The DisGeNET knowledge management platform for disease genomics

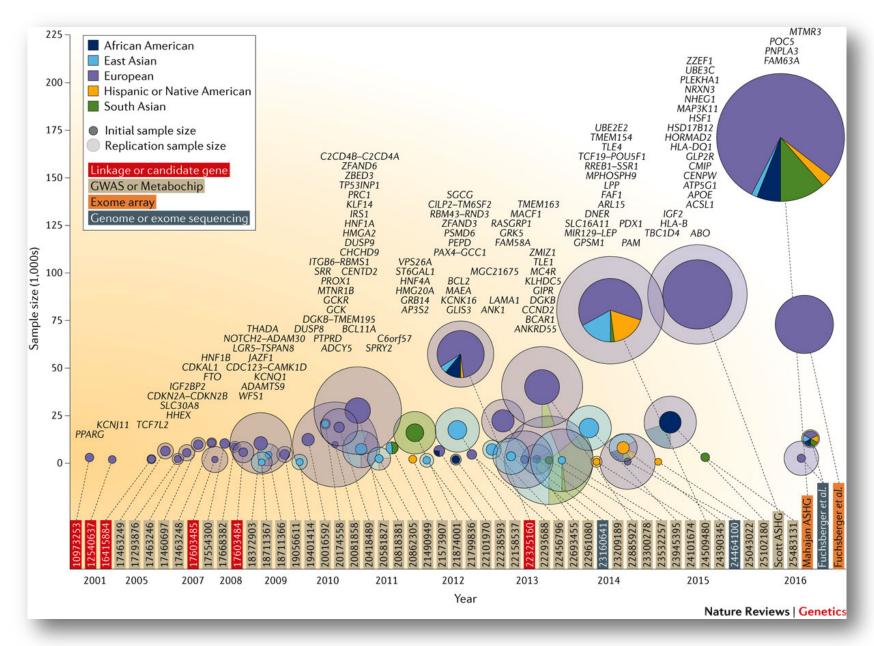
Laura I. Furlong

Research Programme on Biomedical Informatics (GRIB)
Hospital del Mar Medical Research Institute (IMIM)
Pompeu Fabra University (UPF)
ELIXIR-ES









Flannick, J., & Florez, J. C. (2016). Type 2 diabetes: genetic data sharing to advance complex disease research. *Nature Reviews Genetics*, *17*(9), 535.



DIAGRAM Consortium

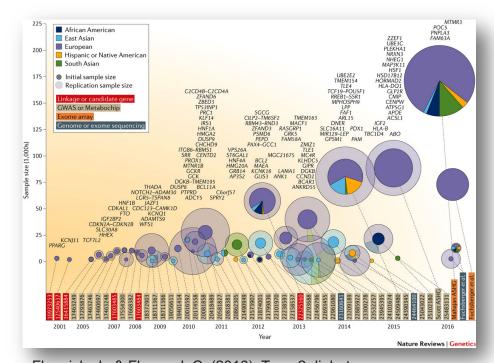
900K individuals 27M SNPs

Inventory of T2D variants

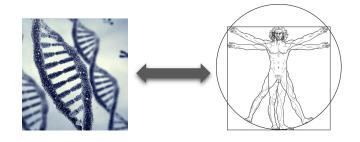
243 loci at genome-wide significance, including 135 new loci for type 2 diabetes

http://www.diagram-consortium.org/

2018

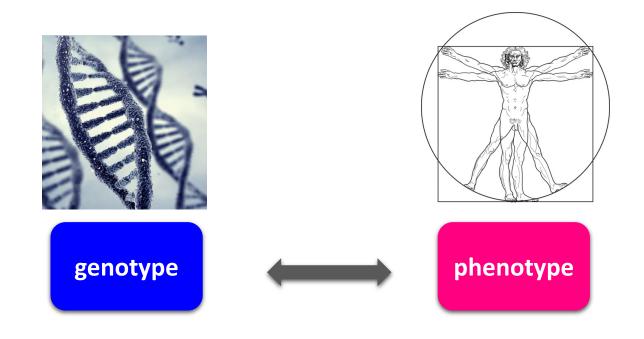


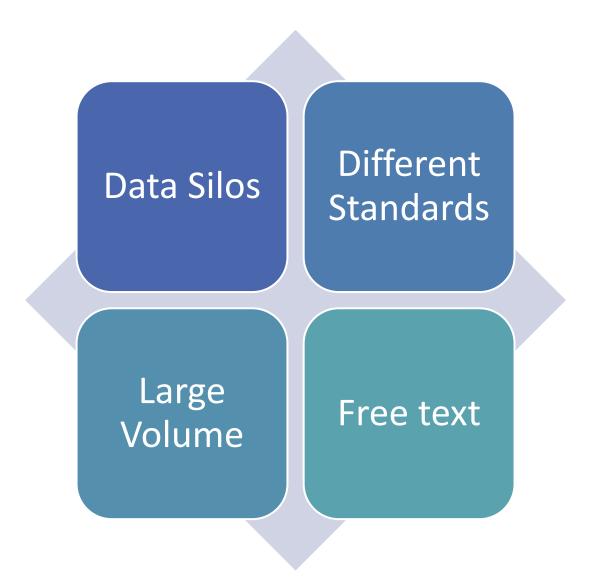
Flannick, J., & Florez, J. C. (2016). Type 2 diabetes: genetic data sharing to advance complex disease research. *Nature Reviews Genetics*, *17*(9), 535.



Genomics studies are generating a vast volume of data, claiming for solutions for data management, data interoperability and knowledge extraction for genotype-phenotype data.

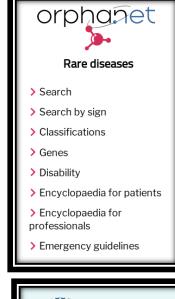
The accumulation of large-scale data requires the development of **computational tools** able to explore and mine the vast amount **of biological knowledge** they contain.

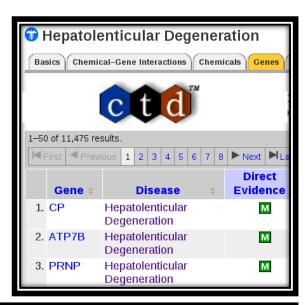


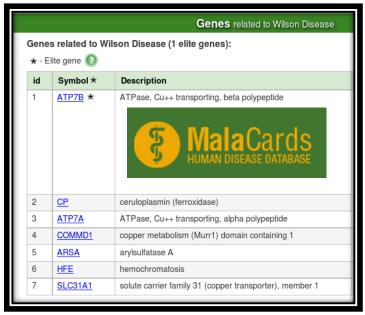


From genotype to phenotype: data silos











TATATCT ClinVar	Gene(s)	Condition(s)
ATP7B, 1-BP DEL, 2511A	ATP7B	Wilson disease
ATP7B, 3-BP DEL, 3892GTC	ATP7B	Wilson disease
ATP7B, 15-BP DEL, NT-441	ATP7B	Wilson disease

From genotype to phenotype: standards

GENE

- ✓ Lipocalin 2
- ✓ 24p3
- ✓ 25 KDa Alpha-2-Microglobulin-Related Subunit Of MMP-9
- ✓ HNL
- ✓ lipocalin 2 (oncogene 24p3)
- ✓ Lipocalin-2
- ✓ Migration-Stimulating Factor Inhibitor
- ✓ MSFI
- ✓ neutrophil gelatinase-associated lipocalin
- ✓ NGAL
- ✓ oncogene 24p3
- ✓ P25
- ✓ Siderocalin

DISEASE

- ✓ Wilson's disease
- ✓ Cerebral Pseudosclerosis
- ✓ Copper Storage Disease
- ✓ Hepatic Form of Wilson Disease
- ✓ Hepato-Neurologic Wilson Disease
- ✓ Hepatocerebral Degeneration
- ✓ Hepatolenticular degeneration
- ✓ Kinnier-Wilson Disease
- ✓ Neurohepatic Degeneration
- ✓ Progressive Lenticular Degeneration
- ✓ Pseudosclerosis
- ✓ WD
- ✓ Westphal-Strumpell Syndrome
- ✓ Wilson Disease
- ✓ Wilson Disease, Hepatic Form

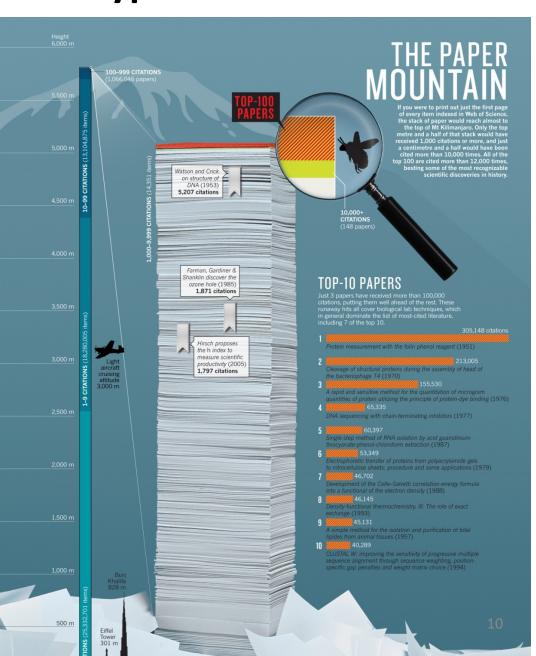
From genotype to phenotype: data volume

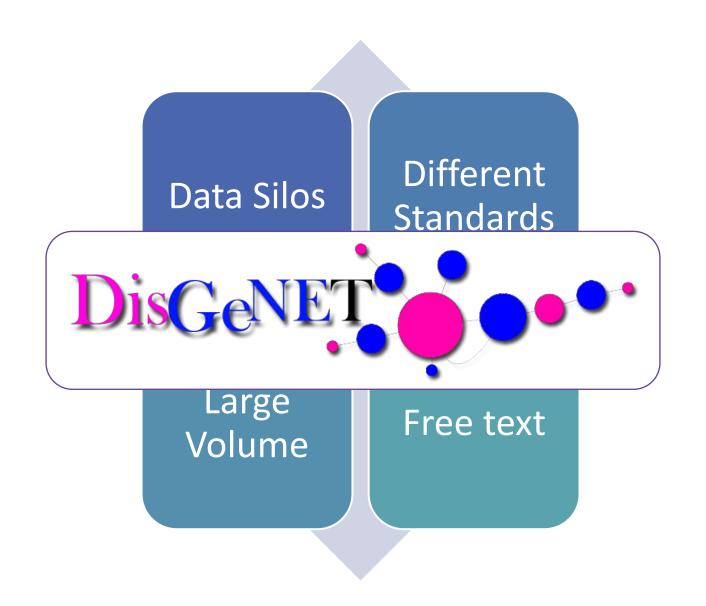


From genotype to phenotype: Free text

- ✓ 25,000 peer-reviewed journals
- ✓ 2.5M articles published per year
- ✓ 2 papers/minute in life sciences
- ✓ 1 article/hour about diseases and genes

Van Noorden, et al. 2014 doi:10.1038/514550a Burger, et al (2014).



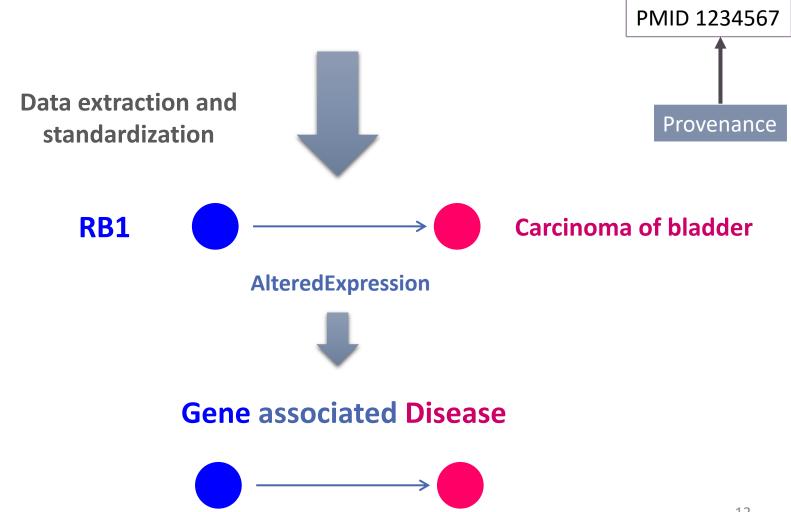


RB1 Protein

Bladder cancer

UniProt

RB is overexpressed in bladder cancer samples as measured by....





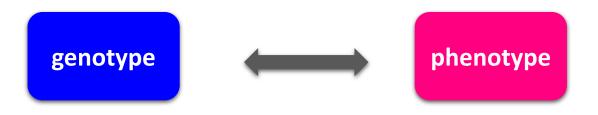
Gene-Disease Association (GDA)



Variant-Disease Association (VDA)



- ✓ Standards
- ✓ Provenance
- ✓ Tools



- Large in scale and growing rapidly (NGS)
- Large studies on genetics of disease available
- HGVS standard for sequence variation nomenclature
- Standards for data exchange
- UniProt, NCBI, Ensembl
- VarioML, VariO

- Phenotype data spans a wide spectrum of possible observations about an individual
- More difficult to capture and to standardize
- Human Phenotype Ontology, Disease Ontology
- Broad phenotype categories used in many studies

Standards in DisGeNET

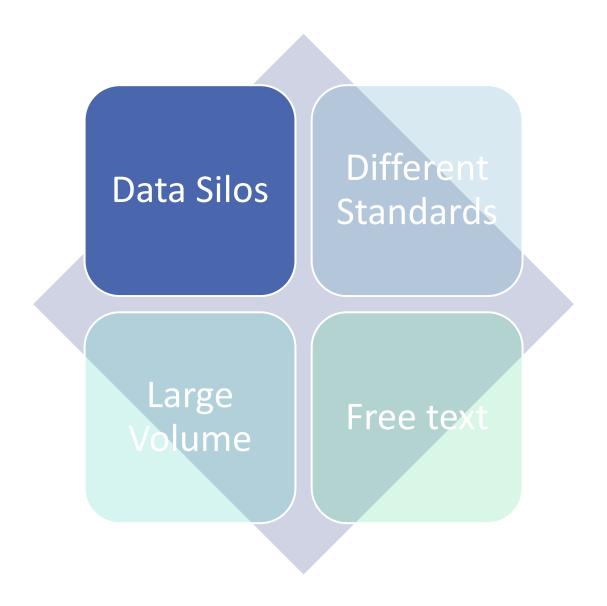
genotype phenotype

- Gene, protein, SNPs
- Official Gene symbol
- NCBI Gene Id
- Uniprot accession
- dbSNP identifier for variants

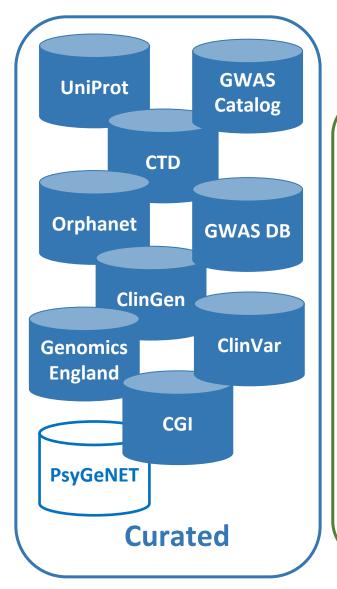
- Diseases, symptoms, phenotypes
- UMLS CUIs
- UMLS semantic types
- Disease Ontology
- Mappings to a variety of phenotype vocabularies and ontologies

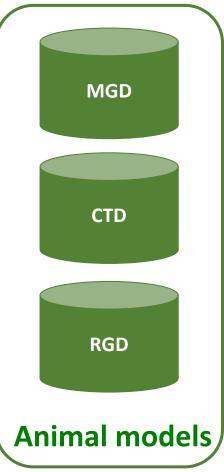
DisGeNET association type ontology

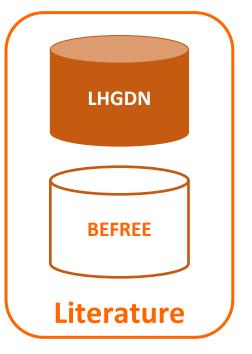
DisGeNET data sources

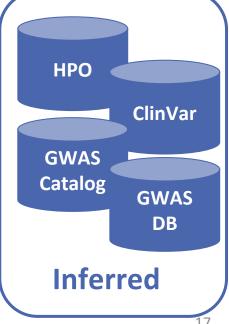


DisGeNET data sources

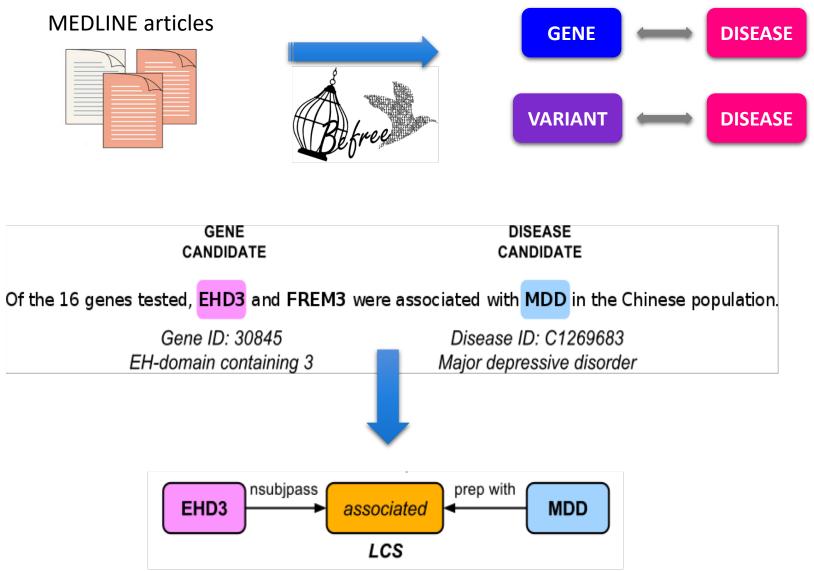








Text mining of GDAs and VDAs



Association types classified according to the DisGeNET ontology

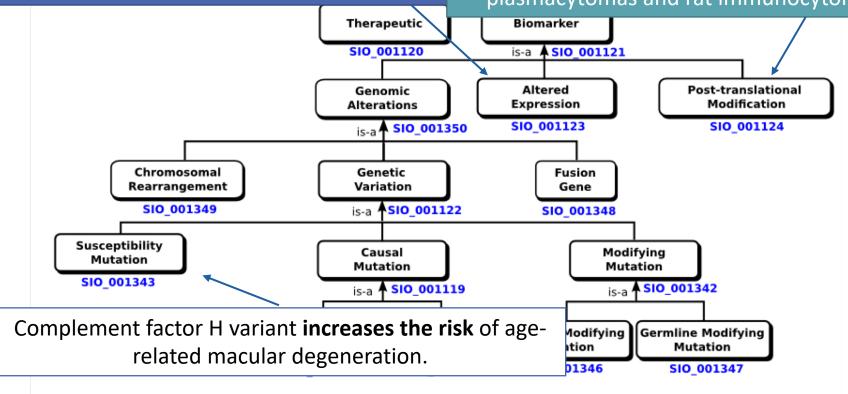
DisCaNET association tuns

Gpc3 expression correlates with the phenotype of the Simpson-Golabi-Behmel syndrome.

phosphorylation state of Ser-129 in human alpha-synuclein determines neurodegeneration in a rat model of Parkinson disease

Unbalanced GLA mRNAs ratio quantified by real-time PCR in Fabry patients' fibroblasts results in Fabry disease.

The amino-terminal **phosphorylation sites** of C-MYC are frequently mutated in Burkitt's lymphoma lines but not in mouse plasmacytomas and rat immunocytomas.



DisGeNET statistics



Gene-Disease Associations (GDAs)

Source	Genes	Diseases*	Associations
Curated	9413	10370	81746
Animal Models	2795	2789	11517
Inferred	8700	13176	163626
Literature	15283	12418	415583
All	17549	24163	628685

^{*}diseases, traits, symptoms, disease groups

66 % are GDAs exclusively provided by BeFree

DisGeNET statistics

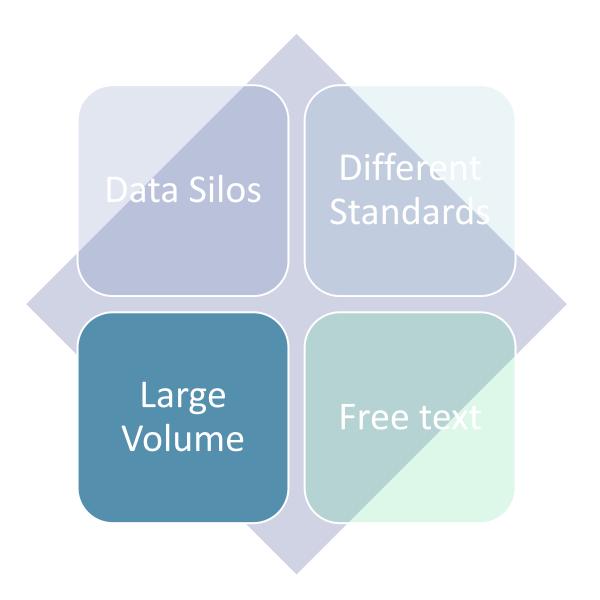


Variant-Disease Associations (VDAs)

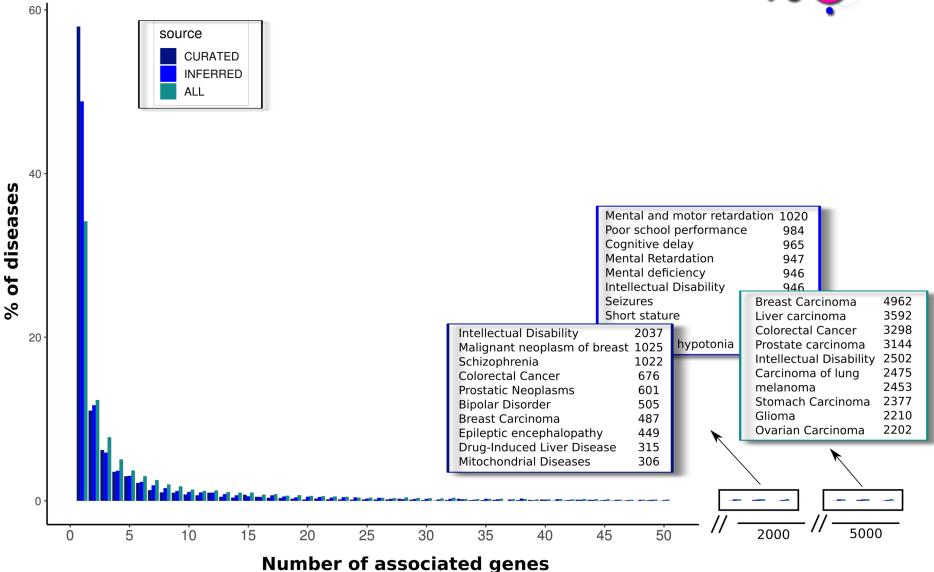
Source	Variants	Diseases*	Associations
Curated	104653	7954	165354
Literature	19407	4228	48998
All	117337	10358	210498

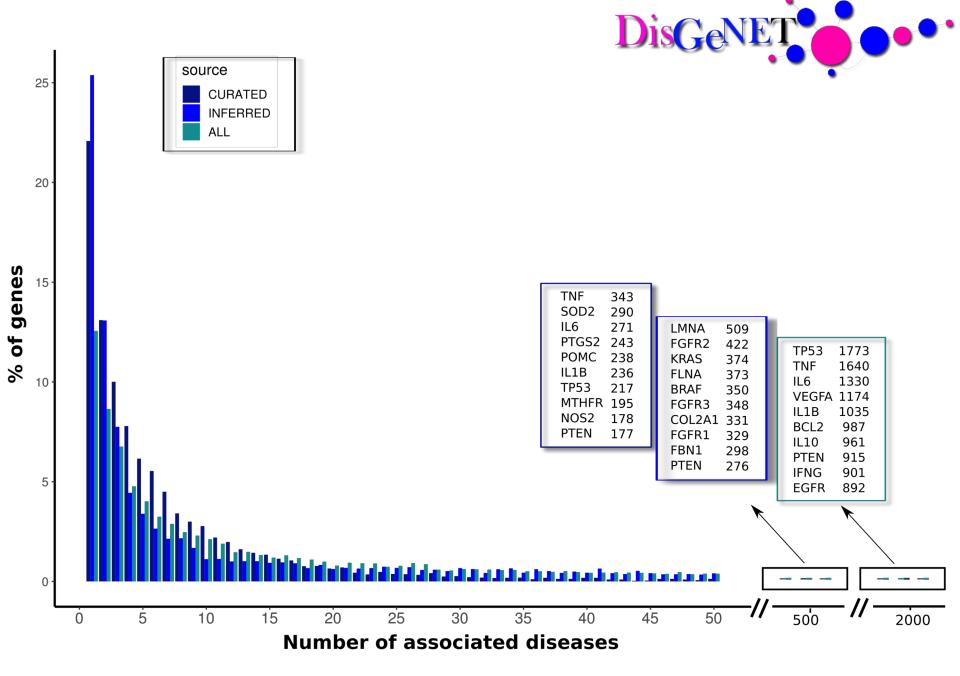
^{*}diseases, traits, symptoms, disease groups

DisGeNET prioritization tools







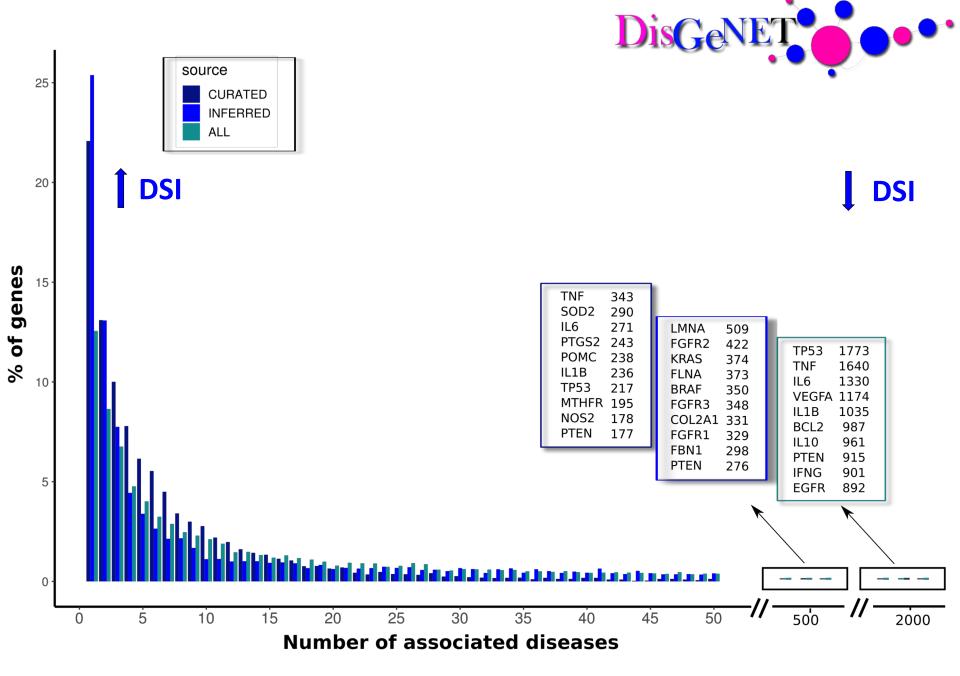




GENE

Tools for prioritization

- ✓ Protein functional classification
- ✓ Tolerance of genes to LoF variation
- ✓ Allele frequency, variant consequence type
- ✓ Disease Specificity Index (DSI)
 A gene/variant is more specific if it is associated to a small number of diseases (DSI closer to 1)





Tools for prioritization

✓ DisGeNET association score: popularity/novelty



GDA score: Indicates **popularity** of a **gene-disease association (GDA)** across all data sources giving higher weight to curated sources vs. animal models GDAs, and to animal models vs. text-mining.

VDA score: Indicates **popularity** of a **variant-disease association (VDA)** across all data sources giving higher weight to curated vs. text-mining VDAs.

Tools for prioritization

- ✓ DisGeNET association score: popularity/novelty
- ✓ DisGeNET association type: insight on biology
- ✓ Evidence level: confidence of the association
- ✓ Evidence Index: controversial field of research
- ✓ Number of publications

What is the advantage of data integration & standardization?

- Human genetics to support drug discovery
- Rare diseases research
- Annotation of NGS and variation data
- Disease comorbidity
- Insight on disease mechanisms and drug mode of action

Genomic data analysis identified 3,000 potentially "druggable" proteins in the human genome.

Only 10% of these potential targets have an FDA approved drug.

Santos, Rita, et al. "A comprehensive map of molecular drug targets." Nature Reviews Drug Discovery (2016).

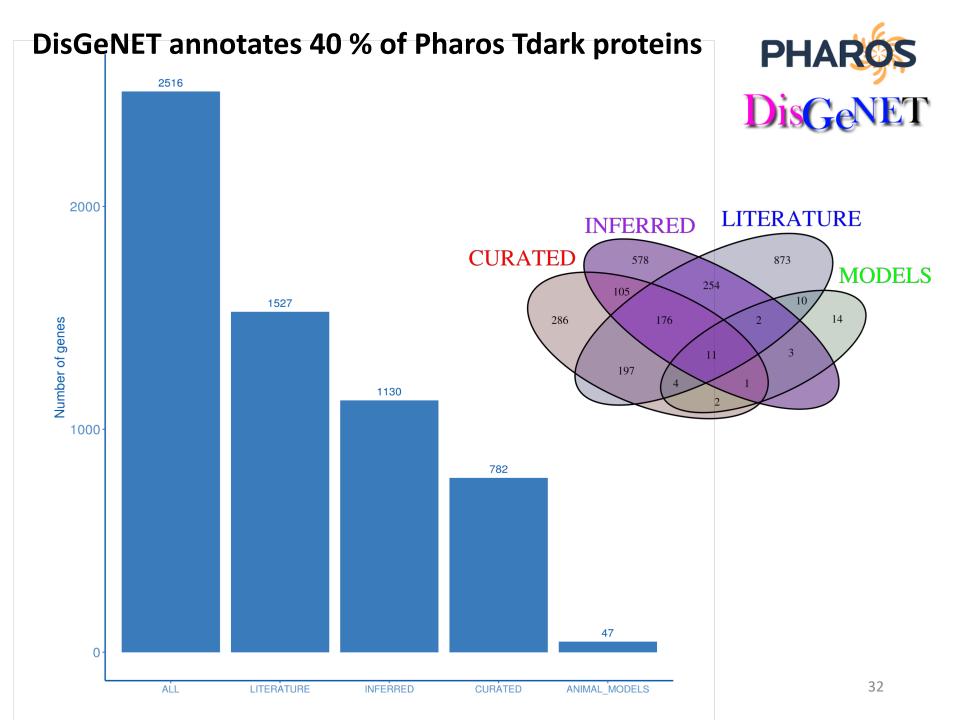
NIH Pharos initiative:

 To shed light on poorly characterized proteins that can potentially be modulated using small molecules or biologics

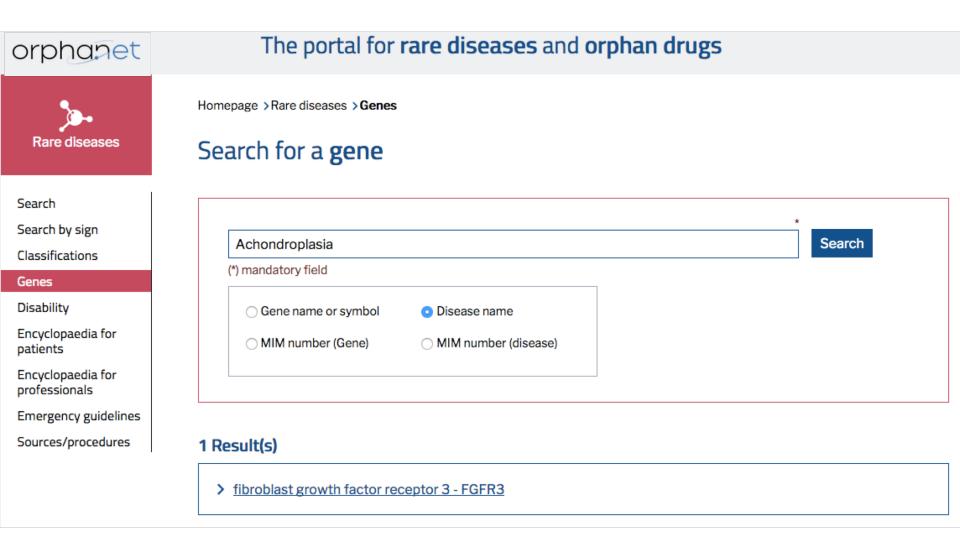
Target "dark" proteins



https://pharos.nih.gov/idg/index



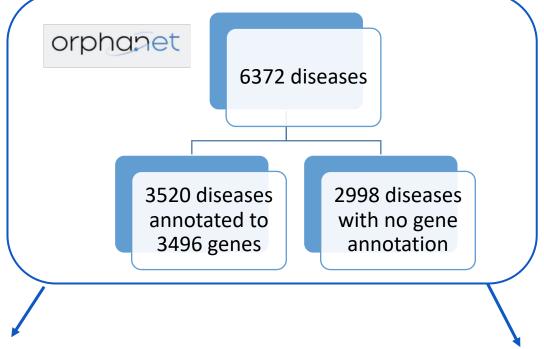
Information on genetic basis of rare diseases



6850 GDAs in Orphanet involving 3496 genes and 3520 diseases



DisGeNET provides annotations to variants for 3455 Orphanet diseases (54 %)



DisGeNET provides additional annotation to the diseases



DisGeNET provides annotations for 1467 diseases (49 %)



Top 10 genes

Gene	Gene name	DisGeNET score	N. PMIDs	N. SNPs
FGFR3	fibroblast growth factor receptor 3	1	133	7
SPRED2	sprouty related EVH1 domain containing 2	0.21	1	0
NPR2	natriuretic peptide receptor 2	0.21	3	0
PTHLH	parathyroid hormone like hormone	0.21	2	0
GH1	growth hormone 1	0.03	3	0
FGF1	fibroblast growth factor 1	0.02	2	0
PTH	parathyroid hormone	0.02	2	0
FGF2	fibroblast growth factor 2	0.02	2	0
NPPC	natriuretic peptide C	0.01	1	0
PTRH1	peptidyl-tRNA hydrolase 1 homolog	0.01	1	0



Variants in FGFR3 gene annotated to Achondroplasia

Variants in the FGFR gene associated to achondroplasia				
variantid	score	npmids most_severe_consequence	ref_alt	Protein_position Amino_acids
rs121913105	0.70	o missense variant	A/C,T	652 K/T
rs121913114	0.70	2 missense variant	A/G,T	279 S/G
rs121913479	0.01	1 missense variant	G/A,T	372 G/S

rs121913114	0.70	2 missense variant	A/G,T	279 S/G
rs121913479	0.01	1 missense variant	G/A,T	372 G/S
rs121913482	0.70	1 missense variant	C/T	248 R/C
rs28931614	0.90	55 missense variant	G/A,C	382 G/R
rs28933068	0.74	5 stop gained	C/A,G,T	542 N/K
rs75790268	0.85	7 missense variant	G/T	377 G/C

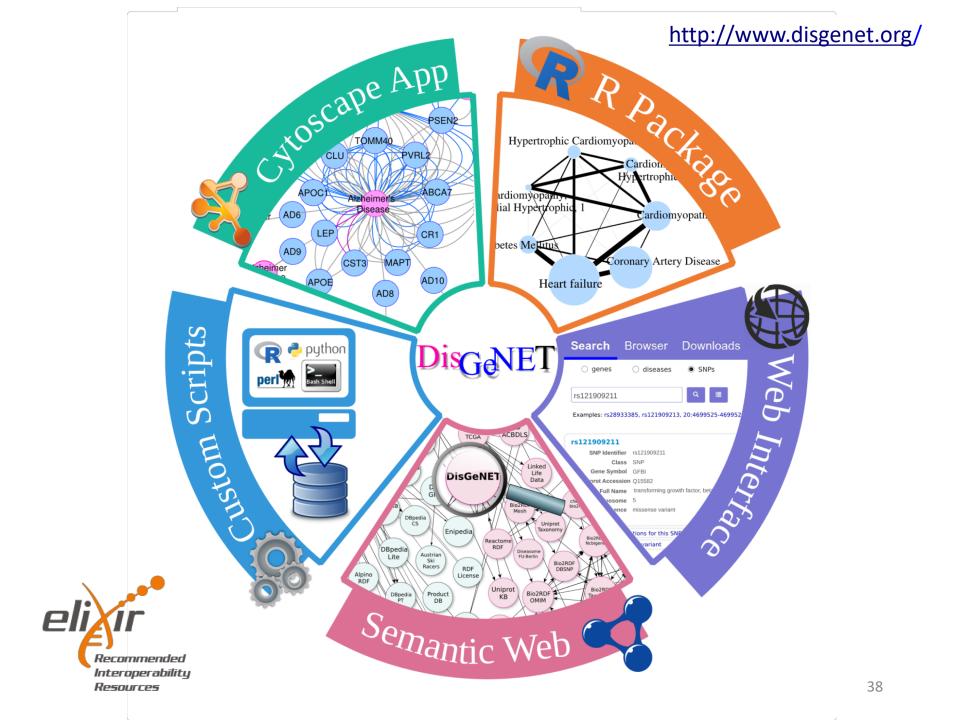


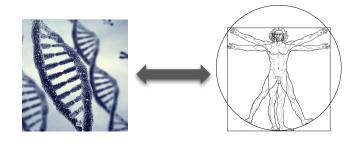


> One of the most comprehensive catalogs of genes and variants associated to human diseases and phenotypes publicly available

➤ Developed by integration of different public resources, including information extracted from the literature by text mining

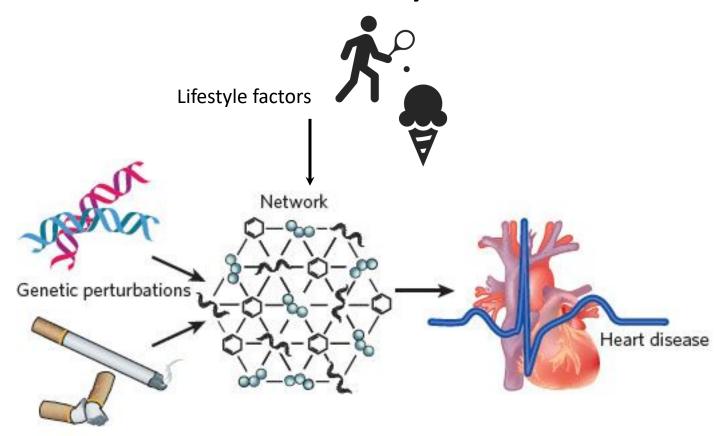
Provides different prioritization metrics and can be accessed with different tools





The accumulation of large-scale data requires the development of **computational tools** able to explore and mine the vast amount **of biological knowledge** they contain.

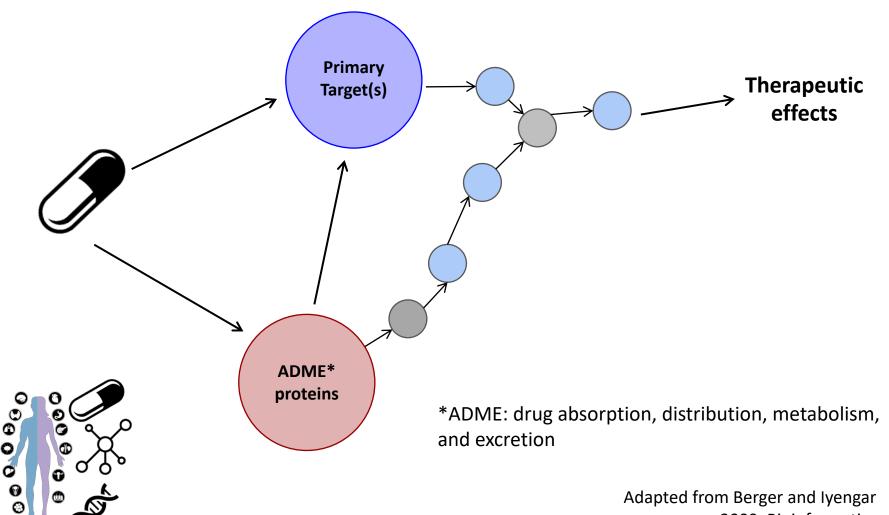
Network medicine to study human diseases



Environmental perturbations

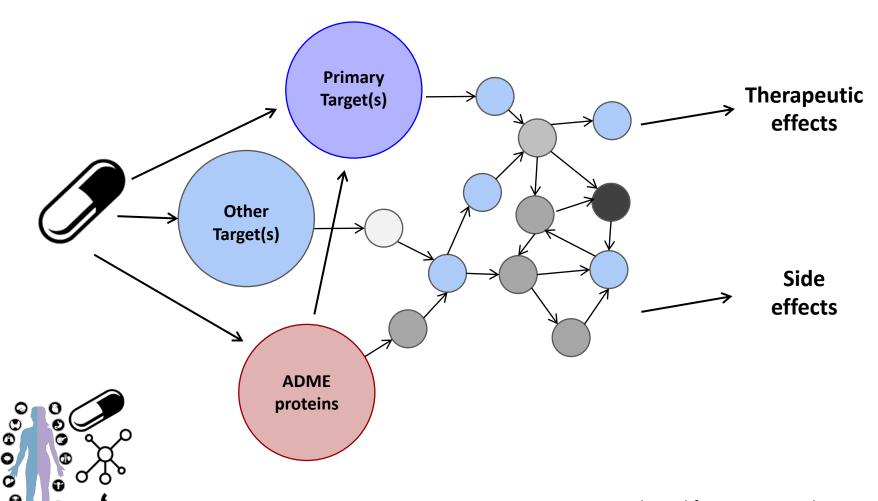
Modified from Schadt, E. E. (2009). Molecular networks as sensors and drivers of common human diseases. *Nature*, *461*(7261), 218.

"Classic" view of drug mode of action



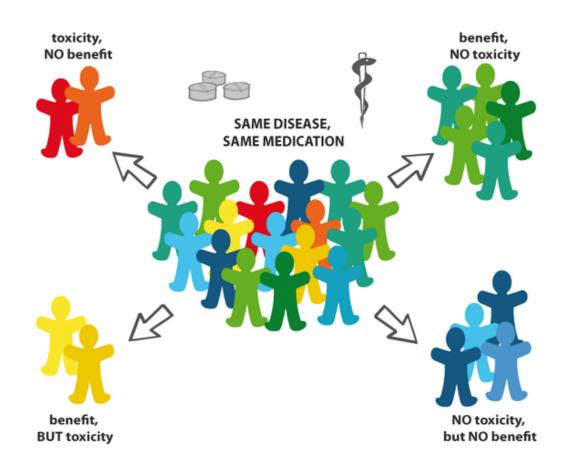
2009, Bioinformatics

"Systems" view of drug mode of action



Adapted from Berger and Iyengar 2009, Bioinformatics,

Variability of drug response

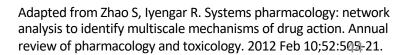


Variability of drug response



Drug	Gene	Effect			
Pharmacokinetics					
Codeine	CYP2D6 (34)	Increase in the amount of active drug by variants			
Clopidogrel	CYP2C19 (80)	Increase in the amount of active drug by variants			
Warfarin	CYP2C9 (81)	Changes in drug levels in blood by variants			





NO toxicity,

but NO benefit

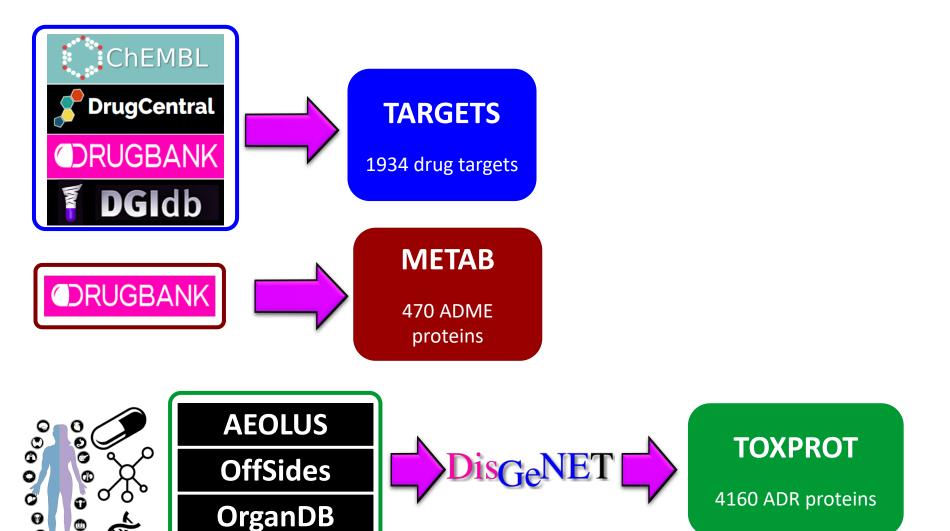
Genes relevant to drug response have different

transcriptomic, genomic and network

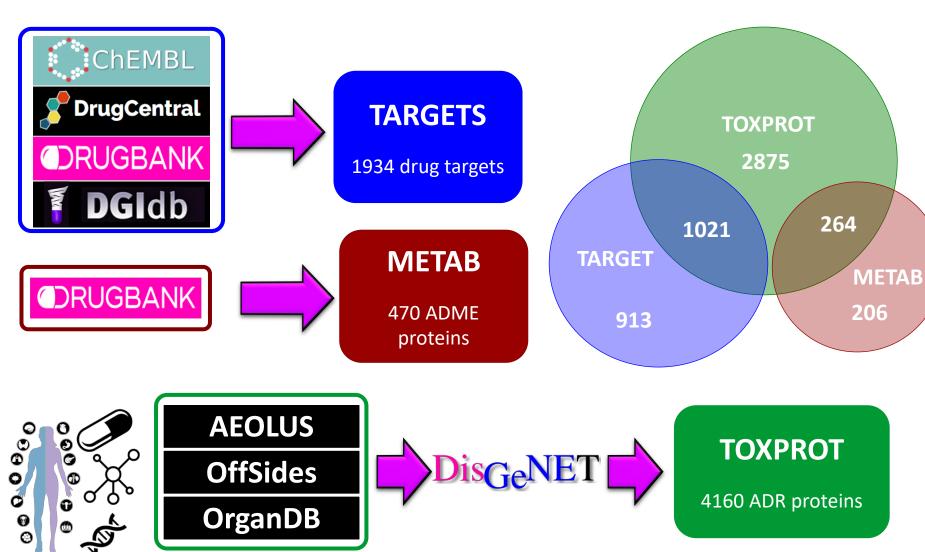
properties



Genes relevant to drug response



Genes relevant to drug response

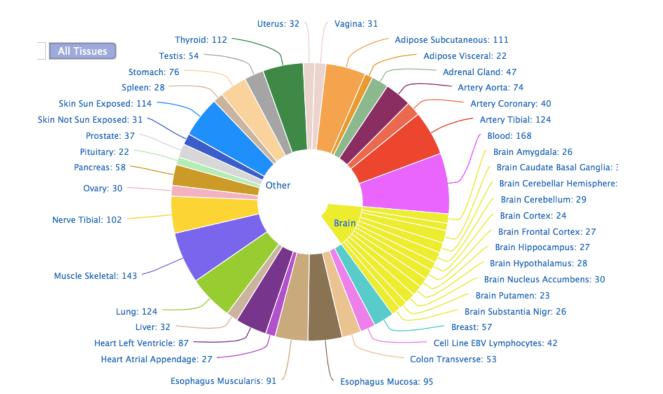


Transcriptomic analysis



53 tissues (TPM >=1)

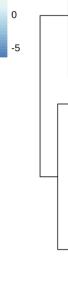












TOXPROT

TT



TARGET

				4.04	₊	0.04	Ditaite		
Ч				4.3*	5.5*	-3.6*	Pituitary		
١,				5.2*	5.2*	-3.3*			
[2.0+		2.8*		Brain.Frontal.Cortex.BA9		
\dashv	[2.2*	2.6*	2.2*	3.5*		Brain.Cortex		
		-2.2*	2.7*	2.3*	3.6*		Brain.Hippocampus		
יון ן	[0.5*	3.2*	4.1*		Brain.Amygdala		
14			2.5*	2.7*	4.2*		Brain.Anterior.cingulate.cortex.BA24		
l li			2.5*	4.2*	5.6*		Brain.Putamen.basal.ganglia		
ון ו			2.4*	4.4*	4.5*		Brain.Caudate.basal.ganglia		
1		2.0*		4.1*	5.1*		Brain.Substantia.nigra		
[-2.0*		4.6*	5.0*		Brain.Spinal.cord.cervical.c.1		
ן ו				3.0*	4.4*		Brain.Nucleus.accumbens.basal.ganglia		
	-6.4*	-5.9*	-2.8*	-3.0*	4.0	1 2*	Brain.Hypothalamus Testis		
Ц	-0.4	-4.5*	2.3*	-3.0		-2.2*	Brain.Cerebellar.Hemisphere		
		-3.7*	2.3		2.6*	-2.2	Brain.Cerebellum		
	5.0*	6.2*		12 5*		15.9*			
_	7.8*	8.5*	2.2*	11.9*		10.9	Lung		
H_{-}	10.5*		4.5*	8.0*	4.7*	-2.1*			
1 4	7.0*	6.1*	3.2*	8.3*	5.5*	-3.6*			
Ι,	2.3*	2.1*	5.2	9.2*	8.5*	-2.2*	Nerve.Tibial		
	2.3*	3.2*		8.8*	7.9*	-2.2*			
ΙΙ	2.2*	3.0*		8.6*	7.3*		Fallopian.Tube		
ין ן	2.0*	2.7*		8.0*	7.1*	-2.0	Esophagus.Muscularis		
	2.6*	2.8*		8.1*	7.6*	-2.1*	Minor.Salivary.Gland		
	2.4*	2.6*		8.2*	7.5*	-2.3*	Vagina		
Ι 1.	2.4	2.0*		6.7*	5.9*	-3.3*			
		2.2*		7.5*	7.1*		Cervix.Endocervix		
	2.1*	2.2		7.2*	7.1*	-2 9*	Colon.Sigmoid		
7 ⊪				7.2*	6.9*	-2.1*	Esophagus.Gastroesophageal.Junction		
1	4			7.1*	6.9*	-2.3*	Cervix. Ectocervix		
				6.2*	6.2*	-2.0*			
1 1 4	2.2*		2.1*	6.9*	6.8*	-2.5*			
111'	2.3*			6.9*	6.9*	-2.4*	Skin.Sun.Exposed.Lower.leg		
$ _{\Gamma}$	3.6*	2.4*	2.7*	7.2*	6.3*		Heart.Left.Ventricle		
,	3.5*	3.1*		7.2*	6.0*	-2.6*	Thyroid		
1114	2.7*	3.0*		8.2*	7.1*		Colon.Transverse		
ווווו	3.4*	3.7*		8.2*	6.9*		Artery.Aorta		
111	3.7*	3.2*		8.0*	6.9*	-2.1*	Artery.Tibial		
4 6	2.8*	2.3*		5.4*	4.6*		Muscle.Skeletal		
,		2.5*		6.8*	5.9*		Adrenal.Gland		
4	г			6.6*	6.2*		Esophagus.Mucosa		
۱ ا				6.7*	6.3*		Pancreas		
	l			7.4*	6.7*		Stomach		
١,	3.8*	5.0*		10.0*	8.2*	2.7*	Kidney.Cortex		
Ιď	3.5*	3.9*		8.8*	7.3*		Small.Intestine.Terminal.Ileum		
Ц,	6.3*	6.3*	2.0*	11.8*	8.9*		Adipose.Visceral.Omentum		
lμ	4.9*	5.5*		10.6*	8.7*		Adipose.Subcutaneous		
4	5.2*	4.2*	2.7*	9.0*	7.5*		Heart.Atrial.Appendage		
4,	4.4*	5.0*		9.1*	7.5*		Artery.Coronary		
٦	3.9*	4.5*		9.8*	8.3*		Breast.Mammary.Tissue		
TAR	-ET	1	07 70XP	<u>مر</u>	OTP	TAB	·		
TAR	600	,	· OXP	40	O, WE	11.			
٧,			10.		,				

Genomic analysis

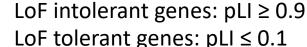


Genomic data

Exome Aggregation Consortium (ExAC)

Germline variants detected across 60k exomes

✓ pLI: the probability of a gene to be intolerant to heterozygous Loss of Function (LoF) mutations





✓ pNull: the probability of a gene to be tolerant to both heterozygous and homozygous LoF variation.



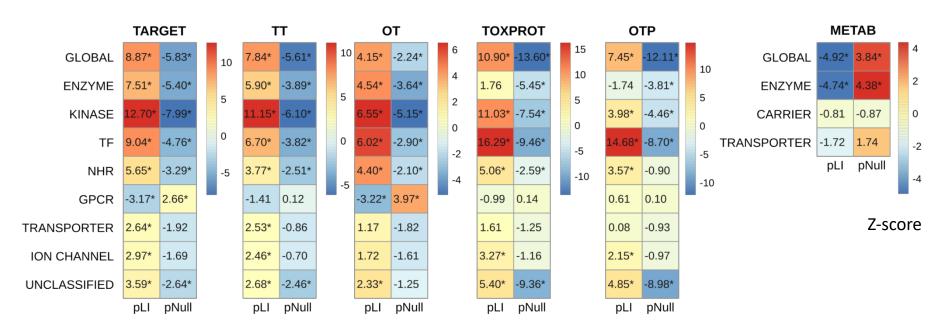
Gene constraint metrics for drug relevant genes

Gene Set		pLI		pNull		
	pLI	z-score	p-value	pNull	z-score	p-value
TARGET	0.380	8.87	7.31E-19	0.167	-5.829	5.58E-09
TOXPROT	0.365	10.9	1.15E-27	0.146	-13.604	3.79E-42
METAB	0.214	-4.92	8.65E-07	0.260	3.843	1.22E-04

- ✓ pLI: the probability of a gene to be intolerant to heterozygous LoF mutations
- ✓ pNull: the probability of a gene to be tolerant to both heterozygous and homozygous LoF variation.



Gene constraint metrics for drug relevant genes

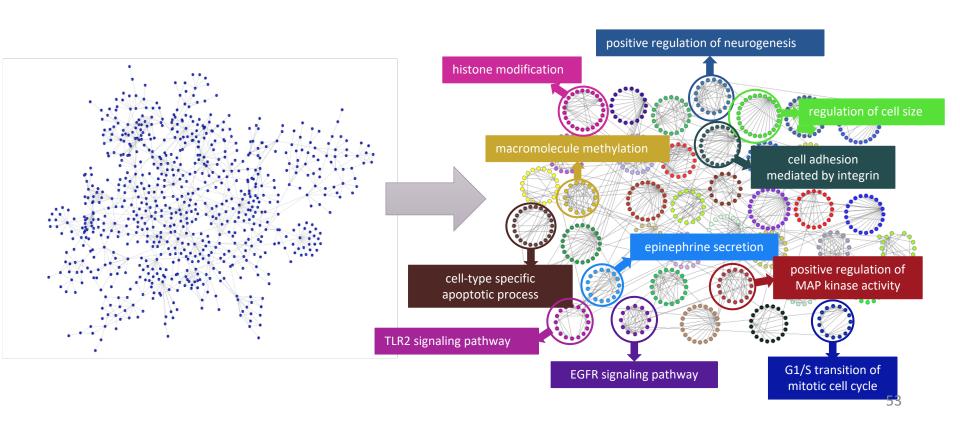


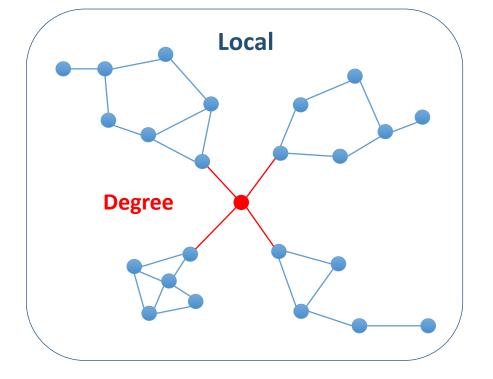


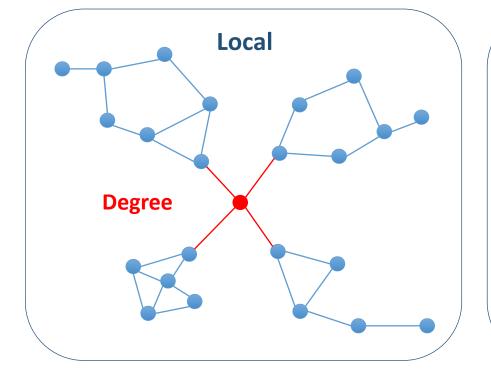
- ✓ pLI: the probability of a gene to be intolerant to heterozygous LoF mutations
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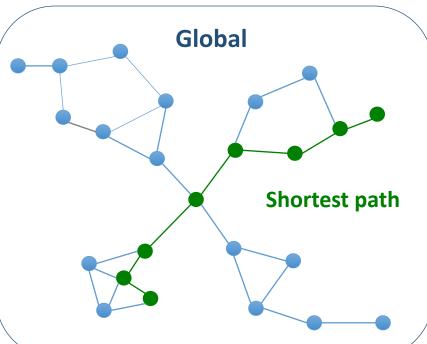
Network analysis

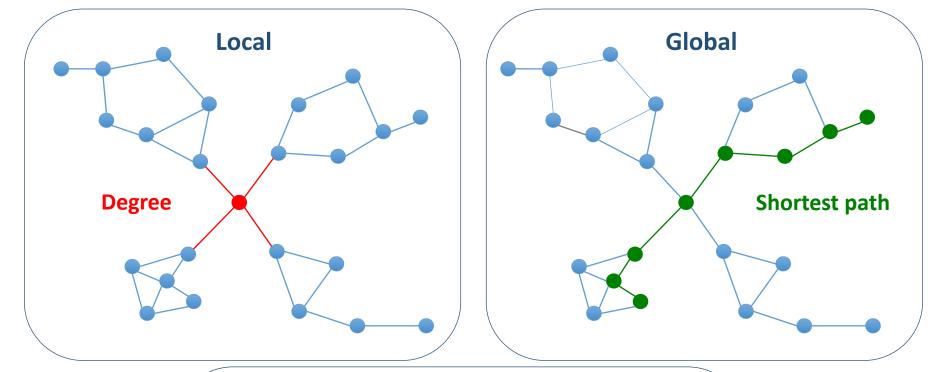
To connect **network structure** to **function**

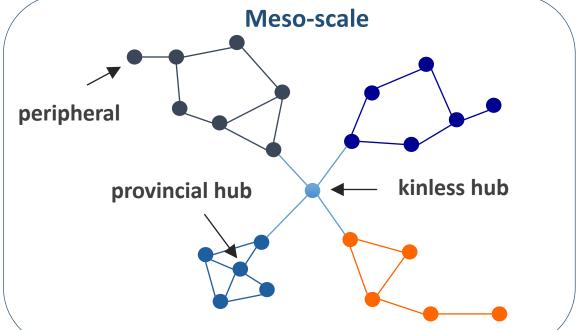




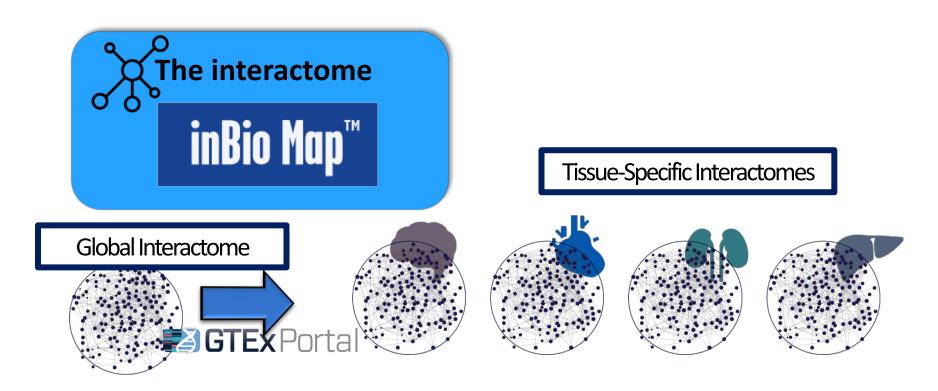








Network analysis





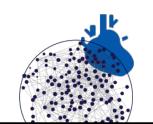
Network analysis



Tissue-Specific Interactomes

Global Interactome









	Network properties
.ocal	Degree
	Clustering coefficient



Global Betweennes centrality

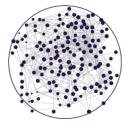
Meso Within-module degree Z

Participation coefficient P

Cartographic roles

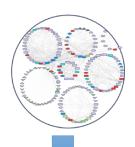
58

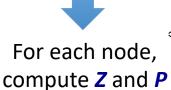
Meso-scale network analysis





Network clustering







Assignment of one of seven cartographic roles to nodes

(Guimerà & Amaral, Nature 2005)

Participation Coefficient

$$P = 1 - \sum_{s=1}^{N_M} \left(\frac{K_{is}}{K_i}\right)^2$$

 K_{is} is the # of links of nodes i in

 \mathcal{K}_i module s is the degree of node i

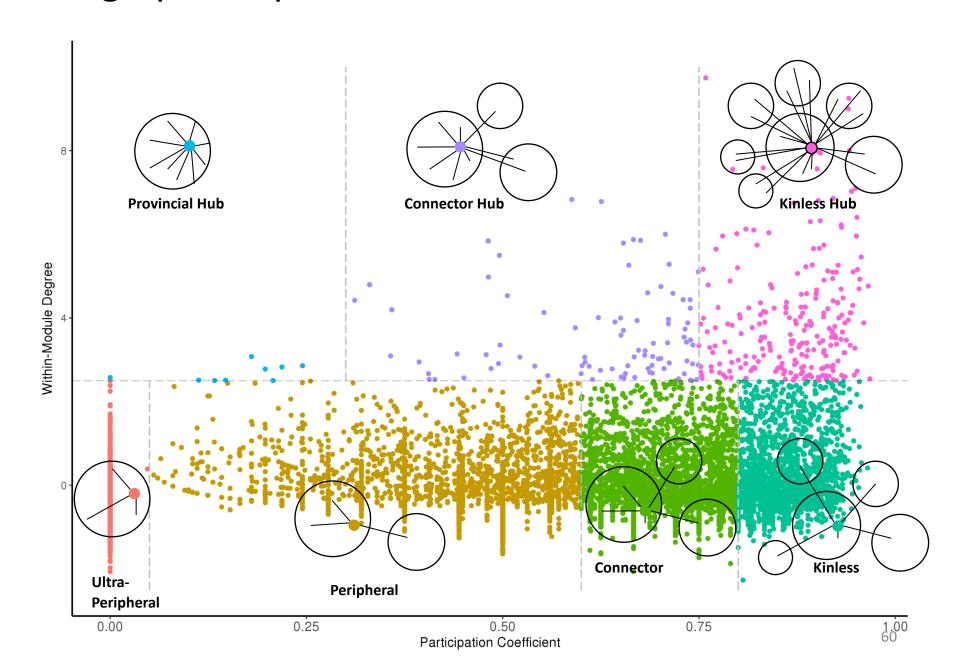
Within-Module_Degree

$$z_i = \frac{K_i - \bar{K}_{s_i}}{\sigma K_{s_i}}$$

 $ar{\mathcal{K}}_{S_i}$ he mean degree of nodes in module \mathbf{s}_i

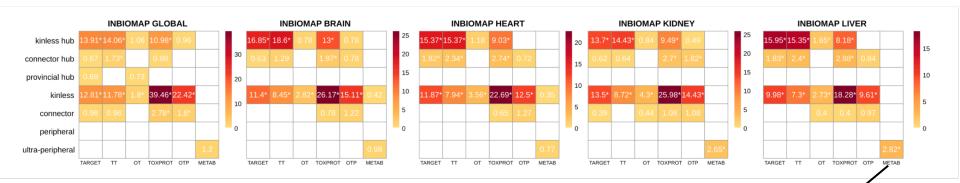
 σK_{s_i} the standard deviation of degree in s_i

Cartographic representation of the interactome





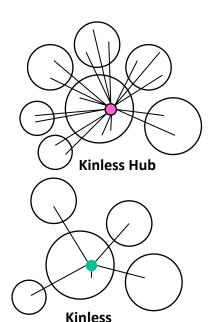
Meso-scale network properties





TOXPROT



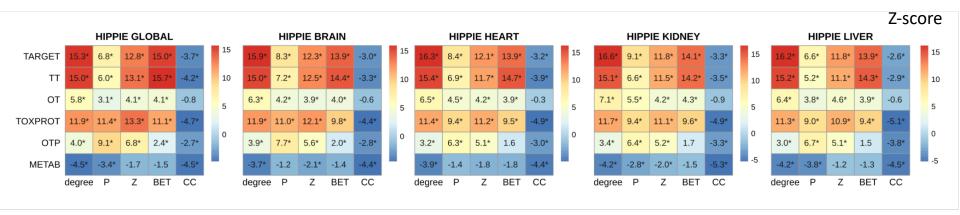






Ultra-Peripheral

Network properties at different scales





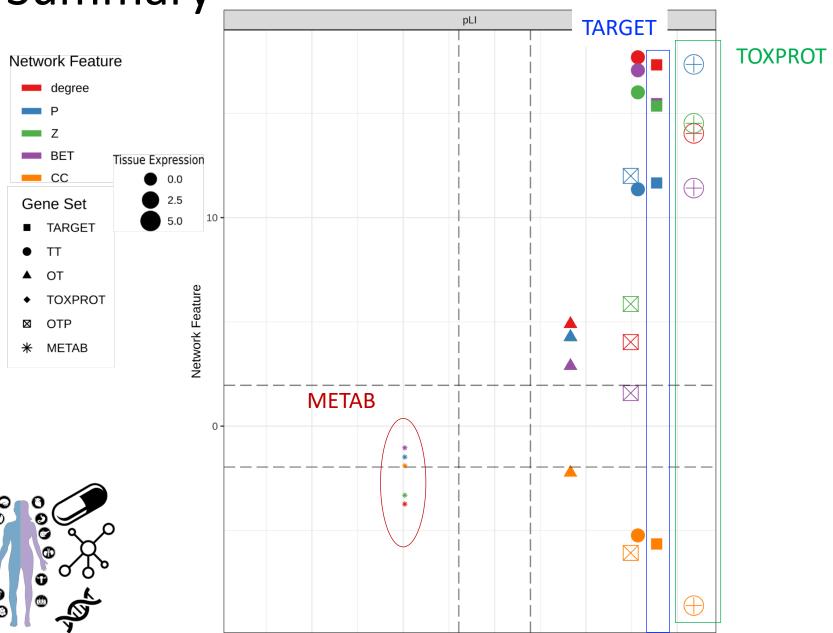
TOXPROT

- ✓ higher degree, participation coefficient,— within-module degree, and betweenness
- ✓ lower clustering coefficient



METAB

 lower degree, participation coefficient, within-module degree Summary



-5

Z-score pLI

-10

10

Take home messages

- ✓ Drug targets that mediate side effects are more central in cellular networks, more intolerant to LoF variation, and show a wider breadth of tissue expression than targets not mediating side effects.
- ✓ Among drug targets, GPCRs are tolerant to LoF variation and not central in the network
- ✓ Drug metabolizing enzymes are less central in the interactome, more tolerant to deleterious variants, and are more constrained in their tissue expression pattern.

Take home messages

The integrated analysis of *omics* and clinical data reveals distinct features of proteins associated to drug response, which could be applied to prioritize drugs with fewer probabilities of causing side effects.



Integrative Biomedical Informatics Group









Josep Saüch Pitarch



















