

My high-throughput experiment generated a long list of genes/proteins...

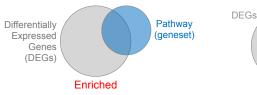
What do I do now?

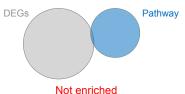
Pathway analysis!
(a.k.a. geneset enrichment)

Use bioinformatics methods to help extract biological meaning from such lists...

Pathway analysis (a.k.a. geneset enrichment)

Principle





- Variations of the math: overlap, ranking, networks... > Not critical, different algorithms show similar performances
- · DEGs come from your experiment
- > Critical, needs to be as clean as possible
- Pathway genes ("geneset") come from annotations > Important, but typically not a competitive advantage

Pathway analysis (a.k.a. geneset enrichment)

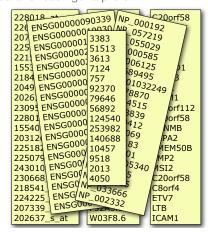
Limitations

- · Post-transcriptional regulation is neglected
- Directionality is hard to capture sensibly
 - e.g. IκBα/NF-κB
- · Tissue-specific variations of pathways are not annotated
 - e.g. NF-κB regulates metabolism, not inflammation, in adipocytes
- · Size bias: stats are influenced by the size of the pathway
- · Geneset annotation bias: can only discover what is already known
- · Non-model organisms: no high-quality genesets available
- Many pathways/receptors converge to few regulators
 - · e.g. tens of innate immune receptors activate 4 TFs: NF-kB, AP-1, IRF3/7, NFAT

Starting point for pathway analysis:

Your gene list

- · You have a list of genes/proteins of interest
- · You have quantitative data for each gene/protein
 - Fold change
 - p-value
 - Spectral counts
 - · Presence/absence



Translating between identifiers

- · Many different identifiers exist for genes and proteins, e.g. UniProt, Entrez, etc.
- · Sometimes you have to translate one set of ids into another
 - · A program might only accept certain types of ids
 - · You might have a list of genes with one type of id and info for genes with another type of id

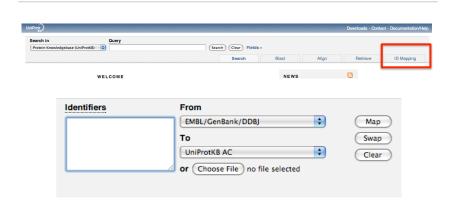
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- Various web sites translate ids -> best for small lists
 - · UniProt < www.uniprot.org>; IDConverter < idconverter.bioinfo.cnio.es >

Translating between identifiers

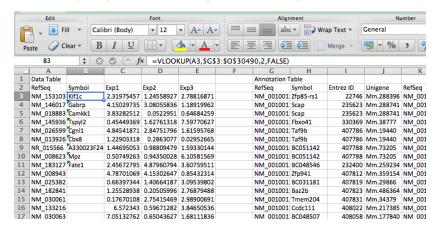
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- · VLOOKUP in Excel good if you are an excel whizz I am not!
 - Download flat file from Entrez, Uniprot, etc; Open in Excel; Find columns that correspond to the 2 IDs you want to convert between: Sort by ID: Use vlookup to translate your list

Translating between identifiers: UniProt < www.uniprot.org >



Translating between identifiers: Excel VLOOKUP

VLOOKUP(lookup_value, table_array, col_index_num)



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- Use the merge() or mapIDs() functions in R fast, versatile & reproducible!
 - Also clusterProfiler::bitr() function and many others... [Link to clusterProfiler vignette]

What functional set databases do you want?

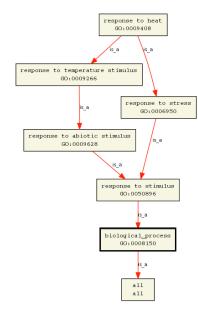
- Commonly used
 - · Gene Ontology (GO)
 - KEGG Pathways (mostly metabolic)
 - · GeneGO MetaBase



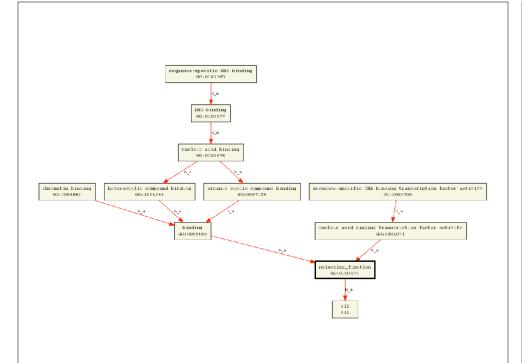
- Ingenuity Pathway Analysis (IPA) INGENUITY
- MSigDB (gene sets based on chromosomal position, cis-regulatory motifs, GO terms, etc)
- · Many others...
 - · Enzyme Classification, Pfam families
 - Open Biomedical Ontologies (OBO, www.obofoundry.org)

GO database < www.geneontology.org >

- What function does HSF1 perform?
 - response to heat; sequence-specific DNA binding; transcription; etc
- Ontology => a structured and controlled vocabulary that allows us to annotate gene products consistently, interpret the relationships among annotations, and can easily be handled by a computer
- GO database consists of 3 ontologies that describe gene products in terms of their associated biological processes, cellular components and molecular functions



- · Terms are nodes
- Relationships are edges
- · Parent terms are more general
- Terms can have multiple parents



GO Annotations

- GO is not a database of genes/proteins or sequences
- Gene products get annotated with GO terms by organism specific databases, such as Flybase, Wormbase, MGI, ZFIN, UniProt, etc
- Annotations are available through AmiGO < amigo.geneontology.org >



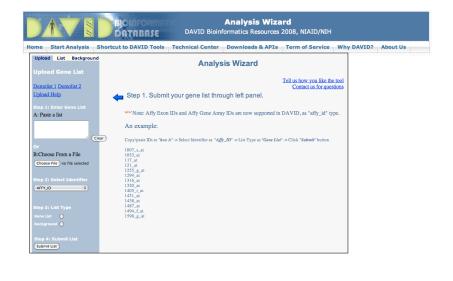
GO evidence codes

Evidence code	Evidence code description Source of evidence		Manually checked	Current number of annotations*	
IDA	Inferred from direct assay	Experimental	Yes	71,050	
IEP	Inferred from expression pattern	Experimental	Yes	4,598	
IGI	Inferred from genetic interaction	Experimental	Yes	8,311	
IMP	Inferred from mutant phenotype	Experimental	Yes	61,549	
IPI	Inferred from physical interaction	Experimental	Yes	17,043	
ISS	Inferred from sequence or structural similarity	Computational	Yes	196,643	
RCA	Inferred from reviewed computational analysis	Computational	Yes	103,792	
IGC	Inferred from genomic context	Computational	Yes	4	
IEA	Inferred from electronic annotation	Computational	No	15,687,382	
IC	Inferred by curator	Indirectly derived from experimental or computational evidence made by a curator	Yes	5,167	
TAS	Traceable author statement	Indirectly derived from experimental or computational evidence made by the author of the published article	Yes	44,564	
NAS	Non-traceable author statement	No 'source of evidence' statement given	Yes	25,656	
ND	No biological data available	No information available	Yes	132,192	
NR	Not recorded	Unknown	Yes	1,185	

October 2007 release

Use and misuse of the gene ontology annotations Seung Yon Rhee, Valerie Wood, Kara Dolinski & Sorin Draghici Nature Reviews Genetics 9, 509-515 (2008)

DAVID at NIAID < <u>david.abcc.ncifcrf.gov</u> >



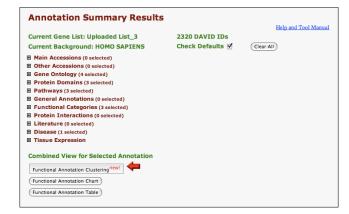
DAVID

Notice that you can pick a Background (Universe)



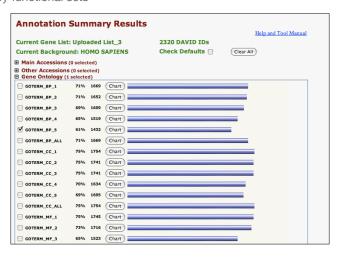
DAVID

Functional Annotation Tool



DAVID

· Specify functional sets



DAVID

· Let's look at the Functional Annotation Chart



DAVID

· Functional Annotation Chart

Functional Annotation Chart											
Current Gene List: Uploaded List_1 Current Background: Homo sapiens 2316 DAVID IDs											
■ Options (Rerun Using Options) (Create Sublist)											
Sublis	t <u>Category</u>	⇔ Term	RT	Genes	Count	* %	P-Value	Benjamini 💠			
	GOTERM_BP_5	regulation of progression through cell cycle	RT	-	98	4.2	3.3E-7	8.6E-4			
	GOTERM_BP_5	apoptosis	RT	=	131	5.7	1.6E-6	2.1E-3			
	GOTERM_BP_5	cell death	RT	=	136	5.9	3.8E-6	3.3E-3			
	GOTERM_BP_5	regulation of transcription from RNA polymerase II promoter	RI	=	83	3.6	3.7E-5	2.4E-2			
	GOTERM_BP_5	protein kinase cascade	RT		71	3.1	4.7E-5	2.4E-2			
	GOTERM_BP_5	regulation of kinase activity	RT	8	48	2.1	5.4E-5	2.3E-2			
	GOTERM_BP_5	negative regulation of cell proliferation	RT	1	48	2.1	1.0E-4	3.7E-2			
	GOTERM_BP_5	regulation of cell size	RT	8	41	1.8	1.2E-4	3.9E-2			
	GOTERM_BP_5	monocarboxylic acid metabolic process	RT		48	2.1	1.3E-4	3.6E-2			
	GOTERM_BP_5	positive regulation of nucleobase, nucleoside, nucleotide and nucleic acid metabolic process	RT	•	61	2.6	1.5E-4	3.8E-2			
	GOTERM_BP_5	positive regulation of cellular metabolic process	RT		72	3.1	1.7E-4	3.8E-2			

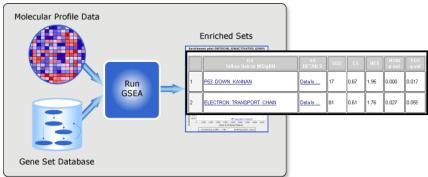
Systematic and integrative analysis of large gene lists using DAVID bioinformatics resources
Da Wei Huang, Brad T Sherman & Richard A Lempicki
Nature Protocols 4, 44 - 57 (2009)

Overlapping functional sets

- Many functional sets overlap, in particular those from databases that are hierarchical in nature (e.g. GO)
- · Hierarchy enables:
 - Annotation flexibility (e.g. allow different degrees of annotation completeness based on what is known)
 - Computational methods to "understand" function relationships (e.g. ATPase function is a subset of enzyme function)
- · Unfortunately, this also makes functional profiling trickier

GSEA < <u>www.broadinstitute.org/gsea</u> >

Download GSEA desktop application

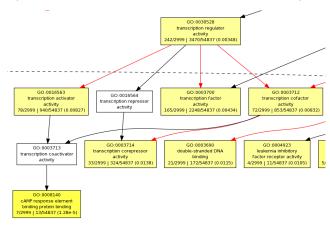


· Excellent tutorial, user's guide and example datasets to work through

Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles Aravind Subramanian, Pablo Tamayo, Vamsi K. Mootha, Sayan Mukherjee, Benjamin L. Ebert, Michael A. Gillette, ...

GOEast < omicslab.genetics.ac.cn/GOEAST >

· Graphical view of enriched GO terms and their relationships

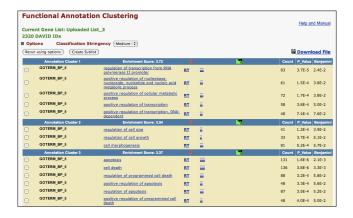


GO SLIMs

- Cut-down versions of the GO ontologies containing a subset of the terms in the whole GO
- · GO FAT (DAVID):
 - filters out very broad GO terms based on a measured specificity of each term

DAVID Functional Annotation Clustering

• Based on shared genes between functional sets



Want more?



- GeneGO < portal.genego.com >
 - MD/PhD curated annotations, great for certain domains (eg, Cystic Fibrosis)
 - Nice network analysis tools
 - · Email us for access
- Oncomine < www.oncomine.org >
 - · Extensive cancer related expression datasets
 - Nice concept analysis tools
 - Research edition is free for academics. Premium edition \$\$\$
- · Lots of other Bioconductor packages in this area!



Advice:

Figure out "What do I want to do with my list?"

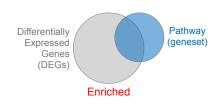
- · Organize/summarize data for presentation or manuscript
 - DAVID: GO FAT -> Functional Annotation Clustering -> Pick threshold
- Infer biological processes from the list
 - DAVID: Functional Annotation Chart -> explore functional databases and see which make sense
 - GSEA: Select MSigDB sets of interest -> e.g., immunologic signatures
 - · Use domain specific database it at all possible!
- Find "missing" genes/proteins not detected by experiment
 - · ConceptGen: Gene-gene enrichment

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