EXPERIMENTAL DESIGN



EXPERIMENTAL DESIGN

Defining the samples to be studied

Number of samples

Biological replicates are parallel measures of biologically distinct samples, which allow to capture random biological variations.

Technical replicates are repeated measures of the same sample, that represent independent measures of the random noise associated with protocols or equipment.

The greater the number of the biological replicates, the more we can trust the results, especially when testing for differential expression. With only one biological replicate, no statistical test can be performed.

EXPERIMENTAL DESIGN

Defining the technical details

Choice of sequencing depth

If we want to measure the expression of known genes, depth can be relatively low (e.g. 20 M reads for polyA+). If we want to discover new genes and transcripts, depth must be higher (e.g. 60 M for polyA+, 120 for total RNA).

Length and pairing of reads

Theoretically speaking, read length should be > 20 bp (they usually are longer than 35 bp). PE reads are usually better (except for small RNA-Seq and Ribo-Seq), but they are more expensive.

Strandedness

It is usually better to have a directional (stranded) sequencing: it costs slightly more, but it is able to discriminate between antisense RNAs.



General RNA-Seq pipeline for Differential Expression



Data format

Usually, the format of the file containing the sequence of the reads is FASTQ. It is composed of four-lines blocks: - the first line begins with @ and contains the ID of the read and optional information. - the second line is the sequence - the third line begins with a '+' character and is optionally followed by the same sequence identifier (and any description) again - the fourth line encodes the quality values for the sequence in Line 2.

For paired end reads, there are two FASTQ files (forward and reverse).



Example



FASTQ format

@SEQILMN03:128:HA5CBADXX:1:1101:1186:2059 2:N:0:GTCGTA NNNNNGTTAAGATTATTGTCATTGGCTAACTAAGCGCTACCAAGTACAAGTACAAATGC +

PHRED quality score

The quality score of a base, also known as a Phred or Q score, is an integer value representing the estimated probability of an error, i.e. that the base is incorrect.

 $Q = -10 \log_{10} P$

A high quality score implies that a base call is more reliable and less likely to be incorrect. For example, for base calls with a quality score of Q40, one base call in 10,000 is predicted to be incorrect. For base calls with a quality score of Q30, one base call in 1,000 is predicted to be incorrect. Table 1 shows the relationship between the base call quality scores and their corresponding error probabilities.

Dave Least 1994

Quality Score	Error Probability
Q40	0.0001 (1 in 10,000)
Q30	0.001 (1 in 1,000)
Q20	0.01 (1 in 100)
Q10	0.1 (1 in 10)



FastQC

FastQC is a quality control tool for high throughput sequence data.





http://www.bioinformatics.babraham.ac.uk/projects/fastqc/Help

DATA ANALYSIS: PREPROCESSING

Issues that can be addressed during pre-processing phase

- If the read is longer than the insert (e.g. in Small RNA-Seq), its sequence will also contain part of the 3' adapter. This
- If the overall quality of the read is low, it must be removed. A trimming is useful if quality decreases too much towards the end of the read.

Amplification

Element 1

Barcode

SP2

Amplification

Element 2

- Sometimes the read terminates with ambiguous (N) bases which must be removed.
- Some of the most common preprocessing tool are FASTX-Toolkit, Cutadapt, Trimmomatic, Prinseq.

Read alignment

- After pre-processing, we can align reads to a reference sequence.
- to align a read means finding the region of the genome to which it belongs.
- if the genome sequence of the organism is known, reads can be aligned to it.
- other approaches have to be used if the genome sequence is not known (de novo transcriptome assembly).

The accurate and fast alignment of millions of reads is not a simple task: many programs have been developed to address this issue.



Main alignment strategies



Main alignment strategies



Alignment of NGS reads

Classical alignment techniques, such as dynamic programming, are not suitable for NGS data, due to the huge size of genomes and the high number of reads.

For this reason, short-read aligners are usually based on a preliminary indexing of the reference sequence. The performance of the aligner heavily depends on the way data are indexed.



 $BAN \Rightarrow 0$ \$ A\$ 5 3 ANA\$ **ANANA\$** $ANA \Rightarrow 1$ **BANANA\$** 0 NAN \Rightarrow 2 \bigcirc NA\$ 4 NANA\$ Seed hash tables Suffix array Many variants, incl. spaced seeds

GENE EXPRESSION REGULATION IN EUKARYOTES - LM-GBM a.a. 2016-2017 Università La Sapienza di Roma

NULL

 $ANA \Rightarrow 3$

NULL

NULL

Main alignment tools

BWA, Soap2 and Bowtie are based on the Burrows-Wheeler transform, an indexing technique which allows to drastically reduce the time required for the alignment compared to older tools like Maq (the alignment of 20M reads is done in few hours).

Aligner	Description	URL
Illumina platform		
ELAND	Vendor-provided aligner for Illumina data	http://www.illumina.com
Bowtie	Ultrafast, memory-efficient short-read aligner for Illumina data	http://bowtie-bio.sourceforge.net
Novoalign	A sensitive aligner for Illumina data that uses the Needleman–Wunsch algorithm	http://www.novocraft.com
SOAP	Short oligo analysis package for alignment of Illumina data	http://soap.genomics.org.cn/
MrFAST	A mapper that allows alignments to multiple locations for CNV detection	http://mrfast.sourceforge.net/
SOLiD platform		
Corona-lite	Vendor-provided aligner for SOLiD data	http://solidsoftwaretools.com
SHRiMP	Efficient Smith-Waterman mapper with colorspace correction	http://compbio.cs.toronto.edu/shrimp/
454 Platform		
Newbler	Vendor-provided aligner and assembler for 454 data	http://www.454.com
SSAHA2	SAM-friendly sequence search and alignment by hashing program	http://www.sanger.ac.uk/resources/software
BWA-SW	SAM-friendly Smith-Waterman implementation of BWA for long reads	http://bio-bwa.sourceforge.net
Multi-platform		
BFAST	BLAT-like fast aligner for Illumina and SOLiD data	http://bfast.sourceforge.net
BWA	Burrows-Wheeler aligner for Illumina, SOLiD, and 454 data	http://bio-bwa.sourceforge.net
Mag	A widely used mapping tool for Illumina and SOLiD; now deprecated by BWA	http://maq.sourceforge.net

Spliced aligners

The algorithms discussed so far are not able to align reads on splicing junctions, unless we use the transcriptome sequence as a reference.

There are several programs that are able to perform spliced alignments: TopHat, STAR, Gsnap, MapSplice, PALMapper, ReadsMap etc.

TopHat uses Bowtie as an alignment "engine". The algorithm can be divided into two main steps:

- Reads are aligned to the reference genome.

- Reads that cannot be aligned directly to the reference are aligned to possible splicing junctions.

From TopHat manual...

"TopHat generates its database of possible splice junctions from two sources of evidence. The first and strongest source of evidence for a splice junction is when two segments from the same read (for reads of at least 45bp) are mapped at a certain distance on the same genomic sequence or when an internal segment fails to map - again suggesting that such reads are spanning multiple exons. With this approach, "GT-AG", "GC-AG" and "AT-AC" introns will be found ab initio. The second source is pairings of "coverage islands", which are distinct regions of piled up reads in the initial mapping. Neighboring islands are often spliced together in the transcriptome, so TopHat looks for ways to join these with an intron. We only suggest users use this second option (--coverage-search) for short reads (< 45bp) and with a small number of reads (<= 10 million). This latter option will only report alignments across "GT-AG" introns"



TopHat



Main alignment programs

Table 1	Selected	list	of RNA-seq	analysis	programs
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Class	Category	Package	Notes	Uses	Input
Read mapping					
Unspliced aligners ^a	Seed methods	Short-read mapping package (SHRiMP) ⁴¹	Smith-Waterman extension	Aligning reads to a reference transcriptome	Reads and reference transcriptome
		Stampy ³⁹ Probabilistic model			
	Burrows-Wheeler transform methods	Bowtie ⁴³			
		BWA ⁴⁴	Incorporates quality scores		
Spliced aligners	Exon-first methods	MapSplice ⁵²	Works with multiple unspliced	Aligning reads to a reference genome. Allows for the identification of novel splice junctions	Reads and reference genome
		SpliceMap ⁵⁰	aligners		
		TopHat ⁵¹	Uses Bowtie alignments		
	Seed-extend methods	GSNAP ⁵³	Can use SNP databases		
		QPALMA ⁵⁴	Smith-Waterman for large gaps		
		Star	Superfast		

Gaber et al., 2011, Nature Methods 8:469

Alignment output

After alignment, mapped and unmapped reads are usually exported in SAM/BAM format.

 - SAM format specification (Sequence Alignment Map, <u>http://samtools.sourceforge.net/SAM1.pdf</u>) describes a generic format for the storing of reads sequence and their alignment on a reference.

- **BAM** is the binary equivalent of SAM.

- **Samtools** is a suite of tools for the analysis and manipulation of SAM/BAM files (visualizaton, sorting, filtering, indexing etc.)



SAM file structure

- A generic SAM/BAM file is composed of two parts:
- header reports general information.
- **body reports information about reads**. Each line describes a read (aligned or not): alignment position, sequence, quality etc.

@HD VN:1.0 S0:coordinate
@SQ SN:chr20 LN:6444167
<pre>@PG ID:TopHat VN:2.0.14 CL:/srv/dna_tools/tophat/tophat -N 3read-edit-dist 5read-read</pre>
lign-edit-dist 2 -i 50 -I 5000max-coverage-intron 5000 -M -o out /data/user446/mapping_tophat/index/chr
20 /data/user446/mapping tophat/L6 18 GTGAAA L007 R1 001.fastq
HWI-ST1145:74:C101DACXX:7:1102:4284:73714 16 chr20 190930 3 100M * 0 0
CCGTGTTTAAAGGTGGATGCGGTCACCTTCCCAGCTAGGCTTAGGGATTCTTAGTTGGCCTAGGAAATCCAGCTAGTCCTGTCTCTCAGTCCCCCCTCT
C BBDCCDDCCDDDDDDDDCDCCCCDBC?DDDDDDDDDDD
AS:i:-15 XM:i:3 X0:i:0 XG:i:0 MD:Z:55C20C13A9 NM:i:3 NH:i:2 CC:Z:= CP:i:55352714 HI:i:0
HWI-ST1145:74:C101DACXX:7:1114:2759:41961 16 chr20 193953 50 100M * 0 0
TGCTGGATCATCTGGTTAGTGGCTTCTGACTCAGAGGACCTTCGTCCCCTGGGGCAGTGGACCTTCCAGTGATTCCCCTGACATAAGGGGCATGGACGA
G DCDDDDEDDDDDDDDDDDDDDCCCDDDDDDEC>DFFEJJJJJIGJJJJIHGBHHGJIJJJJJGJJJJJJJJJJJJJJ
AS:i:-16 XM:i:3 X0:i:0 XG:i:0 MD:Z:60G16T18T3 NM:i:3 NH:i:1
HWI-ST1145:74:C101DACXX:7:1204:14760:4030 16 chr20 270877 50 100M * 0 0
GGCTTTATTGGTAAAAAAGGAATAGCAGATTTAATCAGAAATTCCCACCTGGCCCAGCAGCACCAACCA
C DDDDDDDDDCCDDDDDDDDEEEEEEFFFEFFEGHHHFGDJJIHJJJJJJJIIIIGGFJJIHIIIJJJJJJJIGHFAHGFHJHFGGHFFFDD@BB
AS:i:-11 XM:i:2 X0:i:0 XG:i:0 MD:Z:0A85G13 NM:i:2 NH:i:1
HWI-ST1145:74:C101DACXX:7:1210:11167:8699 0 chr20 271218 50 50M4700N50M * 0
0 GTGGCTCTTCCACAGGAATGTTGAGGATGACATCCATGTCTGGGGTGCACTTGGGTCTCCGAAGCAGAACATCCTCAAATATGACCTCTCG



BAM file visualization

IGV

IGV is a standalone program which allows a highly interactive visualization of BAM files (and other genomic annotation formats).



BAM file visualization

Genome Browser (UCSC)

Visualization is less interactive, but many supplementary tracks are available.



Measures of gene expression

- "The number of read counts mapping to the biological feature of interest (gene, transcript, exon etc.) is considered to be linearly related to the abundance of the target feature." (Tarazona, 2011)



- The raw number of reads mapping on a gene (**read count**) requires a normalization. Why?

- longer genes will have a greater number of reads mapped on them compared to equally expressed shorter genes: to normalize for gene length is important to compare the expression of distinct genes.

- **the number of reads mapped on a gene depends on sequencing depth:** to normalize for the total number of mapped reads is important to compare the expression levels of the same gene obtained from two different sequencing experiments.

- **RPKM** and **FPKM** are two normalized measures of gene expression.

Measures of gene expression: RPKM

- RPKM stands for "Reads per Kilobase of exon per Million mapped reads"

RPKM = $\frac{c}{LN}$

- C : Number of mappable reads on a feature (eg. transcript, exon, etc.)
- ➤L: Length of feature (in kb)

>N: Total number of mappable reads (in millions)

Gene A 600 bases Gene B 1100 bases

RPKM = 12/(0.6*6) = 3.33 RPKM = 24/(1.1*6) = 3.64



RPKM = 19/(0.6*8) = 3.96 RPKM = 28/(1.1*8) =1.94

Measures of gene expression: FPKM

- FPKM stands for "Fragments per Kilobase of exon per Million mapped fragments"

-The unit used for quantification is no longer the single read, but the fragment. In single-end sequencing, each read represents a fragment, so FPKM = RPKM. In paired-end sequencing, each fragment is represented by a read pair: this way, each read pair is not counted twice.







Cufflinks: quantification

Expression values are expressed as FPKM Distinct transcripts belonging to the same gene may share some exons. How does Cufflinks assign reads to the correct isoforms? It uses non-ambiguosly mapping reads to estimate the probability of each ambiguous reads coming from a certain isoform.



The expression of a gene is equal to the sum of the FPKMs of its isoforms.

DATA ANALYSIS: DE NOVO DISCOVERY

Tools for de novo discovery of transcripts

- genome-guided programs use the alignment of reads to the genome to assemble novel transcripts and genes.

- **genome-independent** programs use the overlap between reads to assemble transcripts; alignment to the genome is not required. They are thus useful in the absence of a reference genome, but also to find transcripts coming from genes which underwent structural variations (indels, fusions etc.). These programs are usually slower.

Transcriptome reconstruction						
Genome-guided	Exon identification	G.Mor.Se	Assembles exons	Identifying novel transcripts	Alignments to	
reconstruction Ge as	Genome-guided assembly	Scripture ²⁸	Reports all isoforms	using a known reference	reference genome	
		Cufflinks ²⁹	Reports a minimal set of isoforms	genome		
Genome- independent reconstruction	Genome-independent assembly	^{Velvet⁶¹ TransABySS⁵⁶ Trinity}	Reports all isoforms	Identifying novel genes and transcript isoforms without a known reference genome	Reads	

DATA ANALYSIS: DE NOVO DISCOVERY

Tools for de novo discovery of transcripts



Genomic loci

What is differential expression (DE) analysis?

DE analysis allows to find **genes** (or other genomic features like transcripts and exons) **that are expressed at significantly different levels between two groups of samples** (conditions): patients treated with drugs VS controls, healthy VS sick individuals , different tissues and different differentiation states. There could also be more than two conditions (e.g. time series).

For each analyzed gene, the result will be:

- **Fold Change (FC**): the ratio of the average expression of gene in condition A to the average expression in condition B. log2 transformed fold changes are nicer to work with because the transform is symmetric for reciprocals (positive values for up-regulation, negative for down-regulation).

- **P-value**: it measures the statistical significance of the observed differential expression. The lower the p-value, the higher the probability that the gene underwent a significant deregulation. Goes from 0 to 1, usual cutoff is 0.05. It is often normalized to account for multiple testing.

DATA ANALYSIS: DIFFERENTIAL EXPRESSION ANALYSIS

FC vs p-value

High absolute FC values are not necessarily associated with significant P-values, especially when the expression of the gene is highly variable.





DATA ANALYSIS: DIFFERENTIAL EXPRESSION ANALYSIS

Cuffdiff: differential expression test

Cuffdiff is able to perform a differential expression test, both at isoform and gene level.



Extracting biological meaning from DE gene lists

Once we have obtained a list of differentially expressed genes, we would like to search for a statistically significant association between:

Group of genes	\longleftrightarrow	Bi	ol	og	ical	pro	ocesses	\longleftrightarrow	Phenotype
ub symbo	al description	logFC	Avelapr	t	P.Value a	adj.P.Val B			
8450 RG55	regulator of G-protein signaling 5	4.91391939	8.880288464	26.55260559	4.675-18	2.67E-14 31.2163728			
2862 67837	G protein-coupled receptor 37 (endethelin receptor type B-like)	4.11615058	6.539187355	26.10650437	6.680-10	2.672-14 30.8834034			
55584 CHRNA9	cholinergic receptor, nicotinic, alpha 9	-5.0449004	7.563641815	-24.95123599	1.73E-17	5.20E-14 29.9900318			
64333 XYL13 1293 COL643	wiosyltrenaterese I rollazen tyne M alebo 8	3.50540422	8 788502457	24.35587524	5.545-17	6.68E-14 29.5438205 1.11E-13 28.8904111	~ ^		
6696 SPP1	secreted phospheprotein 1	3.01894272	9.030974328	23,42509429	6.525-17	1.12E-13 28.7360626			
64065 PERP	PERP, TP53 apoptosis effector	-3.1802228	6.959394145	-23.20401784	7.956-17	1.19E-13 28.5469663			
824 CAPN2 8871 SYND	calpain 2, (m/1) large suburit	-1.7384402	50.95750307	-22.63496065	1.346-16	1.895-13 28.0510716			
6285 S1008	5100 caldum binding protein 8	2.53765659	6.799331011	22.35831889	1.736-16	1.89E-13 27.8051084			
29091 57/876	syntaxin blinding protein 6 (amisyn)	2.4108232	6.531105876	21.64130367	3,400-10	3.412-13 27.152374			
1369 CPH1 5340 DOD3	carboxypeptidase N, polypeptide 1 DOD domain controlicios los transact consistor 1	3.6252078	8.059274369	21.17029509	5.382-16	6 205-13 26 2366143	4 .))		
80760 ITH5	inter alpha-trypsin inhibitor heavy chain family, member 5	3.11916914	8.512182227	20.44275884	1.116-15	8.90E-13 26.0079408			
1410 CRYAB	crystallin, alpha 0	1.57221050	7.279028307	20.18269151	1,450-15	1.062-12 23.7504399			
114899 C10TNF3	Clig and tumar necrosis factor related protein 3	3.53843053	7.73904164	20.14703013	1.500-15	1.06E-12 25.7148871			
7058 TH852	thrombospondin 2	2.1106143	8.350588355	19.8572011	2.036-15	1.25E-12 25.4233605		5/11111	
55857 PUX151	polo-like kinase 1 substrate 1	2.46091845	8.45122119	29.80947703	2.130-15	1.250-12 25.37494		YIIL Y	
64750 SMURF2	SMAD specific E3 ubiquitin protein ligase 2	-2.6583314	8.024265502	-19.76050737	2.24E-15	1.25E-12 25.3251319		SILA	
8848 TSC2201	15C22 domain family, member 1	-3.1343571	10.16682523	-19.50950581	2.920-15	1.48E-12 25.0679493		Y NY	
220 ALDHIA3	aldehyde dehydrogenase 1 family, member A3	2.73584765	10.24822998	29,47942767	3.015-15	1.486-12 25.0367886			
4206 MEF2C	myocyte enhancer factor 20	1.41377231	7.076627287	19.45557651	3.096-15	1.48E-12 25.0122306			
55519 WW150 6685 NPTX2	neuronal pentrasin II	4.5671127	9.254508041 8.319689927	-18,9054486	5.575-15	2.460-12 24.4346881			
5329 PLAUR	plasminogen activator, urakinase receptor	-1.8136574	7.886039592	-18.87776049	5.74E-15	2.46E-12 24.4051814			
64397 ZFP106	ainc finger protein 106 homolog (mouse)	1.86356401	8.981908167	18.63102948	7.526-15	3.12E-12 24.1403222			
54034 PDSTC	platelet derived growth factor C	-2.7181405	7.931214772	-18.35627868	1.025-14	3.950-12 23.8412537			
8522 GA57	growth arrest-specific 7	2.11132993	8.068507959	18,2452349	1.166-14	4.33E-12 23.7191245			
3580 (TGA9	integrin, alpha 9 microtraticity screening in the second screen for the	1.88266096	6.676071466	18.21803244	1.196-14	4.33E-12 23.6890948	~		
57228 SMACP	small cell adhesion glycoprotein	-1.8818955	8.236330886	-18 105293	1.355-14	4.58E-12 23.5641664	-		
2274 (HL2	four and a half LIM domains 2	-2.0164106	8.016891523	-18.09124435	1.376-14	4.58E-12 23.5485453			
11352 ACOT7 0055 h535714	acyl-CoA thioesterase 7 1 benarian (ulfute (duronamine) 3.0.4) (Intransferring 341	-1.1238598	9.772260826	-17.87080068	2,065,14	5.73E-12 23.301861 6.50E-12 23.1335054			
1634 DCN	decorin	3.2818759	8.143714414	17.71441636	2.11E-14	6.50E-12 23.1250543			
10276 NET1	reursepithelial cell transforming 1	-2.1105039	8.259864408	-17.65139817	2.271-14	6.821-12 23.0533772			
8728 ADAM19	ADAM metallopeotidase domain 19 anderhalin recenter tune 8	-2.2947678	7.918552548	-17,43585588	2.921-14	8.42E-12 22.8063305 8.42E-12 22.2972215			
202 AIM1	absent in melanoma 1	-3.3043704	8.387248105	-17.08618883	4,406-14	1.21E-11 22.3992264			
2012 EMP1	epithelial membrane protein 1	-3.3090457	7.226480782	-17.08273582	4,425-14	1.210-11 22.3951665			
2934 GSN 8838 WISPS	gesonn WNT1 inducible signaling pathway protein 3	1.66235318	6.725056377	16/92737413	5.30E-14	1.396-11 22.2153587			
10962 MULT11	myeloid/ymphoid or mixed-lineago leukamia (trithorax homelog, D	-2.5624459	10.10282437	-16.92568242	\$.338-14	1.36E-11 22.2096769			
54898 ELOV.2	ELOVE fatty acid elongase 2	1.99792345	5.836927923	16.72604718	6.785-14	1.706-11 21.9715178			
4907 NISE 5047 PAEP	propriation associated endometrial protein	-3.1997583	6.665647235	-16.67307416	7.146-14	1.746-11 21.9198/95			
116372 LVPD1	LYE/PLAUR domain containing 1	-2.2678592	6.79874409	-16.56676339	8.222-14	1.946-11 21.7795586			
83442 SHBBRI	3 943 domain binding glutamic acid-rich protein like 3	-1.7165301	10.57293255	-16.48267181	9.11E-14	2.10E-11 21.6775135			
6480 ST6GAL	ST6 beta-salactoramide alpha-2.6-siabitranferare 1	1.38252423	7.387325433	16.42106549	9,836-14	2.15E-11 21.6024444			
6299 SALL1	sal-like 1 (Drosophila)	2.9392654	6.211291438	-16.41104846	9.95E-14	2.15E-11 21.5902119			
5831 PYCR1	pyrroline 5 carboxylate reductase 1	0.95170269	8.563197304	16.40349911	1.00E-13	2.15E-11 21.5809892 2.55E-11 21.2829892			
5355 PLP2	prateolipid protein 2 (colonic epithelium-enriched)	-0.93274	10.20411481	-15.8859672	1.916-13	3.97E-11 20.9391044			
9945 GFPT2	glutamine-fructose 6 phosphate transaminase 2	1.8261446	8.577522084	-15.85966055	1.98E-13	4.02E-11 20.9059608			
29116 MMLIP	myosan regulatory light chain interacting protein brat cell factor C1 regulator 1 (XRC1 deservicest)	0.96578517	0.618815003	15.84844545	2.015-13	4 02E-11 20.8918156			
54455 (DCP)	(UB domain containing protein 1	-1.9101579	7.887389254	-15.81700404	2,096-11	4.09E-11 20.8521103			
29062 WDR91	WD repeat demain 91	1.14746614	7.201892759	15.80727321	2.125-13	4.03E-11 20.8398072	× ۵ م ۸	ow what?	
5176 SERPINFI	serpin peptidase inhibitor, clade F (alpha-2 antipiasmin, pigment ep antipiasmin, pigment ep	2.95931204	10.47762382	15.76913773	2.22E-13	4.17E-11 20.7915233	And r		
5805 PTS	6-pyruvovitetrahydropterin synthase	-1.351366	8.951585472	-15.70437619	2.416-13	4.396-11 20.7092811			
8324 FZD7	frizzled family receptor 7	2.58118442	7.422131287	15.63598234	2.63E-13	4.72E-11 20.6220873			
2335 SYNM	systemin, intermediate filament protein	1.8794852	8.525408401	15.57000568	2.862-13	5.062-11 20.5376433			
15143 MGU	menophyrevide lipase	2.77082146	8.638205188	15.44156877	3.385-13	5.80F-11 20.8723189			

Extracting biological meaning from DE gene lists

What do we need to perform a functional enrichment analysis?

- A list of "interesting" genes.

- A background gene list, representing the "universe" of possible genes that could be called as significantly regulated in the experiment. This list should contain only genes that are "called" as expressed (to avoid biological bias) in the experiment.

- Functional categories into which we can classify genes.

- A test which is able to tell what categories are significantly over or underrepresented in our list compared to background.

Example of functional categories: Gene Ontology.



Example of functional categories: Kegg pathway.



Example of online functional annotation tool: DAVID.

	DAVID Bioinformatics ABASE National Institute of Allergy and Infecti	Resources 6.8 ious Diseases (NIAID), NIH
Home Start Analysis Shortcut to D	AVID Tools Technical Center Downloads & APIs Tern	n of Service Why DAVID? About Us
***	Welcome to DAVID 6.8 with updated Knowledgebase (<u>mo</u> If you are looking for <u>DAVID 6.7,</u> please visit our <u>developm</u>	<u>re info). ***</u> ient site. ***
Shortcut to DAVID Tools	Recommending: A paper published in Nature Protocols d	lescribes step-by-step procedure to use DAVID!
Functional Annotation	Welcome to DAVID 6.8	Search
Gene-annotation enrichment analysis, functional annotation clustering, BioCarta & KEGG pathway mapping, gene-disease association, homologue	2003 - 2016	What's Important in DAVID?
Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions to others of your choice with the most comprehensive gene Convert list of gene ID/accessions Convert list of gene ID/accessions Convert list of gene ID/accessions Convert list of gene Convert list of gene Convert list of gene Convert list of gene Convert list Convert list Convert Conv	The Database for Annotation, Visualization and Integrated Discovery (DAVID) v6.8 <u>comprises a full</u> <u>Knowledgebase update to the sixth version</u> of our original web-accessible programs. DAVID now provides a comprehensive set of functional annotation tools for investigators to understand biological meaning behind large list of genes. For any given gene list, DAVID tools are able to:	New requirement to cite DAVID IDs of Affy Exon and Gene arrays support Novel Classification Algorithms Pre-built Affymetrix and Illumina backgrounds User's customized gene background Enhanced calculating speed
accessions in the list can also be determined semi-automatically. <u>More</u>	V Identify enriched biological themes, particularly CO	Statistics of DAVID
Display gene names for a given gene list; Search functionally related genes within your list; Oeep links to enriched detailed information. <u>More</u>	 Thermany enriched biological memes, particularly GO terms Discover enriched functional-related gene groups Cluster redundant annotation terms Visualize genes on BioCarta & KEGG pathway maps 	4061
	 G Display related many-genes-to-many-terms on 2-D view. G Search for other functionally related genes not in the list G List interacting proteins G Explore gene names in batch G Link gene-disease associations G Highlight protein functional domains and motifs G Redirect to related literatures G Convert gene identifiers from one type to another. G And more 	 0 0 04 2005 06 2007 08 2009 10 2011 12 2013 14 2019 ≥ 21.000 Citations Average Daily Usage: ~2,600 gene lists/sublists from ~800 unique researchers Average Annual Usage: ~1,000,000 gene lists/sublists from >5 000 research institut

CLIP-Seq

high-throughput sequencing of RNA isolated by crosslinking immunoprecipitation



CLIP-Seq: DATA ANALYSIS



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