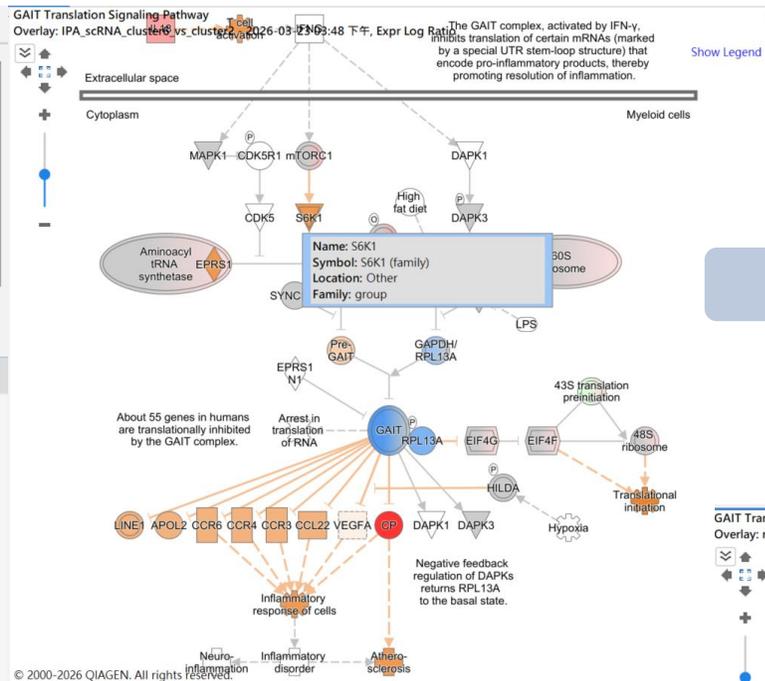
Measurement: Activation z-score -3.317 6.582

Sort Method: Hierarchical Clustering Visualize: z-score

Insignificance Threshold: (absolute value)

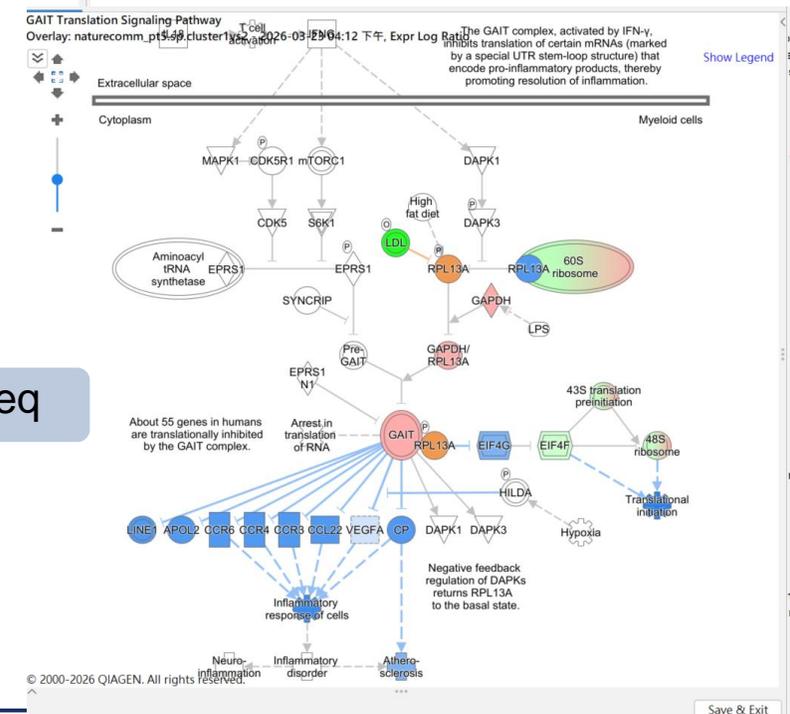
View Report Open Network Gene Heatmap Expand Header Cluster Columns

- GAIT Translation Signaling Pathway
- Neutrophil degranulation
- RHO GTPase cycle
- Nonsense-Mediated Decay (NMD)
- G alpha (i) signalling events
- S100 Family Signaling Pathway
- Signaling by ROBO receptors
- Phagosome Formation
- Major pathway of rRNA processing in the nucleolus and cytosol
- Keratinization
- Neutrophil Extracellular Trap Signaling Pathway
- Ribosomal Quality Control Signaling Pathway
- Role of Macrophages, Fibroblasts and Endothelial Cells in Rheu...
- Eukaryotic Translation Elongation
- SRP-dependent cotranslational protein targeting to membrane
- Eukaryotic Translation Initiation
- Eukaryotic Translation Termination
- Exosome Signaling Pathway
- Selenoamino acid metabolism
- IL-10 Signaling
- Antioxidant Action of Vitamin C
- Tuberculosis Active Signaling Pathway
- SPINK1 Pancreatic Cancer Pathway
- PTEN Signaling
- VDR/RXR Activation
- PPAR Signaling



scRNA

Spatial RNA-seq



Upstream regulator

Filter ?

Measurement: Activation z-score -4.301  6.325

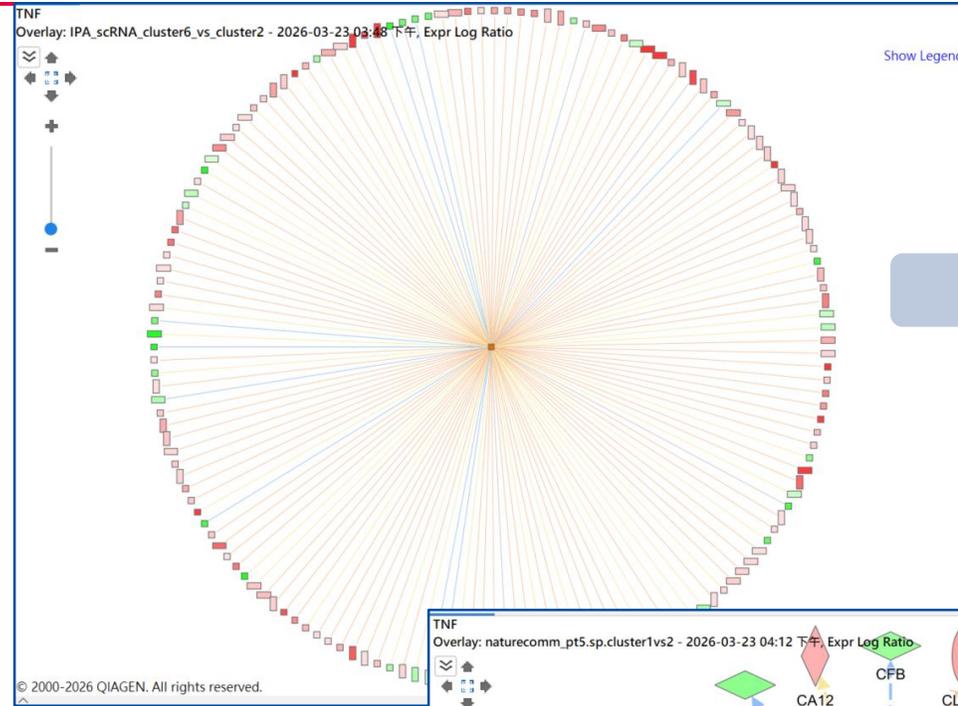
Sort Method: Hierarchical Clustering Visualize: z-score

Insignificance Threshold: (absolute value)

Open Network Gene Heatmap Expand Header Cluster Columns

Upstream Regulators

Upstream Regulators	IPA_scRNA_cluster...	naturecomm_pt5 sp...
TNF		
EHMT1		
CHUK		
SYVN1		
NFkB (complex)		
IFNG		
IL1B		
EZH2		
IL17A		
IL1A		
IL17F		
estrogen receptor		
TP53		
EHF		
TGM2		
FOXC1		
TLR3		
IFNL1		
STAT1		
GLI1		
CBX5		
TGFB2		



scRNA

Spatial RNA-seq

