Microarray data analysis

Introduction

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http://www.gepas.org.

http://www.babelomics.org

http://bioinfo.cipf.es







Background

Progress in science depends on new techniques, new discoveries and new ideas, probably in that order.

Sydney Brenner, 1980



The introduction and popularisation of high-throughput techniques has drastically changed the way in which biological problems can be addressed and hypotheses can be tested.

But not necessarily the way in which we really address or test them...

The pre-genomics paradigm

Genes in the DNA...

...code for proteins...

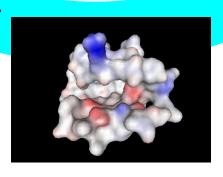
...produces the final phenotype

>protein kunase

acctgttgatggcgacagggactgtatgctgatc tatgctgatgcatgcatgctgactactgatgtggg ggctattgacttgatgtctatc.... From genotype to phenotype.

...whose structure accounts for function...





Now: 22240 (NCBI build 35 12/04) 50-70% display alternative splicing 25%-60% unknown

Transfrags

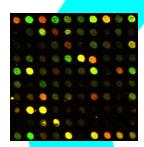
Genes in the DNA..

>protein kunase

acctgttgatggcgacagggactgtatgctgatc tatgctgatgcatgcatgctgactactgatgtggg ggctattgacttgatgtctatc...

...when expressed in the proper moment and place...

A typical tissue is expressing among 5000 and 10000 genes



From genotype to phenotype.

(in the functional post-genomics scenario)

...code for proteins...

That undergo posttranslational modifications, somatic recombination...

100K-500K proteins

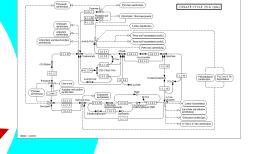
...whose structures account for function...

...which can be different because of the variability.

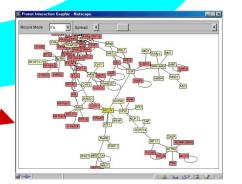
10 million **SNPs**



...whose final effect configures the phenotype...



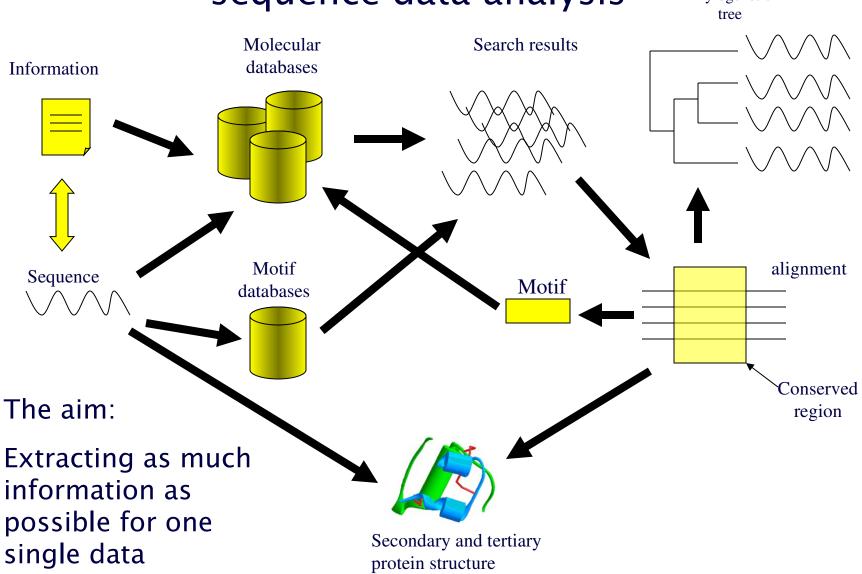
...conforming complex interaction networks...



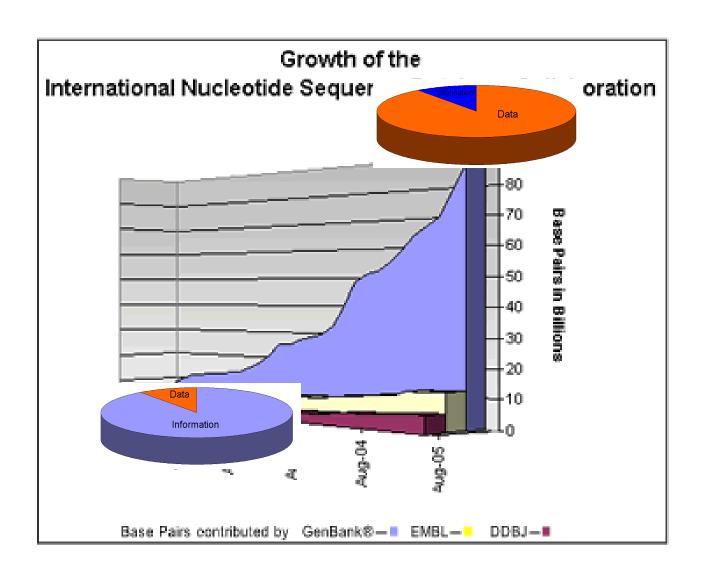
Each protein has an average of 8 interactions

...in cooperation with other proteins...

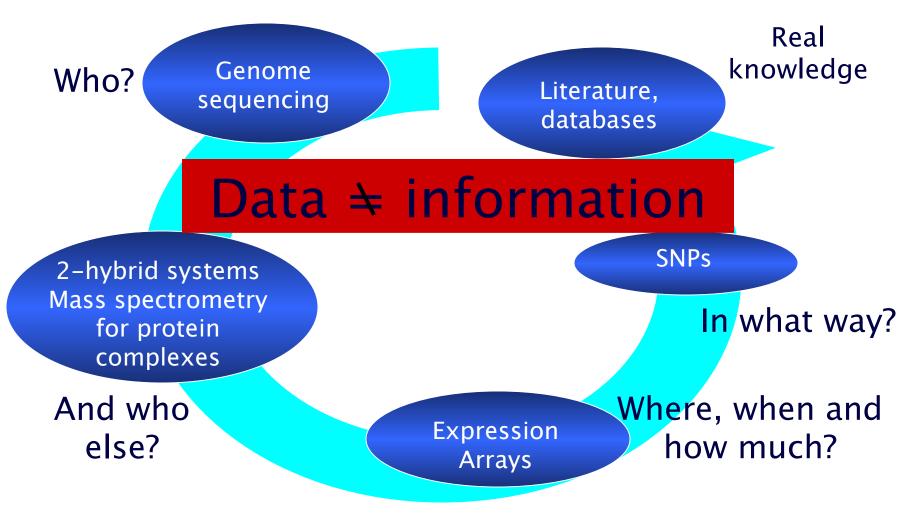
Bioinformatics tools for pre-genomic sequence data analysis Phylogenetic



Post-genomic vision



Post-genomic vision



Our capacity of producing data surpasses our capacity of analysing data

Guilty by association

Genome wide data and a note of caution:

Risks of the "guilty by association" concept.

Genome-wide technologies allows us to produce vast amounts of data.

But... dealing with many data (omic data) increase the occurrence of spurious associations due to chance

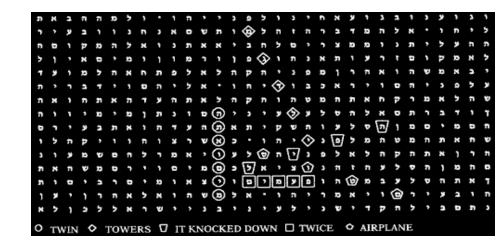
Hypothesis → Experiment → test

Is gene A involved in process B?

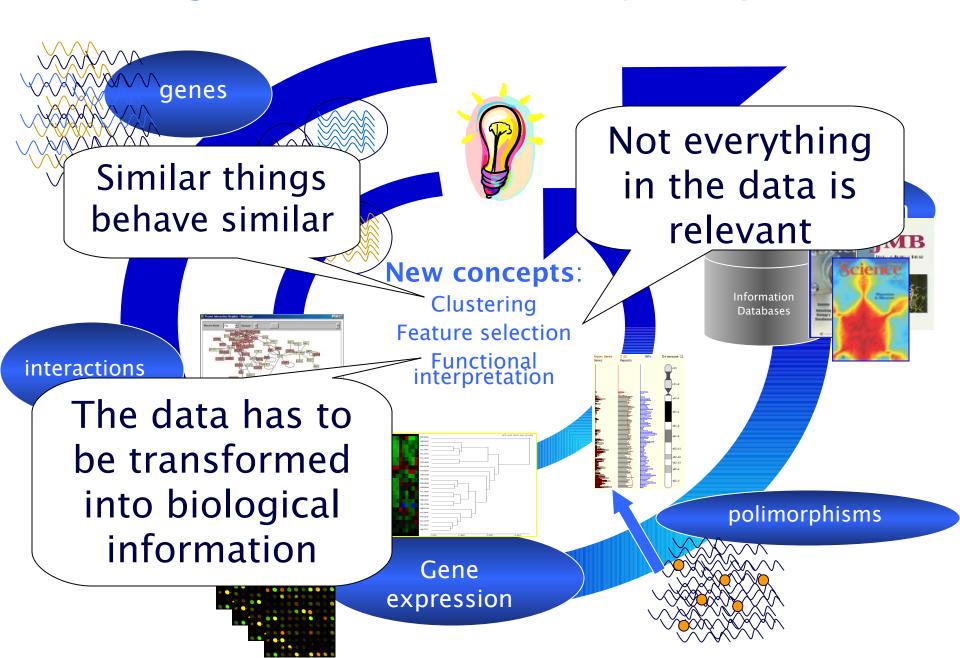
Is there any gene (or set of genes) involved in any process?

Sure, but... Is it real? (many hypotheses are rejected while this one is accepted *a posteriori*: numerology)

The test is dependent on the hypothesis and not *vice versa*

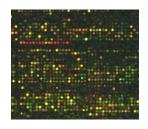


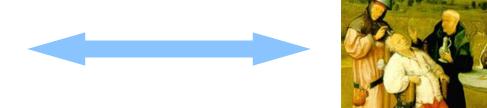
Post-genomic vision: whole system picture



Gene expression profiling. Historic perspective

Differences at phenotype level are the visible cause of differences at molecular level which, in many cases, can be detected by measuring the levels of gene expression. The same holds for different experiments, treatments, strains, etc.





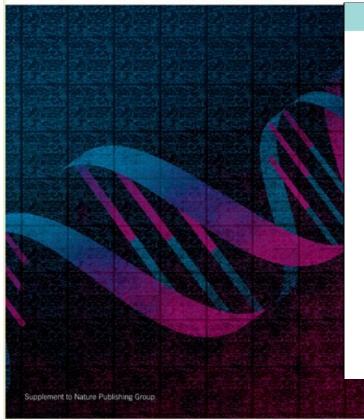
- Classification of phenotypes / experiments. Can I distinguish among classes (either known or unknown), values of variables, etc. using molecular gene expression data? (sensitivity)
- Selection of differentially expressed genes among the phenotypes / experiments. Did I select the relevant genes, all the relevant genes and nothing but the relevant genes? (specificity)
- Biological roles the genes are carrying out in the cell. What general biological roles are really represented in the set of relevant genes? (interpretation)

Microarrays arrive to an acceptable level of reproducibility





The MicroArray Quality Control Consortium



ARTICLES

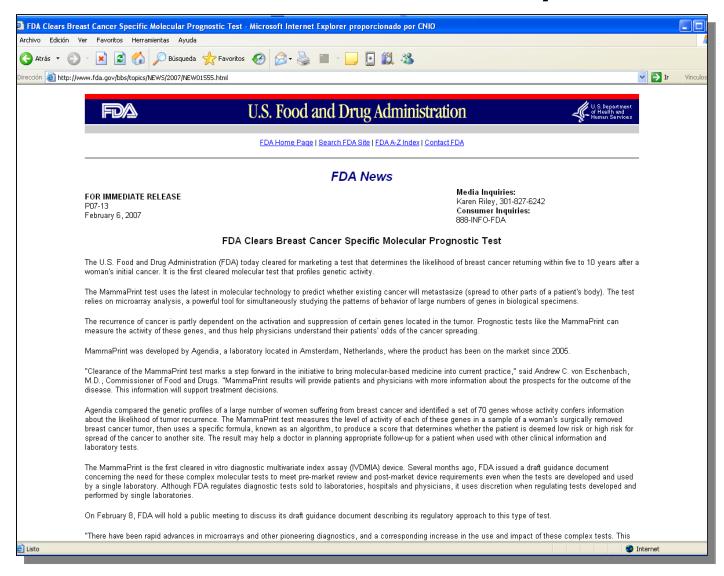
nature biotechnology

The MicroArray Quality Control (MAQC) project shows inter- and intraplatform reproducibility of gene expression measurements

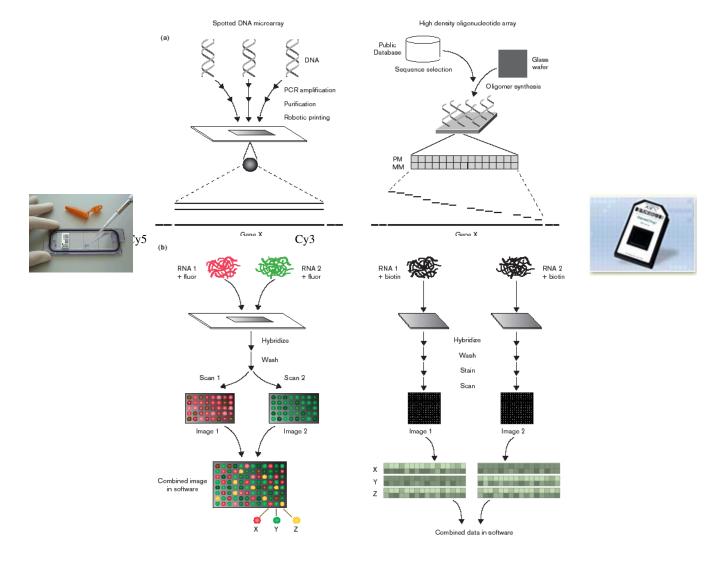
MAQC Consortium*

Over the last decade, the introduction of microarray technology has had a profound impact on gene expression research. The publication of studies with dissimilar or altogether contradictory results, obtained using different microarray platforms to analyze identical RNA samples, has raised concerns about the reliability of this technology. The MicroArray Quality Control (MAQC) project was initiated to address these concerns, as well as other performance and data analysis issues. Expression data on four titration pools from two distinct reference RNA samples were generated at multiple test sites using a variety of microarray-based and alternative technology platforms. Here we describe the experimental design and probe mapping efforts behind the MAQC project. We show intraplatform consistency across test sites as well as a high level of interplatform concordance in terms of genes identified as differentially expressed. This study provides a resource that represents an important first step toward establishing a framework for the use of microarrays in clinical and regulatory settings.

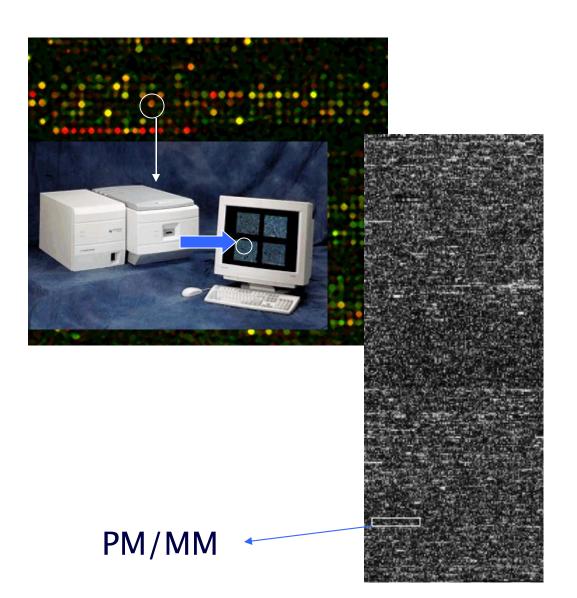
FDA approves the first predictor based on microarrays



DNA microarrays: the paradigm of a post-genomic technique



Transforming images into numbers



Two-color

Test sample labeled red (Cy5)
Reference sample labeled green (Cy3)
Red: gene overexpressed in test
sample

Green: gene underexpressed in test sample

Yellow – equally expressed red/green – ratio of expression

One color

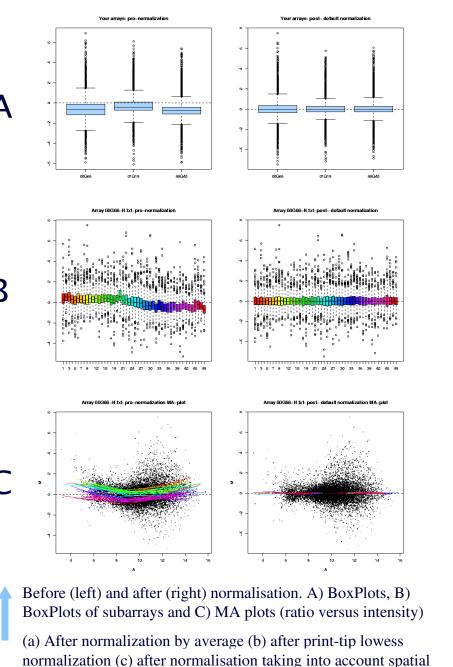
Intensity of a gene using the probes

Affymetrix

Intensity of a gene using the probes PM and in MM

Scanners generate a graphic file.

Software analyzes the file: GenePix Pro (by Axon Instruments, Inc.) or Imagene (By Biodiscovery, Inc.)
There are free systems too: TIGR Spotfinder, ScanAlyze, etc

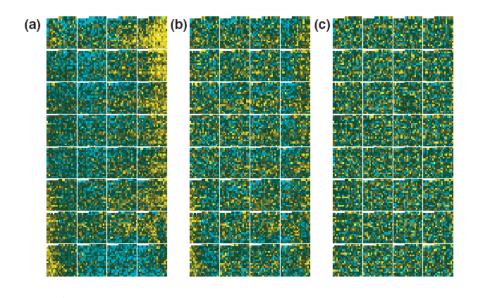


effects

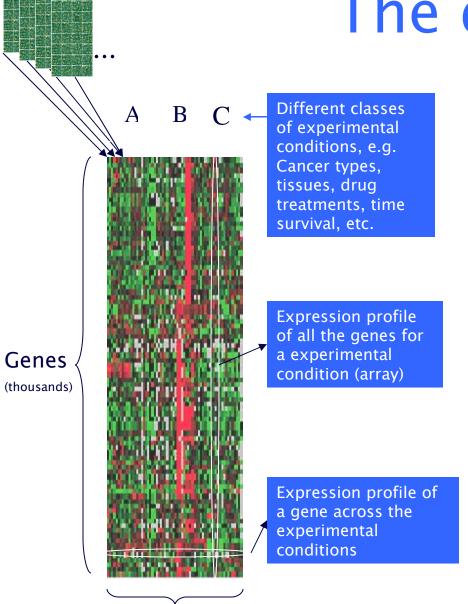
Normalisation

There are many sources of error that can affect and seriously bias the interpretation of the results. Differences in the efficiency of labelling, the hybridisation, local effects, etc.

Normalisation is a necessary step before proceeding with the analysis



The data



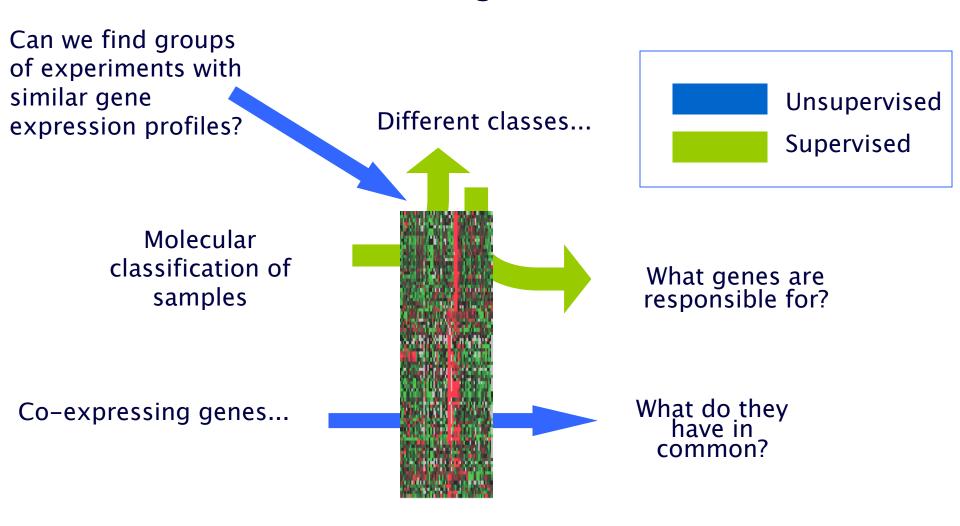
Characteristics of the data:

- We NEVER deal with individual arrays, we deal with collections of arrays obtained for a given experimental design
- Most of the genes are not informative with respect to the trait we are studying (account for unrelated physiological conditions, etc.)
- Number of variables (genes) is several orders of magnitude larger than the number of experiments
- Low signal to noise ratio

Experimental conditions (from tens up to no more than a few houndreds)

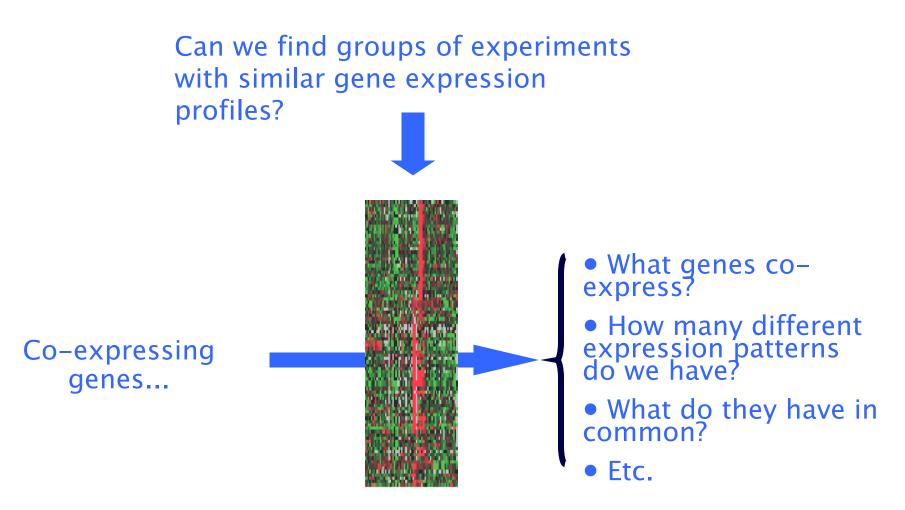
Studies must be hypothesis driven.

What is our aim? Class discovery? sample classification? gene selection? ...

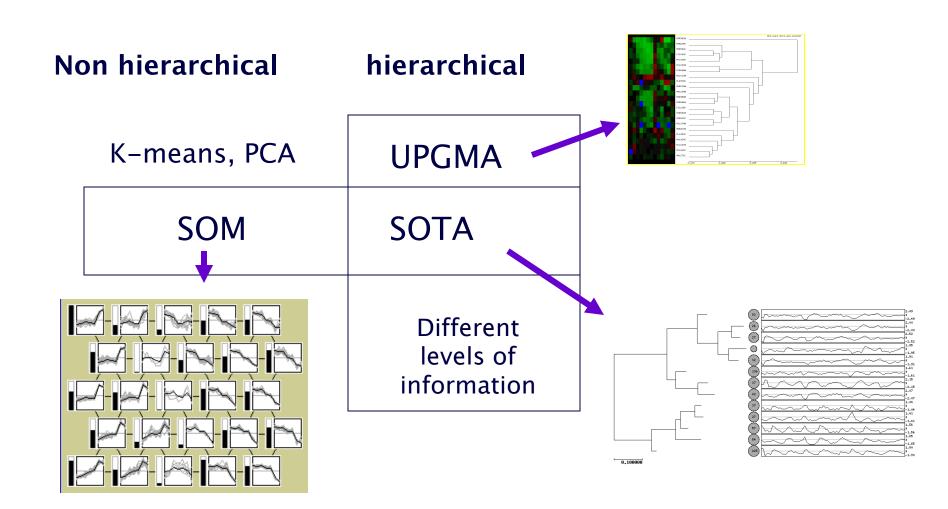


Unsupervised problem: class discovery

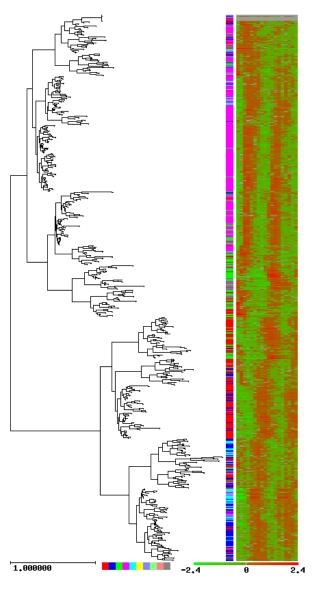
Our interest is in discovering clusters of items (genes or experiments) which we do not know beforehand



Unsupervised clustering methods: Method + distance: produce groups of items based on its <u>global</u> similarity



An unsupervised problem: clustering of genes.



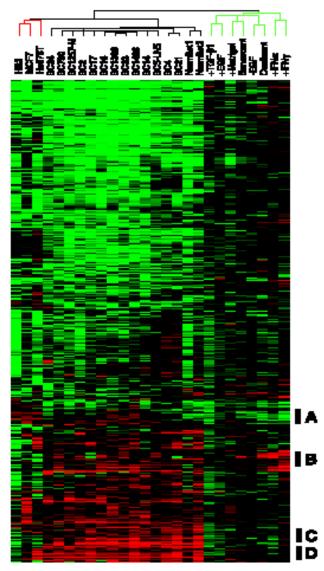
- Gene clusters are previously unknown
- Distance function
- Cluster gene expression patterns based uniquely on their similarities.
- Results are subjected to further interpretation (if possible)

Clustering of experiments: The rationale

If enough genes have their expression levels altered in the different experiments, we might be able of finding these classes by comparing gene expression profiles.

Distinctive gene expression patterns in human mammary epithelial cells and breast cancers

Overview of the combined *in vitro* and breast tissue specimen cluster diagram. A scaled-down representation of the 1,247-gene cluster diagram The black bars show the positions of the clusters discussed in the text: (A) proliferation-associated, (B) IFNregulated, (C) B lymphocytes, and (D) stromal cells.





Perou et al., PNAS 96 (1999)

Clustering of experiments: The problems

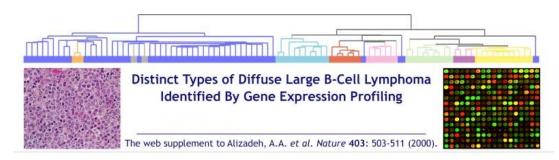
Any gene (regardless its relevance for the classification) has the same weight in the comparison.

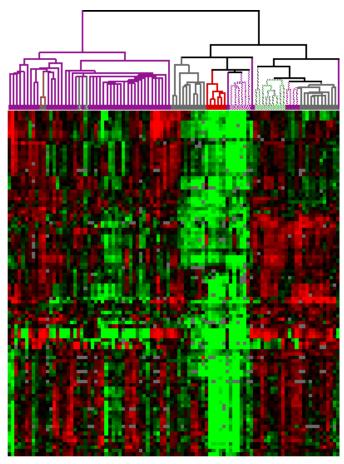
If relevant genes are not in overwhelming majority we will find:

Noise

and/or

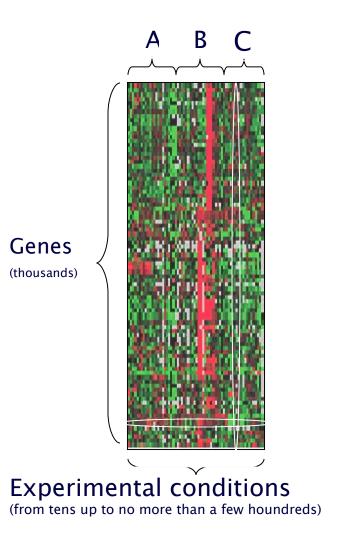
irrelevant trends





Supervised problems: Class prediction and gene selection, based on gene expression profiles

Information on classes (<u>defined on criteria external to the gene expression measurements</u>) is used.



Problems:

How can classes A, B, C... be distinguished based on the corresponding profiles of gene expression?

How a continuous phenotypic trait (resistance to drugs, survival, etc.) can be predicted?

And

Which genes among the thousands analysed are relevant for the classification?

Class prediction

Gene selection

Gene selection.

The simplest way: univariant gene-bygene. Other multivariant approaches can be used

Two classes

T-test

Bayes

Data-adaptive

Clear

Multiclass

Anova

Clear

Continuous variable (e.g. level of a metabolite)

Pearson

Spearmam

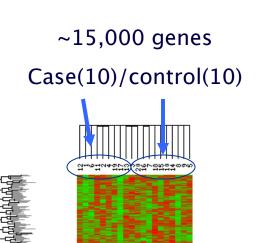
Regression

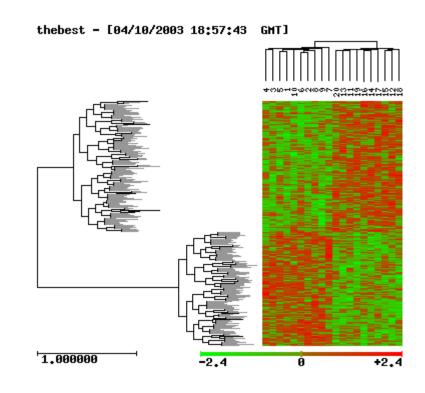
Survival

Cox model



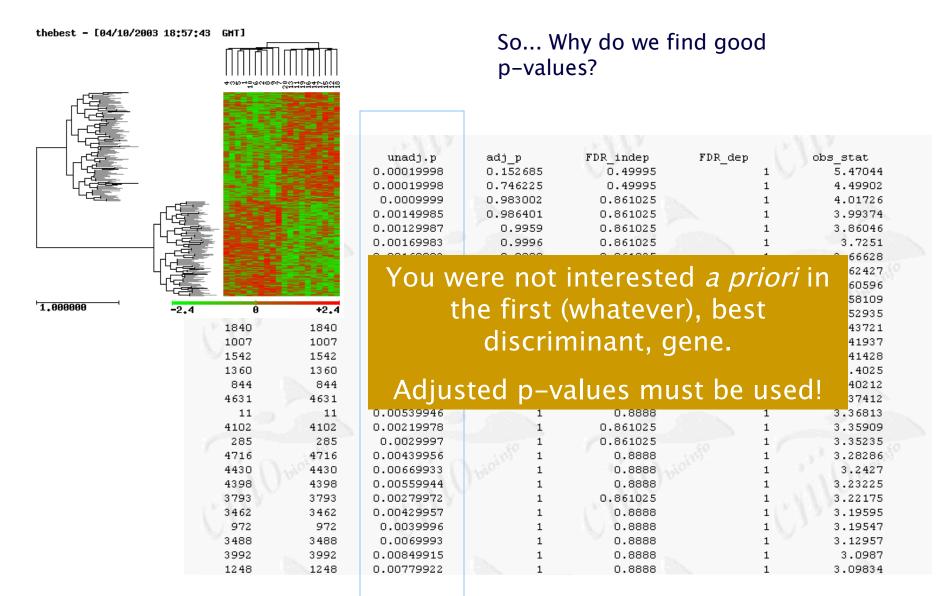
A simple problem: gene selection for class discrimination





Genes differentially expressed among classes (t-test), with p-value < 0.05

Sorry... the data was a collection of random numbers labelled for two classes



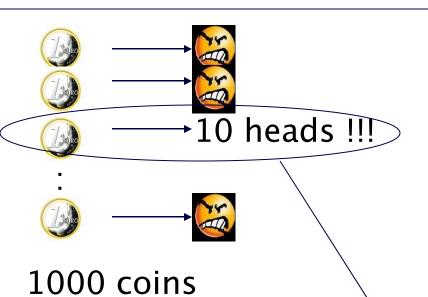
On the problem of multiple testing





 $= 10 \text{ heads. P} = 0.5 \stackrel{10}{=} 0.00098$

Take one coin, flip it 10 times. Got 10 heads? Use it for betting



$$P = 1 - (1 - 0.5^{19})^{1000} = 0.62$$

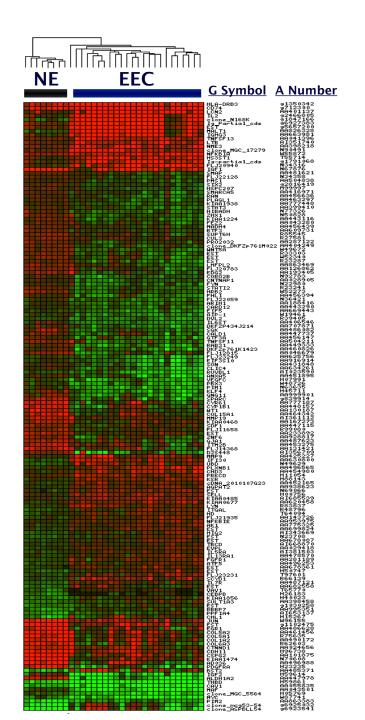
It is not the same getting 10 heads with my coin than getting 10 heads in one among 1000 coins

Will you still use this coin for betting?

Genes differentially expressed between normal endometrium and endometrioid endometrial carcinomas

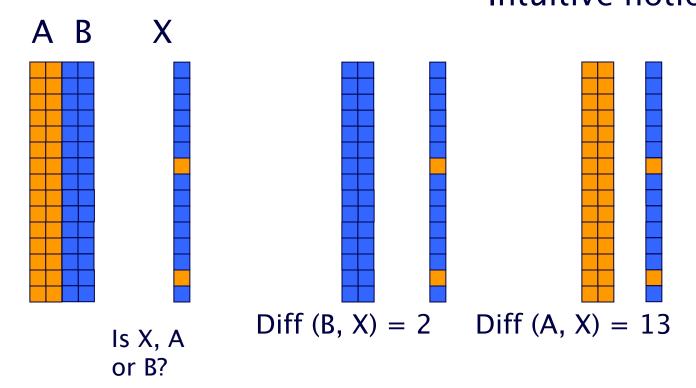
Hierarchical Clustering of 86 genes with different expression patterns between Normal Endometrium and Endometrioid Endometrial Carcinoma (FDR adjusted p<0.05) selected among the ~7000 genes in the CNIO oncochip

Moreno et al., 2003 Cancer Research 63, 5697-5702



Of predictors and molecular signatures

What is a predictor? Intuitive notion:



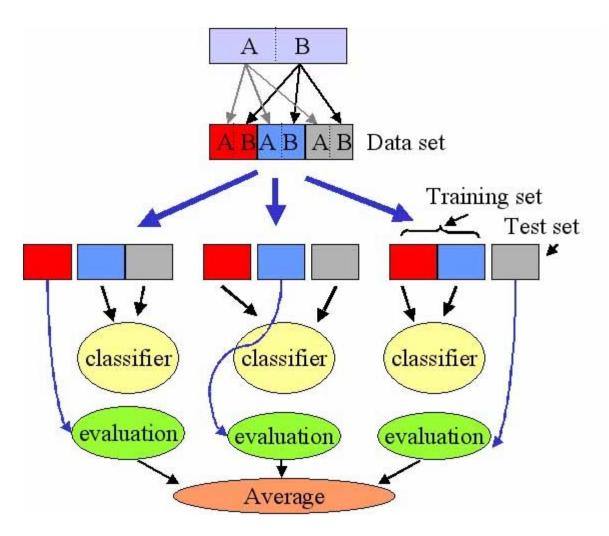
Most probably X belongs to class B

Algorithms: DLDA, KNN, SVM, random forests, PAM, etc.

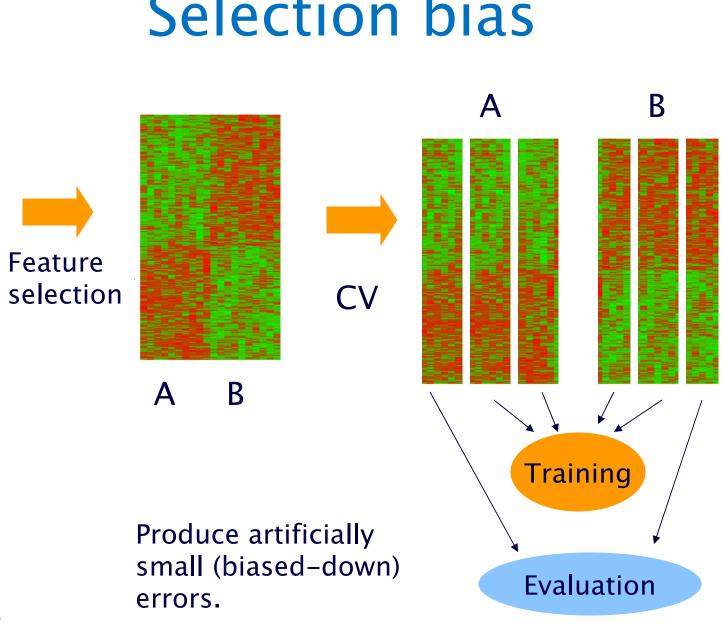
Cross-validation

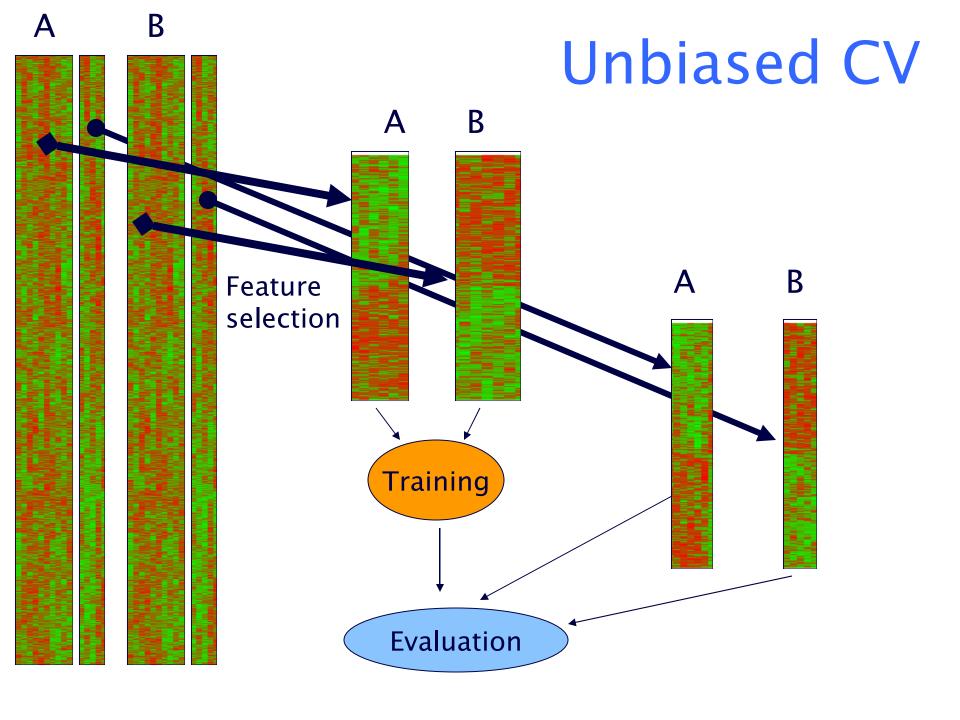
The efficiency of a classifier can be estimated through a process of crossvalidation.

Typical are threefold, ten-fold and leave-one-out (LOO), in case of few samples for the training

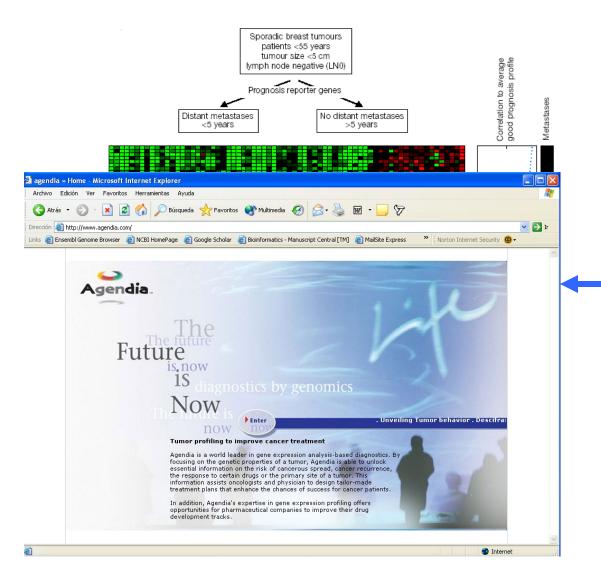


Selection bias





Predictor of clinical outcome in breast cancer

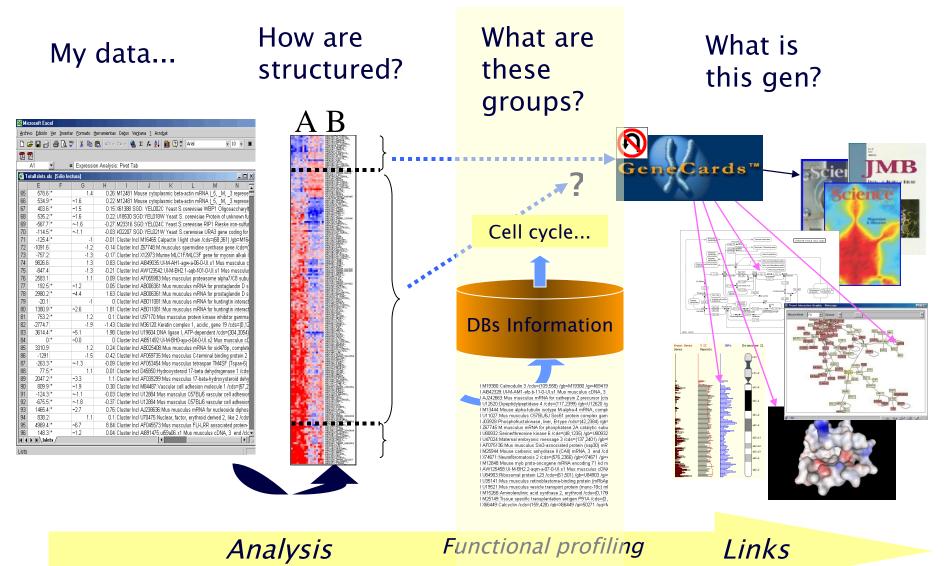


Genes are arranged to their correlation eith the pronostic groups

Pronostic classifier with optimal accuracy

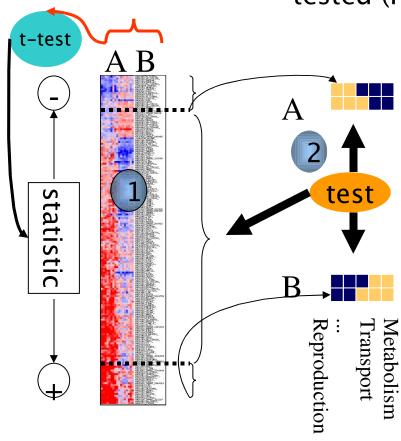
van't Veer et al., Nature, 2002

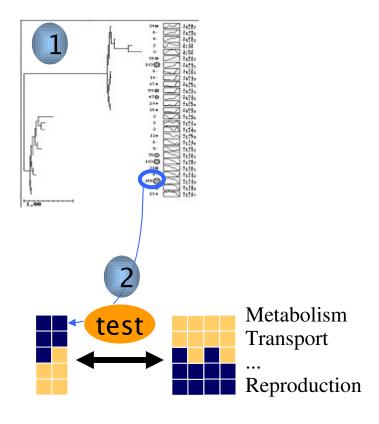
Functional profiling of genome-scale experiments in the post-genomic era



Two-steps functional interpretation

- Genes are selected based on their experimental values and...
- Enrichment in functional terms is tested (FatiGO, GoMiner, etc.)

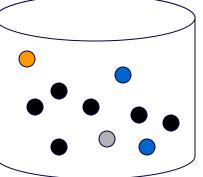




Testing two GO terms

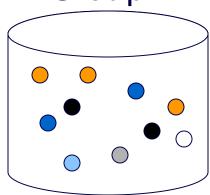
(remember, we have to test thousands)





Are this two groups of genes carrying out different biological roles?

Group B



Biosynthes.

•		
6	4	
2	8	
	_	

The popular Fisher's test

Biosynthesis 60%



Biosynthesis 20%

Sporulation 20%



Sporulation 20% ●

Genes in group A have significantly to do with biosynthesis, but not with sporulation.

GO terms found in sets of 50 genes

GO	Definition	p-value	Adjusted p-value
GO:0006790	sulfur metabolism	0.0595683	1
GO:0042592	homeostasis	0.0157944	0.300094
GO:0016265	death	0.116317	1
GO:0050874	organismal physiological process	0.151987	1
GO:0008152	metabolism	0.129865	1
GO:0019058	viral infectious cycle	0.016503	0.181353
GO:0019059	initiation of viral infection	0.0123062	0.459417
GO:0009056	catabolism	0.0276032	1
GO:0006766	vitamin metabolism	0.00875837	0.604328
GO:0007155	cell adhesion	0.122953	1

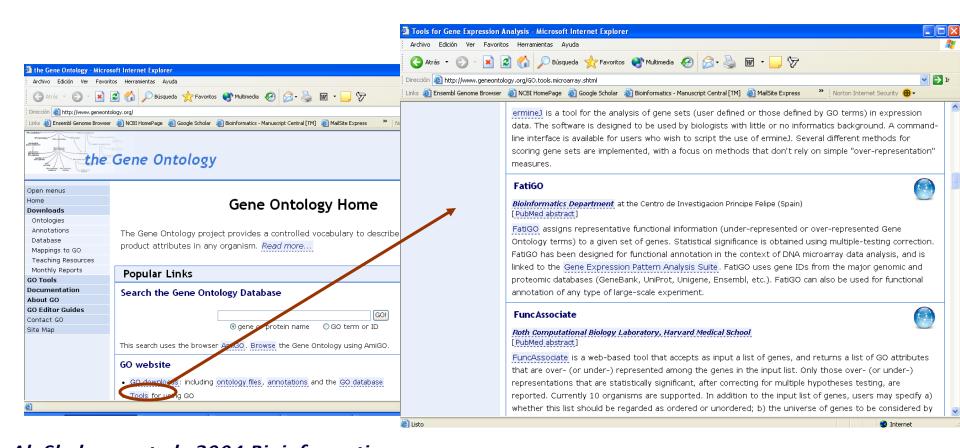
Each row corresponds to a random selection of 50 genes from the *E. coli* genome, compared with respect to the rest of the genome.

GO terms in blue (p-value < 0.05 in individual test) have assymetrical distributions by chance (see adjusted p-values).

How to test significant differences in the distribution of biological tems between groups of genes?

FatiGO: GO-driven data analysis

Provides a statistical framework able to deal with multiple-testing hipothesis



Al-Shahrour et al., 2004 Bioinformatics (3rd most cited paper in computing sciences. Source: ISI Web of knowledge.)

Al-Shahrour et al., 2005 Bioinformatics. Al-Shahrour et al., 2005 NAR

Al-Shahrour et al., 2006 NAR. Al-Shahrour et al., 2007 BMC Bioinformatics

Al-Shahrour et al., 2007 NAR

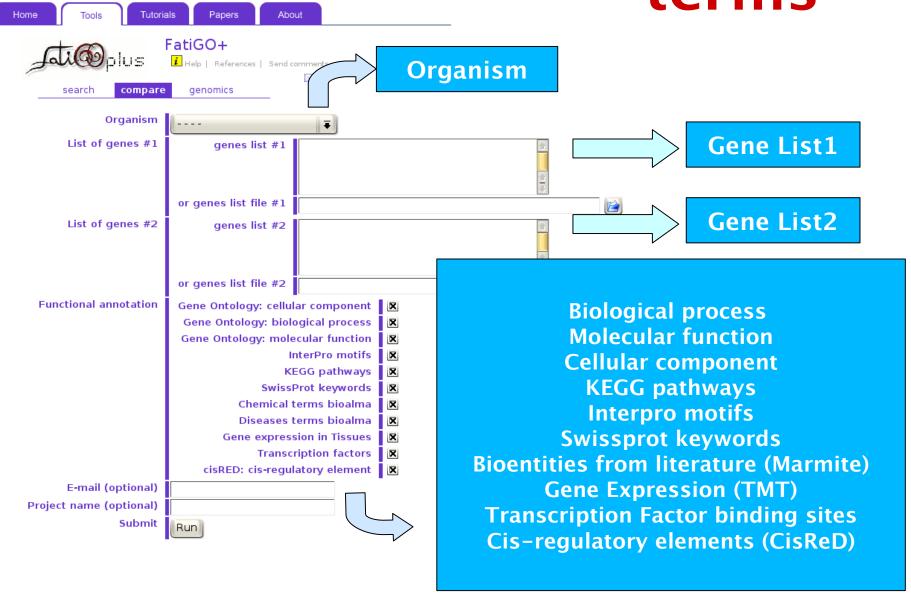
Compilation of tools for functional interpretation of sets of genes

Tool	Statistical model	Correction for multiple experiments	Functional labels	Site (web-based applications)	Reference
Babelomics	Fisher's exact test, t-test, Kolmogorov-Smirnov	FDR, q-value	GO, KEGG, protein domains, swissprot keywords, Transfac motifs, CisRed motifs, chromosomal location, tissues, bioentities (text-mining)	http://www.babelomics.org	(Al-Shahrour et al., 2006; Al-Shahrour et al., 2005)
BayGO	hypergeometric	bayesian	GO		(Vencio et al., 2006)
DAVID / EASEonline	Fisher's exact test	Bonferroni	GO, pathways, diseases, protein domains, interactions	http://david.abcc.ncifcrf.gov/	(Dennis et al., 2003; Hosack et al., 2003)
FatiGO+	Fisher's exact test	step-down minP, FDR	GO, KEGG, protein domains, swissprot keywords, Transfac motifs, CisRed motifs, chromosomal	http://www.fatigo.org	(Al-Shahrour et al., 2004)
FuncSpec	hypergeometric	Bonferroni	GO, phenotypes, protein interactions, etc. (only for yeast)	http://funspec.med.utoronto.ca/	(Robinson et al., 2002)
GeneMerge	hypergeometric	Bonferroni	GO, KEGG, chromosomal location, other.	http://genemerge.bioteam.net/	(Castillo-Davis & Hartl, 2003)
GO:TermFinder	hypergeometric	Bonferroni	GO		(Boyle et al., 2004)
GoMiner	Fisher's exact test	FDR	GO		(Zeeberg et al., 2003; Zeeberg et al., 2005)
GOstat	X2 Fisher's exact test	FDR, Holm	GO	http://gostat.wehi.edu.au/	(Beissbarth & Speed, 2004)
GoSurfer	X2	g-value	GO		(Zhong et al., 2004)
GOToolBox	hypergeometric, binomial, Fisher's exact test	Bonferroni	GO	http://crfb.univ-mrs.fr/GOToolBox/index.php	(Martin et al., 2004)
Ontology Traverser	hypergeometric	FDR	GO	http://franklin.imgen.bcm.tmc.edu/rho- old/services/OntologyTraverser/	(Young et al., 2005)
Onto-Tools	X2, binomial, hypergeometric Fisher's exact test	Sidak, Holm, Bonferroni, FDR	GO, KEGG	http://vortex.cs.wayne.edu/projects.htm	(Draghici et al., 2003; Khatri et al., 2005)
					(5.1.1.222)
FuncAssociate	Fisher's exact test		GO	http://llama.med.harvard.edu/cgi/func/funcassociate	(Berriz et al., 2003)
GOTM	hypergeometric		GO	http://bioinfo.vanderbilt.edu/gotm/	(Zhang et al., 2004)
CLENCH	Hypergeometric, X2, binomial		GO (only for A. thaliana)	<u> </u>	(Shah & Fedoroff, 2004)



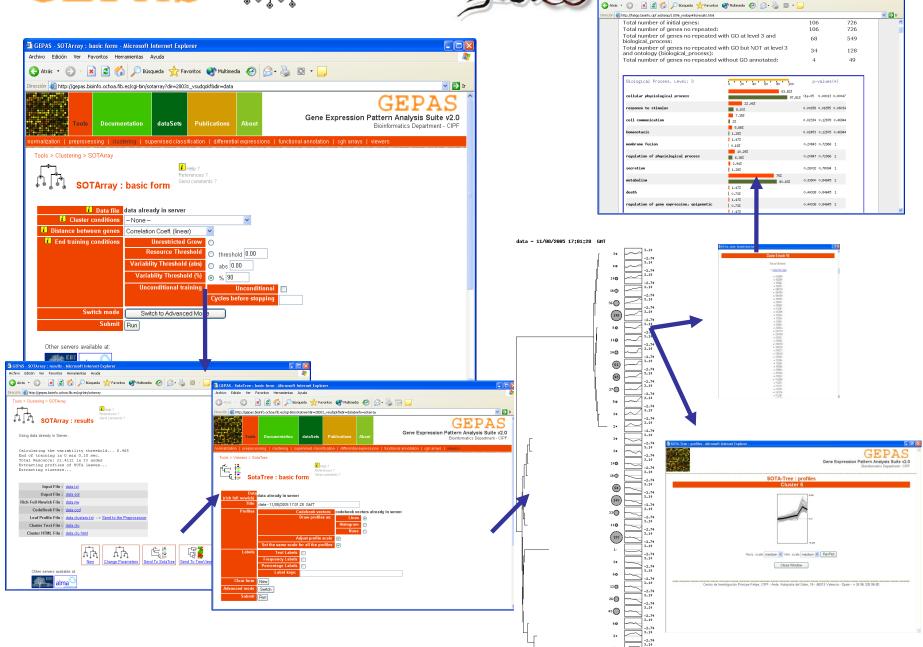


Functional terms









1,00

Understanding why genes differ in their expression between two different conditions

Limphomas from mature lymphocytes (LB) and precursor T-lymphocyte (PTL).

Genes differentially expressed, selected among the ~7000 genes in the CNIO oncochip

Genes differentially expressed among both groups were mainly related to immune response (activated in mature lymphocytes)

Martinez et al., Clinical Cancer Research. 10: 4971–4982.

Biological processes shown by the genes differentially expressed among PTL-LB

				Cluster Query	/ Clus	ster Reference
Total number of initial genes:				162		4764
Total number of genes no repeated:				129		4731
Total number of Cluster IDs retired - their currer				7 - 23	4	49 - 1627
Total number of genes no repeated with current				145		5909
Total number of genes no repeated with GO at le	_			88		2610
Total number of genes no repeated with GO but I Total number of genes no repeated without GO a		ia ontology	(Obvious?	NO	
		<u> </u>	You r	now knov	w tha	at there
Gene Ontology Term	0 20	40 60	are n	o other o	co-v	ariables
response to external stimulus	11.65%	36.36%	(e.g.	age, sex	, etc)
response to stress	21.59	oz 💮			_	
	6.86%	3	lf vou	ı do not	have	9
signal transduction		39.77%	•			
	26.0	05%	previ	ously a s	tron	ıg
cell motility	9.09%		hiolo	gical hyp	oth	ocic
	3.79%					C313,
resistance to pathogenic bacteria	1.14%		now v	you have	an	
	0.04%					
viral replication	1.14%		expla	nation		
	0.15%		V.102	.> V.500/ I	-	
cell death	9.09%					
	5.75%		0.170	0.9912 1	1	
regulation of gene expression, epigenetic	1.14%					
	l n 10%		0.180	6 0.9940 1	1	1

Weaknesses of the two-steps, functional enrichment approach

Low sensitivity of conventional gene selection methods

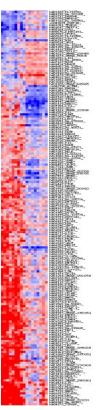
AB

Δ

8 with impaired tolerance (**IGT**) + 18 with type 2 diabetes mellitus (**DM2**)

В

17 with normal tolerance to glucose (**NTG**)

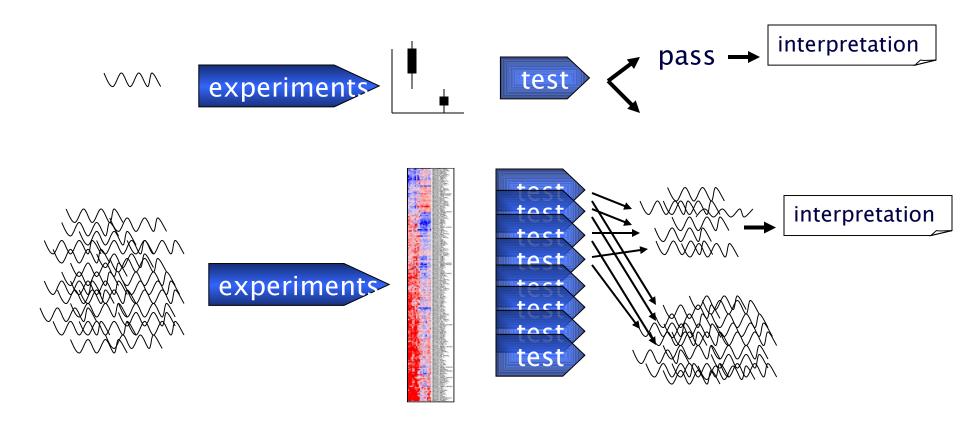


Instability of molecular Signatures. Variable selection with microarray data can lead to many solutions that are equally good from the point of view of prediction rates, but that share few common genes (Ein-Dor 2006 PNAS)

Platform comparison. There are still some concerns with the cross-platform coherence of results. Paradoxically, despite the fact that gene-by-gene results are not always the same, the biological themes emerging from the different platforms are increasingly consistent (Bammler 2005 Nat Methods)

(Mootha et al., 2003)

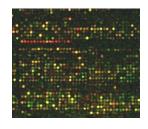
Functional enrichment approach reproduces pre-genomics paradigms



Context and cooperation between genes is ignored

Functional genomics. Historic perspective and future

Differences at phenotype level are the visible cause of differences at molecular level which, in many cases, can be detected by measuring the levels of gene expression. The same holds for different experiments, treatments, strains, etc.

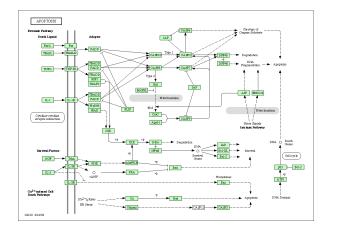




- Classification of phenotypes / experiments. Sensitivity
- Selection of differentially expressed genes Specificity
- Biological roles the genes are carrying out in the cell. Interpretation
- Reformulating the questions. Are we asking the proper questions? What are the real bricks that account for the cellular behaviour and for the phenotype or the response to environmental stimuli? The genes or other higher level units?

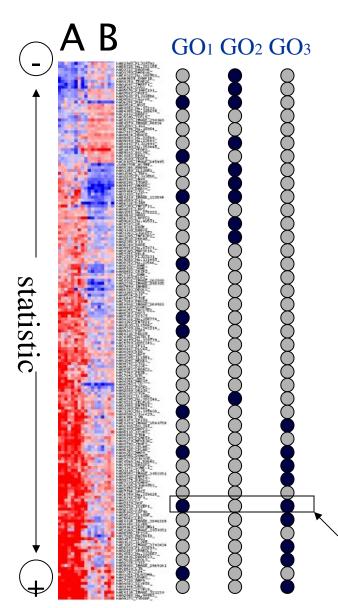
What is the basic functional component in the cell?





e.g. KEGG pathway defines a functional module

Cooperative activity of genes can be detected and related to a macroscopic observation



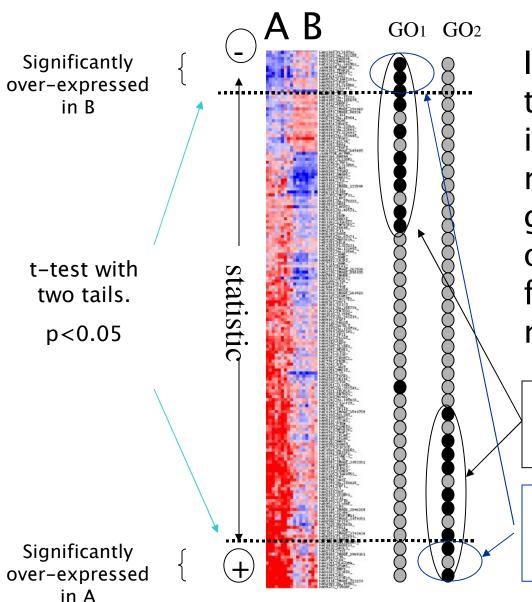
Ranking: A list of genes is ranked by their differential expression between two experimental conditions **A** and **B** (using fold change, a t-test, etc.)

Distribution of GO: Rows GO1, GO2 and GO3 represent the position of the genes belonging to three different GO terms across the ranking.

The first GO term is completely uncorrelated with the arrangement, while GOs 2 and 3 are clearly associated to high expression in the experimental conditions B and A, respectively.

Note that genes can be multi-functional

A previous step of gene selection causes loss of information and makes the test insensitive

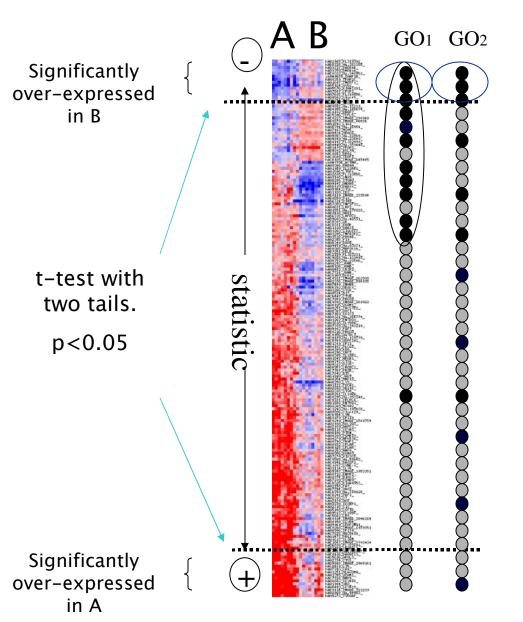


If a threshold based on the experimental values is applied, and the resulting selection of genes compared for over-abundance of a functional term, this migh not be found.

Classes expressed as blocks in A and B

Very few genes selected to arrive to a significant conclussion on GOs 1 and 2

A previous step of gene selection causes loss of information and makes the test insensitive



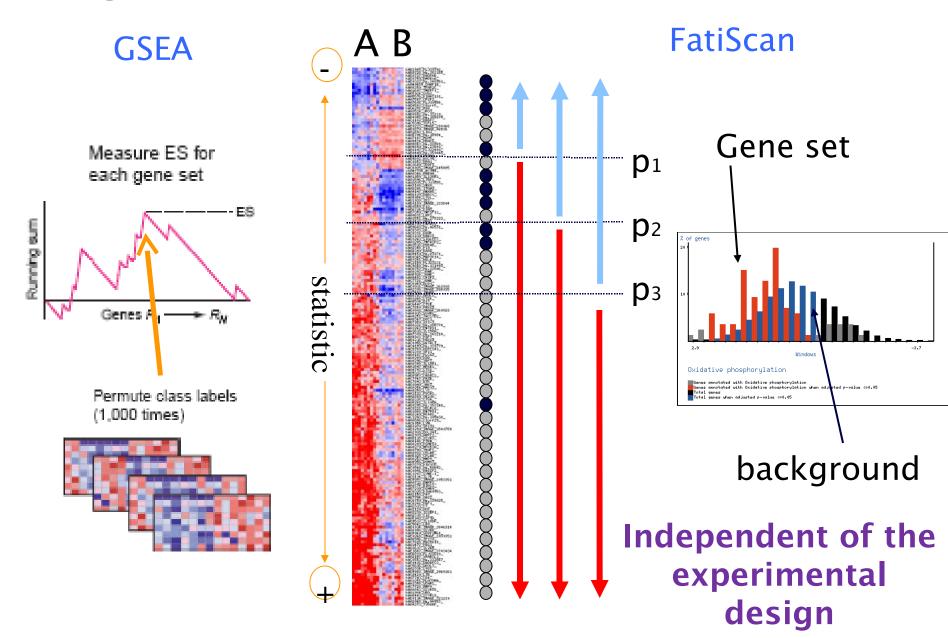
The main problem is that the two-steps approach cannot distinguish between these two different cases.

We put both sides of the partition into two bags and destroy the structure of the data.

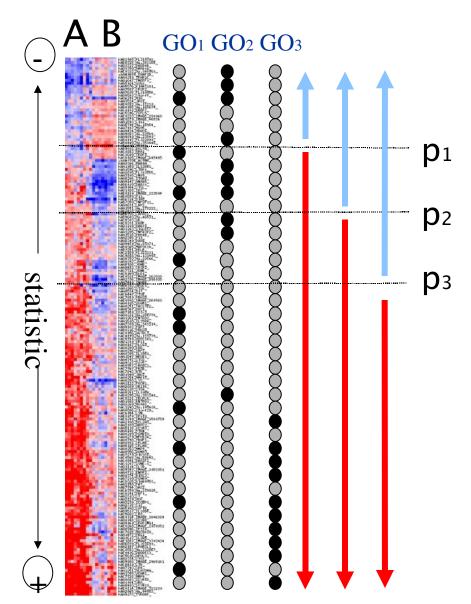
	up	down
GO	3	9
no GO	0	25

Same contingency table for GO₁ and GO₂!!

Gene-set enrichment methods



FatiScan, a segmentation test, provides an easy approach to directly testing functional terms



E.g., term GO_2 , partition p_1

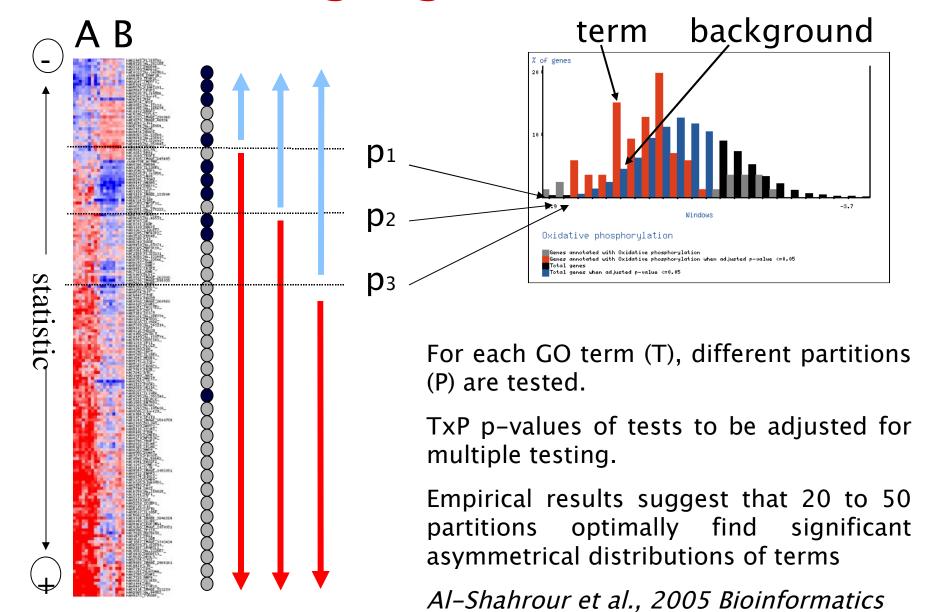
	up	down
GO	4	6
no GO	2	30

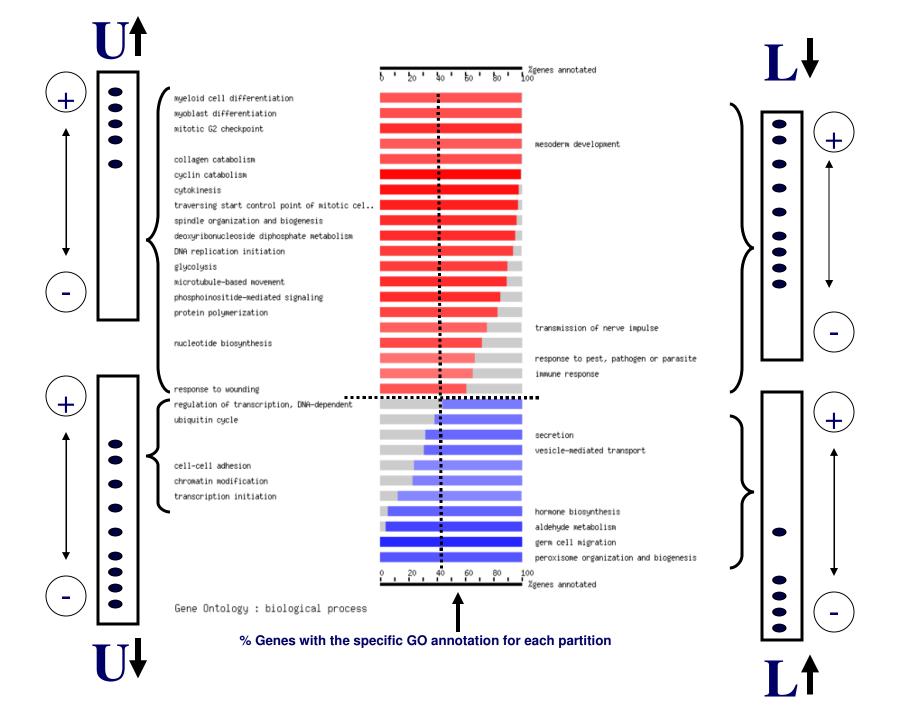
GOs can be directly tested by a segmentation test. A series of partitions of the list are performed (**p1**, **p2**, **p3**...) and the GO terms for each functional class in the upper part are compared to the corresponding ones in the lower part by a Fisher test. Asymmetrical distributions of terms towards the extremes of the list will produce significant values of the test.

Finally, p-values are adjusted by FDR

Al-Shahrour et al., 2005 Bioinformatics

Obtaining significant results





Case study: functional differences in a class comparison experiment

A

8 with impaired tolerance (**IGT**) + 18 with type 2 diabetes mellitus (**DM2**)

R

17 with normal tolerance to glucose (**NTG**)

No one single gene shows significant differential expression upon the application of a t-test

100	BURNEY.						
400	DOMESTIC OF THE PARTY OF THE PA					Repository	
猫			Healthy vs diabetic	Functional class	GO	KEGG	Swissprot keyword
1	Ma con-			Oxidative phosphorylation	X	X	
-				ATP synthesis		X	
				Ribosome		X	
40	Mine.	HHI.		Ubiquinone			X
			1	Ribosomal protein			X
		FatiScan	T	Ribonucleoprotein			X
43			Up-	Mitochondrion	X		X
e -			regulated	Transit peptide			X
				Nucleotide biosynthesis	X		
	2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2			NADH dehidrogenase (ubiquinone) activity	X		
. 49				Nuclease activity	X		
1.0			Dow-	Insulin signalling		X	
	TO SEE STATE		regulated	pathway		1	
100	Will Street						

Nevertheless, many pathways, and functional blocks are significantly activated/deactivated

(Mootha et al., 2003)

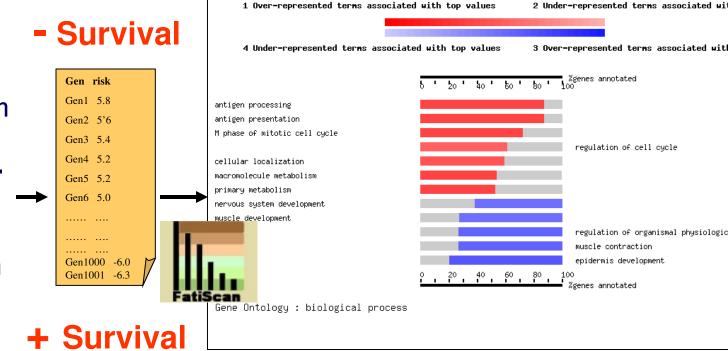
Beyond discrete variables: Survival data

Microarrays
34 samples from
tumours of
hypopharyngeal
cancer (GEO
GDS1070)

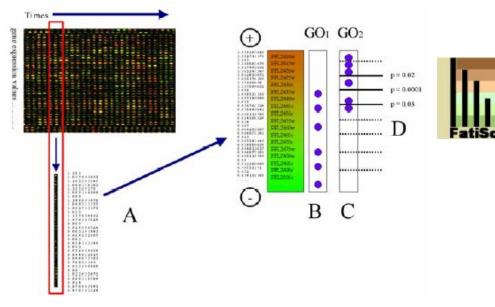


Gene selection

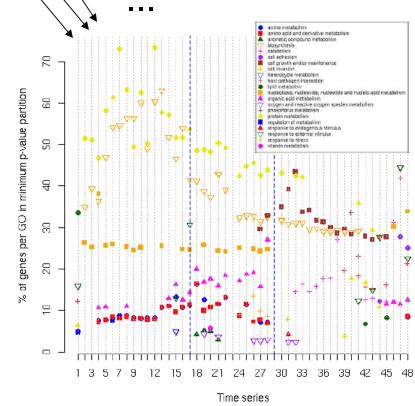
Cox Proportional-Hazards model to study how the expression of each gene across patients is related to their survival Since FatiScan depends only on a list of ordered genes, and not on the original experimental values, it can be applied to different experimental designs



Functional analysis of a time series in *P. falciparum*



- -Genes at each time point are ranked from highest (red) to lowest (green) relative expression with respect to time 1.
- For each list of ranked genes generated in any time point, the significant over-represented GO terms in the tail corresponding to the highest expression values are recorded.
- -The partitions used to decide that a given term is significantly over-represented in the upper tail of the list with respect to the lower part are used for the graphical representation.



Comparison of gene set methods at a glance

			R	epository		Method			
Healthy vs diabetic	Functional class	GO	KEGG	Swissprot keyword	Defined in GSEA	FatiScan	GSEA	PAGE	Tian et al.
	Oxidative phosphorylation	+	+		+	yes	yes	yes	yes
	ATP synthesis		+			yes	-	-	-
	Ribosome		+			yes	-	-	-
	Ubiquinone			+		yes	-	-	-
	Ribosomal protein			+		yes	-	-	-
	Ribonucleoprotein			+		yes	-	-	-
Up-	Mitochondrion	+		+	+	yes	yes	yes	yes
regulated	Transit peptide			+		yes	-	-	-
	Nucleotide biosynthesis	+			+	yes	yes	yes	yes
	NADH dehidrogenase (ubiquinone) activity	+				yes	-	-	-
	Nuclease activity	+				yes	-	-	-
Dow- regulated	Insulin signalling pathway		+			yes	-	-	-

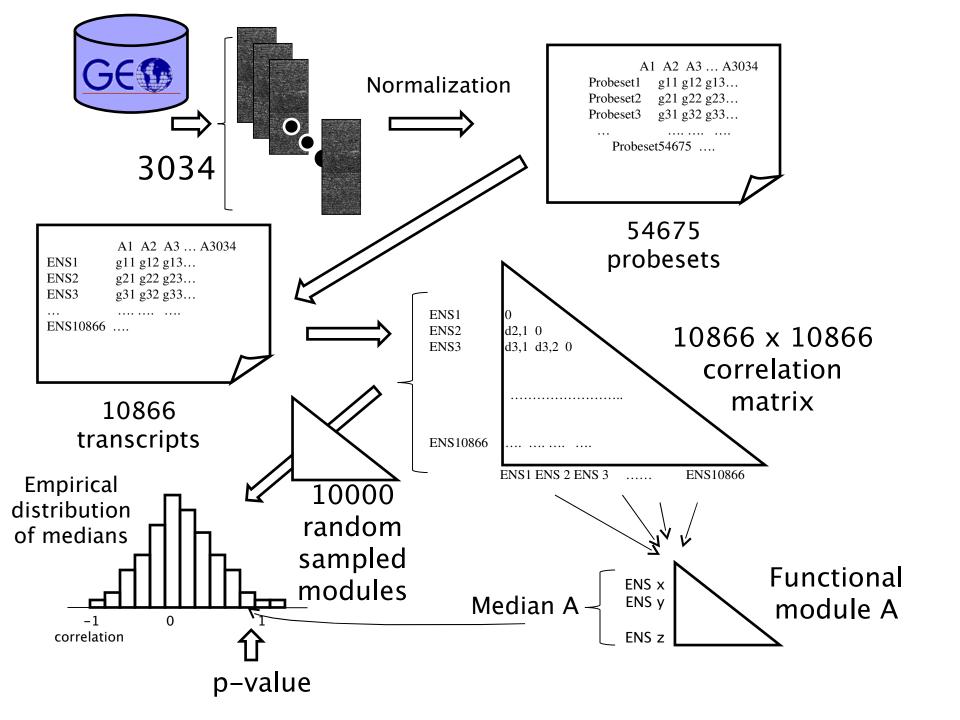
Terms from distinc repositories, reported by different methods in the diabetes dataset (Mootha et al., 2003)

Still one more problem... are functional modules defining real co-expression classes?

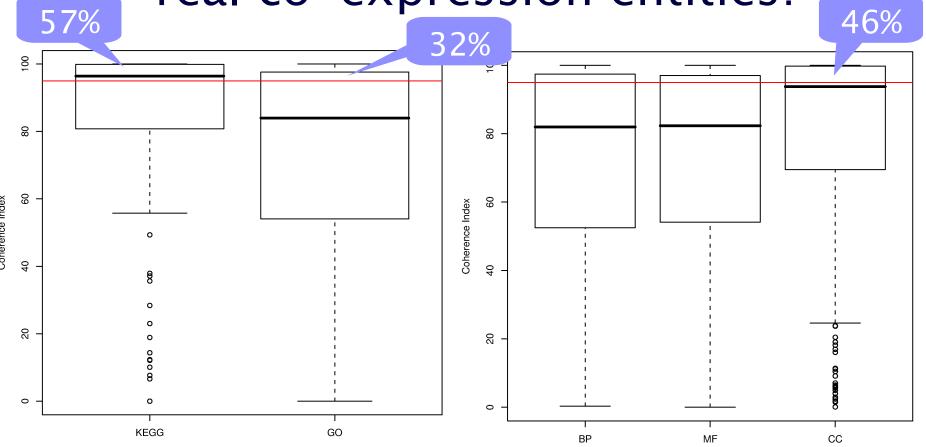
Not a naïve and trivial question.

Functional enrichment methods and gene set analysis methods rely on the assumption that the modules tested do coexpress

There are tens of thousands GO terms and hundreds of KEGG pathways



But are functional modules defining real co-expression entities?



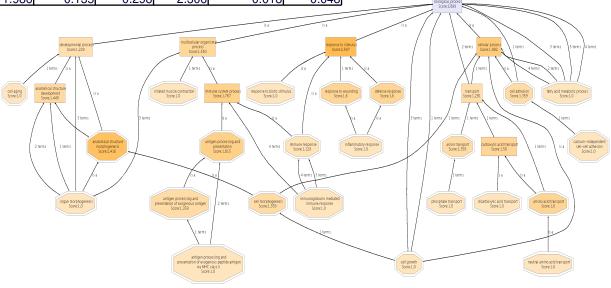
Coherence index: (1-p-value)*100.

CI > 95% means internal co-expression significantly higher than random co-expression

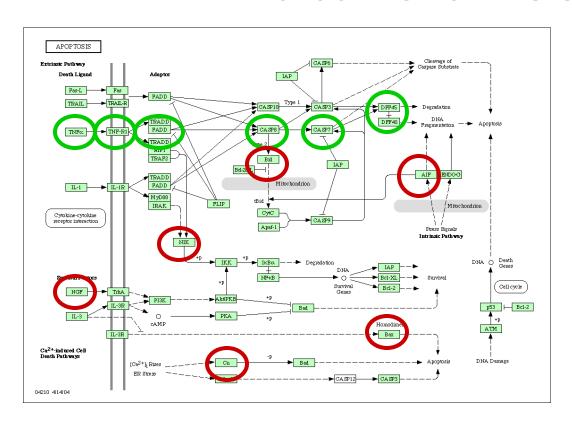
Weighting gene module membership by co-expression

	Unweighted test	Unweighted test			Weighted test		
KEGG pathway	statistic	p-value	adjusted p-value	statistic	p-value	Adjusted p-value	
Caprolactam degradation	2.741	0.059				-	
Cell cycle	2.588	0	0	2.711	0	0	
Maturity onset diabetes of the young	2.517	0.075	0.289	2.734	0.008	0.034	
RNA polymerase	2.497	0.077	0.289	2.657	0.009	0.034	
One carbon pool by folate	2.497	0.077	0.289	2.766	0.007	0.034	
Urea cycle and metabolism of amino groups	2.497	0.077	0.289	2.674	0.009	0.034	
Heparan sulfate biosynthesis	2.478	0.078	0.289	2.818	0.006	0.034	
Alanine and aspartate metabolism	2.386	0.087	0.289	2.497	0.012	0.04	
Amyotrophic lateral sclerosis (ALS)	2.386	0.087	0.289	2.91	0.005	0.034	
beta-Alanine metabolism	2.318	0.094	0.289	2.668	0.009	0.034	
Basal transcription factors	2.125	0.116	0.298	2.431	0.014	0.04	
Benzoate degradation via CoA ligation	2.072	0.123	0.298	2.468	0.013	0.04	
Limonene and pinene degradation	1.986	0.135	0.298	2.306	0.018	0.048	

Very simple weight schema:
W=2 if correlation is positive
W=0.5 if negative
W=1 if not in the class



Future directions



Testing hierarchies is better
Functions and pathways are correlated.
Testing models will increase our sensitivity

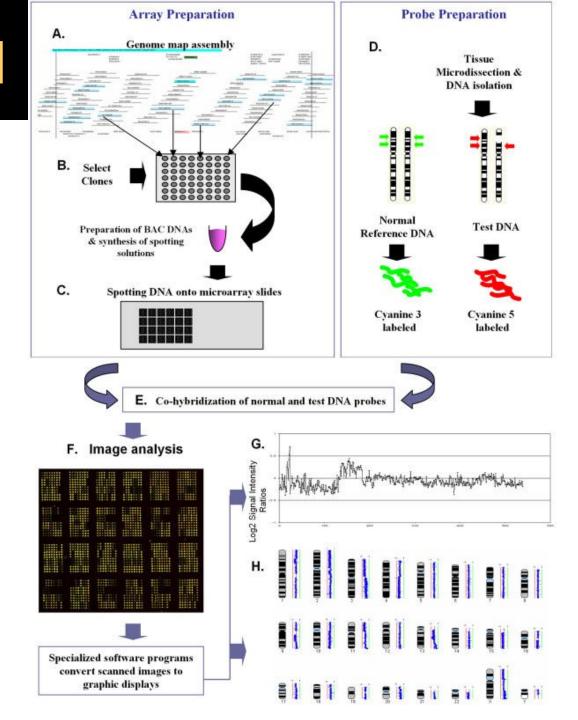
Pathways are not categorical variables

In general (systems) biology is behind. Our questions must be inspired directly by biology

Array CGH

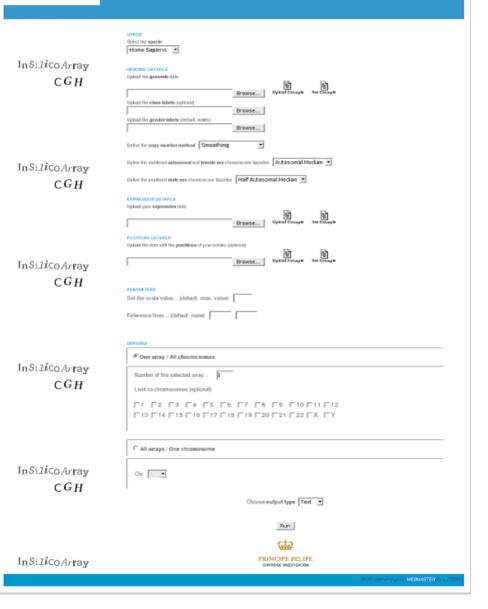
A new way of studying copy number alterations with virtually a few bases resolution...

Jump over

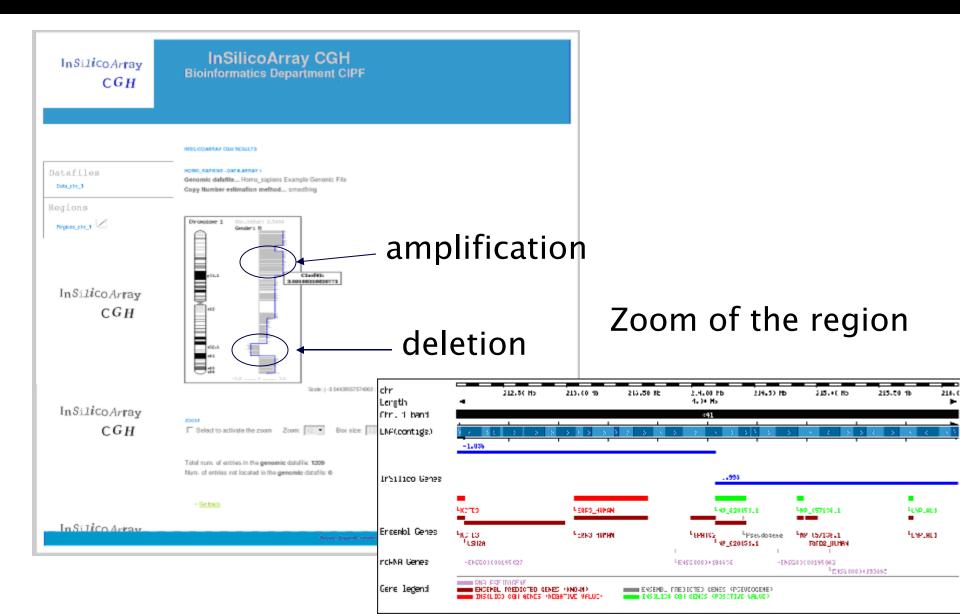


ISA CGH (*In silico* array–CGH)

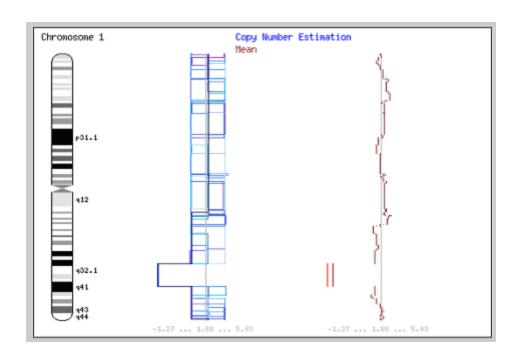
Estimating copy number, corelation copy number – expression and the minimum common amplified / lost region InSilicoArray
CGH
Bioinformatics Department CIPF



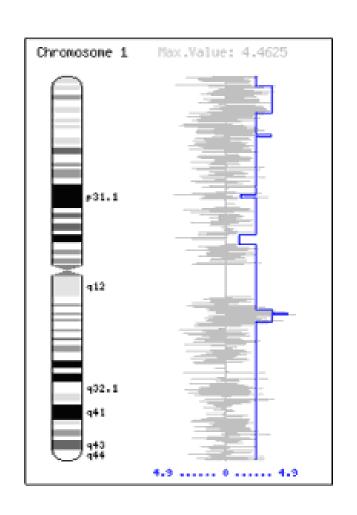
Estimating copy number

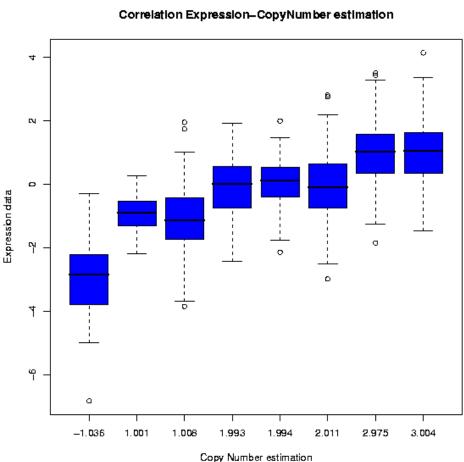


Minimum region with consistent losses or gains

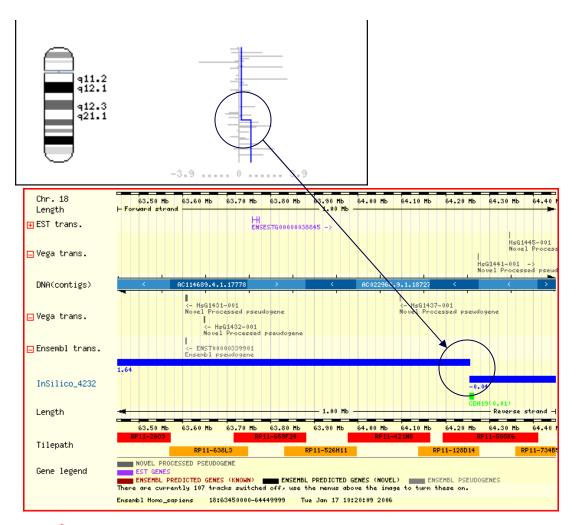


Correlation copy number to expression value





Array-CGH. DAS server



Detection of copy number alterations (two new methods)

Relationship expression / copy number alteration

Functional annotation of altered regions

DAS server



What to use Web tools gain popularity

- Interactive
- Heavy calculations at server side
- Large databases at server side
- Always the last version

Microarray data analysis webtools with at least 10 citations¹.

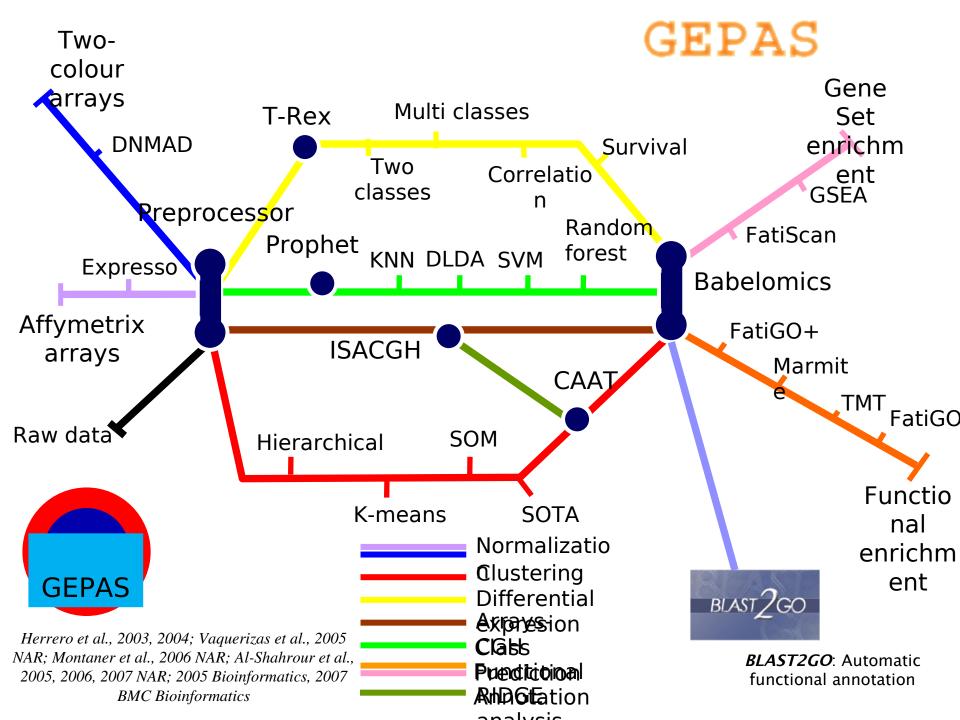
Web tool	URL	Citations ¹
GEPAS	http://www.gepas.org	252
ExpressionProfiler	http://www.ebi.ac.uk/expressionprofiler	46
caGEDA	http://bioinformatics.upmc.edu/GEDA.html	30
GenePublisher	http://www.cbs.dtu.dk/services/GenePublisher	25
ExpressYourself	http://bioinfo.mbb.yale.edu/expressyourself	24
RACE	http://race.unil.ch/	22
ArrayPipe	http://www.pathogenomics.ca/arraypipe	19
VAMPIRE	http://genome.ucsd.edu/microarray/	17
MIDAW	http://muscle.cribi.unipd.it/midaw/	13
t-profiler	http://www.t-profiler.org	12
CARMAweb	https://carmaweb.genome.tugraz.at	10

¹⁾ Scholar Google citations over all the references of the tool.

GEPAS



Since october 2007, GEPAS 4.0



Some numbers

297 papers cite GEPAS during the last three years
260 papers cite Babelomics/FatiGO (source ISI Web of Knowledge, December 2007)

More than 150,000 experiments analysed during the last year.

More than 500 experiments per day.



Web tools for functional profiling

Web tools with 10 or more Scholar Google citations

Tool	URL	Analysis type	References	Citations
GSEA	http://www.broad.mit.edu/gsea/	GSA	(3,33)	1013
DAVID	http://www.DAVID.niaid.nih.gov	FE	(34)	504
GOMiner	http://discover.nci.nih.gov/gominer/	FE	(35,36)	408
Babelomics	http://www.babelomics.org	FE, GSA	(11-13,29)	402
MAPPFinder	http://www.GenMAPP.org	FE	(37)	379
GOStats	http://gostat.wehi.edu.au/	FE	(27)	249
Ontotools	http://vortex.cs.wayne.edu/ontoexpress/	FE	(38,40-43)	223
GOTM	http://genereg.ornl.gov/gotm/	FE	(44)	164
FunSpec	http://funspec.med.utoronto.ca webcite	FE	(45)	100
GeneMerge	http://www.oeb.harvard.edu/hartl/lab/publications/GeneMerge.html	FE	(46)	96
FuncAssociate	http://llama.med.harvard.edu/Software.html	FE, GSA	(39)	91
GOToolBox	http://gin.univ-mrs.fr/GOToolBox	FE	(28)	74
GFINDer	http://www.medinfopoli.polimi.it/GFINDer/	FE	(47,48)	49
WebGestalt	http://bioinfo.vanderbilt.edu/webgestalt/	FE	(49)	46
GOAL	http://microarrays.unife.it	GSA	(50)	25
Pathway Explorer	https://pathwayexplorer.genome.tugraz.at/	FE	(51)	25
PLAGE	http://dulci.biostat.duke.edu/pathways/	GSA	(52)	18
t-profiler	http://www.t-profiler.org/	GSA	(53)	12
WebBayGO	http://blasto.iq.usp.br/~tkoide/BayGO/	FE	(54)	10

Other tools (non-commertial)

To cover more specific analysis requirements

Bioconductor: http://www.bioconductor.org

BRB tools: http://linus.nci.nih.gov/BRB-ArrayTools.html

TM4 (MeV): http://www.tm4.org/mev.html

The bioinformatics department at the Centro de Investigación Príncipe Felipe (Valencia, Spain)...

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...the INB, National Institute of Bioinformatics (Functional Genomics Node) and the CIBER-ER Nertwork of Centers for Rare Diseases

