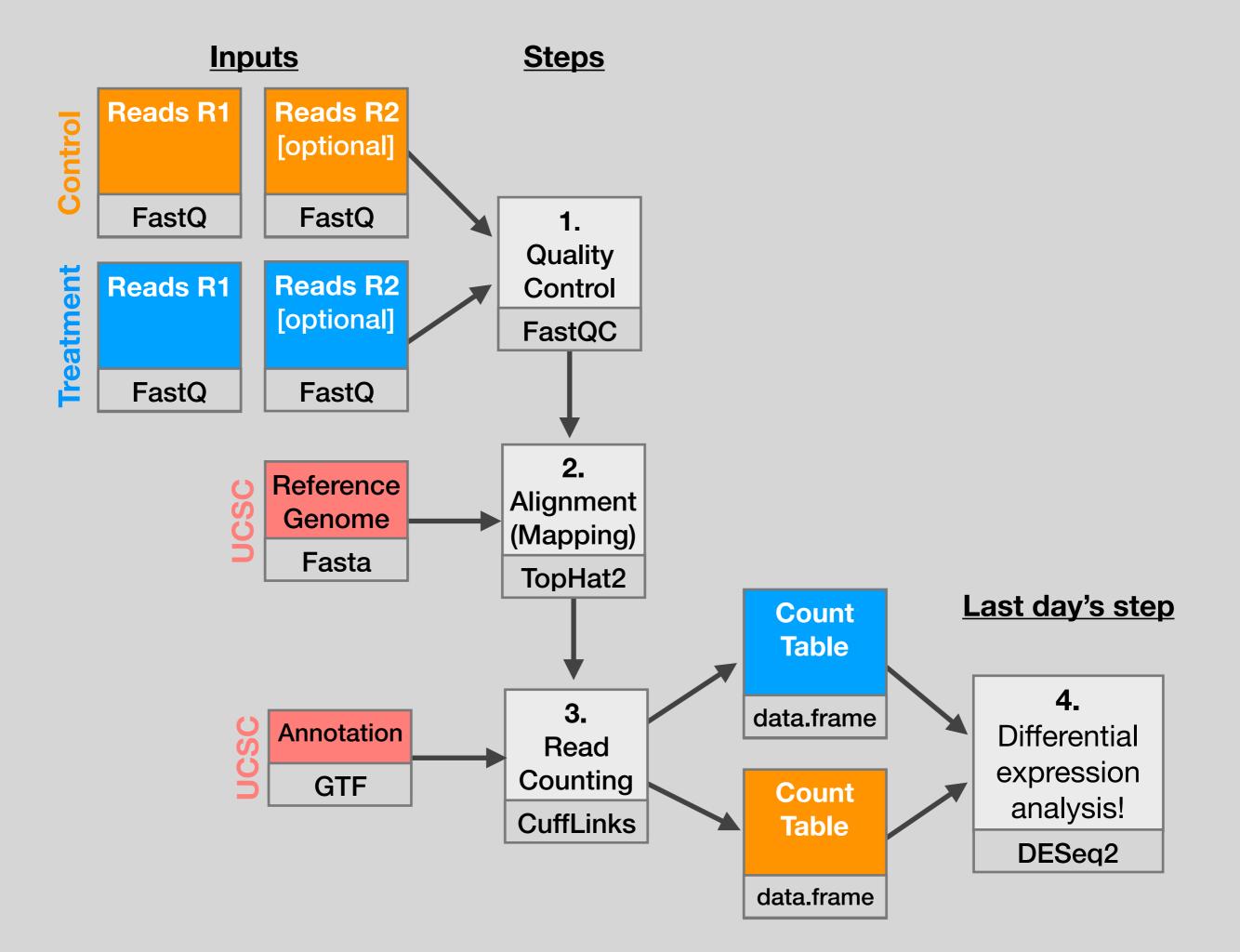
BIMM 143 Pathway Analysis and the Interpretation of Gene Lists

Lecture 15

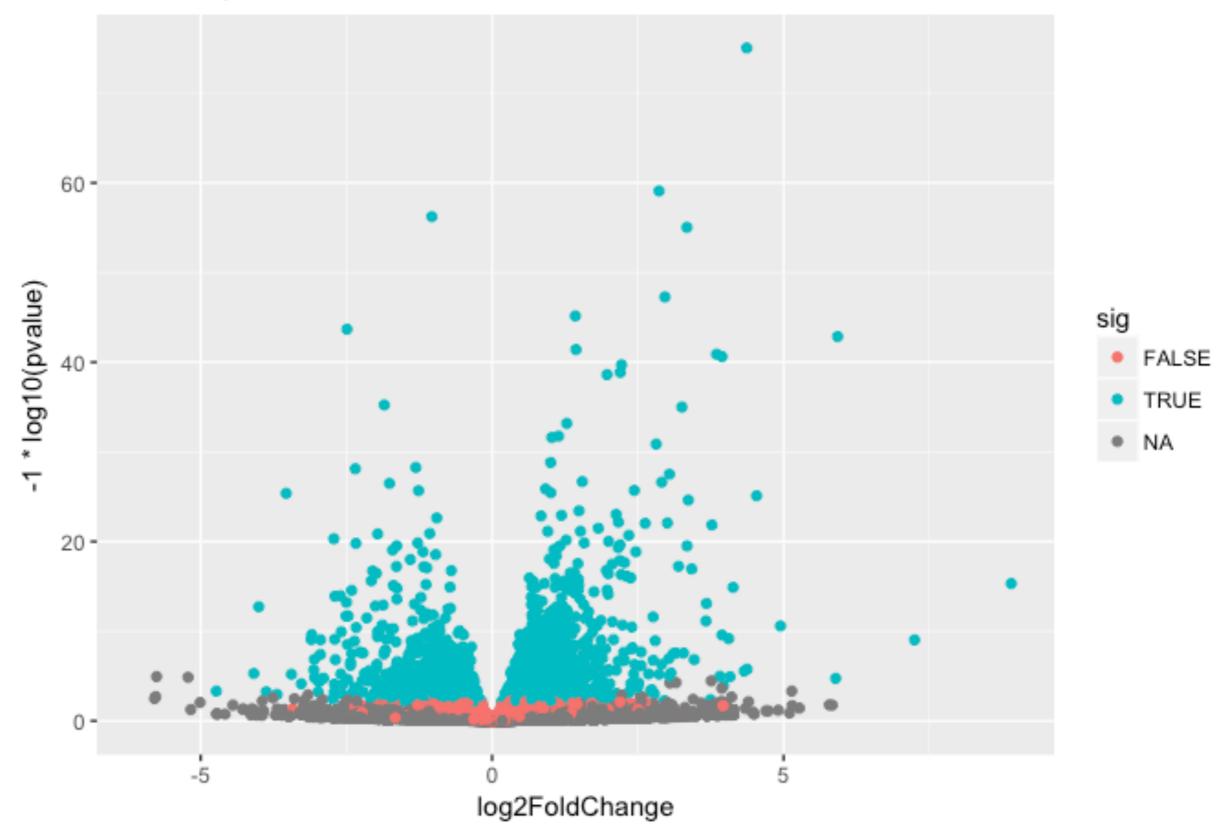
Barry Grant UC San Diego

http://thegrantlab.org/bimm143



x \$	baseMean 🗘	log2FoldChange 🗘	lfcSE [‡]	stat 🗘	¢ pvalue	padj [‡]	symbol 🗘
ENSG00000152583	954.77093	4.3683590	0.23713648	18.421286	8.867079e-76	1.342919e-71	SPARCL1
ENSG00000179094	743.25269	2.8638885	0.17555825	16.313039	7.972621e-60	6.037267e-56	PER1
ENSG00000116584	2277.91345	-1.0347000	0.06505273	-15.905557	5.798513e-57	2.927283e-53	ARHGEF2
ENSG00000189221	2383.75371	3.3415441	0.21241508	15.731200	9.244206e-56	3.500088e-52	MAOA
ENSG00000120129	3440.70375	2.9652108	0.20370277	14.556557	5.306416e-48	1.607313e-44	DUSP1
ENSG00000148175	13493.92037	1.4271683	0.10036663	14.219550	6.929711e-46	1.749175e-42	STOM
ENSG00000178695	2685.40974	-2.4890689	0.17806407	-13.978501	2.108817e-44	4.562576e-41	KCTD12
ENSG00000109906	439.54152	5.9275950	0.42819442	13.843233	1.397758e-43	2.646131e-40	ZBTB16
ENSG00000134686	2933.64246	1.4394898	0.10582729	13.602255	3.882769e-42	6.533838e-39	PHC2
ENSG00000101347	14134.99177	3.8504143	0.28490701	13.514635	1.281894e-41	1.941428e-38	SAMHD1
ENSG00000096060	2630.23049	3.9450524	0.29291821	13.468102	2.409807e-41	3.317866e-38	FKBP5
ENSG00000166741	7542.25287	2.2195906	0.16673544	13.312050	1.970000e-40	2.486304e-37	NNMT
ENSG00000125148	3695.87946	2.1985636	0.16700546	13.164621	1.402400e-39	1.633797e-36	MT2A
ENSG00000162614	5646.18314	1.9711402	0.15020631	13.122885	2.434854e-39	2.633990e-36	NEXN
ENSG00000106976	989.04683	-1.8501713	0.14778657	-12.519211	5.861471e-36	5.918132e-33	DNM1
ENSG00000187193	199.07694	3.2551424	0.26090711	12.476250	1.006146e-35	9.523804e-33	MT1X
ENSG00000256235	1123.47954	1.2801193	0.10547438	12.136779	6.742862e-34	6.007096e-31	SMIM3
ENSG00000177666	2639.57020	1.1399947	0.09606884	11.866436	1.768422e-32	1.487930e-29	PNPLA2
ENSG00000164125	7257.00808	1.0248523	0.08657600	11.837603	2.494830e-32	1.988642e-29	FAM198B
ENSG00000198624	2020.04495	2.8141014	0.24063429	11.694515	1.359615e-31	1.029569e-28	CCDC69
ENSG00000123562	5008.55294	1.0045453	0.08901501	11.285123	1.554241e-29	1.120904e-26	MORF4L2
ENSG00000144369	1283.77980	-1.3090041	0.11714863	-11.173875	5.473974e-29	3.768333e-26	FAM171B
ENSG00000196517	241.91536	-2.3456877	0.21047366	-11.144804	7.591120e-29	4.998588e-26	SLC6A9
ENSG00000135821	19973.40000	3.0413943	0.27601796	11.018828	3.100706e-28	1.956675e-25	GLUL

Volcano plot



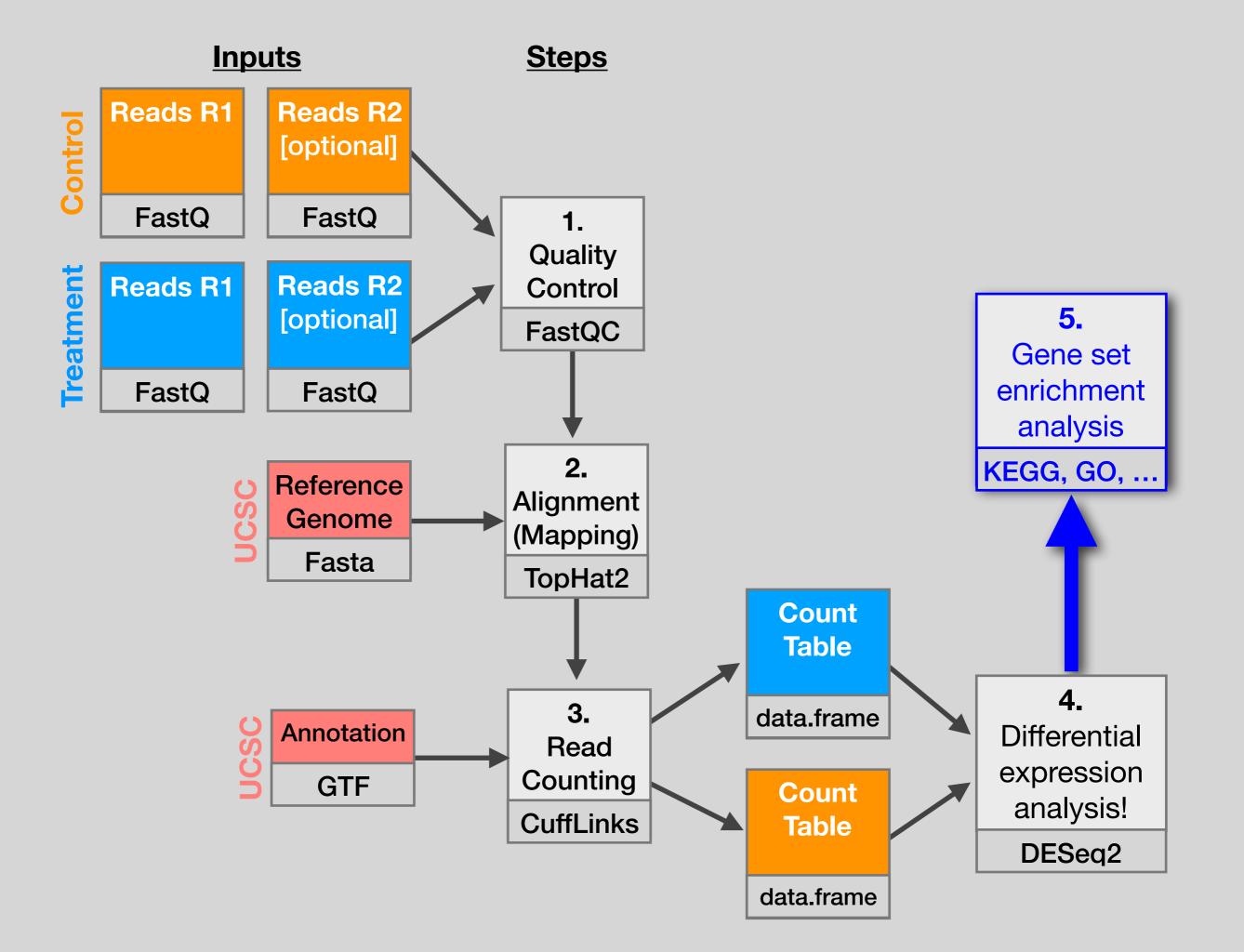
My high-throughput experiment generated a long list of genes/proteins...



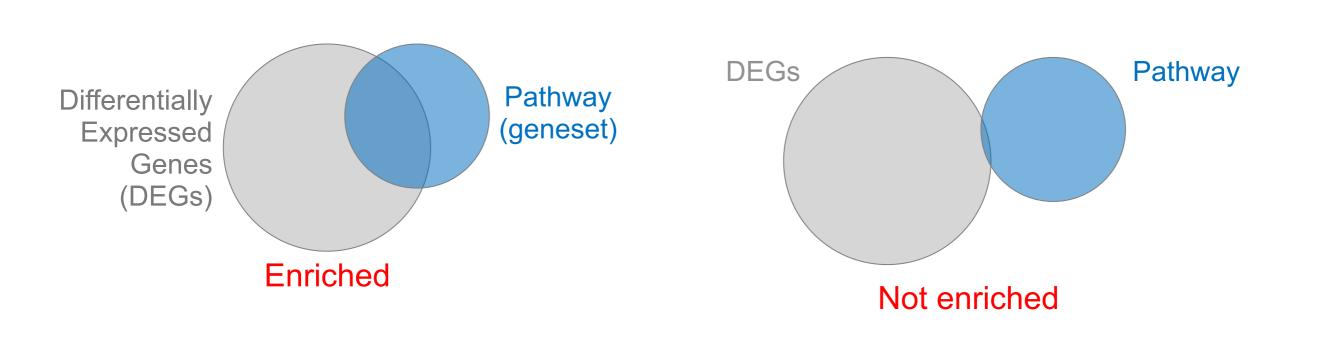
What do I do now?

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



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

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

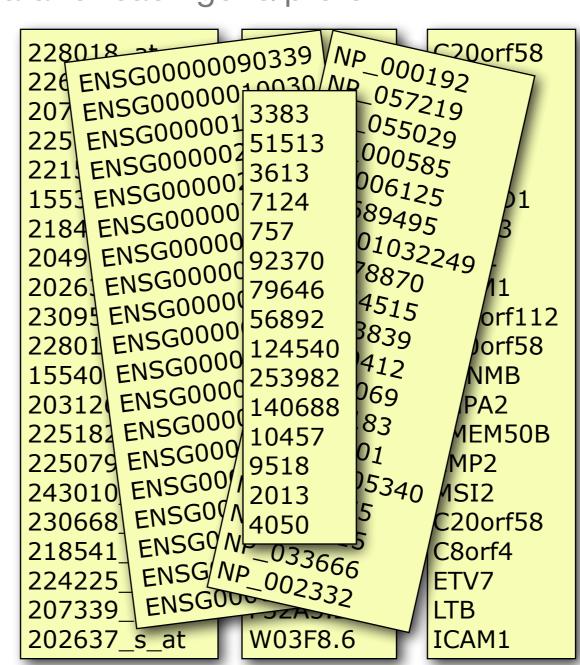
Geneset annotation bias: can only discover what is already known

Side note.

- Post-transcriptional regulation is neglected
- 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
- Non-model organisms: no high-quality genesets available
- Many pathways/receptors converge to few regulators
 - e.g. Tens of innate immune receptors activate four 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 < <u>www.uniprot.org</u>>; IDConverter < <u>idconverter.bioinfo.cnio.es</u> >

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

UniProt		Downloads · Contact · Documentation/Help
Search in Query Protein Knowledgebase (UniProtKB) \$	Search Clear Fields » Search Blast Align	Retrieve ID Mapping
WELCOME	NEWS	
Identifiers	From EMBL/GenBank/DDBJ	Map Swap Clear

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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: Excel VLOOKUP

VLOOKUP(lookup_value, table_array, col_index_num)

	Edit	-		Font			Align	ment		Nu	umber
f	🕂 🗸 Fill 🔻 Calibri (Body) 🔹 12 🔹 🗛 🗛 📰 📰 abc 🖷 🔐 Wrap Text 🛪 General										
Pa	Paste 🖉 Clear • B I U 🔄 • 🖄 • A • 🗮 🗮 🗮 🗐 🖬 Merge • 🦉 • % • 🗣										
	B3										
_	A	B	C	D	E	F	G	Н	1	J	K
1	Data Table						Annotation T	able			
2	RefSeq	Symbol	Exp1	Exp2	Exp3		RefSeq	Symbol	Entrez ID	Unigene	RefSeq
3	NM_153103	Kif1c ,	2.31975457	1.24558927	2.78816871		NM_001001	Zfp85-rs1	22746	Mm.288396	NM_001
4	NM_146017	Gabrp	4.15029735	3.08055836	1.18919962		NM_001001	Scap	235623	Mm.288741	NM_001
5	NM_018883	Camkk1	3.83282512	0.0522951	0.64684259		NM_001001	Scap	235623	Mm.288741	NM_001
6	NM_145936	Tspyl2	0.45449369	1.62761318	7.59770627		NM_001001	Fbxo41	330369	Mm.38777	NM_001
7	NM_026599	Cgnl1	4.84541871	2.84751796	1.61595768		NM_001001	Taf9b	407786	Mm.19440	NM_001
8	NM_013926	Cbx8	1.22903318	0.2863077	0.02952665		NM_001001	Taf9b	407786	Mm.19440	NM_001
9	NR_015566	A330023F24	1.44695053	0.98809479	1.59330144		NM_001001	BC051142	407788	Mm.73205	NM_001
10	NM_008623	Mpz	0.50749263	0.94350028	6.10581569		NM_001001	BC051142	407788	Mm.73205	NM_001
11	NM_183127	Fate1	2.45672795	4.87960794	3.60759511		NM_001001	BC048546	232400	Mm.259234	NM_001
12	NM_008943		4.78701069	4.15302647	0.85432314		NM_001001	Zfp941	407812	Mm.359154	NM_001
13	NM_025382		0.66397344	1.40664187	3.09539802		NM_001001	BC031181	407819	Mm.29866	NM_001
14	NM_182841		1.25528938	0.20505996	2.76879488		NM_001001	Baz2b	407823	Mm.486364	NM_001
15	NM_030061		0.17670108	2.75415469	2.98900691		NM_001001	Tmem204	407831	Mm.34379	NM_001
16	NM_133216		6.572343	0.59671282	3.84650536		NM_001001	Ccdc111	408022	Mm.217385	NM_001
17	NM 030063		7.05132762	0.65043627	1.68111836		NM 001001	BC048507	408058	Mm.177840	NM 001

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 two ids you want to convert between; Use vlookup to translate your list
- Use the merge() or mapIDs() functions in R <u>fast</u>, *versatile* & reproducible!
 - Also clusterProfiler::bitr() function and many others... [Link to clusterProfiler vignette]

bitr: Biological Id TranslatoR

clusterProfiler provides bitr and bitr_kegg for converting ID types. Both bitr and bitr_kegg support many species including model and many non-model organisms.

x <- c("GPX3",	"GLRX",	"LBP",	"CRYAB",	"DEFB1",	"HCLS1",	"SOD2",	"HSPA2",
"ORM1",	"IGFBP1",	"PTHLH",	"GPC3",	"IGFBP3"	,"ТОВ1",	"MITF",	"NDRG1",
"NR1H4",	"FGFR3",	"PVR",	"IL6",	"PTPRM",	"ERBB2",	"NID2",	"LAMB1",
"COMP",	"PLS3",	"MCAM",	"SPP1",	"LAMC1",	"COL4A2",	"COL4A1",	"MYOC",
"ANXA4",	"TFPI2",	"CST6",	"SLPI",	"TIMP2",	"СРМ",	"GGT1",	"NNMT",
"MAL",	"EEF1A2",	"HGD",	"TCN2",	"CDA",	"PCCA",	"CRYM",	"PDXK",
"STC1",	"WARS",	"HMOX1",	"FXYD2",	"RBP4",	"SLC6A12",	"KDELR3",	"ITM2B")
<pre>eg = bitr(x, fr</pre>	omType="SY	MBOL", to	Туре="ЕМТ	'REZID", OI	<mark>rgDb="org.</mark> H	s.eg.db")	
head(eg)							

##		SYMBOL	ENTREZID
##	1	GPX3	2878
##	2	GLRX	2745
##	3	LBP	3929
##	4	CRYAB	1410
##	5	DEFB1	1672
##	6	HCLS1	3059

See package vignette:

https://bioconductor.org/packages/release/bioc/html/clusterProfiler.html

What functional set databases do you want?

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



- Ingenuity Pathway Analysis (IPA) INGENUITY
- **MSigDB** (Molecular Signatures Database: gene sets based on chromosomal position, cis-regulatory motifs, GO terms, etc)
- Many others...
 - Enzyme Classification, PFAM, Reactome, Disease Ontology, Chemical Entities of Biological Interest, Network of Cancer Genes etc...
 - See: Open Biomedical Ontologies (<u>www.obofoundry.org</u>)

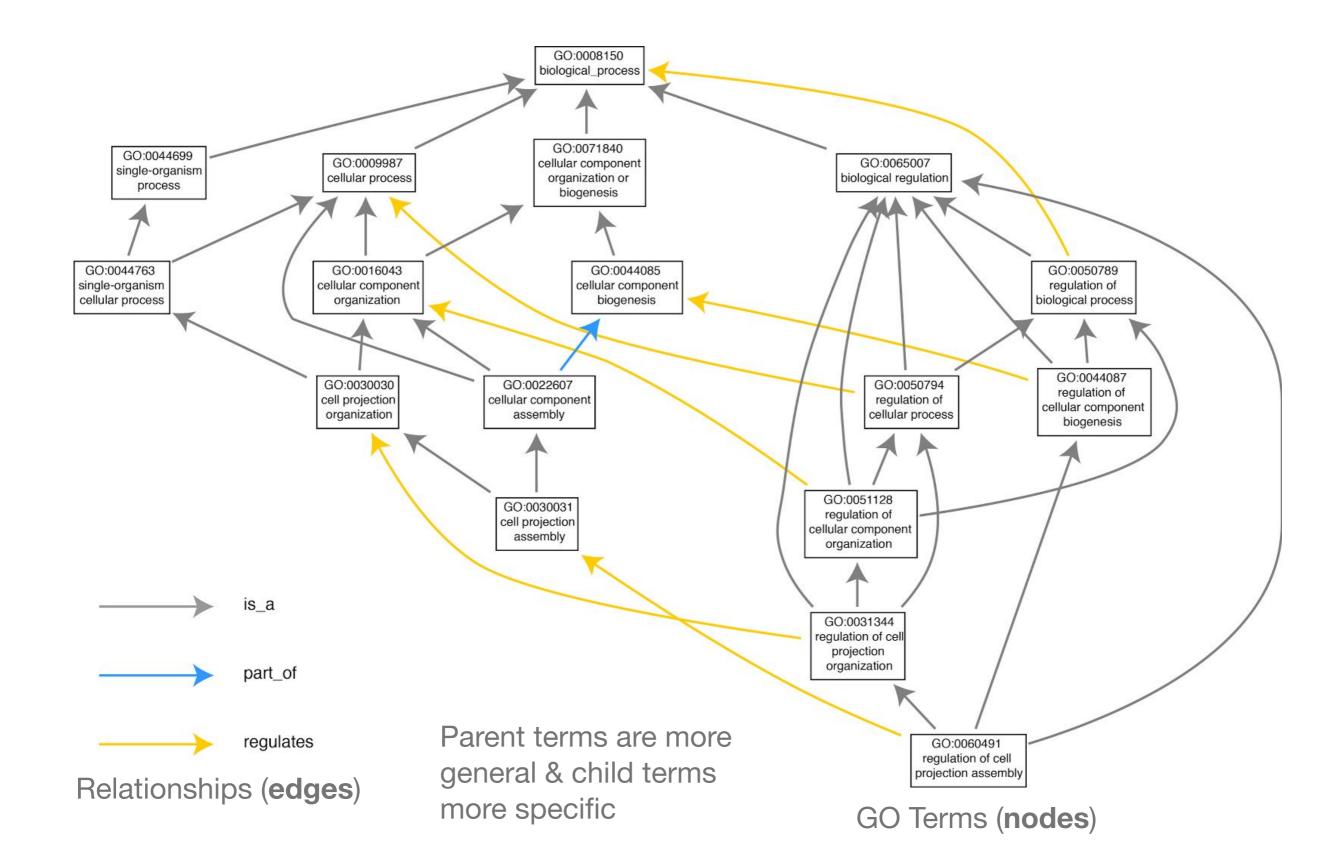
GO database < <u>www.geneontology.org</u> >

- 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

GO is structured as a "directed graph"



GO Annotations

- GO is <u>not</u> 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 < <u>amigo.geneontology.org</u> >

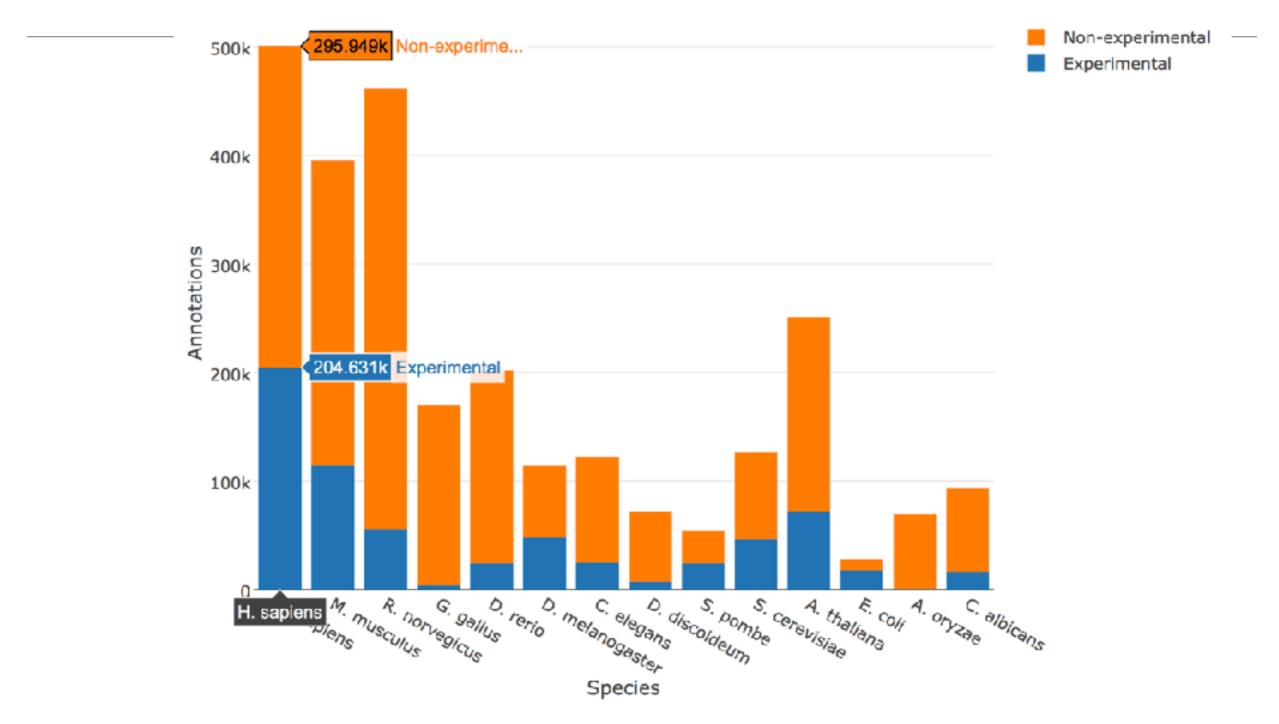
Bit states Bit scharger Bit scharger Bit states Bit states Bit scharger Bit scha	th	e Gen	Α	miC	GO		
	Search	Browse	BLAST	Homolog Annotations	Tools & Resources	Help	
			Searc	h the Gene Ontology datab	oase		
		0	GO terms	• genes or proteins	exact match		AmiGO 2 a
AmiGO versio Try AmiGO L					GO datab <u>Cite this data</u> • <u>Terms</u> Copyright © 1999 2		helpdesk

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) Experimental annotations by species

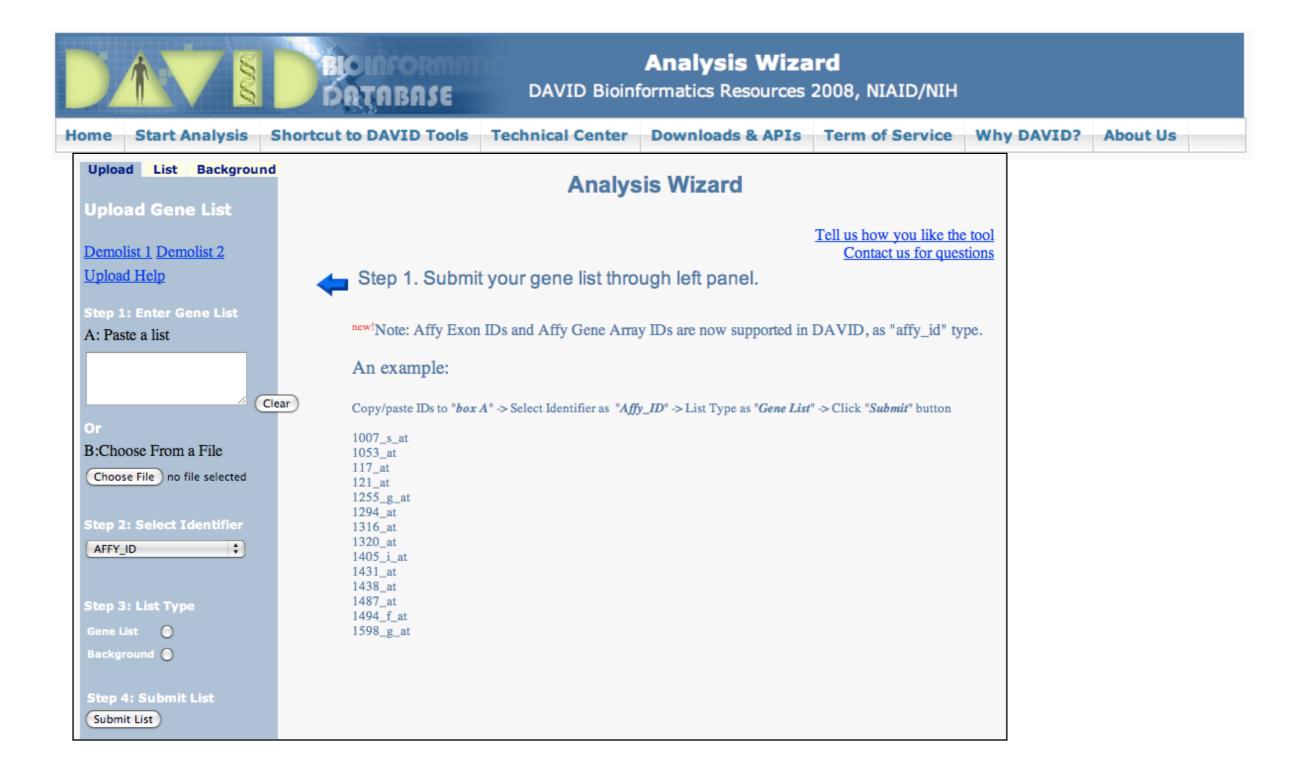


• See AmiGO for details: <u>http://amigo.geneontology.org/amigo/base_statistics</u>

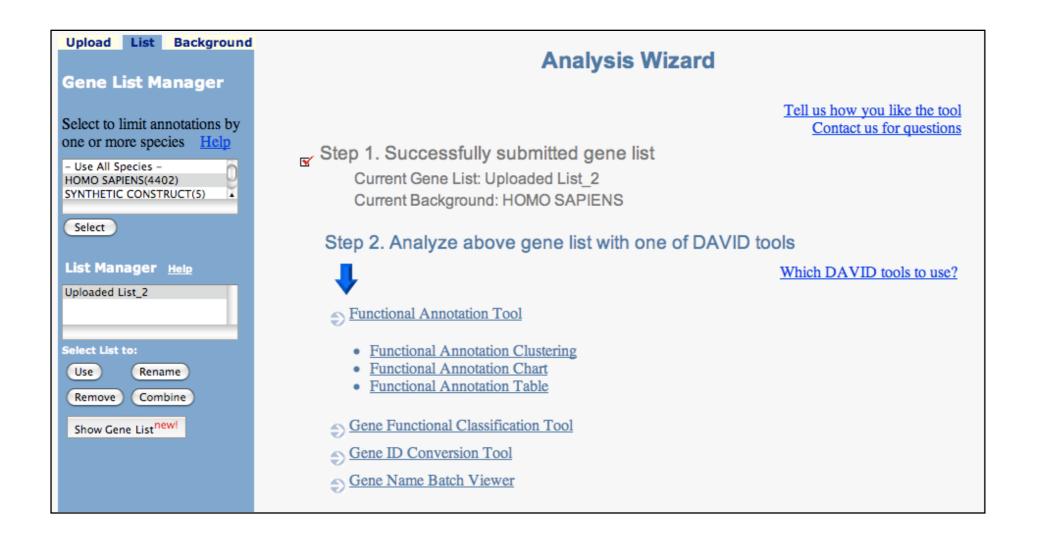
Can now do gene list analysis with GeneGO

	pantherdb.org/webservices/go/overrep.jsp 🔿	• • • +
	ANTHER Classification System	CONTACT US
Home About PANTHER Data PANTHER Tools Wo New! PANTHER13.1 released.	kspace Downloads Help/Tutorial	
Search Gene List Analysis	Browse Sequence Search cSNP Scoring Keyword	d Search
Go Please refer to our a Error parsing reques Quick links	ticle in <u>Nature Protocols</u> for detailed instructions on how to use this page. <i>t, no input specified</i>	
Whole genome function Views Genome statistics Data Version How to cite PANTHER NEW! Recent publication describing PANTHER News PANTHER13.1 Released Click for additional info. Newsletter subscription Enter your Email:	1. Enter ids and or select file for batch upload. Else enter ids or select file or list from workspace for comparing to a reference list. Enter IDs: separate IDs Supported IDs separate IDs by a space or comma Upload IDs: Choose File no file selected File format Please login to be able to select lists from your workspace. Select List Type: ID List Previously exported text search results Workspace list PANTHER Generic Mapping File VCF File Flanking region 2. Select organism.	
Subscribe CC Postgre	Homo sapiens Mus musculus Rattus norvegicus Gallus gallus Danio rerio 3. Select Analysis.	
	 Functional classification viewed in gene list 	

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



• Notice that you can pick a *Background* (Universe)



• Functional Annotation Tool

Annotation Summary Results		
		Help and Tool Manual
Current Gene List: Uploaded List_3	2320 DAVID IDs	
Current Background: HOMO SAPIENS	Check Defaults 🗹	Clear All
Main Accessions (0 selected)		
Other Accessions (0 selected)		
Gene Ontology (4 selected)		
Protein Domains (3 selected)		
Pathways (3 selected)		
General Annotations (0 selected)		
Functional Categories (3 selected)		
Protein Interactions (0 selected)		
Literature (0 selected)		
Disease (1 selected)		
Tissue Expression		
Combined View for Selected Annotation		
Functional Annotation Clustering ^{new!}		
Functional Annotation Chart		
Functional Annotation Table		

Specify functional sets

Annotation	Summary Results
	Help and Tool Manual
	t: Uploaded List_3 2320 DAVID IDs
Current Backgrou	und: HOMO SAPIENS Check Defaults Clear All
Main Accessions	6 (0 selected)
 Other Accessions Gene Ontology (1) 	
GOTERM_BP_1	71% 1669 (Chart)
GOTERM_BP_2	71% 1652 (Chart)
GOTERM_BP_3	69% 1609 Chart
GOTERM_BP_4	65% 1519 Chart
GOTERM_BP_5	61% 1432 Chart
GOTERM_BP_ALL	71% 1669 Chart
GOTERM_CC_1	75% 1754 Chart
GOTERM_CC_2	75% 1741 Chart
GOTERM_CC_3	75% 1741 Chart
GOTERM_CC_4	70% 1634 Chart
GOTERM_CC_5	69% 1605 Chart
GOTERM_CC_ALL	75% 1754 Chart
GOTERM_MF_1	75% 1745 Chart
GOTERM_MF_2	73% 1716 Chart
GOTERM_MF_3	65% 1523 Chart

• Let's look at the Functional Annotation Chart

Annotation Summary Results		
		Help and Tool Manual
Current Gene List: Uploaded List_3	2320 DAVID IDs	
Current Background: HOMO SAPIENS	Check Defaults 🗹	Clear All
Main Accessions (0 selected)		
Other Accessions (0 selected)		
Gene Ontology (4 selected)		
Protein Domains (3 selected)		
Pathways (3 selected)		
General Annotations (0 selected)		
Functional Categories (3 selected)		
Protein Interactions (0 selected)		
Literature (0 selected)		
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Tissue Expression		
Combined View for Selected Annotation		
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Functional Annotation Chart		
Functional Annotation Table		

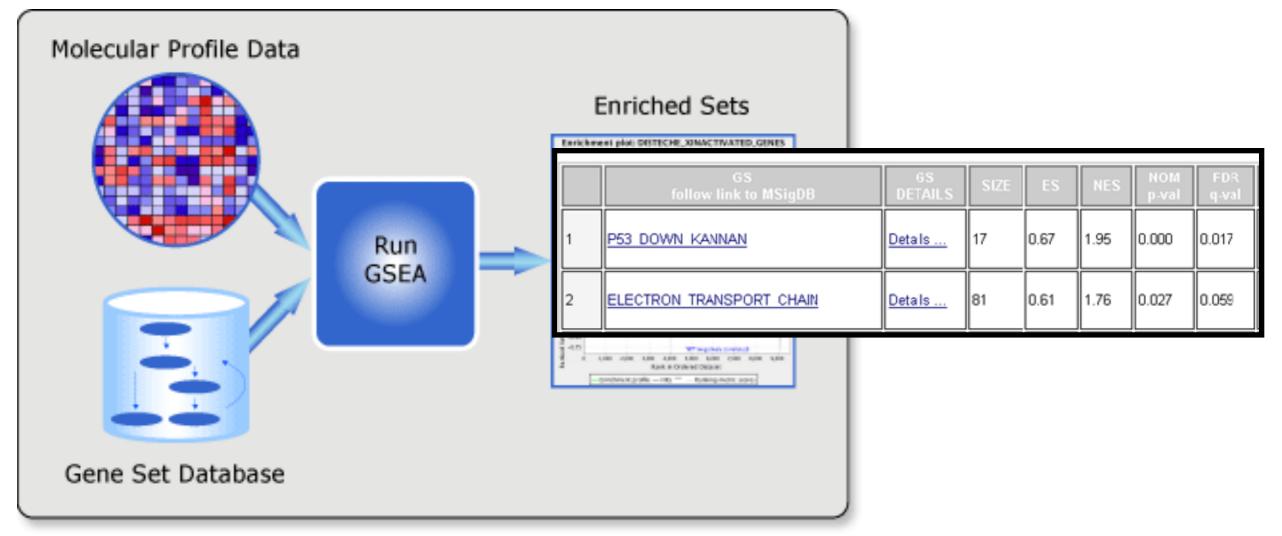
• Functional Annotation Chart

Functional Annotation Chart Current Gene List: Uploaded List_1 Current Background: Homo sapiens 2316 DAVID IDs								
Options Rerun Using								Download File
Sublist		🗧 Term	RT	Genes	Count	\$ <u>%</u>	P-Value	
	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	<u>cell death</u>	RT	-	136	5.9	3.8E-6	3.3E-3
	GOTERM_BP_5	regulation of transcription from RNA polymerase II promoter	RT	=	83	3.6	3.7E-5	2.4E-2
	GOTERM_BP_5	protein kinase cascade	RT	Ξ.	71	3.1	4.7E-5	2.4E-2
	GOTERM_BP_5	regulation of kinase activity	RT	E	48	2.1	5.4E-5	2.3E-2
	GOTERM_BP_5	negative regulation of cell proliferation	RT	Ξ.	48	2.1	1.0E-4	3.7E-2
	GOTERM_BP_5	regulation of cell size	RT	2 - C	41	1.8	1.2E-4	3.9E-2
	GOTERM_BP_5	monocarboxylic acid metabolic process	RT	Ξ.	48	2.1	1.3E-4	3.6E-2
	GOTERM_BP_5	positive regulation of nucleobase, nucleoside, nucleotide and nucleic acid metabolic process	<u>RT</u>	=	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)*

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, ... *PNAS* **102**, 15545-15550 (2005)

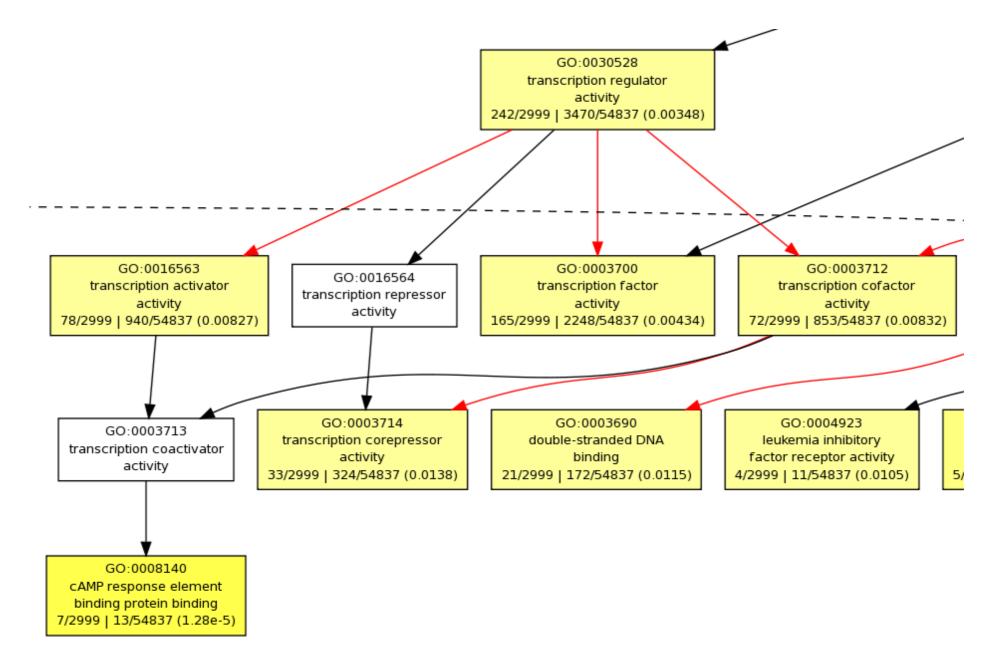
Overlapping functional sets

- 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

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

• 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

Currer	Functional Annotation Clustering Current Gene List: Uploaded List_3 2320 DAVID IDs											
🗉 Optic	Options Classification Stringency Medium											
Rerun	Rerun using options Create Sublist											
	Annotation Cluster 1	Enrichment Score: 3.72	G			Count	P_Value	Benjamini				
	GOTERM_BP_5	regulation of transcription from RNA polymerase II promoter	RT	=		83	3.7E-5	2.4E-2				
	GOTERM_BP_5	positive regulation of nucleobase, nucleoside, nucleotide and nucleic acid metabolic process	RT	=		61	1.5E-4	3.8E-2				
	GOTERM_BP_5	positive regulation of cellular metabolic process	RT	a 11		72	1.7E-4	3.8E-2				
	GOTERM_BP_5	positive regulation of transcription	RT	÷		58	3.8E-4	5.0E-2				
	GOTERM_BP_5	positive regulation of transcription, DNA- dependent	RT	a 11		48	7.4E-4	7.6E-2				
	Annotation Cluster 2	Enrichment Score: 3.54	G		1	Count	P_Value	Benjamini				
	GOTERM_BP_5	regulation of cell size	<u>RT</u>	Ξ.		41	1.2E-4	3.9E-2				
	GOTERM_BP_5	regulation of cell growth	RT	1 C - 1		33	3.7E-4	5.1E-2				
	GOTERM_BP_5	cell morphogenesis	RT	=		81	5.2E-4	5.7E-2				
	Annotation Cluster 3	Enrichment Score: 3.37	G			Count	P_Value	Benjamini				
	GOTERM_BP_5	apoptosis	RT	=		131	1.6E-6	2.1E-3				
	GOTERM_BP_5	<u>cell death</u>	RT	=		136	3.8E-6	3.3E-3				
	GOTERM_BP_5	regulation of programmed cell death	RT	=		88	3.2E-4	5.8E-2				
	GOTERM_BP_5	positive regulation of apoptosis	RT	.		48	3.3E-4	5.6E-2				
	GOTERM_BP_5	regulation of apoptosis	RT	=		87	3.5E-4	5.2E-2				
	GOTERM_BP_5	positive regulation of programmed cell death	RT	Ξ.		48	4.0E-4	5.0E-2				

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 and lots other R/Bioconductor packages in this area!!!

Hands-on time!

Do it Lourser

https://bioboot.github.io/bimm143_S18/lectures/#15

Data structure: counts + metadata

<u>countData</u>

gene	ctrl_1	ctrl_2	exp_1	exp_1
geneA	10	11	56	45
geneB	0	0	128	54
geneC	42	41	59	41
geneD	103	122	1	23
geneE	10	23	14	56
geneF	0	1	2	0

countData is the count matrix (number of reads coming from each gene for each sample)

<u>colData</u>

id	treatment	sex	
ctrl_1	control	male	
ctrl_2	control	female	
exp_1	treatment	male	
exp_2	treatment	female	

Sample names: ctrl_1, ctrl_2, exp_1, exp_2

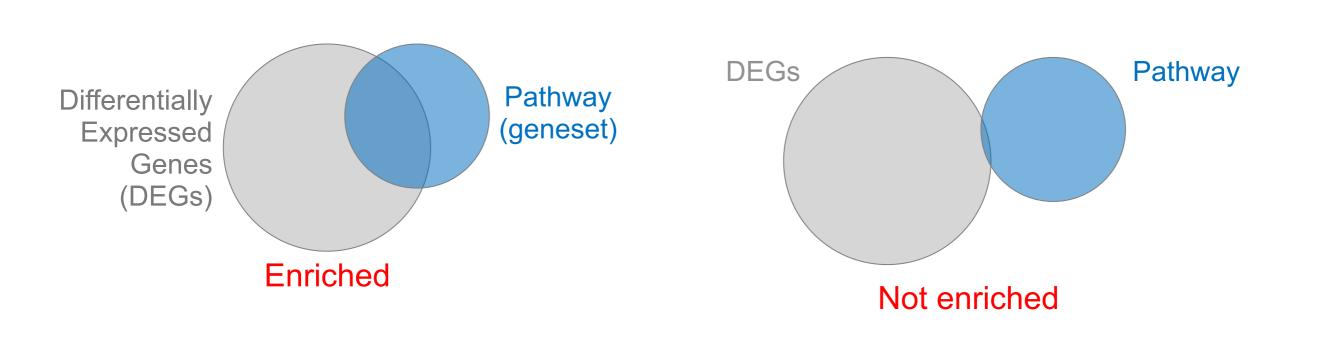
colData describes metadata about the *columns* of countData

First column of colData must match column names of countData (-1st)

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

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



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

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

- Post-transcriptional regulation is neglected
- **Directionality** is hard to capture sensibly
 - e.g. IкBa/NF-кВ
- 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

