

Enrichment analyses and results contextualisation with Knowledge Graphs

Summer School Multi-omics Data Analysis and Integration

Maxime DELMAS - 07/09/2023

Enrichment analyses

- [*Gene sets, pathways, metabolites*] enrichment analyses



~ **over-representation**

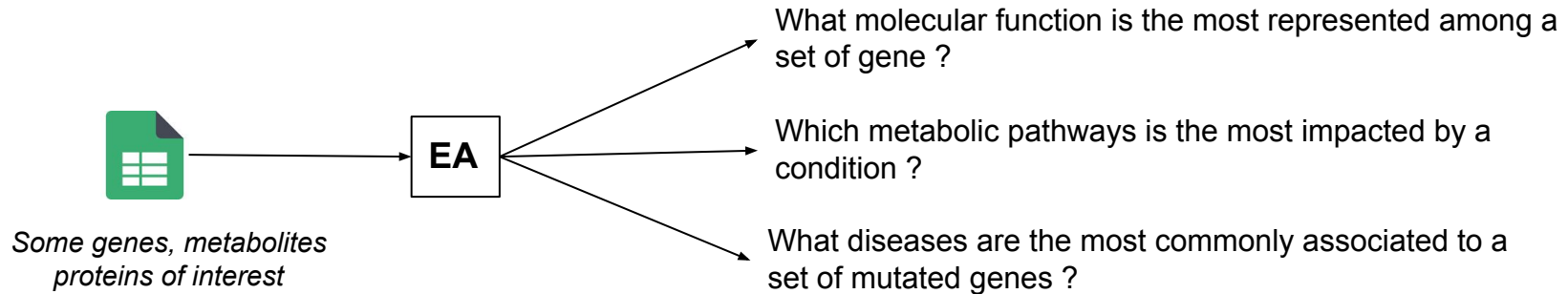
Enrichment analyses

- [Gene sets, pathways, metabolites] enrichment analyses



~ **over-representation**

- Give directions for results interpretation



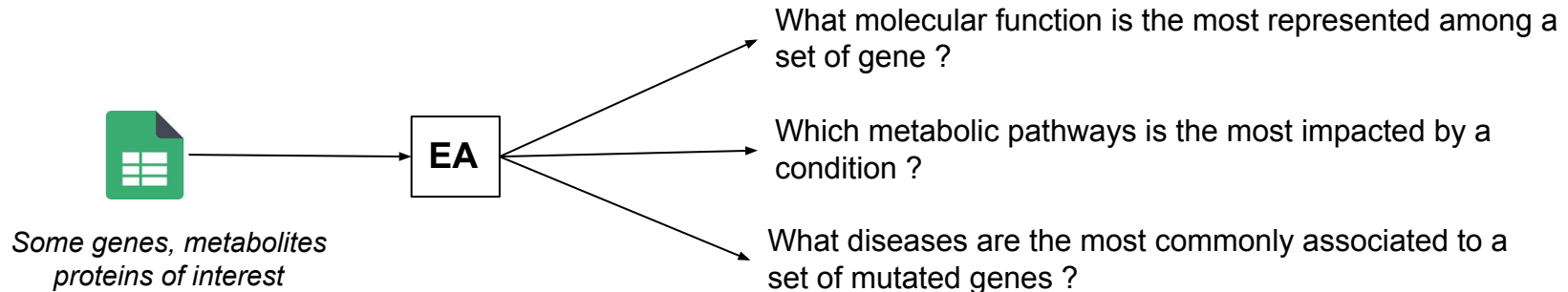
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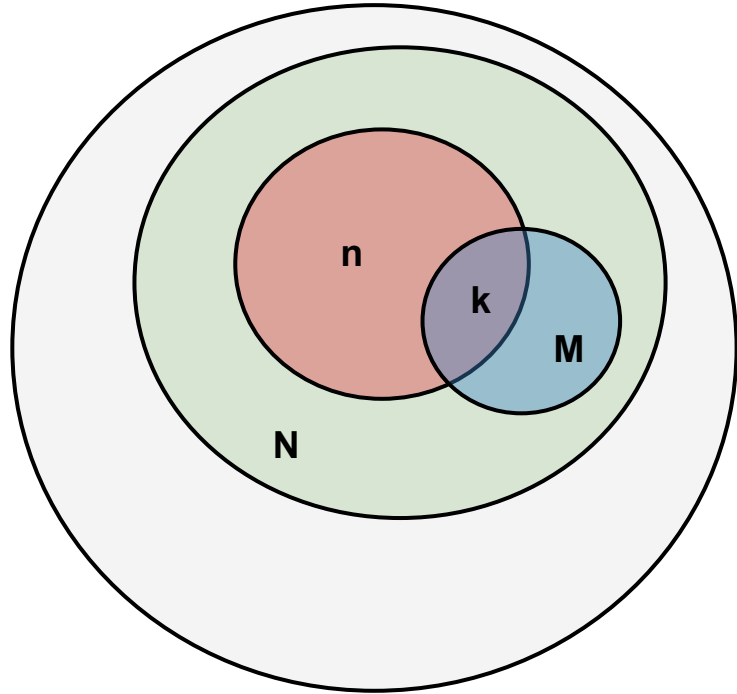
- Give directions for results interpretation



- Families of approaches:
 - Over-Representation Analysis (ORA)
 - Functional Class Scoring (eg. GSEA)
 - Topology-based methods

ORA: Over-Representation Analysis

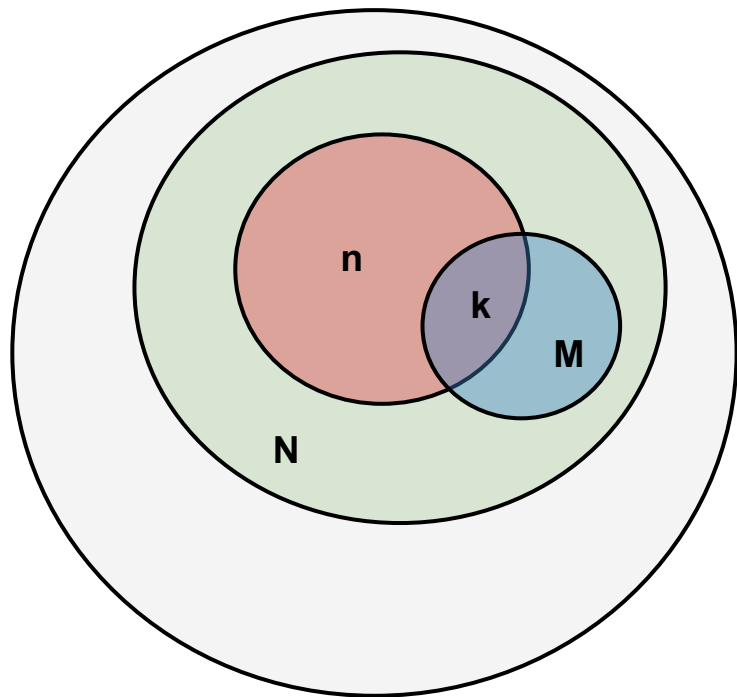
What does an ORA ? it compare **overlap** between **sets**.



- Sets of genes, proteins, metabolites, organisms, etc.
 - a Universe (size = N) - or background set
 - a set of interest (size = n)
 - a reference set (size = M) (share a common biological theme)
 - an overlap k

ORA: Over-Representation Analysis

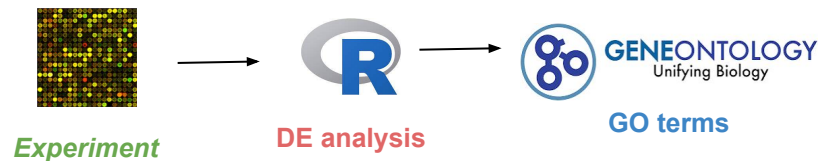
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In a classic RNA-seq analysis



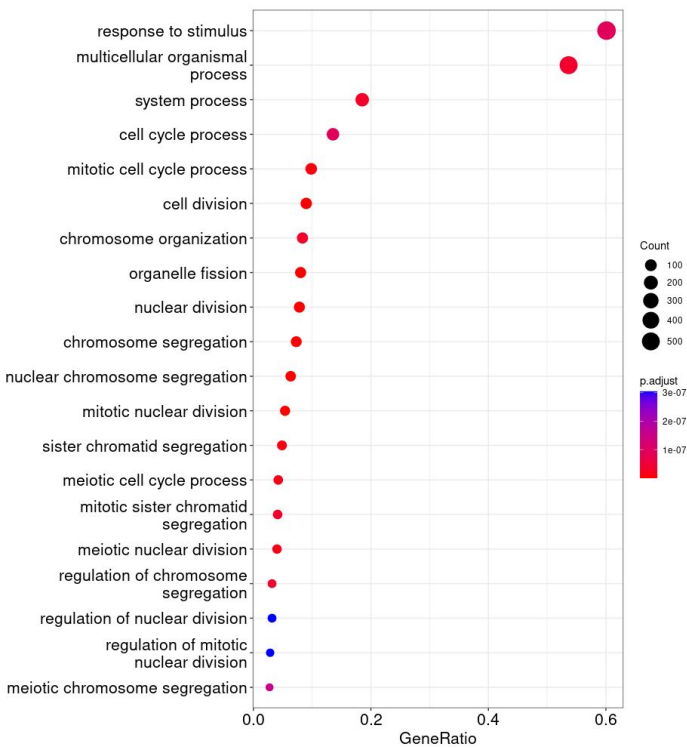
- **N** genes measured in the assay
- **n** genes differentially expressed
- **M** genes annotated to a GO term of interest
- an overlap **k**

ORA: A practical example (1)



TCGA-BRCA: 5 Normal .vs. 5 Tumor samples → GDE analysis → 1068 DE genes

R packages for ORA:



Standard GO (*Biological processes*) Enrichment analysis

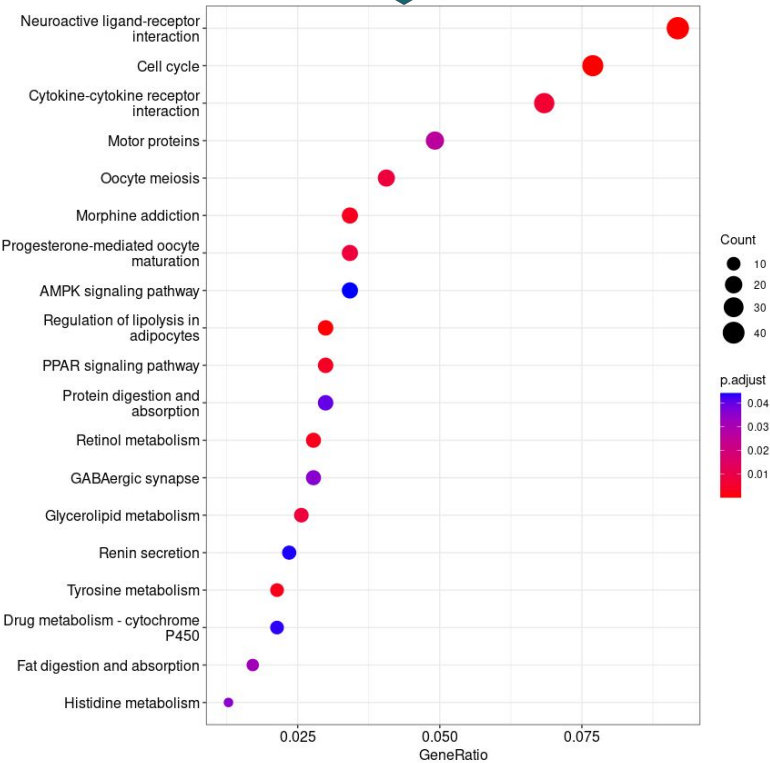
```
ego <- enrichGO(gene = DE.set,  
  universe = universe,  
  OrgDb = HS.annotation,  
  ont = "BP",  
  keyType = "SYMBOL",  
  minGSSize = 1,  
  maxGSSize = 100000,  
  pAdjustMethod = "BH")
```

ORA: A practical example (2)



TCGA-BRCA: 5 Normal .vs. 5 Tumor samples → GDE analysis → 1068 DE genes

R packages for ORA:



Standard KEGG (*Pathway*) Enrichment analysis



```
ekegg <- enrichKEGG(gene = DE.set2,  
  organism = "hsa",  
  keyType = "ncbi-geneid",  
  pAdjustMethod = "BH",  
  universe = universe2,  
  use_internal_data = FALSE)
```


ORA: Back to the fundamentals



ID	Description	GeneRatio	BgRatio	p.value	p.adjust	q.value
GO:0006836	neurotransmitter transport	22/945	191/15568	0.002881322	0.04909408	0.04278198

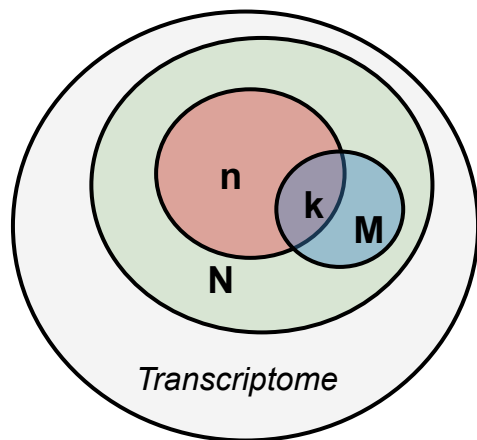
2 equivalent ways of representing and computing

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2 equivalent ways of representing and computing



Hypergeometric distribution

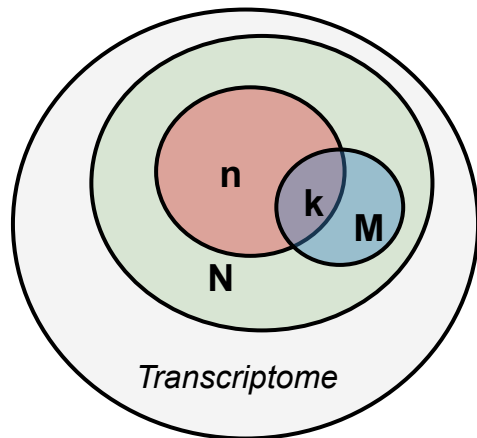
$$P(X \geq k) = 1 - \sum_{i=0}^{k-1} \frac{\binom{M}{i} \binom{N-M}{n-i}}{\binom{N}{n}}$$

ORA: Back to the fundamentals



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Contingency table

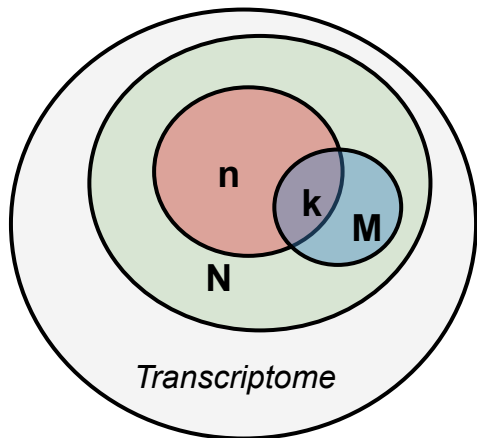
	in BP set	not in BP set
in Gene set	k = 22	923
not in Gene set	169	14454

ORA: Back to the fundamentals



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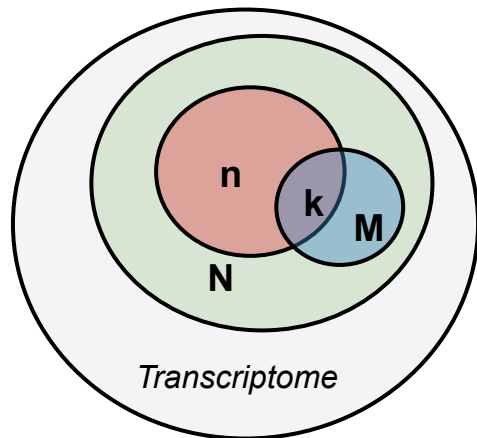


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M

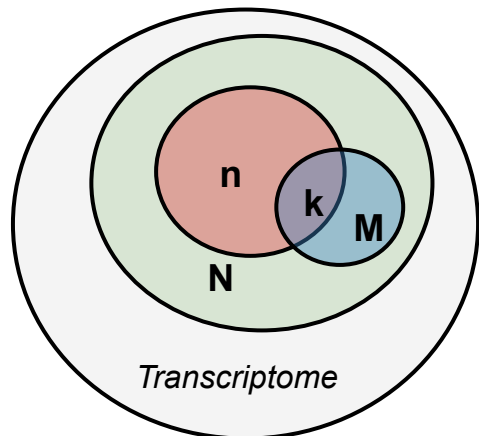
N

ORA: Back to the fundamentals



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2 equivalent ways of representing and computing



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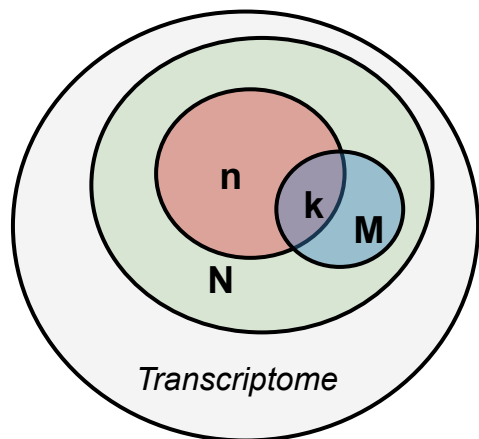
	in BP set	not in BP set	
in Gene set	k = 22	923	$\rightarrow n$
not in Gene set	169	14454	
	$\downarrow M$	$\downarrow N$	

ORA: Back to the fundamentals



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M

N



Right-tailed fisher exact test

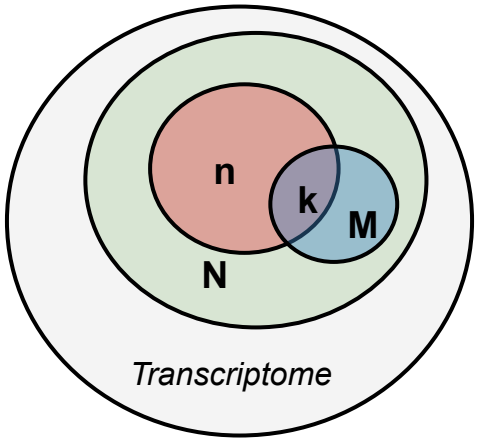
= *Testing Independence*

ORA: Back to the fundamentals



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2 equivalent ways of representing and computing



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p.value=0.002881322

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M (blue arrow from 22), N (green arrow from 14454)

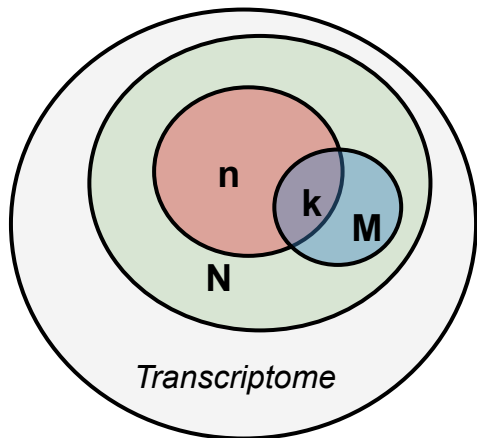
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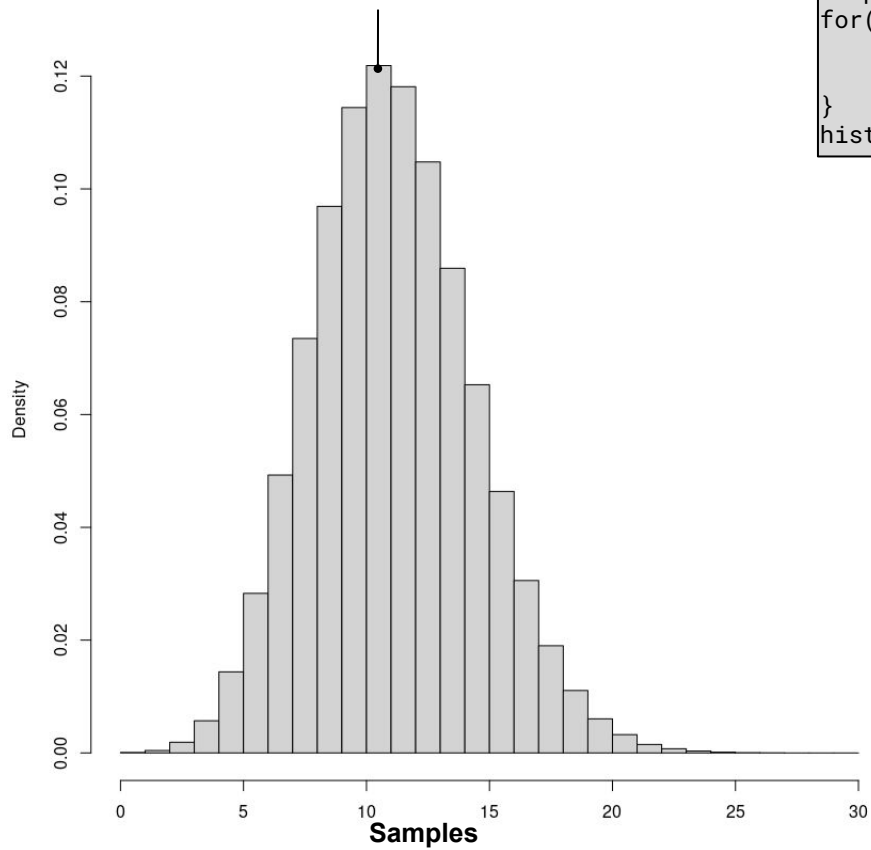
p.value=0.002881322

+ correction for multiple-tests

q.value

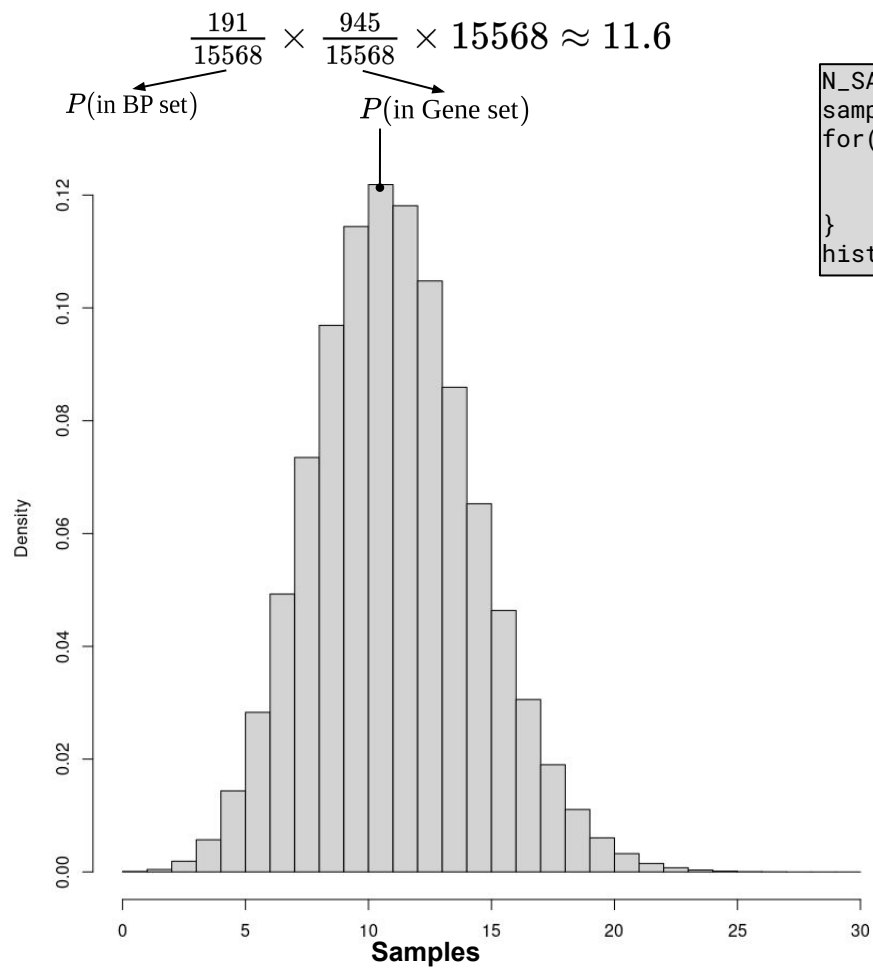
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ORA: Intuition via random sampling



```
N_SAMPLES <- 1000000
samples <- vector(mode = "numeric", length = N_SAMPLES)
for(i in 1:N_SAMPLES){
  s <- sample(size = 945, x = universe, replace = F)
  samples[i] <- sum(s %in% G0.0006836)
}
hist(samples, freq = F, breaks = seq(0,30,1))
```

ORA: Intuition via random sampling

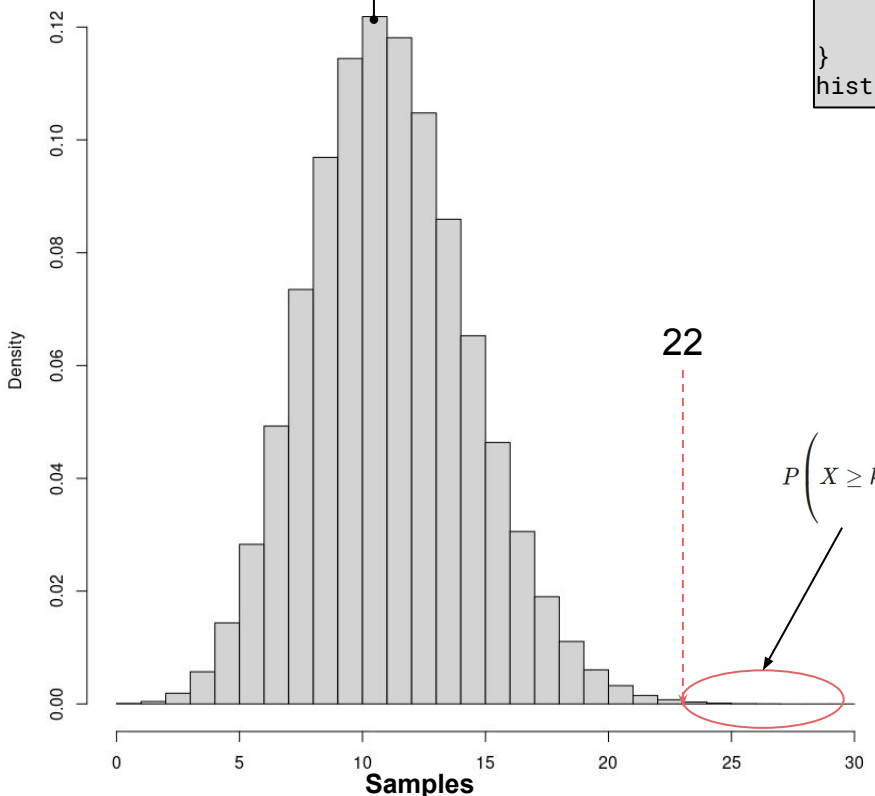


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```

ORA: Intuition via random sampling

$$\frac{191}{15568} \times \frac{945}{15568} \times 15568 \approx 11.6$$

\swarrow $P(\text{in BP set})$ \swarrow $P(\text{in Gene set})$



```

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```

What proportion of **random sets** sampled from the universe show more than 22 genes included in GO:0006836 ?

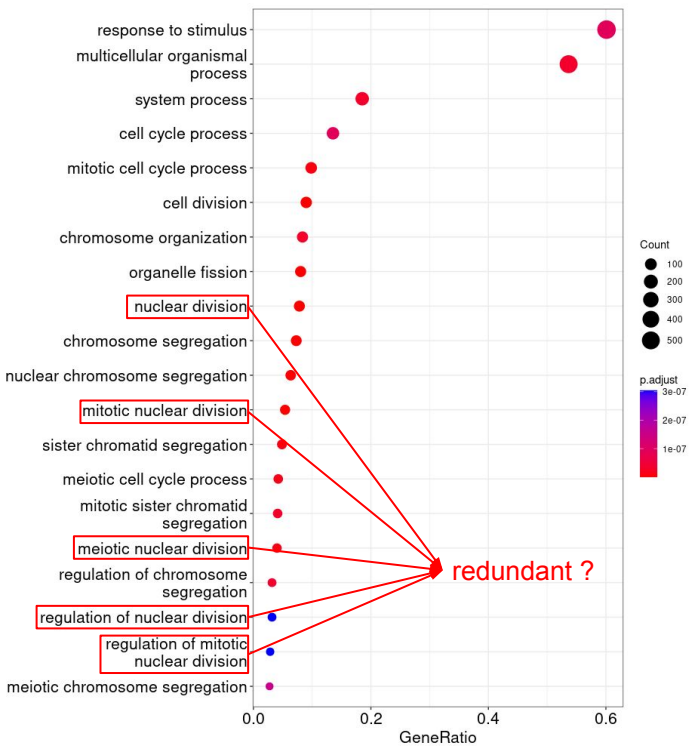
estimate = 0.002816

ORA: A practical example (1)



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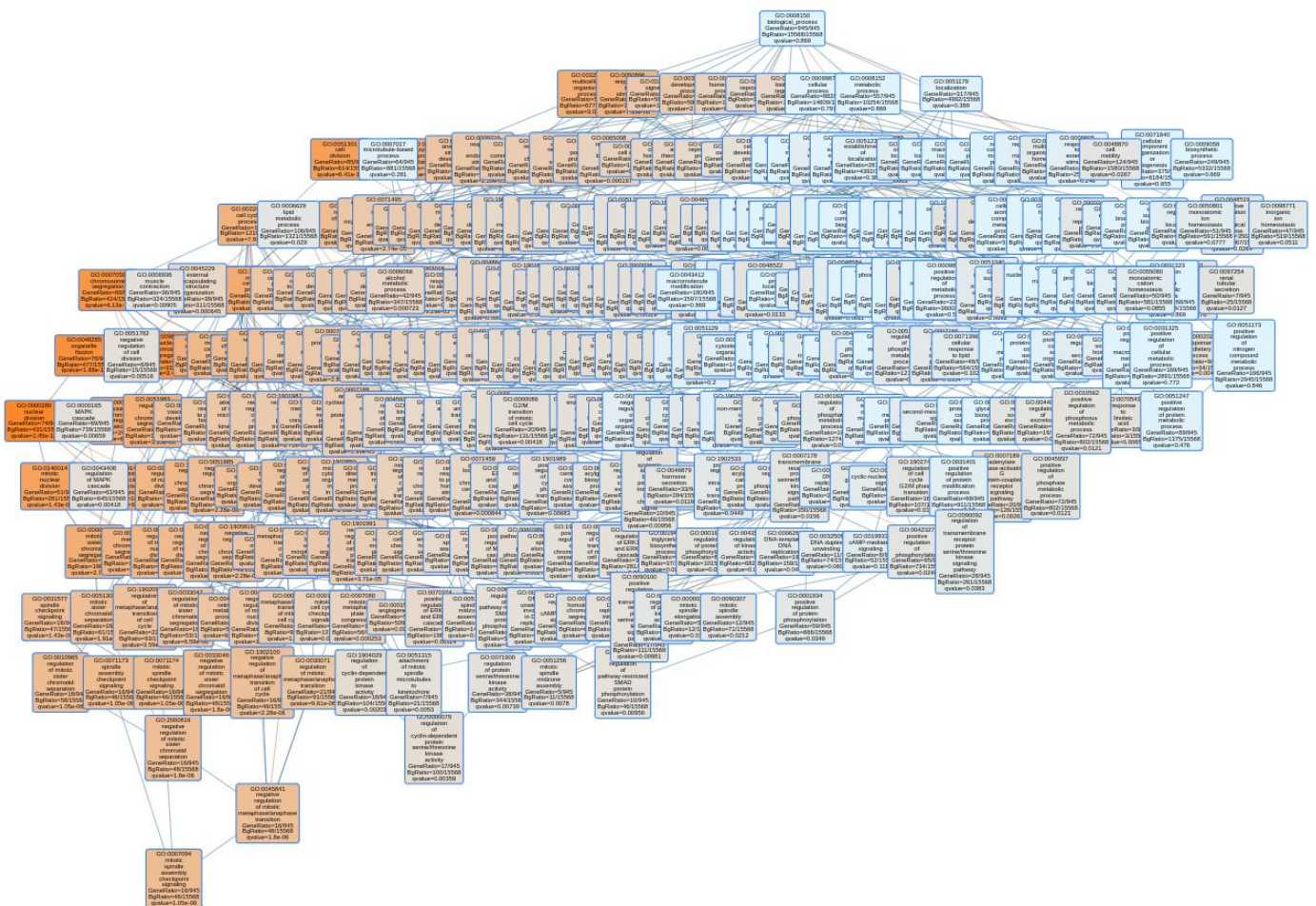
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ORA: A practical example (1) - a broader DAG view



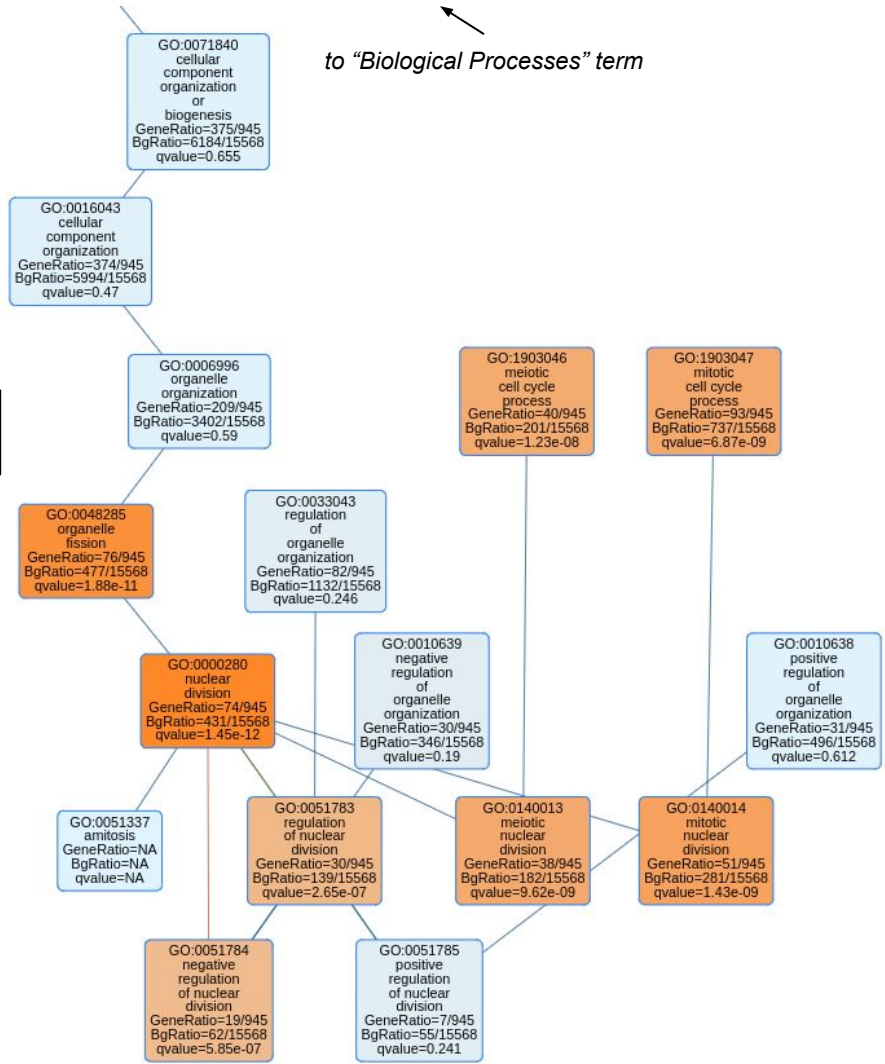
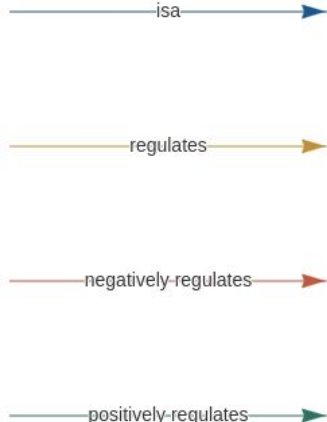
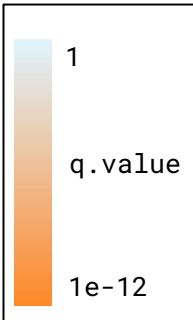
1

q.value

1e-12

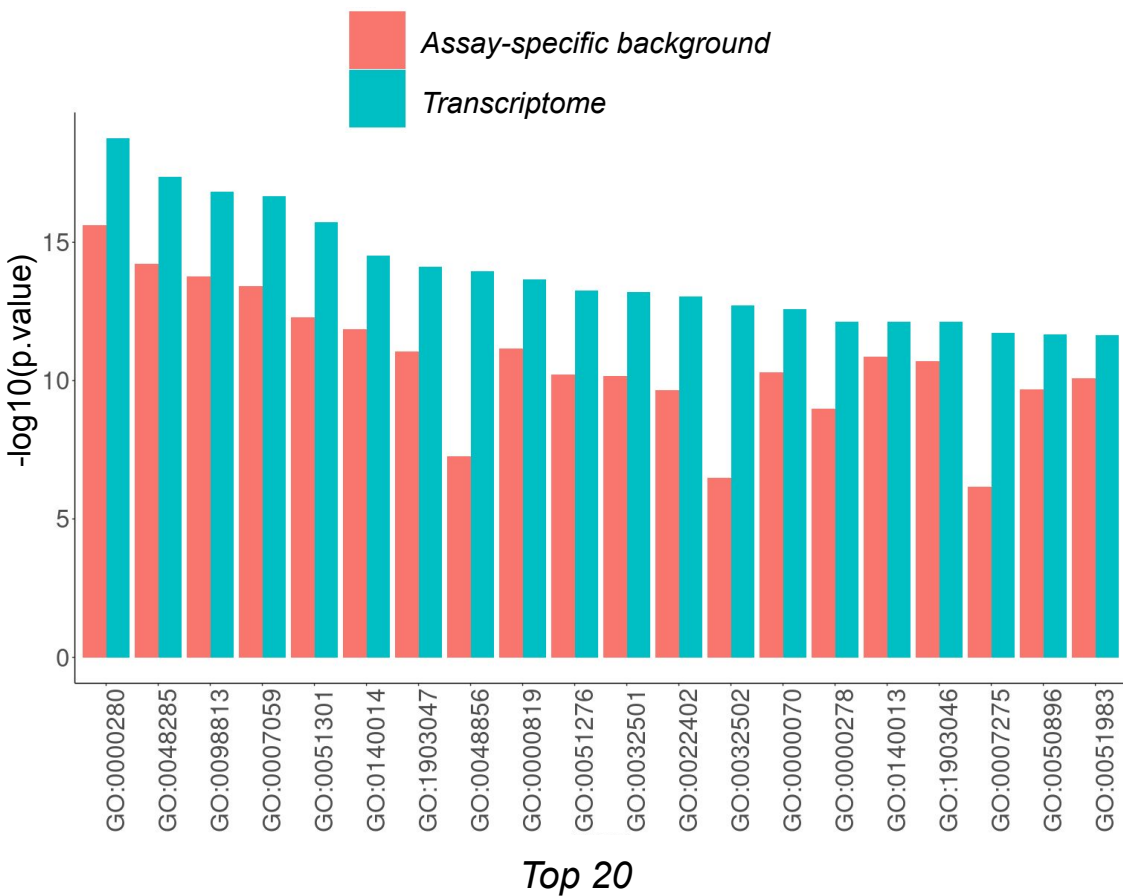
ORA: A practical example (1) - DAG view

The Gene Ontology in a DAG (Directed Acyclic Graph)

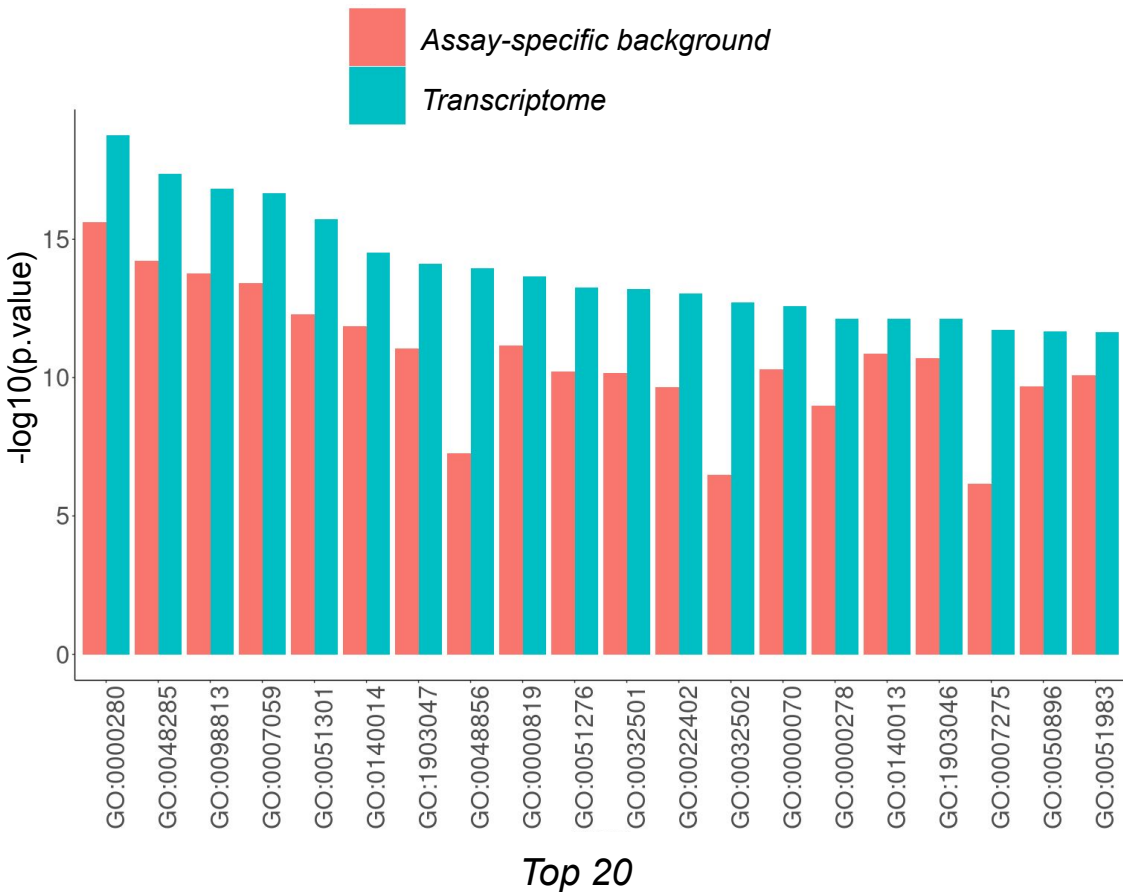


to "Biological Processes" term

ORA: The Impact of the *universe* definition



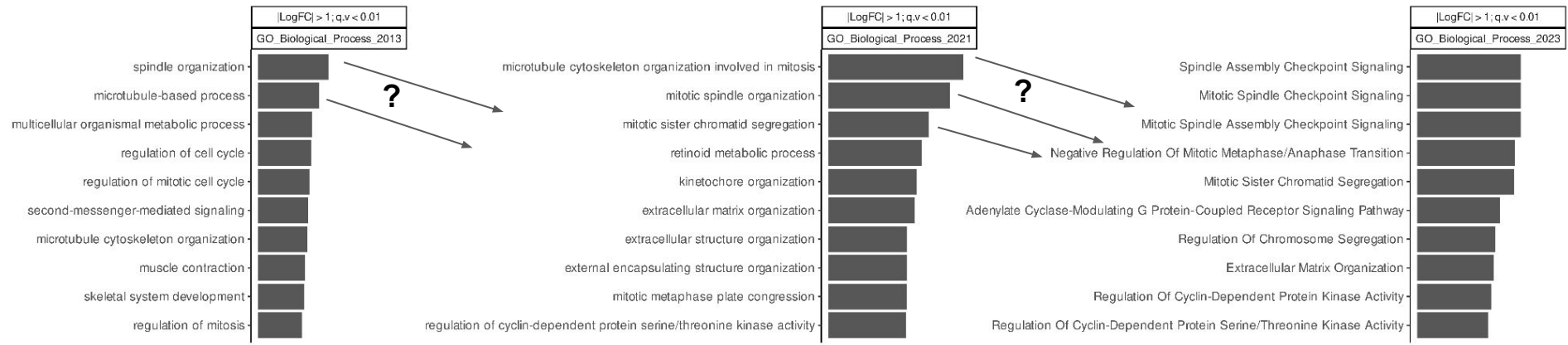
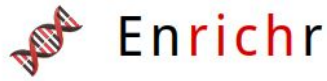
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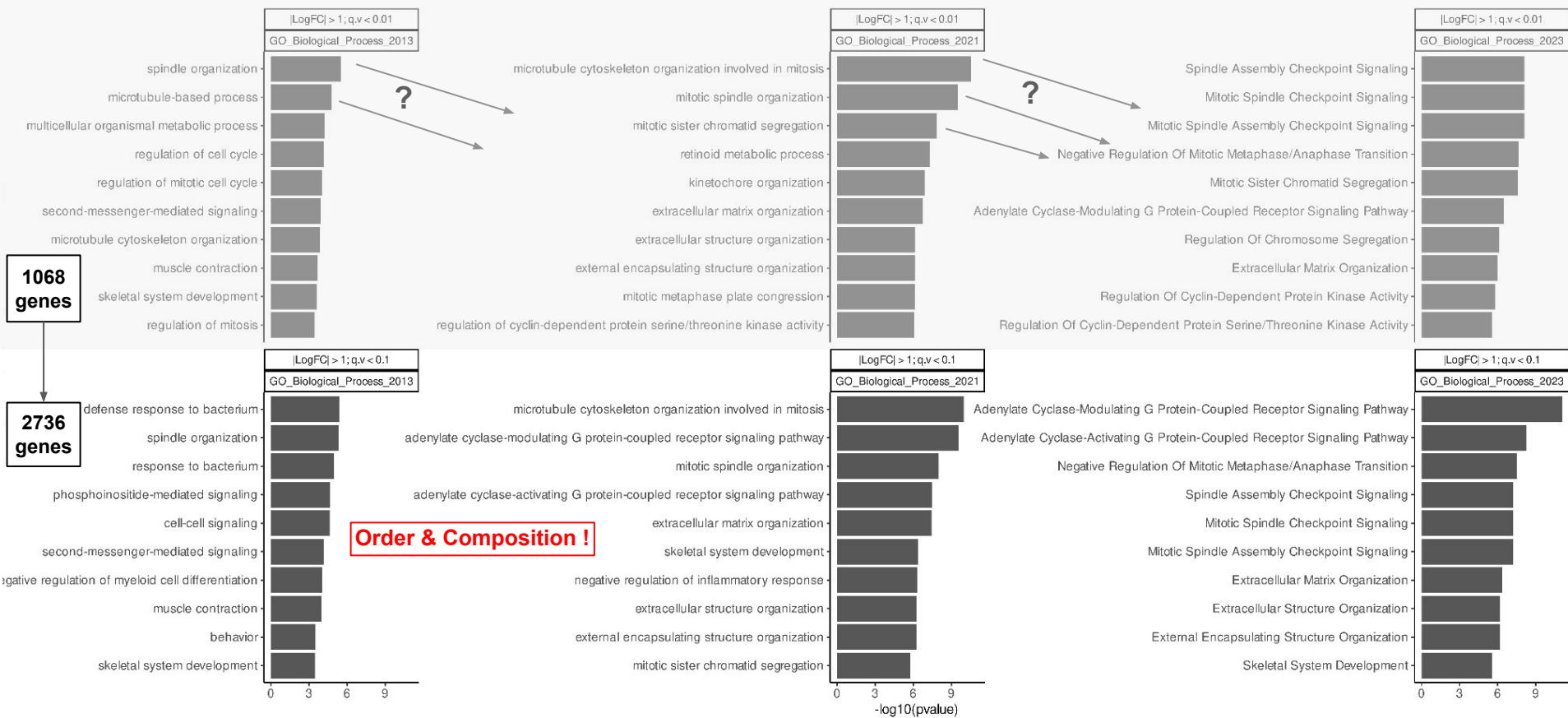
Leads to overestimation of the p-value
+
Order ~ preserved
↓
Increase false positive enriched terms

**133 vs 218 enriched GO terms
(q.value <= 1e.3)**

ORA: Impact of the database and gene set thresholds choices



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How many significantly enriched Biological Processes ? ($q.value < 0.01$)

	GO BP 2013	GO BP 2021	GO BP 2023
2736 genes	q.value < 0.1 8	37	30
1068 genes	q.value < 0.01 4	44	40

Thresholds and database choices also have an impact of the number of enriched terms

ORA: Several biases

- All parameters are important

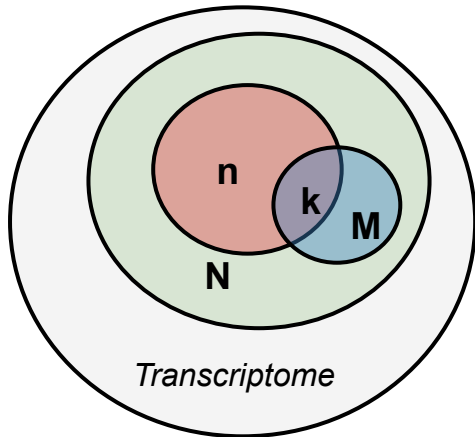
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Unspecific universe (*background set*) can create false positives

Selection thresholds are important:

- Too large = noisy detection
- Too small = low detection

Reference database and versions can an impact of results



ORA: Several biases

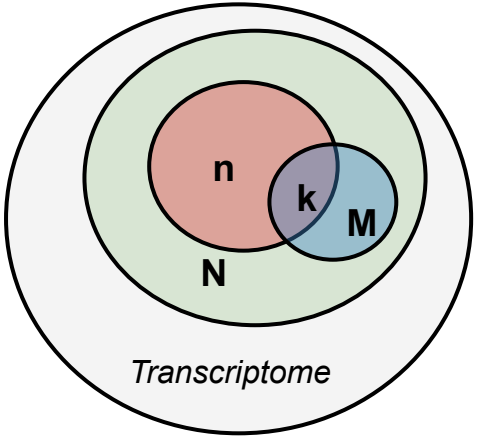
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Selection thresholds are important:

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Always specify the background set, the applied thresholds and the database version

Good results = **Reproducible** results

ORA: It can be any gene sets - WGCNA example

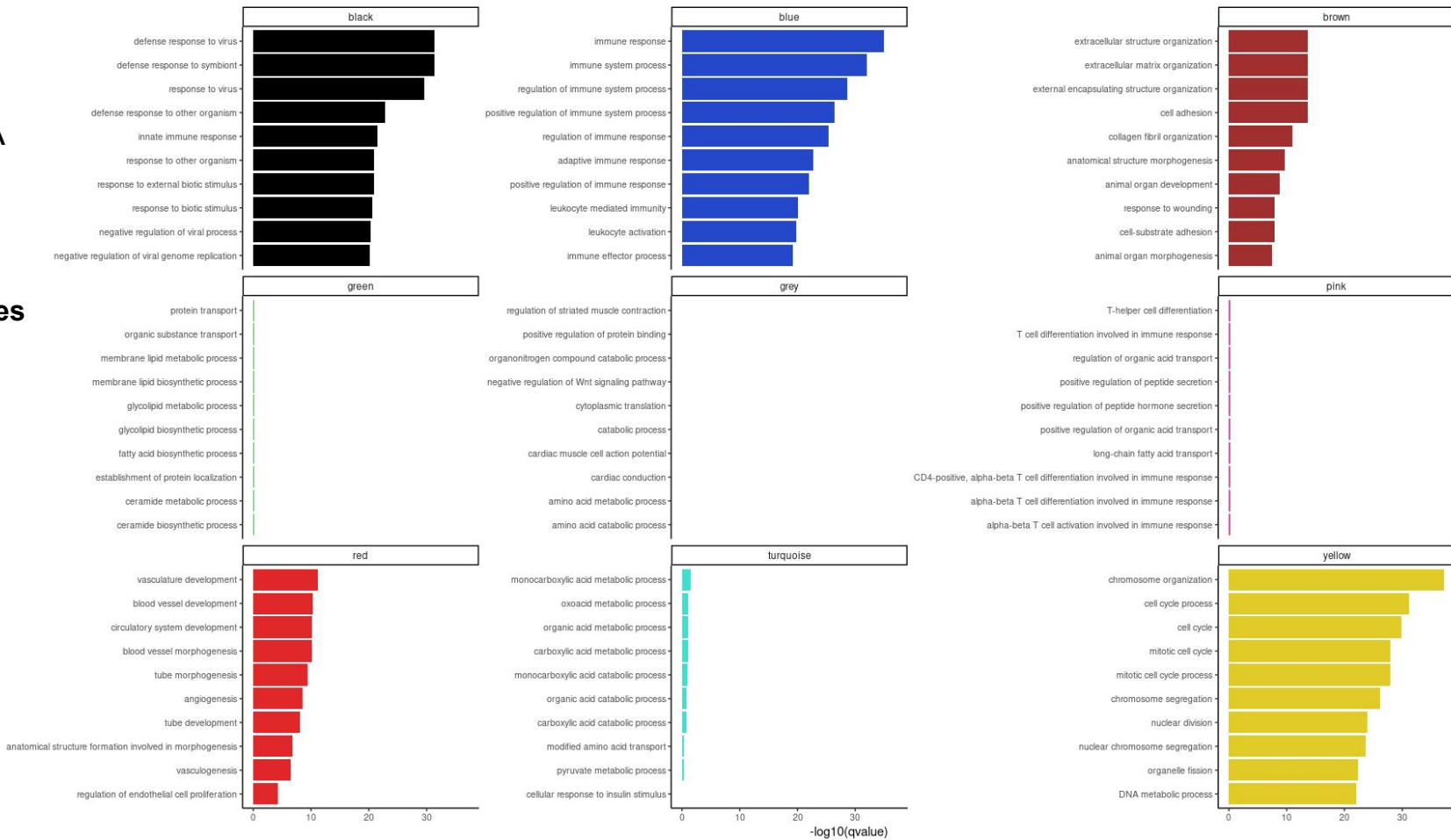
TP WGCNA



9 gene modules

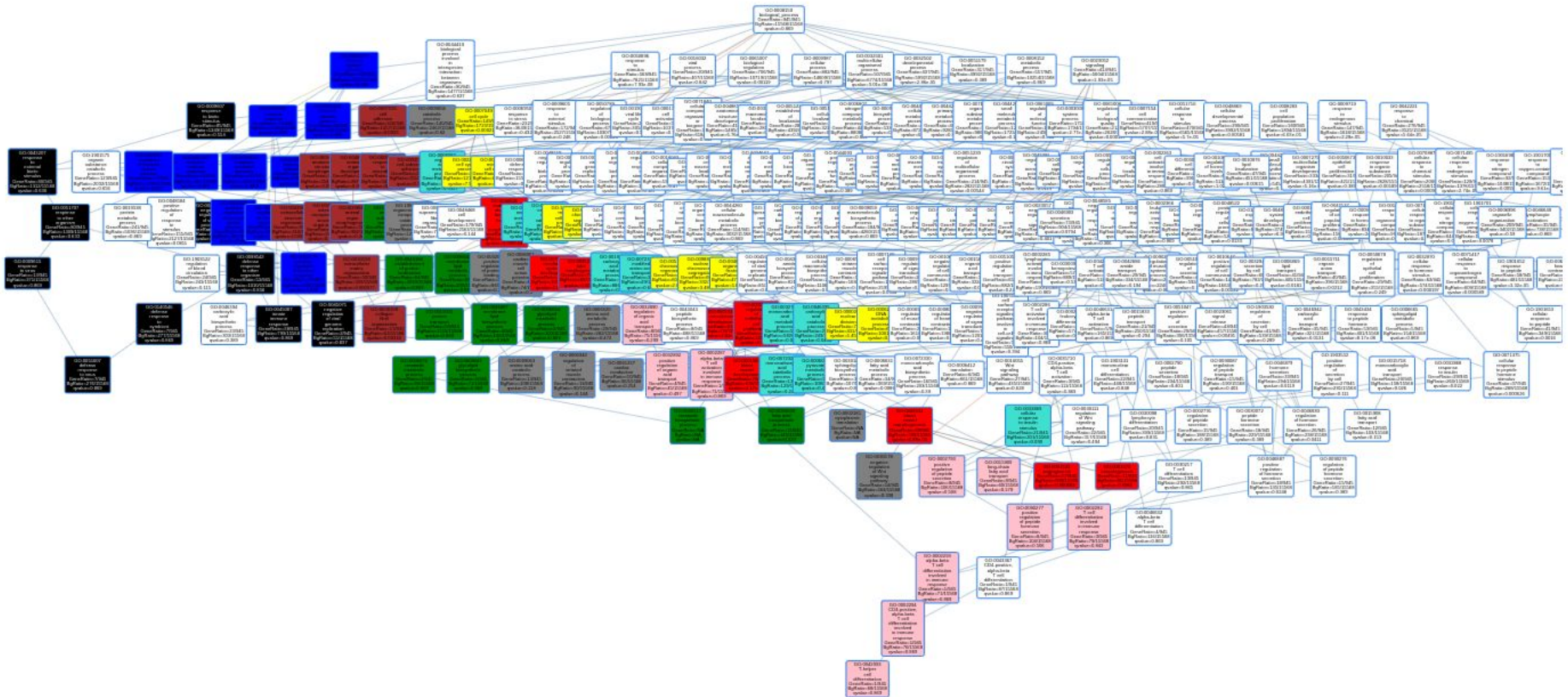


Enrichment analysis on modules



ORA: It can be any gene sets - WGCNA example mapping on DAG

Mapping of the top 10 per modules on the GO BP DAG



GSEA: A Function scoring method

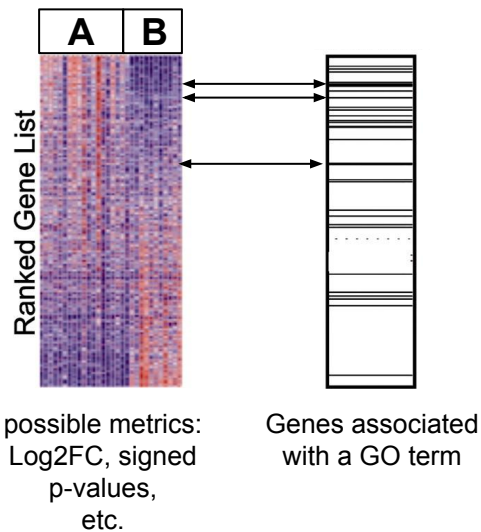
- Recall of the impact of the threshold (q.value & logFC) on the ORA results
- All genes are not equivalent: sign and intensity of variation

—————→ **GSEA**

GSEA: A Function scoring method (1)

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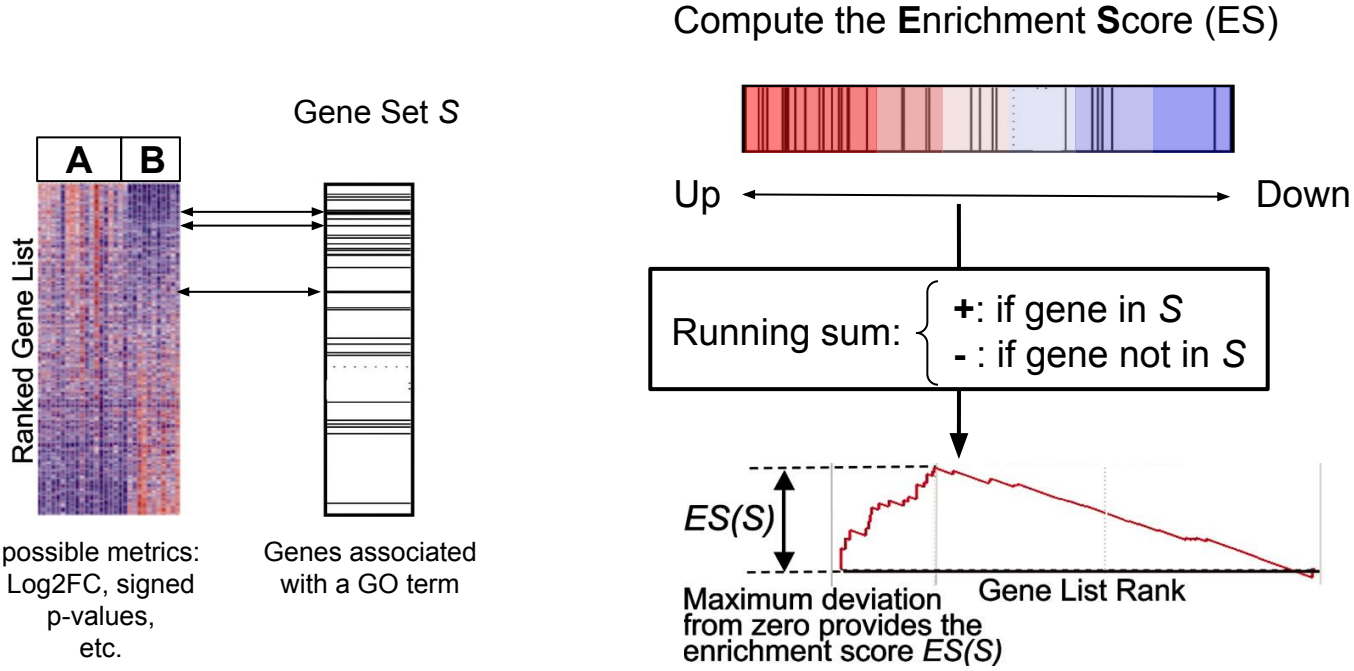
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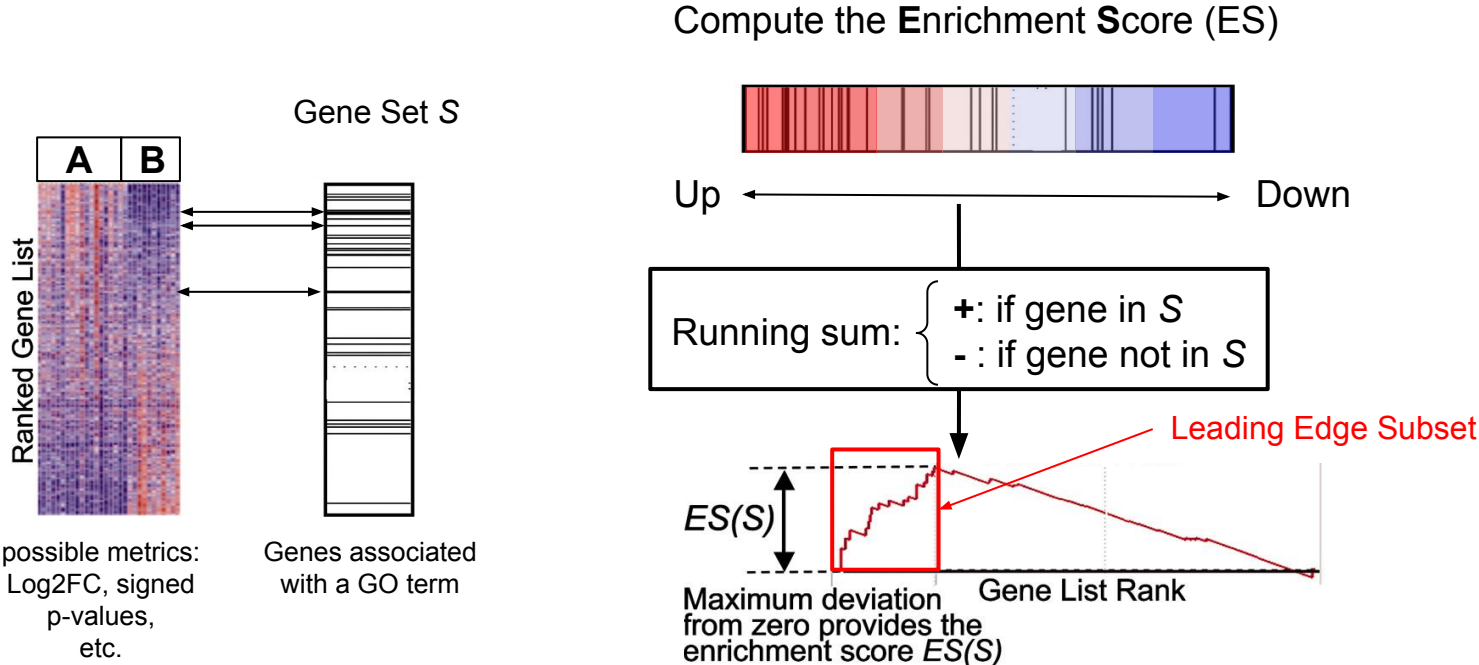


Subramanian, A. et al., 2005. Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles.
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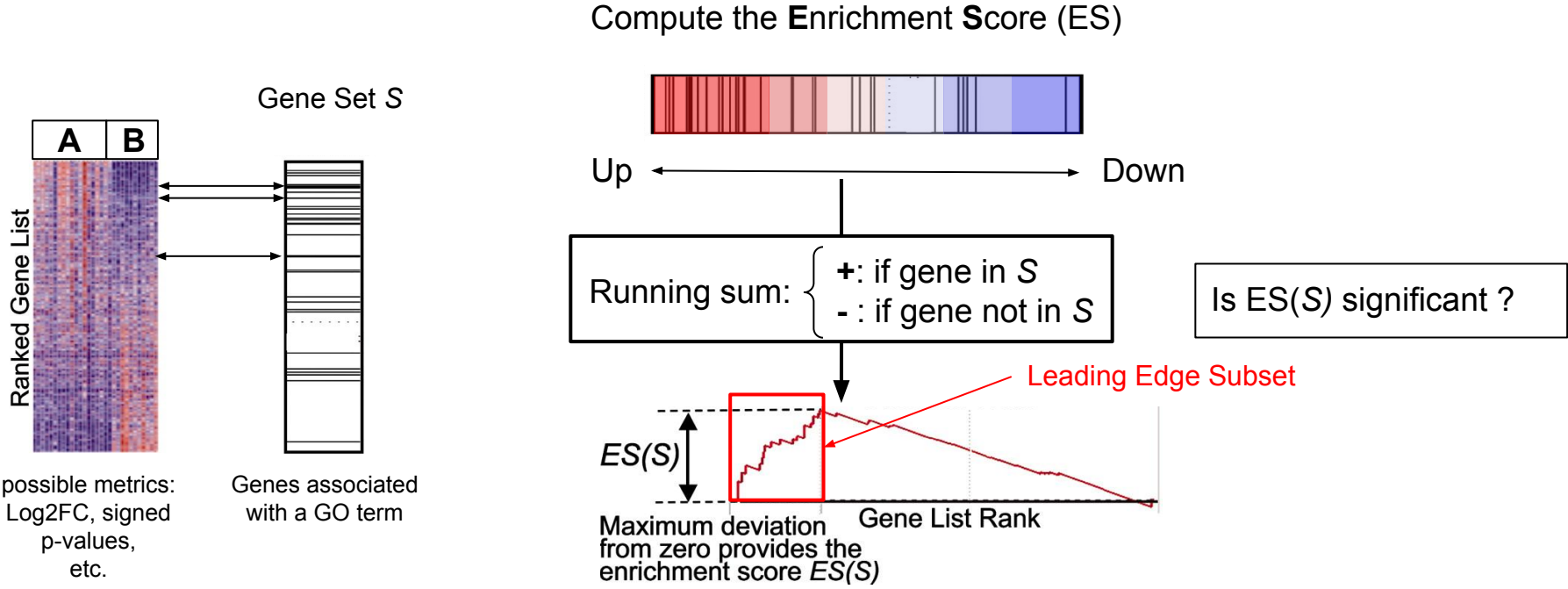


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GSEA: A Function scoring method (2)

Is ES(S) significant ?

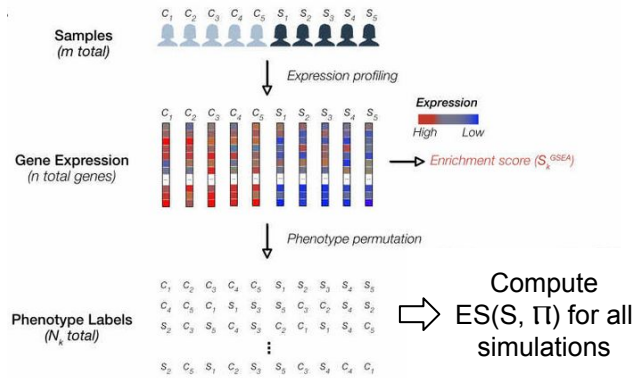
- in unweighted settings (first version of GSEA): exact p-value estimation with KS-test

GSEA: A Function scoring method (2)

Is ES(S) significant ?

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- in weighted settings (common): empirical estimation via permutation test (simulations Π)

Phenotype permutation
(better if enough sample)

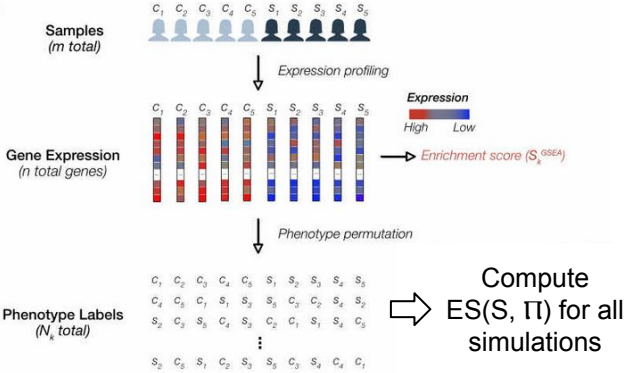


GSEA: A Function scoring method (2)

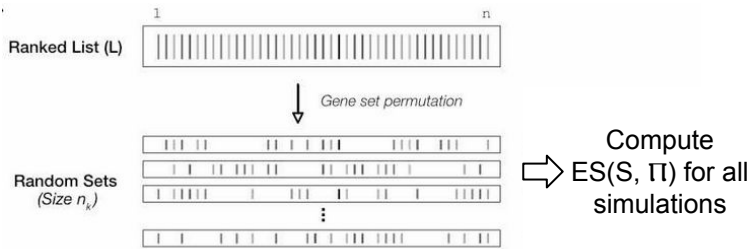
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Phenotype permutation (better if enough sample)



Gene set Permutation (most common but less efficient)

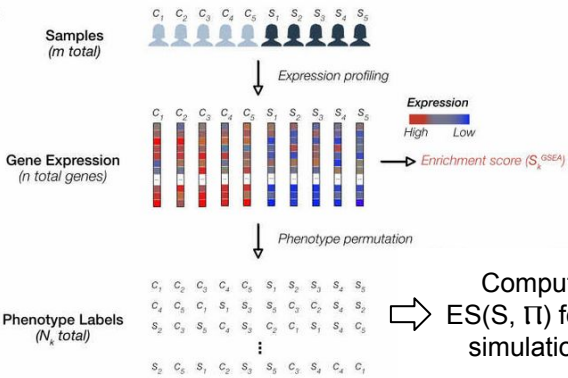


GSEA: A Function scoring method (2)

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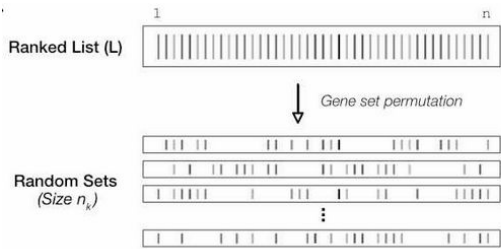
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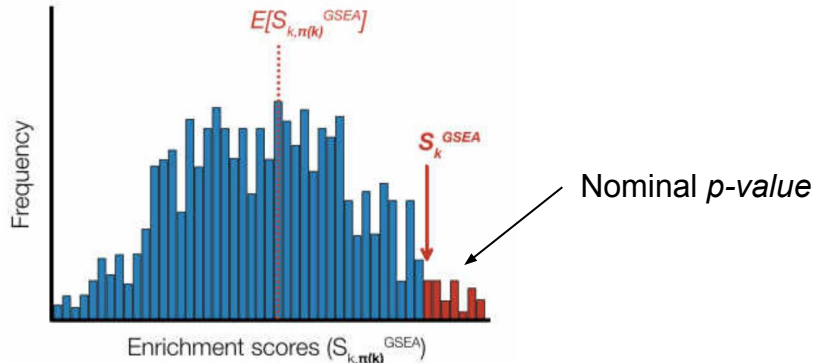


Compute $ES(S, \Pi)$ for all simulations

Gene set Permutation (most common but less efficient)



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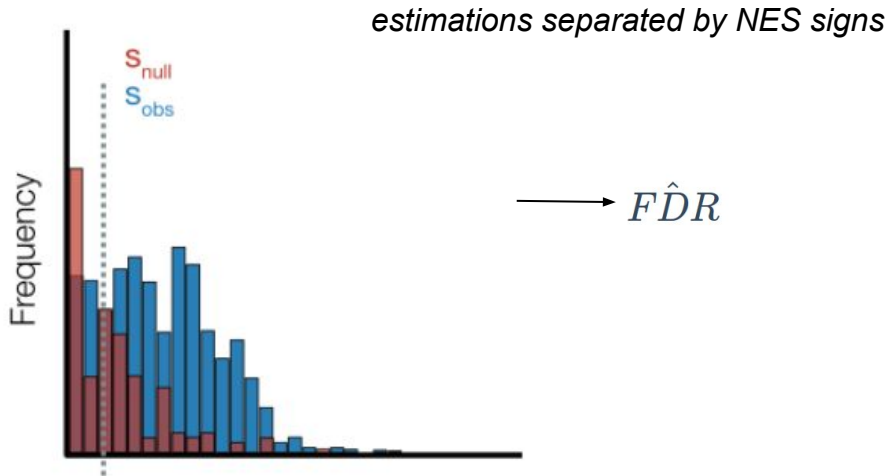
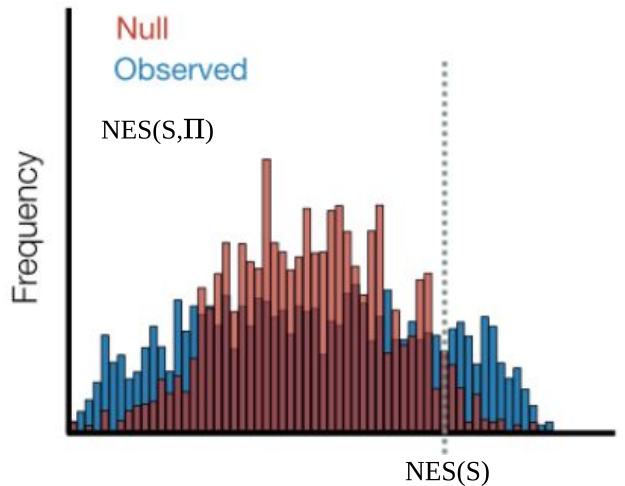
GSEA: A Function scoring method (3)

- How to account for Gene set size differences ?

NES (Normalised Enrichment Score)

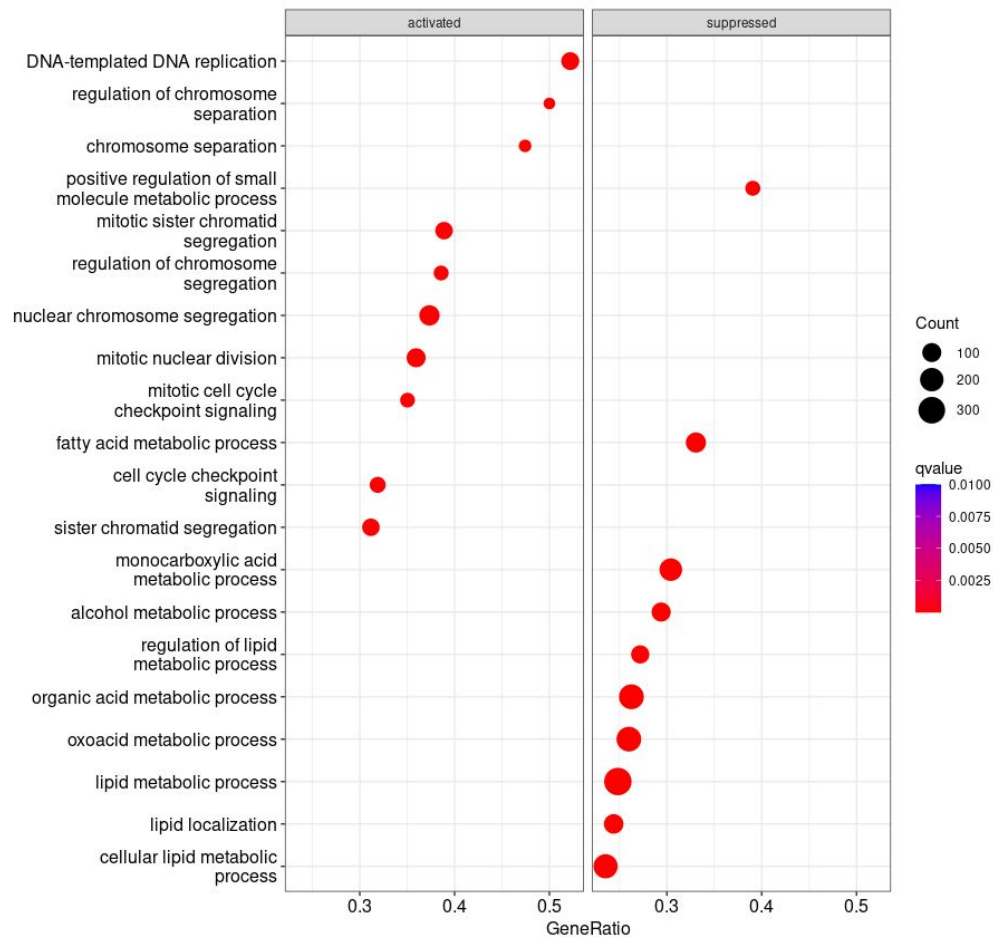
$$NES(S) = \frac{ES(S)}{E[ES(S, \Pi)]} \leftarrow \text{ Gives the direction of regulation + correct for gene set size + signed}$$

- Multiple-test correction: FDR estimation

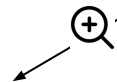
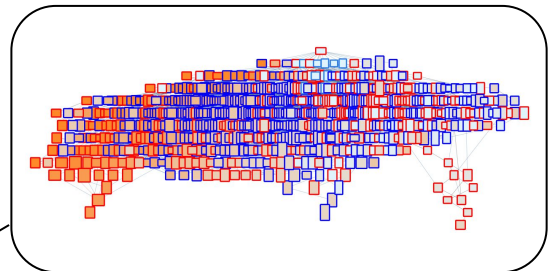


GSEA: A Function scoring method - example

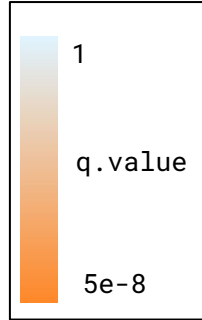
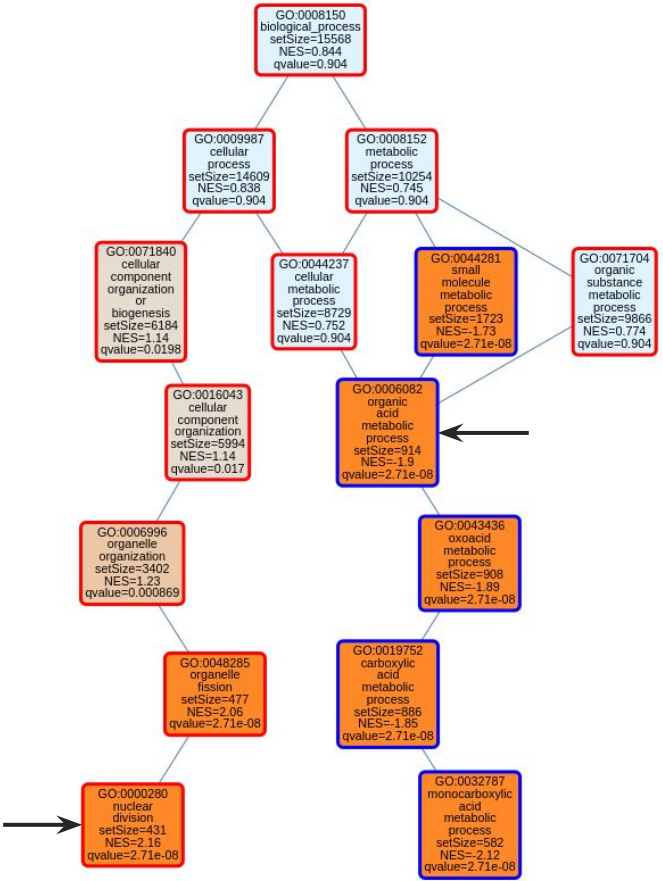
- No need of a cutoff on qvalue or LogFC, just a ranking metric !
- Results are separated between over and under expression BP
- Leading Edge subset can help to identify key actors
- However, same biases apply for database choices !



GSEA: Visualisation - example



Up and Down regulated branch of the DAG

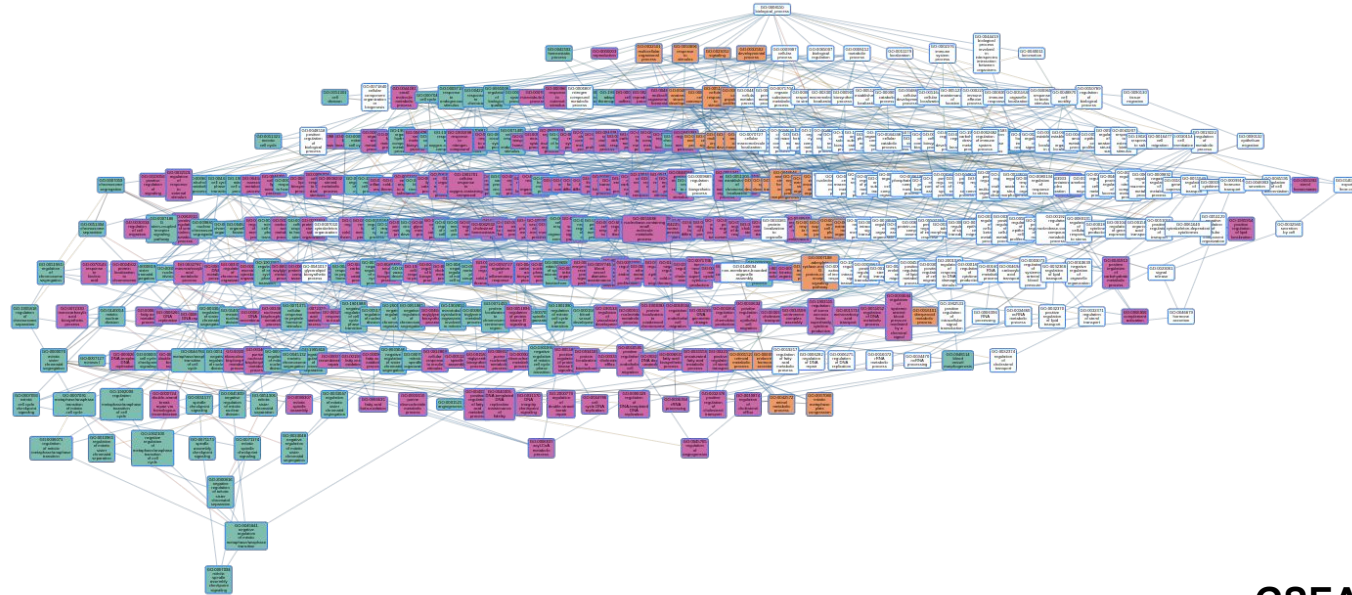



 up-regulated
 down-regulated




isa →



ORA vs GSEA: A visual comparison on the GO DAG graph



 $q.value < 1e-3$

	Only GSEA
	Both ORA and GSEA
	Only ORA

GSEA is more sensitive !

Enrichment Analyses - Conclusion

- Enrichment analyses (ORA or GSEA) are a powerful tool to suggest direction of interpretation and hypotheses
- ORA are simple and universal, but results can be affected by several biases: threshold, databases, universe.
- GSEA is not affected by thresholding and gives more weight to the most discriminant genes
- Several biases remain:
 - Internal structure of pathway / interconnection between entities in a pathway
 - Overlap / interconnections between pathways
 - What about gene variants ?

**Topological
methods**

To Be Continued



Extend contextualisation with Biomedical Knowledge Graph

What is a Graph ?

A graph is defined by a set of **nodes** and **edges**



Attributes/Properties



Relations/Paths

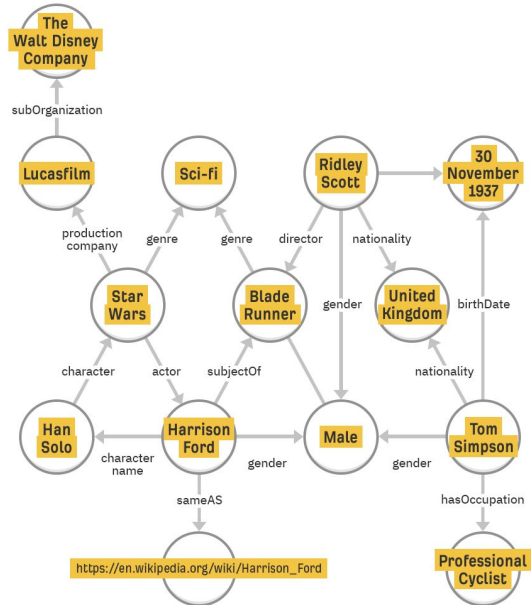
Different questions, different visualisation, different methods

What's a Knowledge Graph ?

Connect the knowledge  Knowledge Graphs




Google knowledge graph




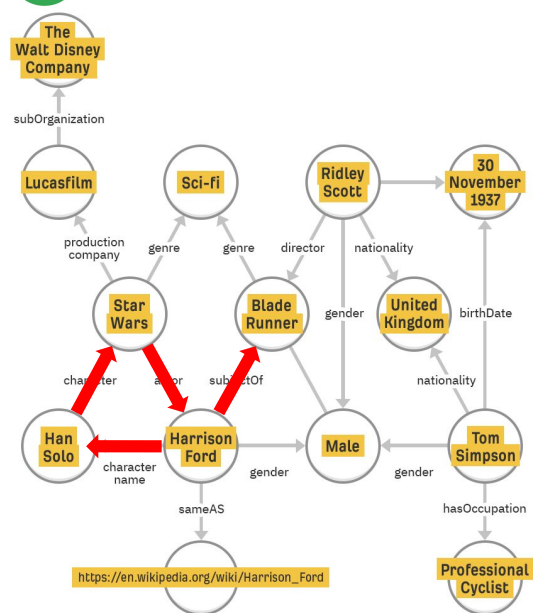
source: ahrefs

Key:  Edges  Nodes

What's a Knowledge Graph ?

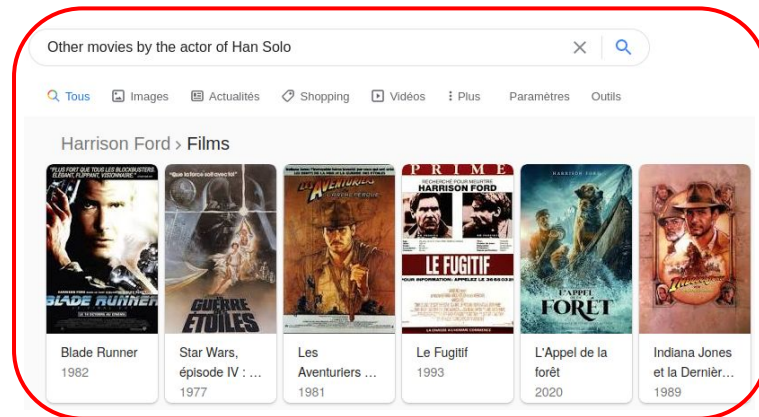
Connect the knowledge  Knowledge Graphs

 Google knowledge graph



source: ahrefs


Key:  Edges  Nodes

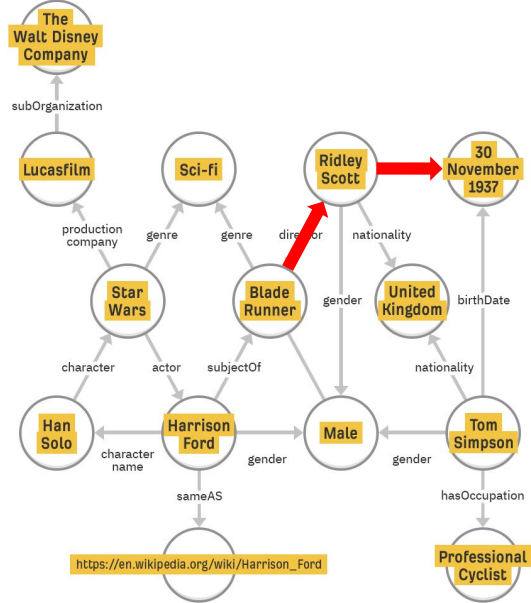


Complex Information Retrieval

What's a Knowledge Graph ?

Connect the knowledge  Knowledge Graphs

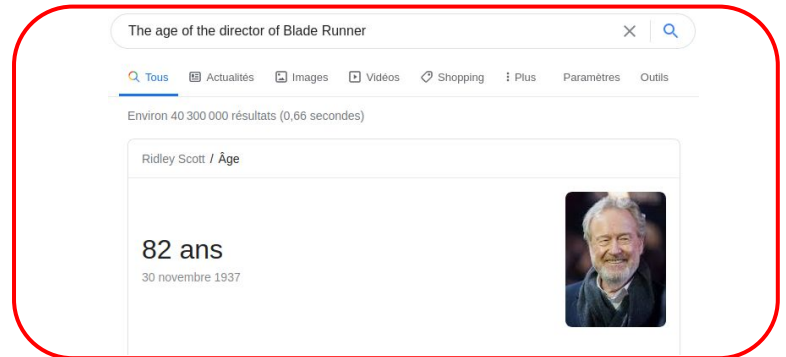
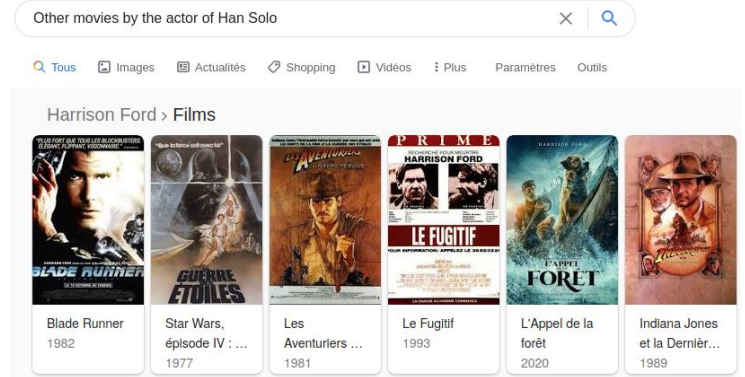
 Google knowledge graph




source: ahrefs


Key:  Edges  Nodes

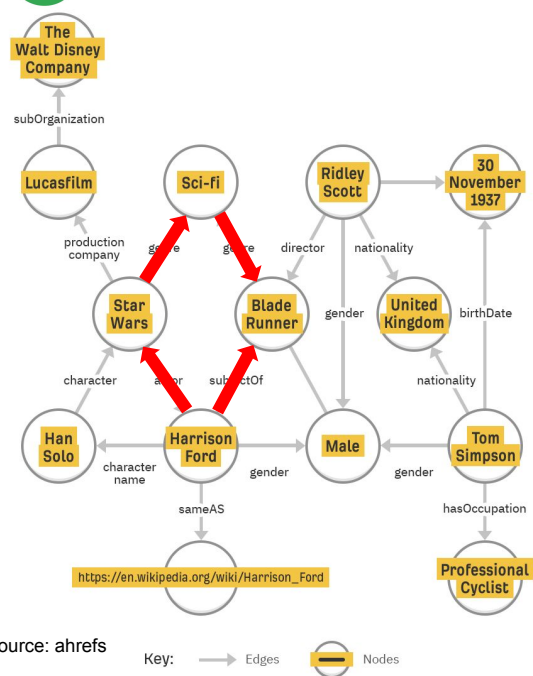
Complex Information Retrieval



What's a Knowledge Graph ?

Connect the knowledge  Knowledge Graphs

 Google knowledge graph



source: ahrefs

Key:  Edges  Nodes

Complex Information Retrieval 

The screenshot shows a search engine interface. At the top, a search bar contains the text 'Other movies by the actor of Han Solo'. Below it, navigation tabs include 'Tous', 'Images', 'Actualités', 'Shopping', 'Vidéos', 'Plus', 'Paramètres', and 'Outils'. The main content area is titled 'Harrison Ford > Films'. A search bar within this section contains 'Science fiction movies with harrison ford'. Below this, there are tabs for 'Tous', 'Actualités', 'Vidéos', 'Images', 'Shopping', 'Plus', 'Paramètres', and 'Outils'. The section is titled 'À regarder' with sub-links for 'Recommandations' and 'En savoir plus'. Below this, a heading reads 'Films / SF / Harrison Ford'. A row of five movie posters is displayed: Blade Runner, Blade Runner 2049, La Stratégie Ender, Star Wars, épisode IV : Un nouvel espoir, and Cowboys et envahisseurs. A red rounded rectangle highlights the search bar and the movie posters.

Extend contextualisation with Biomedical Knowledge Graph

What is a Graph ?

A graph is defined by a set of **nodes** and **edges**



Attributes/Properties



Relations/Paths

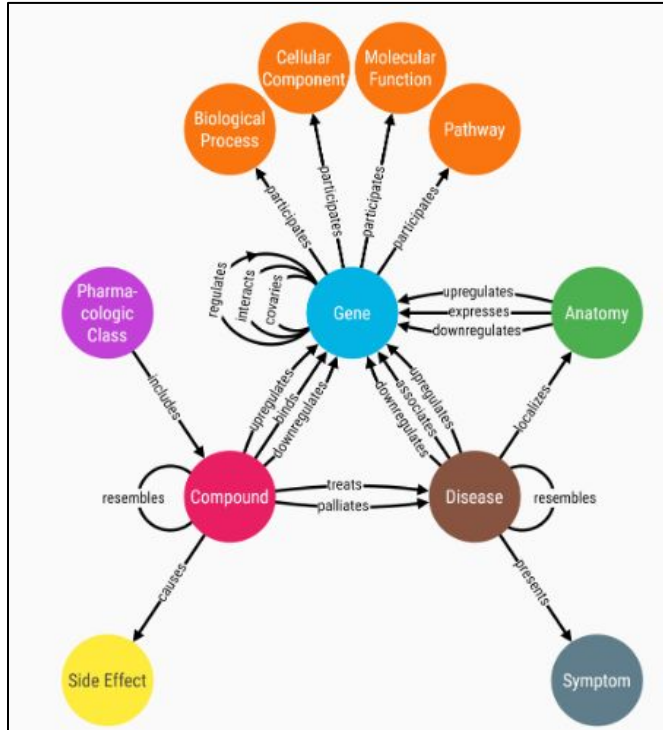
Different questions, different visualisation, different methods

What is a Biomedical Knowledge Graph ?

It's a directed and labeled multi-graph describing biomedical entities and their relations

- Different Model: RDF (in Semantic Web) and **LPG** (Labeled Property Graph)
- Efficient for complex information extraction
- Examples: Hetionet, Wikidata, PharmKG, FORUM, etc.

Example of Hetionet



How to request a Knowledge Graph (in Neo4J) - LPG



3 main clauses:

- MATCH: Specify the graph pattern
- WHERE: Add restrictions to the nodes or edges properties
- RETURN: Define what is included in the results

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How to write:

nodes: (variable:Label)

(Label is optional)

edges: -[variable:Label]->

How to request a Knowledge Graph (in Neo4J) - LPG



3 main clauses:

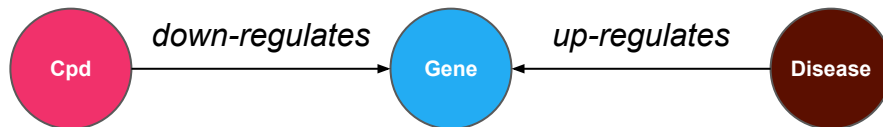
- MATCH: Specify the graph pattern
- WHERE: Add restrictions to the nodes or edges properties
- RETURN: Define what is included in the results

How to write:

nodes: (variable:Label)

(Label is optional)

edges: -[variable:Label]->



```
MATCH (c:Compound)-[r1:DOWNREGULATES_CdG]->(g:Gene)<-[r2:UPREGULATES_DuG]-(d:Disease)
WHERE g.name IN [ "BRCA1", "BRCA2", ... ]
RETURN c, r1, g, r2, d
```

Extend contextualisation with Biomedical Knowledge Graph

Visit the *Hetionet Neo4J Browser*

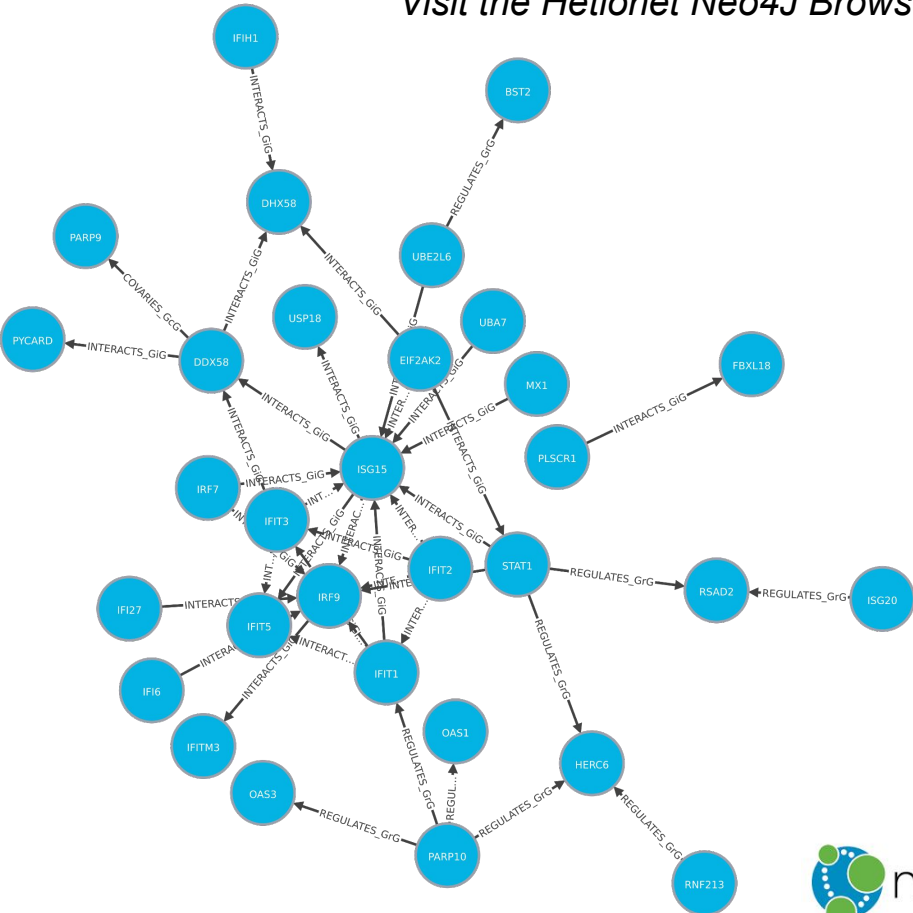
TP WGCNA



Black gene module



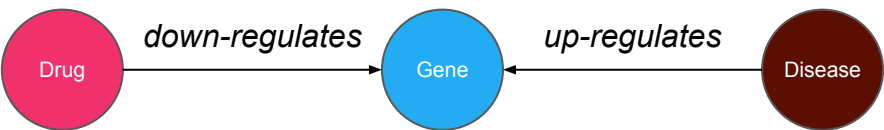
Explore relations between genes in a module



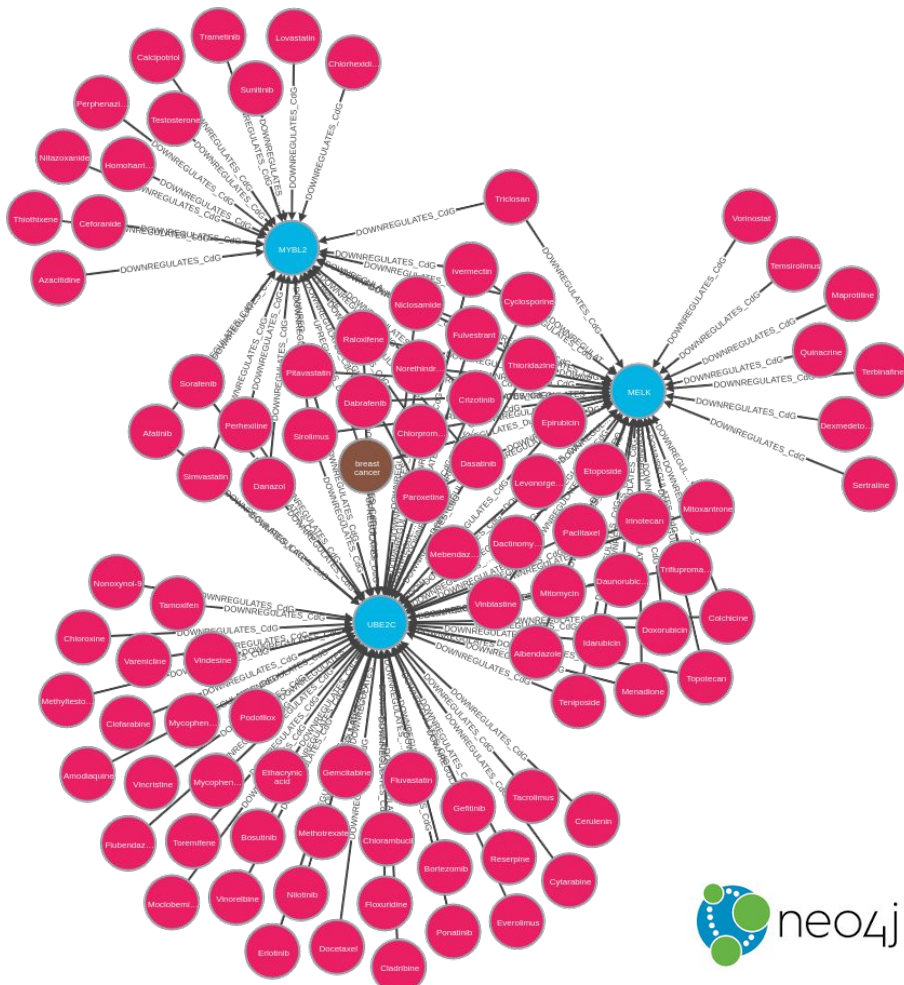
Extend contextualisation with Biomedical Knowledge Graph

A more complex path

By selecting only the up-regulated genes (LogFC > 5)



Drugs
Thioridazine
Doxorubicin
Dabrafenib
Teniposide



Extend contextualisation with Biomedical Knowledge Graph

Biomedical Knowledge Graphs as a resource to train link-prediction systems



Google Scholar

Articles Environ 294 résultats (0,06 s) **294**

Rechercher parmi les articles qui s'y rapportent

OpenBiolink: a benchmarking framework for large-scale biomedical link prediction peerj arxiv.org
A Bhat, S Ch, A Alkhalaf, M Sammad - Bioinformatics, 2020 - academic.oup.com
... have shown potential for predicting undiscovered links in biomedical knowledge networks, ...-quality and highly challenging biomedical link prediction benchmark to transparency and ...
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An ensemble learning approach to perform link prediction on large scale biomedical knowledge graphs for drug repurposing and discovery peerj biorxiv.org
V Prabhakar, C Vu, J Crawford, J White, K Liu - bioRxiv, 2023 - biorxiv.org
... link prediction from the KG&E models trained on each subgraph are then aggregated to generate a consolidated set of link prediction - link prediction - as well as general link prediction ...
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Neuro-symbolic XAI: Application to drug repurposing for rare diseases peerj arxiv.org
M Drance - International Conference on Database Systems for ..., 2022 - Springer
In this project, we focus on OIR using link prediction algorithm. Link prediction consists of ... creating methods allowing to make transparent prediction in the context of drug repurposing ...
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Adapting Neural Link Predictors for Complex Query Answering peerj arxiv.org
R Anagnostou, F Mirzaei, J Lapanjani - arXiv preprint arXiv:2301.12313, 2023 - arxiv.org
... We must also factor in the neural link prediction link prediction scores by backpropagating through the complex query-answering process. More formally, let q denote a neural link ...
☆ Enregistrer Citer Autres articles Les 2 versions

Neuro-symbolic XAI for Computational Drug Repurposing. peerj sciexpress.org
M Drance, M Boudin, F Mirzaei, J Lapanjani - KEIO, 2023 - sciexpress.org
... of link prediction in a knowledge graph-based computational drug repurposing. Link prediction ... how the organization of data in a knowledge graph changes the quality of predictions ...
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Neural multi-hop reasoning with logical rules on biomedical knowledge graphs peerj arxiv.org
V Liu, M Hildebrandt, M Zaman, M Piroozmand - The Semantic Web, 18th ..., 2021 - Springer
... We formalize this task as a link prediction problem where both compounds and diseases correspond to ... several state-of-the-art methods for link prediction while providing interpretability. ...
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LinkExplorer: predicting, explaining and exploring links in large biomedical knowledge graphs peerj biorxiv.org
S Ch, A Barbosa-Silva, M Sammad - Bioinformatics, 2022 - academic.oup.com
... together with predicted links and their ... the predictions of a state-of-the-art link prediction algorithm. We also report highly competitive evaluation results of our explainable link prediction ...
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Drug-drug interaction prediction on a biomedical literature knowledge graph peerj google.com
K Barakat, L Aijoun, A Hamdy, A Khatib - Artificial Intelligence in ..., 2020 - Springer
... network and performs link prediction to construct an integrative model of drug efficacy ... Knowledge Graph and the development of a link prediction model consists of a sequence of ...
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A Meta-Path-Based Prediction Method for Disease Comorbidities
B Gu, B Valler, M Pacheco - ..., 2021, IEEE 34th ..., 2021 - IEEE
... The identification of new disease-disease relationships using link prediction methods has not only improved our understanding of their etiology and pathogenesis, but has also made it ...
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A computational approach to drug repurposing using graph neural networks peerj nih.gov
S Dost, S Chatur - Computers in Biology and Medicine, 2022 - Elsevier
... We perform link prediction using considered GNN models on the constructed graphs, starting with the only drug-disease two-layered graph, followed by the individual addition of the ...

Extend contextualisation with Biomedical Knowledge Graph

Biomedical Knowledge Graphs as a resource to train link-prediction systems



Google Scholar

Articles Environ 294 résultats (0,06 s) **294**

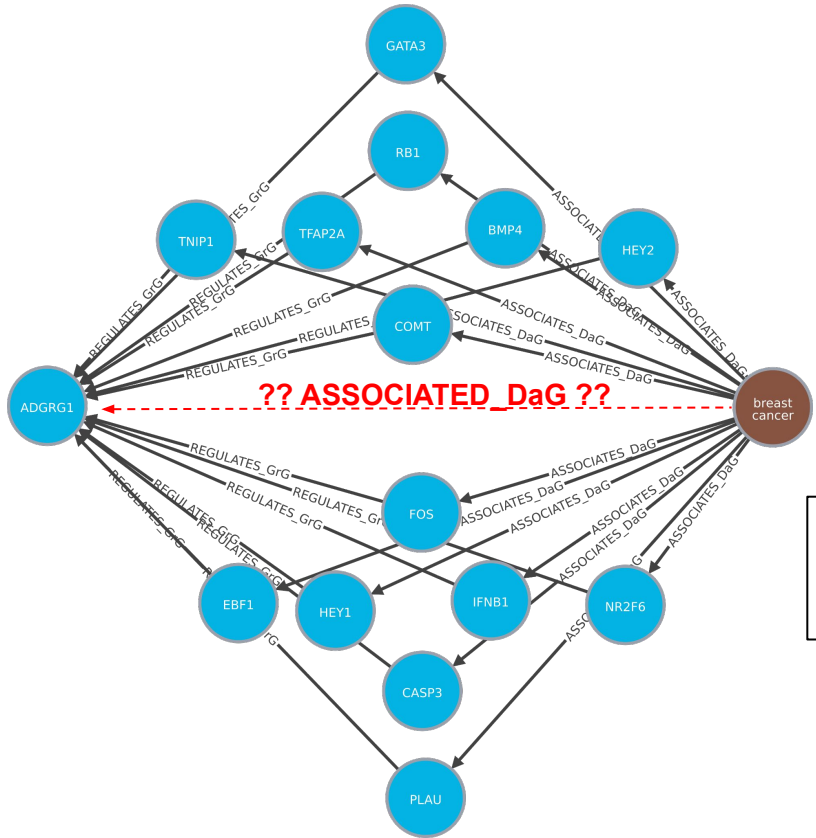
Date indifférente
Depuis 2023
Depuis 2022
Depuis 2019
Période spécifique...

Trier par pertinence
Trier par date

Toutes les langues
Rechercher dans les pages en Français

Créer l'alerte

Systematic integration of biomedical knowledge prioritizes drugs for repurposing
OpenBioLink: a benchmarking framework for large-scale biomedical link prediction
An ensemble learning approach to perform link prediction on large scale biomedical knowledge graphs for drug repurposing and discovery
Neuro-symbolic XAI: Application to drug repurposing for rare diseases
Adapting Neural Link Predictors for Complex Query Answering
Neuro-symbolic XAI for Computational Drug Repurposing
Neural multi-hop reasoning with logical rules on biomedical knowledge graphs
LinkExplorer: predicting, explaining and exploring links in large biomedical knowledge graphs
Drug-drug interaction prediction on a biomedical literature knowledge graph
A Meta-Path-Based Prediction Method for Disease Comorbidities
A computational approach to drug repurposing using graph neural networks



E.g Adamic Adar

$$A(x, y) = \sum_{u \in N(x) \cap N(y)} \frac{1}{\log |N(u)|}$$

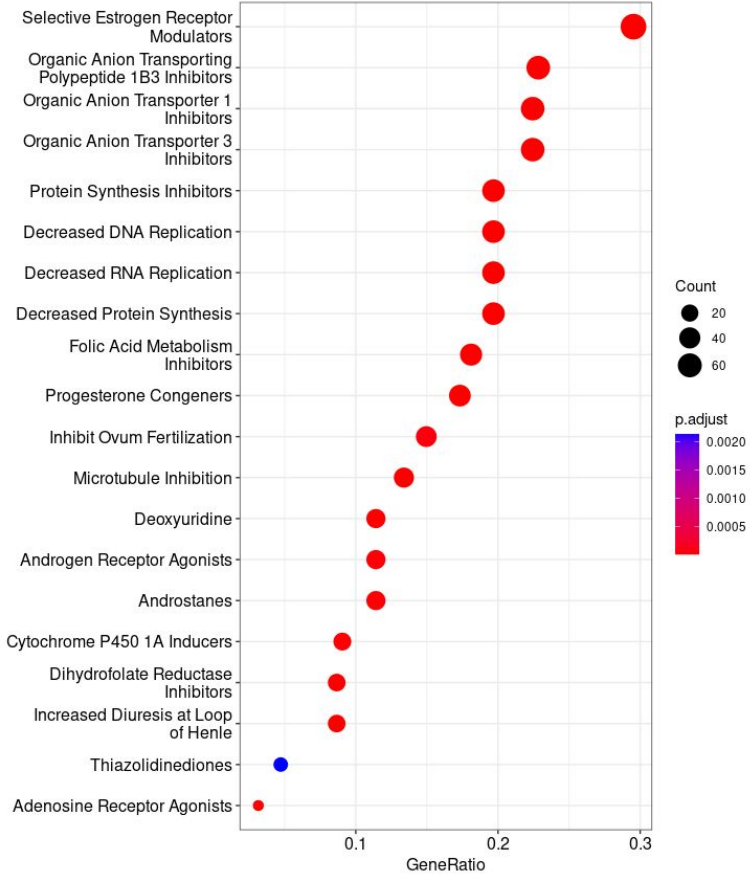
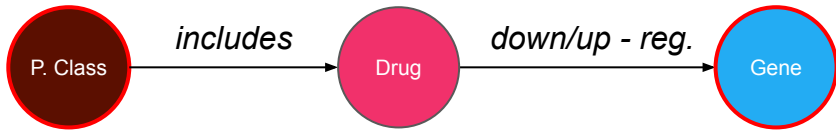
"Friend of a friend"

+ Embeddings,
rule-based,
Supervised, etc.

Extend contextualisation with Biomedical Knowledge Graph

Use a Biomedical Knowledge Graph to build a Enrichment custom background set

What class of drugs is enriched for their relation with the set of genes of interest ? (ORA)

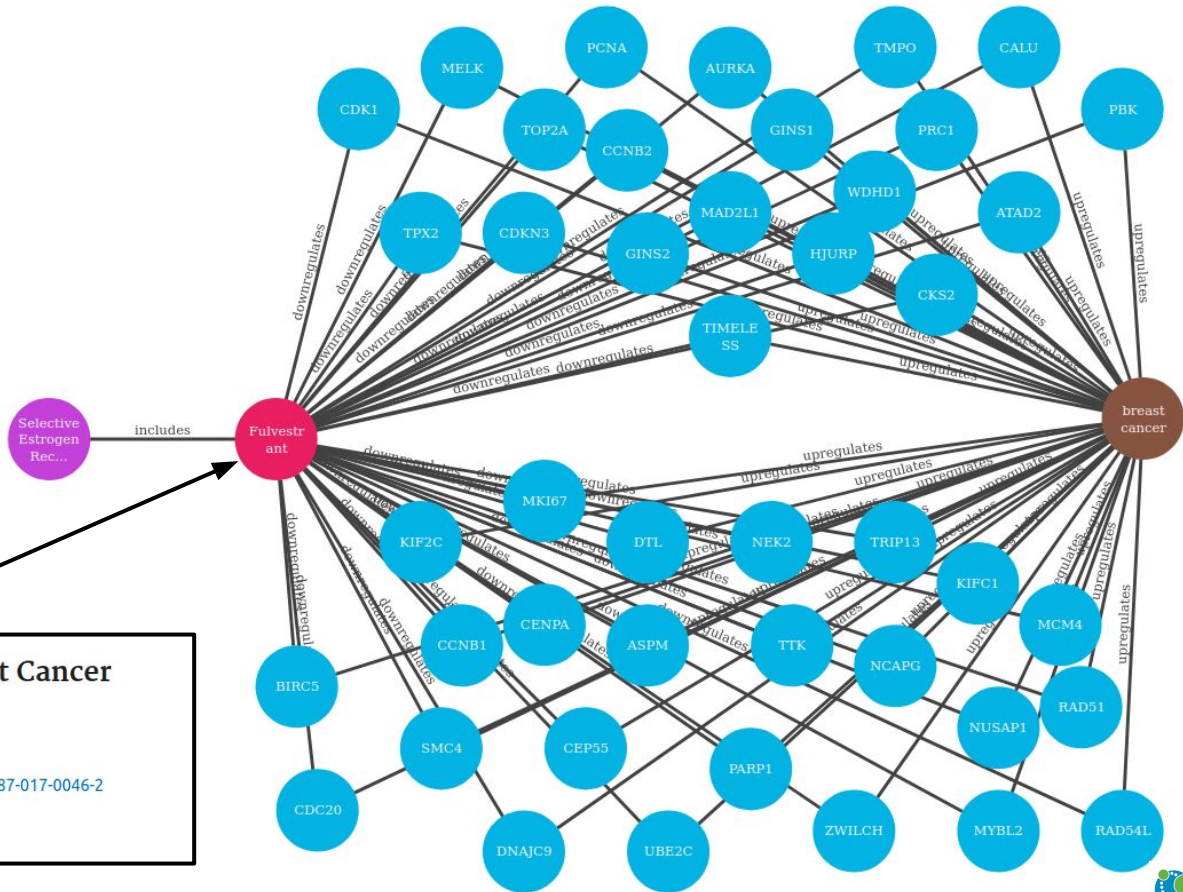


Extend contextualisation with Biomedical Knowledge Graph

Connectivity search

Give it a try: <https://het.io/search>

A Review of Fulvestrant in Breast Cancer
Mark R Nathan ¹, Peter Schmid ¹
Affiliations + expand
PMID: 28680952 PMCID: PMC5488136 DOI: 10.1007/s40487-017-0046-2
[Free PMC article](#)



From LPG to Semantic Web

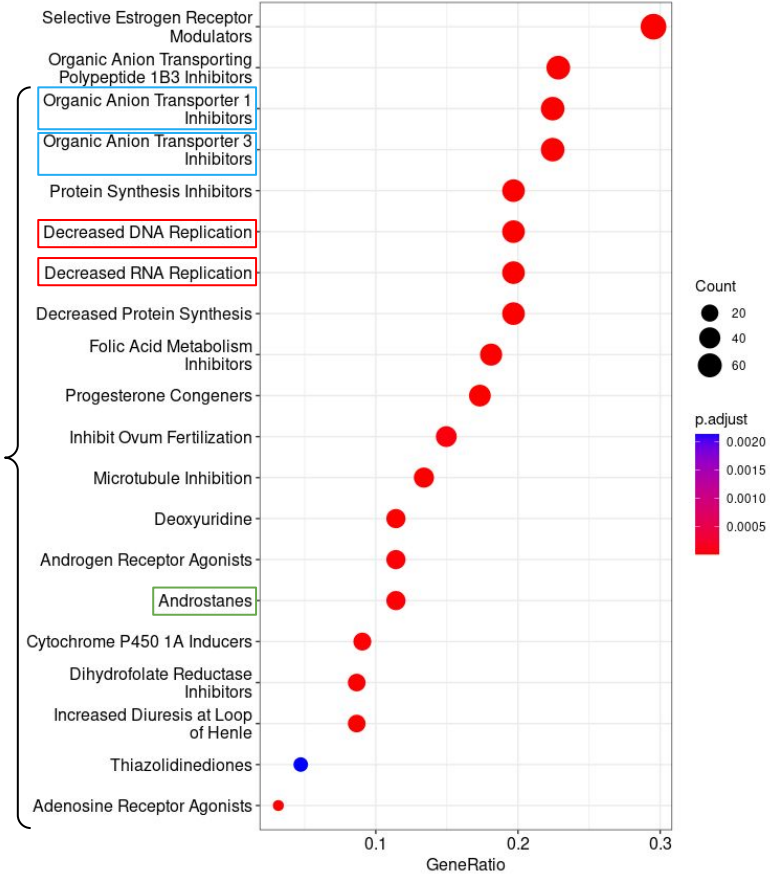
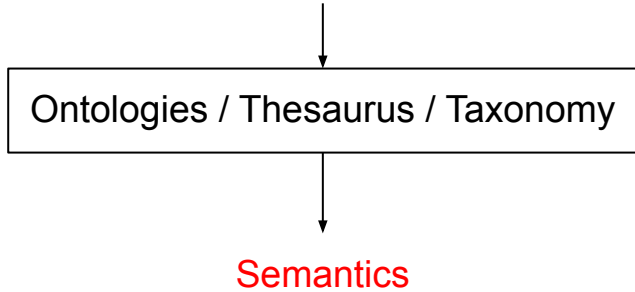
Labeled Property Graph (LPG) - eg. Neo4J

- Efficient extraction of relations (or paths) between entities
- The graph is flexible

Q1: *But what if we want to use relations beyond what is stored in Hetionet ?
Like information from UniProt, Rhea, Wikidata, etc.*

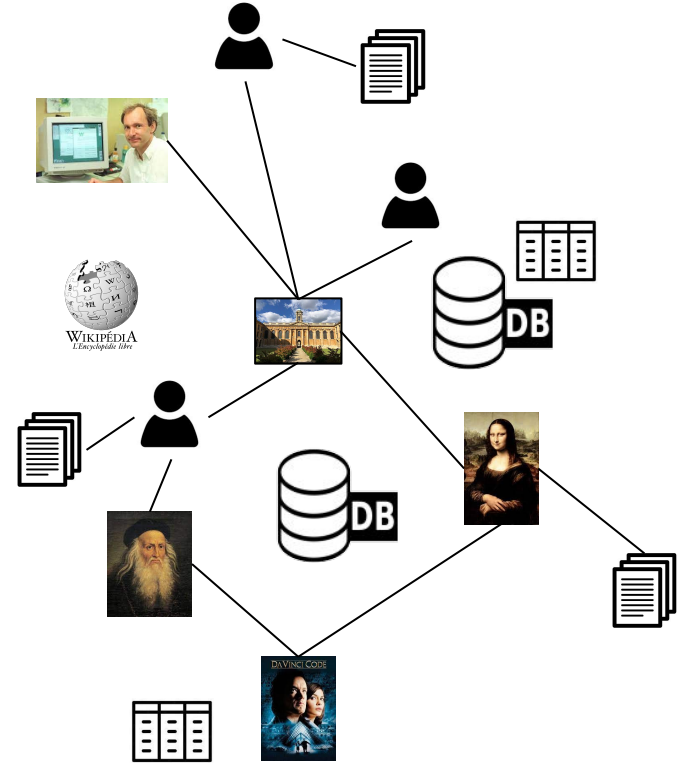
Q2: *What if we want to reason on the graph ?*

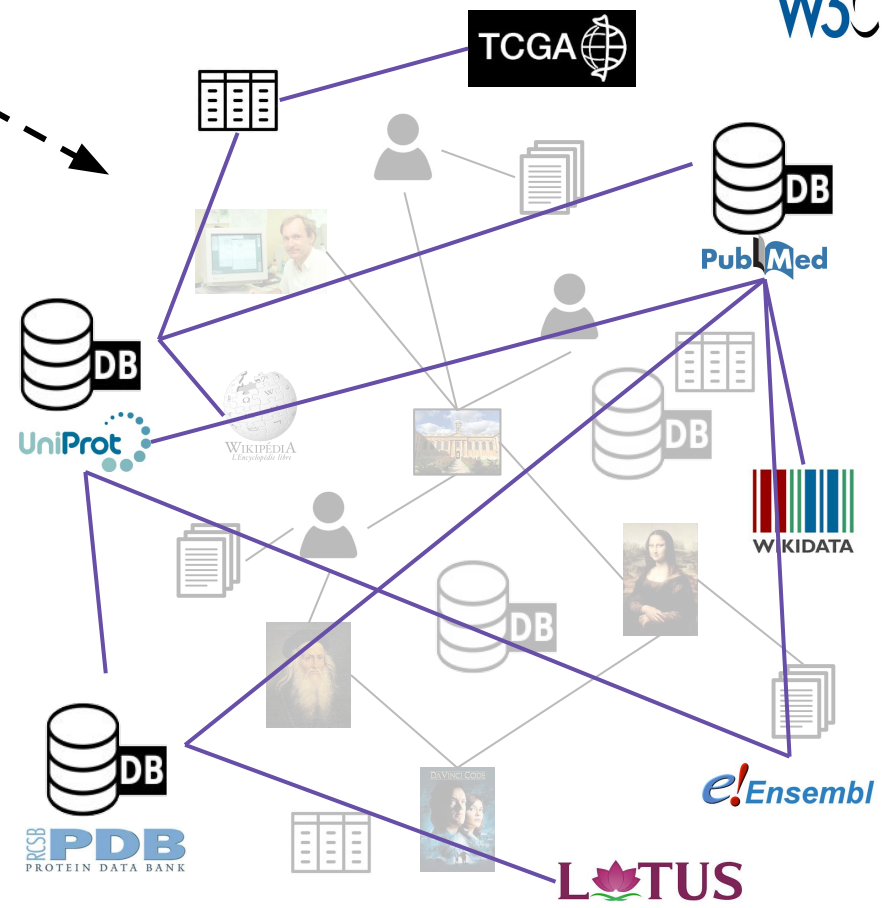
We would need something like the Gene **Ontology**, but for pharmacological classes !



Semantic Web

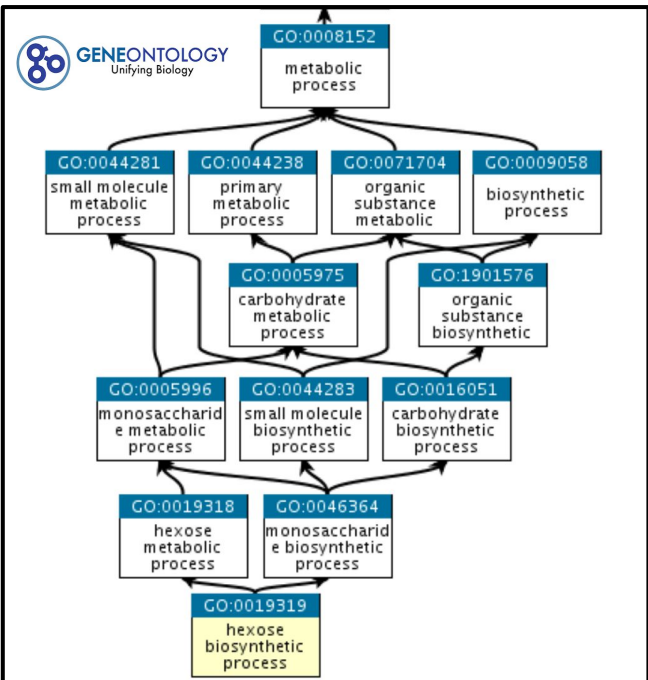
Semantic Web





A collection of resources

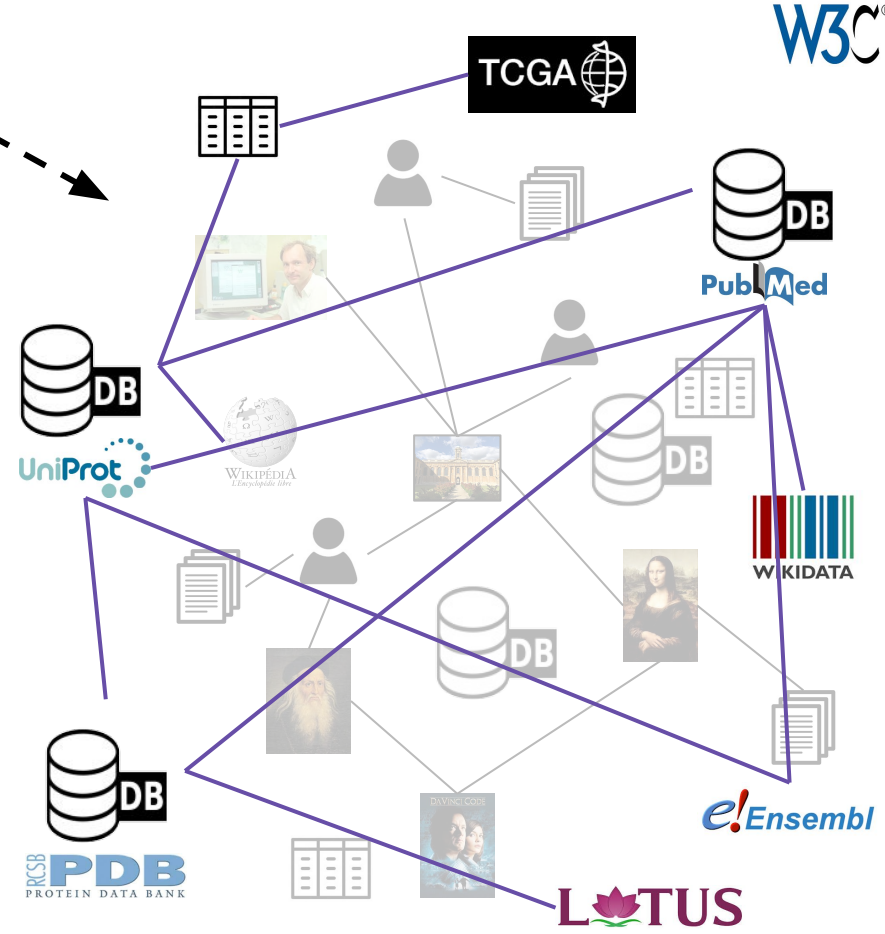
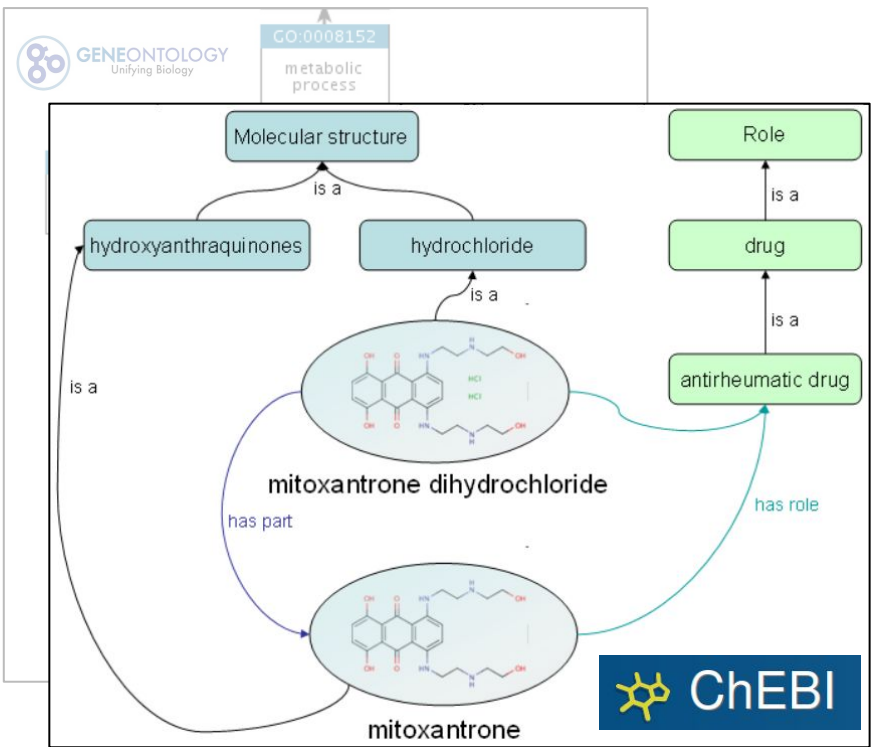
Semantic Web



A collection of resources

Semantic Web

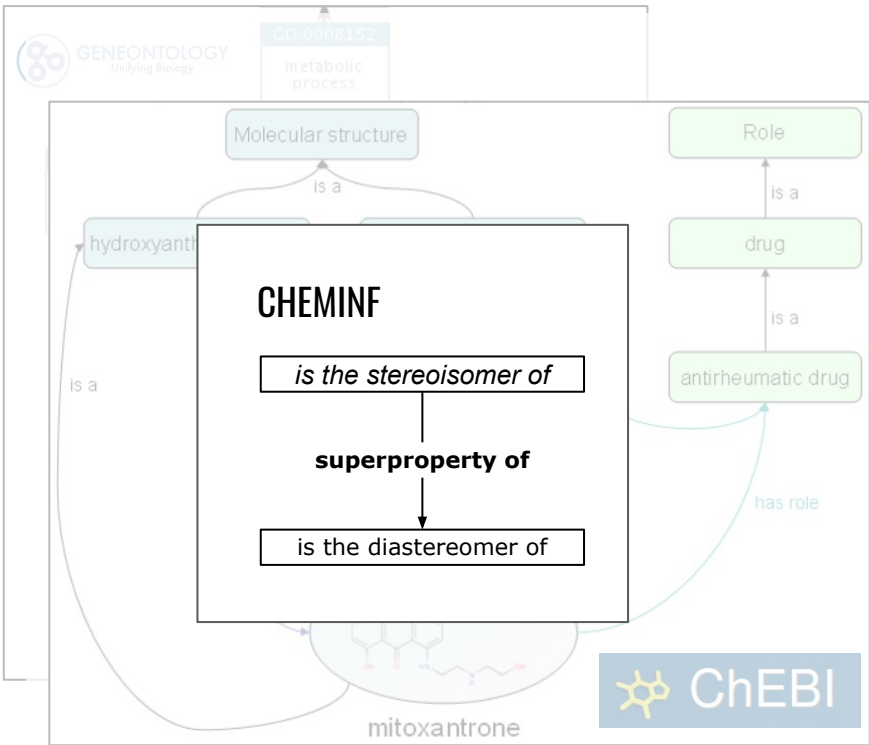
Semantic Web



A collection of resources

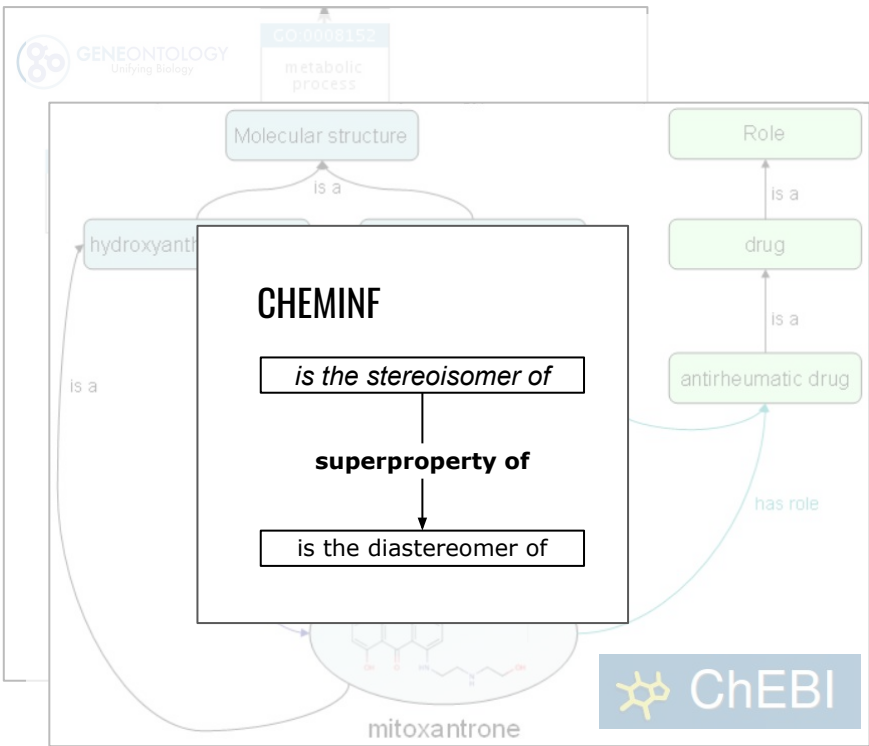
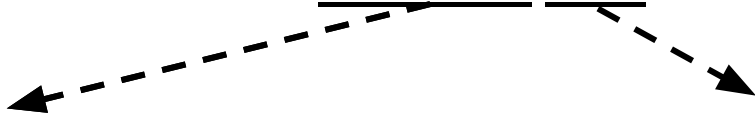
Semantic Web

Semantic Web

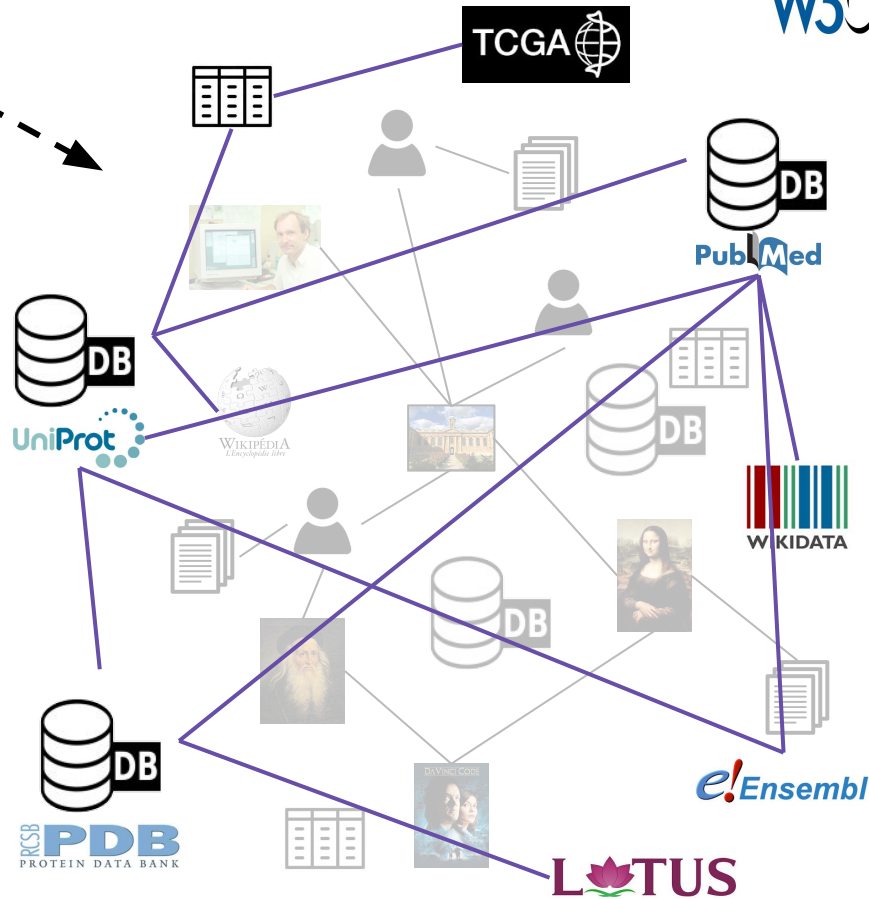


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Semantic Web

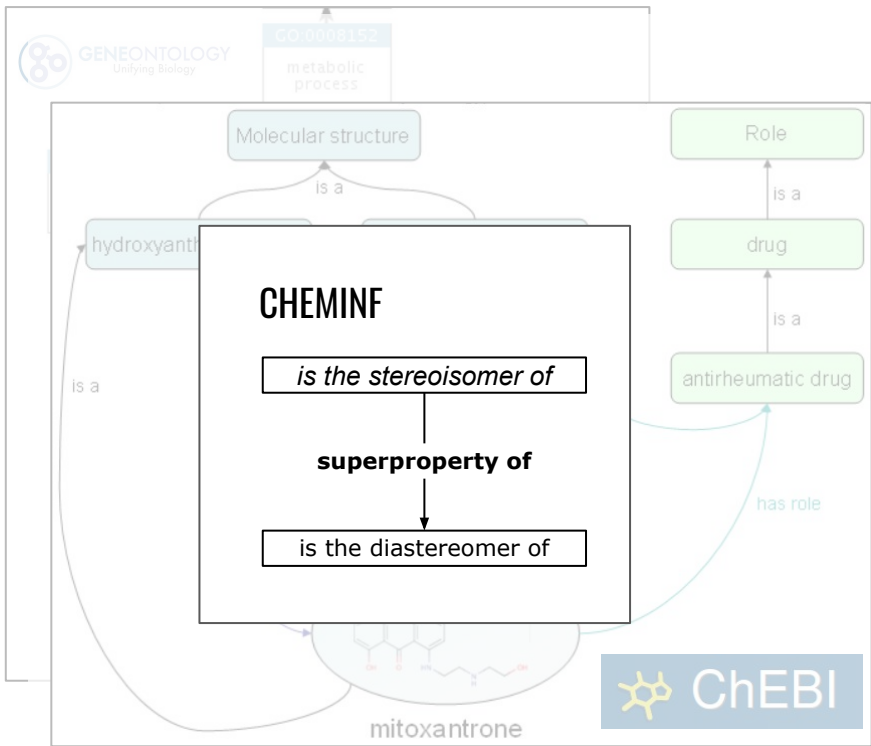


A Semantic description of entities and relations

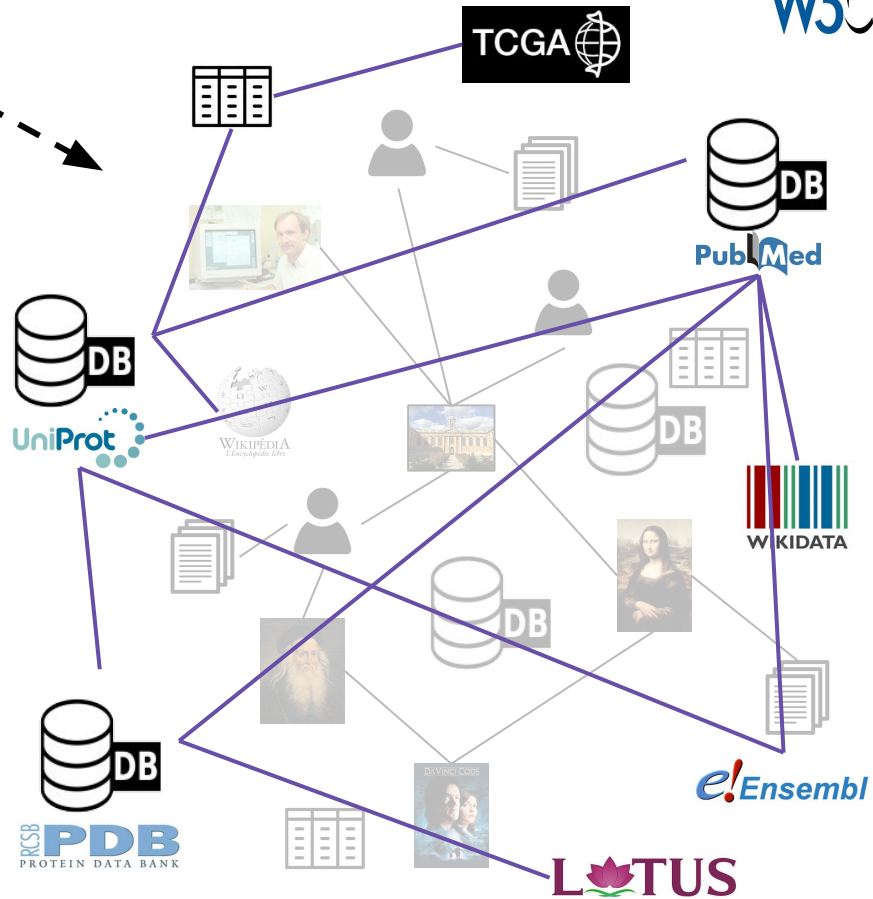


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Semantic Web



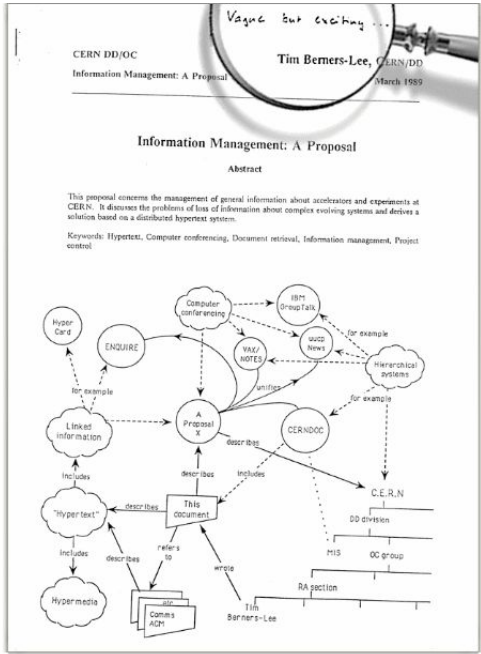
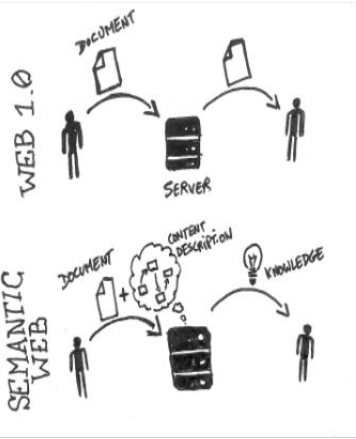
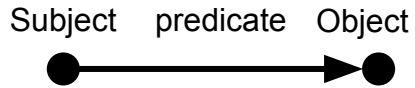
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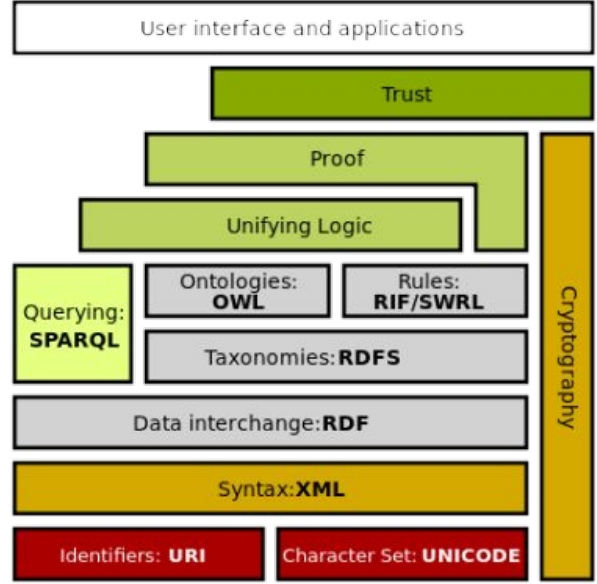
A collection of resources

Semantic Web: technical introduction

A common formalism:



A stack of technologies



Even Aussois is described in a Knowledge Graph ...

About: [Aussois](#)

An Entity of Type: [place](#), from Named Graph: <http://dbpedia.org>, within Data Space: [dbpedia.org](#)

Aussois (French pronunciation: [oswa]) is a commune in the Vanoise massif, in the Savoie department in the Auvergne-Rhône-Alpes region in south-eastern France. The village is on the border of France's first National Park, the Vanoise National Park. Although not as well known as other resorts right on the other side of the mountain like Val Thorens, it is popular with the French as ski resort in winter and as mountain destination in summer. At 8 km (5.0 mi) from Modane, it is ideally located in the Maurienne region with good transport links in and out of Lyon, Geneva, Grenoble and Chambéry. Aussois can also be reached from Turin via the Fréjus Road Tunnel, linking Bardonecchia in Italy and Modane. Nearby Gare de Modane is a large railway station with a high-speed service (TGV) Paris - Cham

[thumbnail](#)

Property	Value
dbo:PopulatedPlace/area	<ul style="list-style-type: none">• 41.94
dbo:abstract	<ul style="list-style-type: none">• Aussois (French pronunciation: [oswa]) is a commune in the Vanoise massif, in the Savoie department in the Auvergne-Rhône-Alpes region in south-eastern France. The village is on the border of France's first National Park, the Vanoise National Park. Although not as well known as other resorts right on the other side of the mountain like Val Thorens, it is popular with the French as ski resort in winter and as mountain destination in summer. At 8 km (5.0 mi) from Modane, it is ideally located in the Maurienne region with good transport links in and out of Lyon, Geneva, Grenoble and Chambéry. Aussois can also be reached from Turin via the Fréjus Road Tunnel, linking Bardonecchia in Italy and Modane. Nearby Gare de Modane is a large railway station with a high-speed service (TGV) Paris - Chambéry - Turin - Milan.The resort offers 55 km (34 mi) of slopes, 21 slopes (6 Green, 5 Blue, 8 Red, 2 Black). (en)
dbo:area	<ul style="list-style-type: none">• 41940000.000000 (xsd:double)
dbo:canton	<ul style="list-style-type: none">• dbr:Modane
dbo:country	<ul style="list-style-type: none">• dbr:France
dbo:inseeCode	<ul style="list-style-type: none">• 73023
dbo:intercommunality	<ul style="list-style-type: none">• dbr:Communauté_de_communes_Haute_Maurienne_Vanoise

Even Aussois is described in a Knowledge Graph ...

About: [Aussois](#)

An Entity of Type: [place](#), from Named Graph: <http://dbpedia.org>, within Data Space: [dbpedia.org](#)

Aussois (French pronunciation: [oswa]) is a commune in the Vanoise massif, in the Savoie department in the Auvergne-Rhône-Alpes region in south-eastern France. The village is on the border of France's first National Park, the Vanoise National Park. Although not as well known as other resorts right on the other side of the mountain like Val Thorens, it is popular with the French as ski resort in winter and as mountain destination in summer. At 8 km (5.0 mi) from Modane, it is ideally located in the Maurienne region with good transport links in and out of Lyon, Geneva, Grenoble and Chambéry. Aussois can also be reached from Turin via the Fréjus Road Tunnel, linking Bardonecchia in Italy and Modane. Nearby Gare de Modane is a large railway station with a high-speed service (TGV) Paris - Cham

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dbo:area	<ul style="list-style-type: none">41940000.000000 (xsd:double)
dbo:canton	<ul style="list-style-type: none">dbr:Modane
dbo:country	<ul style="list-style-type: none">dbr:France
dbo:inseeCode	<ul style="list-style-type: none">73023
dbo:intercommunality	<ul style="list-style-type: none">dbr:Communauté_de_communes_Haute_Maurienne_Vanoise

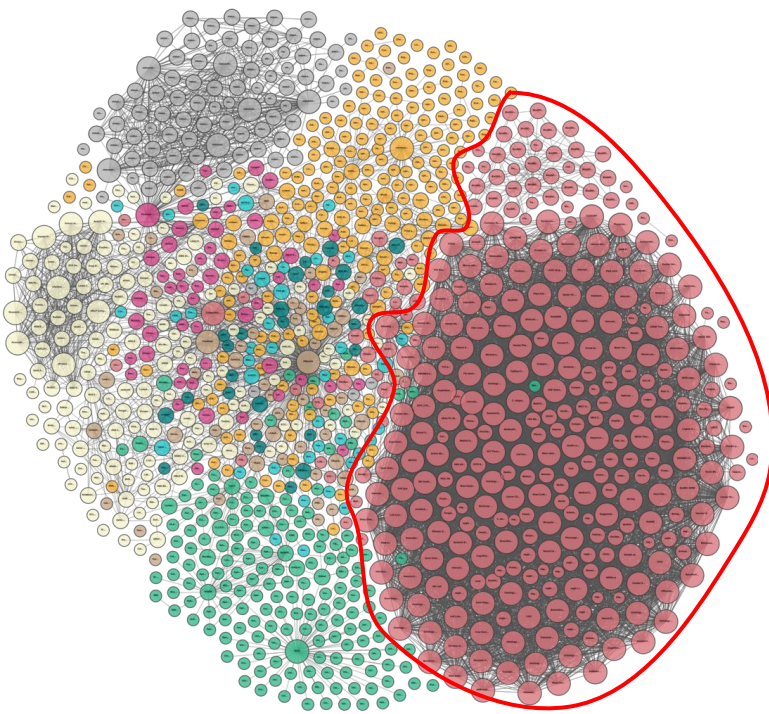
And behind is just triples



http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://www.w3.org/2002/07/owl#Thing
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/ontology/Place
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/ontology/Location
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://schema.org/Place
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://www.wikidata.org/entity/Q486972
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/ontology/PopulatedPlace
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/class/yago/WikicatCommunesOfSavoie
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://www.w3.org/2003/01/geo/wgs84_pos#SpatialThing
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/class/yago/WikicatSkiAreasAndResortsInFrance
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/class/yago/AdministrativeDistrict108491826
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/class/yago/Area108497294
http://dbpedia.org/resource/Aussois	http://www.w3.org/1999/02/22-rdf-syntax-ns#type	http://dbpedia.org/class/yago/Commune108541609

The Web of Life Sciences

- Legend
- Cross Domain
- Geography
- Government
- Life Sciences
- Linguistics
- Media
- Publications
- Social Networking
- User Generated
- Incoming Links
- Outgoing Links



Life science datasets



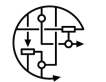
222,843,516



188,410,158,927 entries



8,780,371,866 entries



WIKIPATHWAYS
Pathways for the People

38,733,142 entries



198,762,693 entries



1,366,976 entries

Data Sharing
+
decentralisation

...

The Web of Life Sciences: As a identifier mapping tool

```
SELECT ?gene ?ensembl_gene_id ?entrez_id ?civic_id ?hgnc_id ?OMID_id ?mesh_id WHERE {  
  ?gene wdt:P31 wd:Q7187 ;  
        wdt:P703 wd:Q15978631 . } A Human gene  
  
OPTIONAL { ?gene wdt:P594 ?ensembl_gene_id . }  
OPTIONAL { ?gene wdt:P351 ?entrez_id . }  
OPTIONAL { ?gene wdt:P11277 ?civic_id . }  
OPTIONAL { ?gene wdt:P354 ?hgnc_id . }  
OPTIONAL { ?gene wdt:P492 ?OMID_id . }  
OPTIONAL { ?gene wdt:P486 ?mesh_id . }  
  
}  
LIMIT 1000
```

Map different identifiers



gene	ensembl_gene_id	entrez_id	civic_id	hgnc_id	OMID_id	mesh_id
Q wd:Q227339	ENSG00000012048	672	6	1100	113705	D019398
Q wd:Q238509	ENSG000000178394	3350		5286	109760	
Q wd:Q248215	ENSG000000158560	1780		2963	603772	
Q wd:Q282418	ENSG000000150455	114609		17192	606252	
Q wd:Q286987	ENSG000000165029	19		29	600046	
Q wd:Q289013	ENSG000000175899	2		7	103950	
Q wd:Q369310	ENSG000000125651	2962		4652	189968	
Q wd:Q372645	ENSG000000213780	2968		4658	601760	
Q wd:Q390540	ENSG000000151617	1909		3179	131243	
Q wd:Q390543	ENSG000000136160	1910		3180	131244	
Q wd:Q40108	ENSG000000139687	5925	4795	9884	614041	
Q wd:Q407983	ENSG000000087085	43		108	100740	

The Web of Life Sciences: A federated query example

Find compounds used as drugs for diseases caused by mutations on BRCA2

```
SELECT distinct ?cpd ?mesh ?chebi ?role_label
WHERE
{
```

```
  SERVICE <http://rdf.disgenet.org/sparql/> {
    SELECT distinct ?mesh
    WHERE {
      ?gda sioc:SI0_000628 <http://identifiers.org/ncbigene/675>, ?disease ;
        rdf:type sioc:SI0_001122 ;
        sioc:SI0_000216 ?scoreIRI .

      ?scoreIRI sioc:SI0_000300 ?score .
      FILTER (?score >= 0.9)

      ?disease a ncit:C7057 .
      ?disease skos:exactMatch ?mesh .
      FILTER(strstarts(str(?mesh), "http://id.nlm.nih.gov/mesh/"))
    }
  }
```



Get all disease for which BRCA2 is a *biomarker*

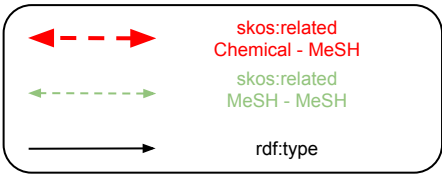
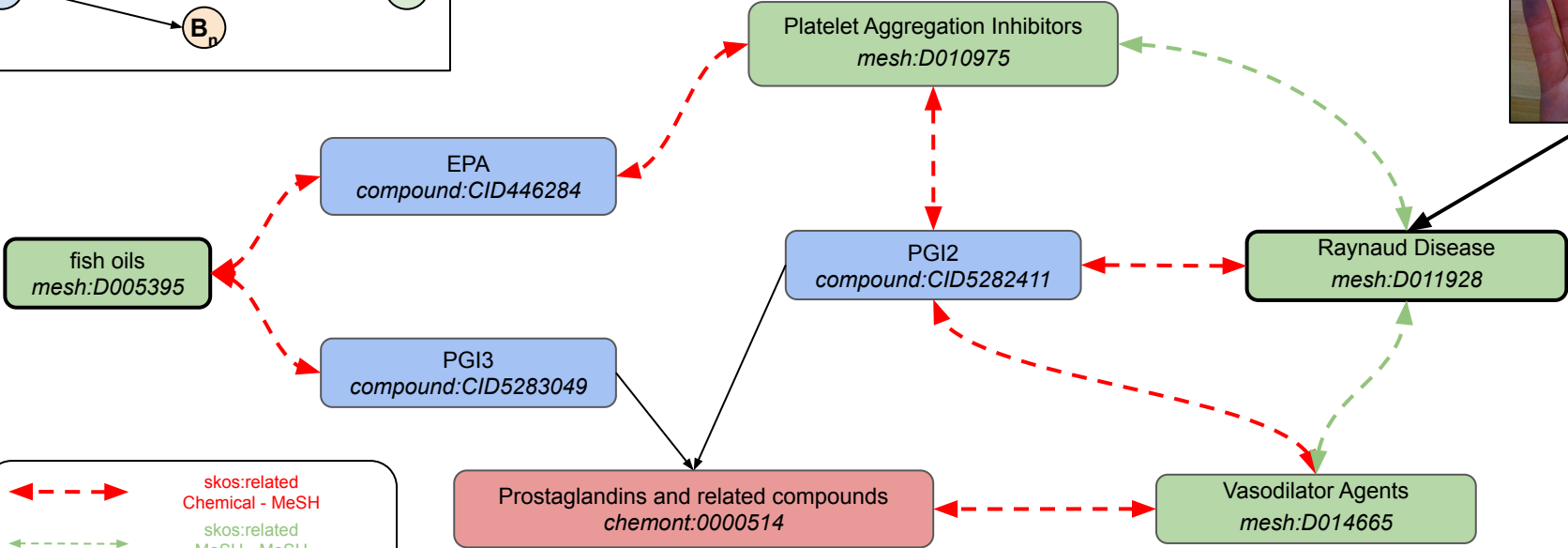
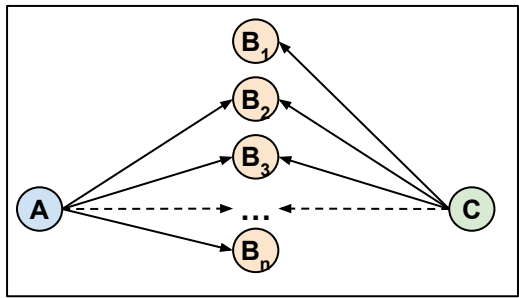
```
  ?mesh (meshv:treeNumber/meshv:parentTreeNumber*) ?tn .
  mesh:D009369 meshv:treeNumber ?tn .
  ?cpd skos:related ?mesh .
  ?cpd a ?chebi .
  ?chebi rdfs:subClassOf [ a owl:Restriction ;
    owl:onProperty <http://purl.obolibrary.org/obo/RO_0000087> ;
    owl:someValuesFrom ?role ] .

  ?role rdfs:subClassOf* chebi:23888 .
  ?role rdfs:label ?role_label
```



Find all related compounds that are classified as *drug*

The Web of Life Sciences: An example of Literature discovery



Biomedical Knowledge Graph

- Biomedical KG can help to explore new connections between entities
- They can also be used for building a custom background set in enrichment.
- Semantic Web act as a bridge between biomedical databases on the Web
 - An unified framework to describe entities and their relations
 - Integrates vocabulary, ontologies for a semantic description
- Need to understand the **schema** of the KG, before requesting
- Build your own Biomedical KG ! Use **BioCypher**



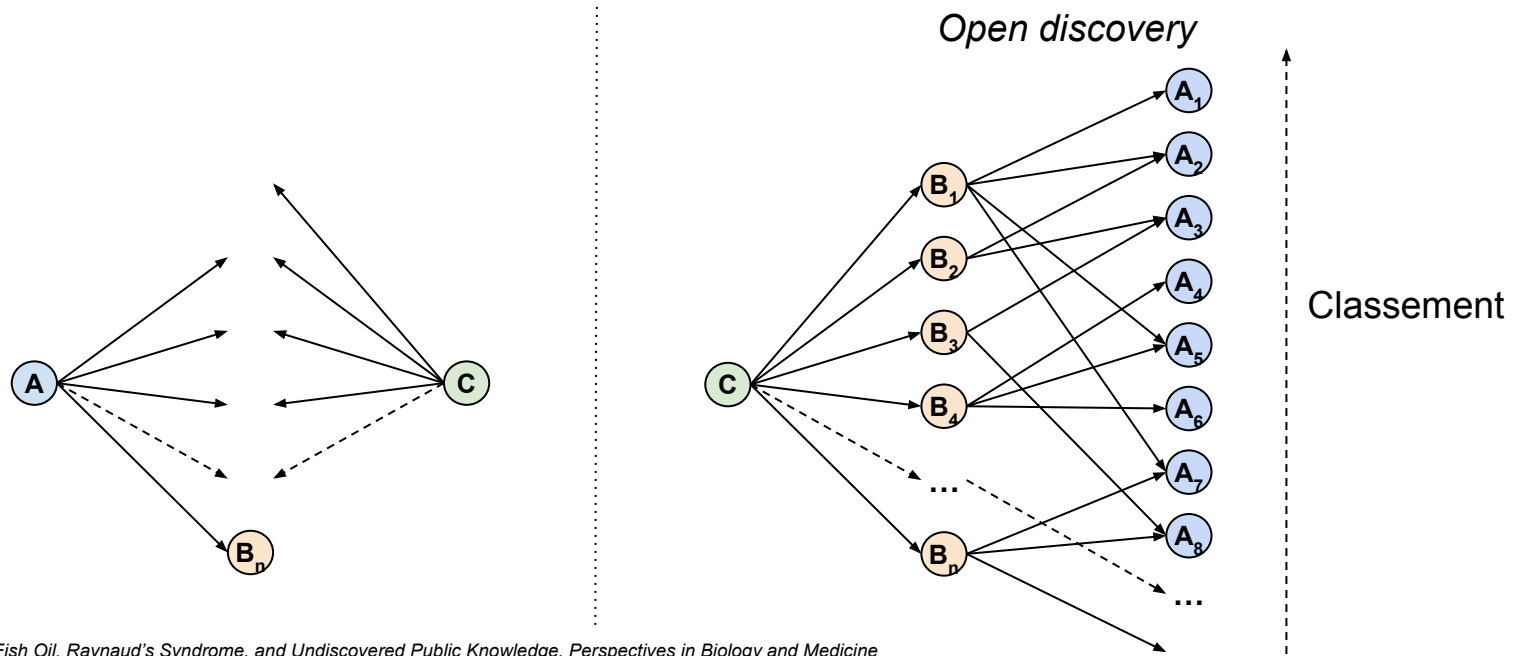
The End

Resources

- Enrichment analysis
 - Biblio & Resources
 - Wieder, C. et al. Pathway analysis in metabolomics: Recommendations for the use of over-representation analysis. PLoS Comput Biol 17
 - https://colab.research.google.com/drive/18pLzc_pv7Fpclotx4byYh9qMDjtnyG_u?usp=sharing
 - García-Campos, M.A. et al. 2015. Pathway Analysis: State of the Art. Front Physiol
 - Subramanian, A. et al., 2005. Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles.
 - James H Joly et al., 2019, Differential Gene Set Enrichment Analysis: a statistical approach to quantify the relative enrichment of two gene sets, Bioinformatics.
 - https://www.pathwaycommons.org/guide/primers/data_analysis/gsea/
 - Biomedical KG & Co.
 - LPG
 - *Hetionet*: <https://het.io/about>
 - *Drug Repurposing Knowledge Graph (DRKG)*: <https://github.com/gnn4dr/DRKG>
 - *BioKG*: <https://github.com/dsi-bdi/biokg>
 - *PharmKG*: <https://academic.oup.com/bib/article/22/4/bbaa344/6042240>
 - Web-Semantic
 - MetaNetX: <https://www.metanetx.org/>
 - Wikidata: https://www.wikidata.org/wiki/Wikidata:Main_Page
 - DisGeNeT: <https://www.disgenet.org/>
 - Rhea: <https://www.rhea-db.org/>
 - UniProt: <https://www.uniprot.org/help/uniprotkb>
 - Other resources
 - *Cypher Cheat Sheet*: <https://neo4j.com/docs/cypher-cheat-sheet/5/auradb-enterprise/>
 - *BioCypher*: <https://biocypher.org/>
 - Web-semantic MOOC: <https://www.fun-mooc.fr/fr/cours/web-semantic-et-web-de-donnees/>
 - Neo4J: <https://www.youtube.com/channel/UCvze3hU6OZBkB1vkhH2IH9Q>

Resources

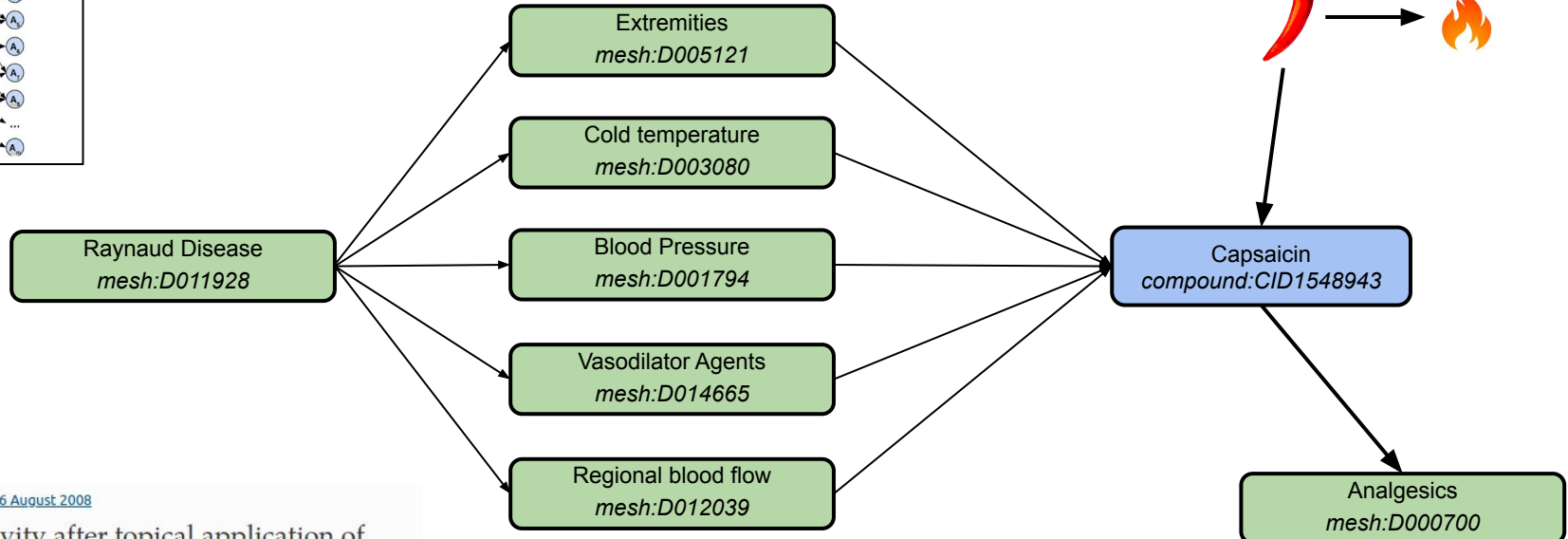
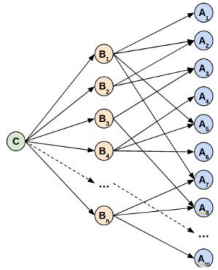
- https://www.wikidata.org/wiki/Wikidata:SPARQL_query_service/queries/examples
- <https://www.wikipathways.org/sparql.html>
- Others Enrichment analysis methods:
 - <https://pubmed.ncbi.nlm.nih.gov/14693814/>
 - <https://pubmed.ncbi.nlm.nih.gov/15647293/>
 - <https://pubmed.ncbi.nlm.nih.gov/15941488/>



Swanson, D.R., 1986. Fish Oil, Raynaud's Syndrome, and Undiscovered Public Knowledge. *Perspectives in Biology and Medicine*

S. Henry and B. T. McInnes. Literature Based Discovery : Models, methods, and trends. *Journal of Biomedical Informatics*, 74 :20–32, Oct. 2017.

Open Discovery



Research Article | Published: 16 August 2008

Cold hyposensitivity after topical application of capsaicin in humans

Mikkel G. Callsen, Anette T. Moller, Karsten Sorensen, Troels S. Jensen & Nanna B. Finnerup

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+61 concepts