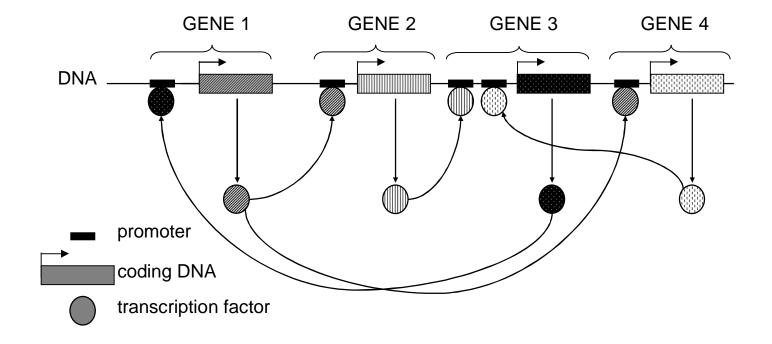
Introduction to Microarray Data Analysis and Gene Networks lecture 7

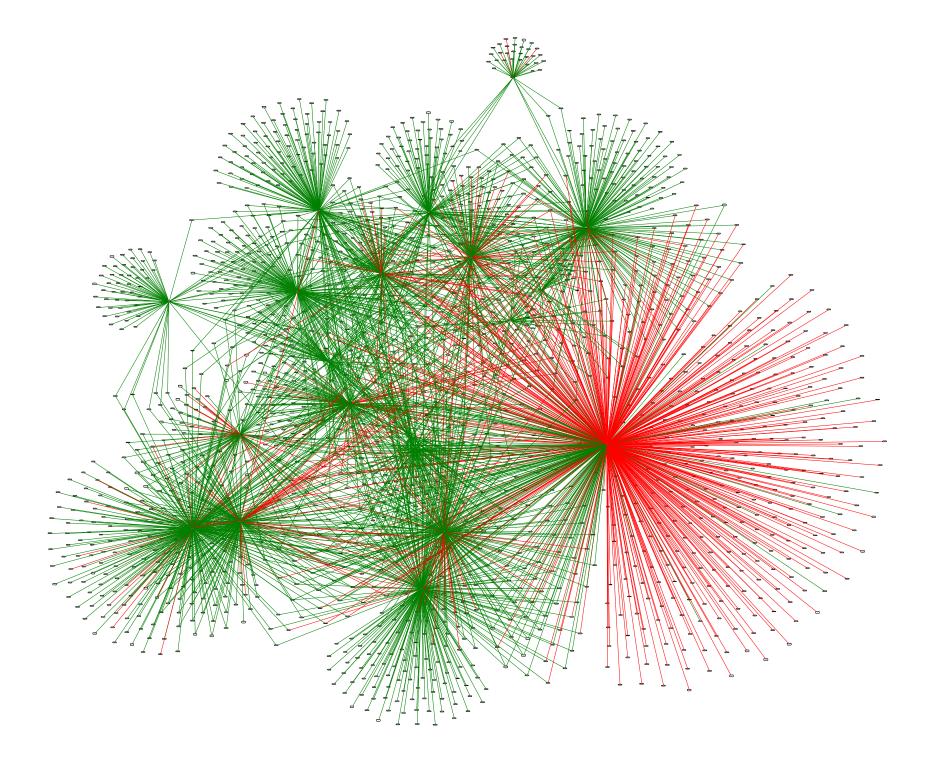
Alvis Brazma

European Bioinformatics Institute

Lecture 7

Gene networks – part 1





Questions I want to ask

- What does it mean to understand a network of thousands of genes and connections?
- How does a simple cell (with < 6000 genes) work?
- What does it mean to understand 'how does a cell work'?
- Can a descriptive approach to biology ever provide the answer?

Modelling approach

- Develop a model (a formal language) describing gene networks
- Study the properties of the model instead of the real world gene networks directly
- Make predictions about real world gene networks based on the properties of the model
- Test the predictions in the real world
- If the predictions are correct the model is correct

All models are wrong, but some are useful

- George E. P. Box

Simulation and reverse engineering of gene networks

- Simulation given a model, observe its behaviour and compare to gene expression data from real networks
- Reverse engineering given gene expression data construct a particular model (in the given model class) that is consistent with the data

Approach to gene network modelling - four levels of hierarchical description

- Parts list genes, transcription factors, promoters, binding sites, ...
- Topology a graph describing the connections between the parts
- Control logics how combinations of regulatory signals interact (e.g., promoter logics)
- Dynamics how does it all work in real time

Each level models different network properties, each next level includes more detail

Gene Networks - four levels of hierarchical description

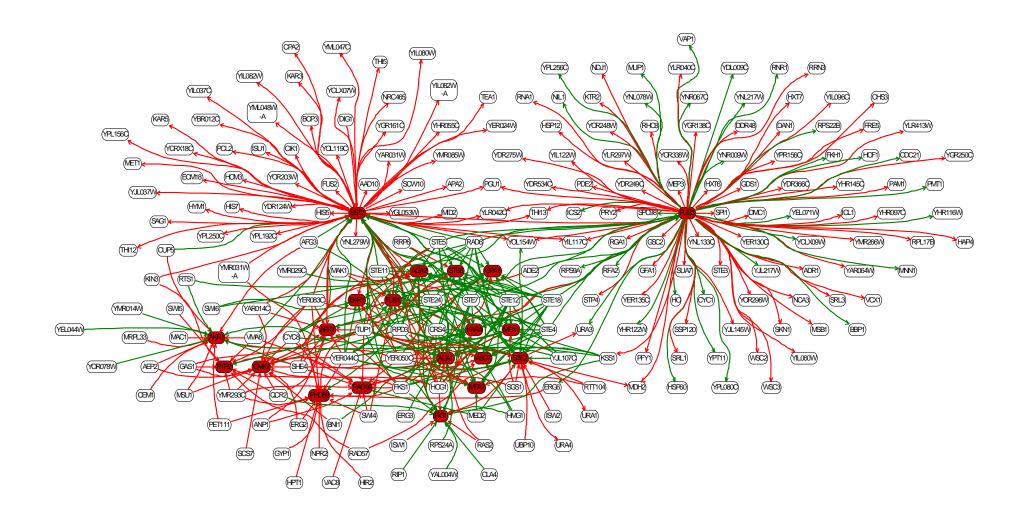
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Genes and gene products, proteins

Organism	The number of predicted genes	Part of the genome that encodes proteins (exons)
E.Coli (bacteria)	5000	90%
Yeast	6000	70%
Worm	18,000	27%
Fly	14,000	20%
Weed	25,500	20%
<u>Human</u>	25,000	< 5%

Gene Networks - four levels of hierarchical description

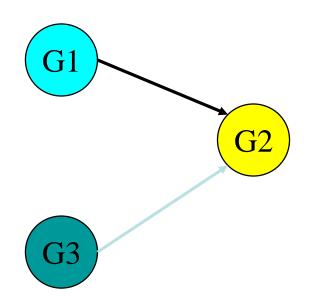
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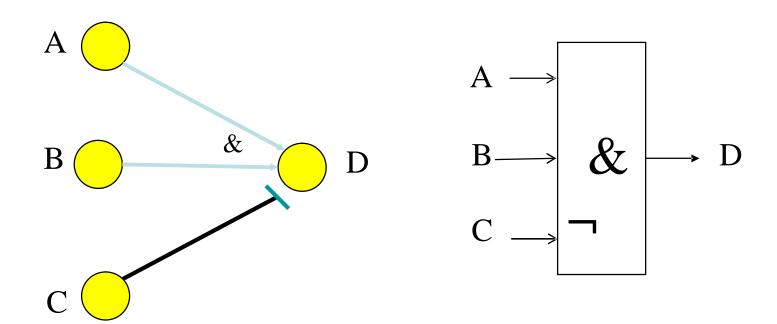
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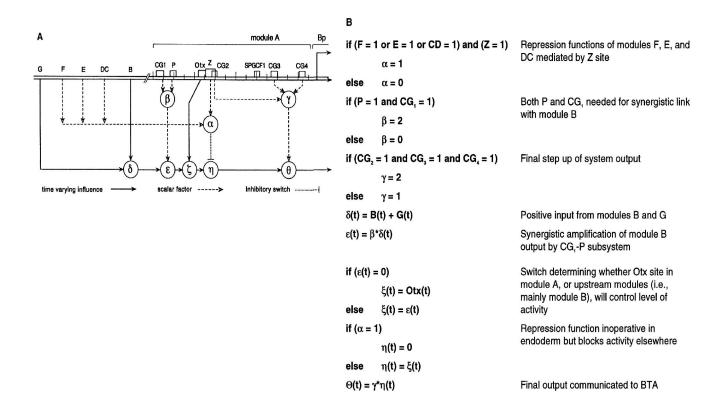
Gene activation, repression, more complex combinatorial effects



Logics



$$D = A \& B \& \neg C$$

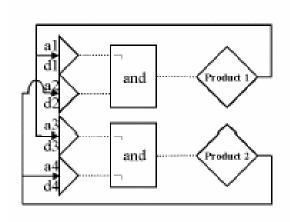


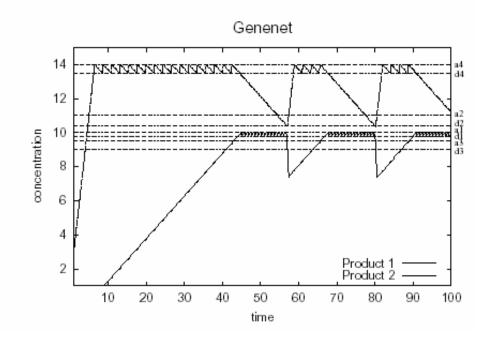
Yuh, C.H., Bolouri, H. and Davidson, E.H. (1998) Genomic cisregulatory logic: experimental and computational analysis of a sea urchin gene. Science 279, 1896-902

Gene Networks - four levels of hierarchical description

- Parts list genes, transcription factors, promoters, binding sites, ...
- Topology a graph describing the connections between the parts
- Control logics how combinations of regulatory signals interact (e.g., promoter logics)
- Dynamics how does it all work in real time

Simulations on a FSLM





Gene Networks - four levels of hierarchical description

- Parts list genome scale
- Topology genome scale for smaller genomes (Yeasts, E. Coli)
- Control logics tens of genes
- Dynamics typically a couple of genes

Gene Networks - four levels of hierarchical description

- Parts list genome scale
- Topology genome scale for smaller genomes (Yeasts, E. Coli)
- Control logics tens of genes
- Dynamics typically a couple of genes

Parts list

- Classification of all genes and their products (transcripts, proteins) – an ontology or a database
 - Some particularly important for regulation classes of genes – transcription factors, signalling proteins
 - Transcription factor binding sites, promoters e.g, TRANSFAC database

Gene Ontology (GO)

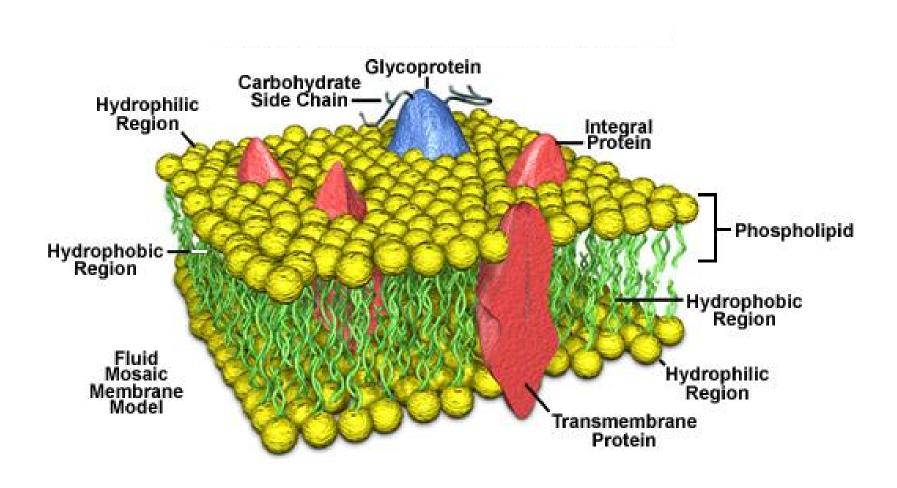
What information might we want to capture about a gene product?

- What does the gene product do?
- Where and when does it act?
- Why does it perform these activities?

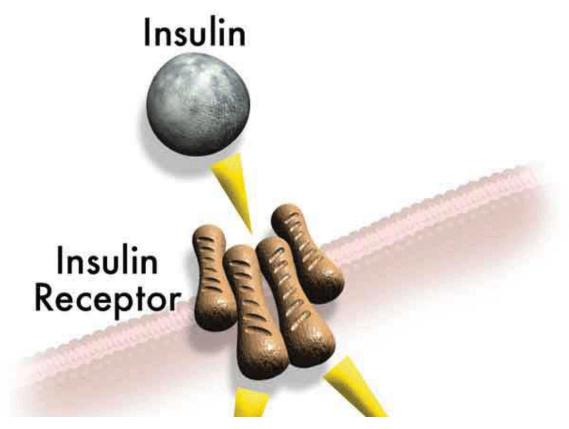
GO structure

- GO terms divided into three parts:
 - cellular component
 - molecular function
 - biological process

Cellular Component



Molecular Function

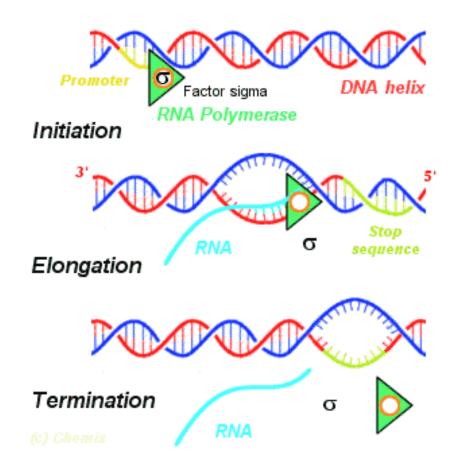


insulin binding insulin receptor activity

Molecular Function

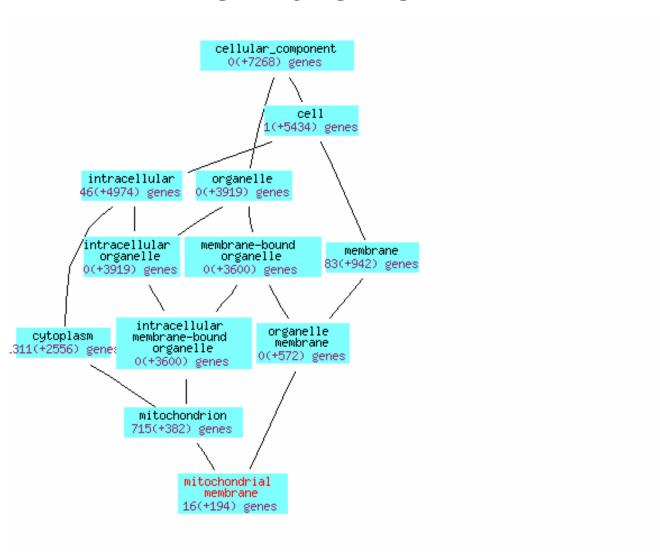
- A gene product may have several functions; a function term refers to a single reaction or activity, not a gene product.
- Sets of functions make up a biological process.

Biological Process

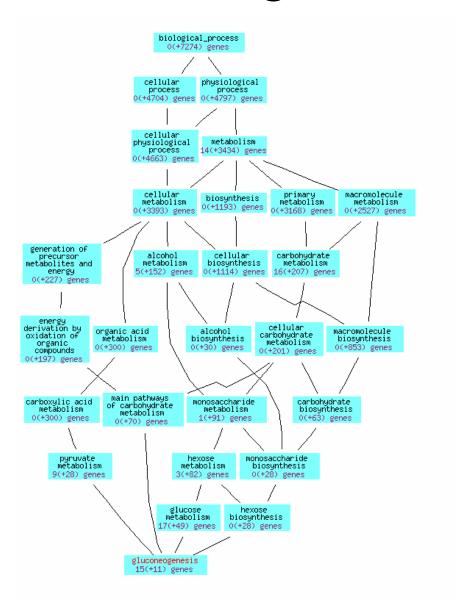


transcription

DAG structure - Mitochondrial membrane



Gluconeogenesis

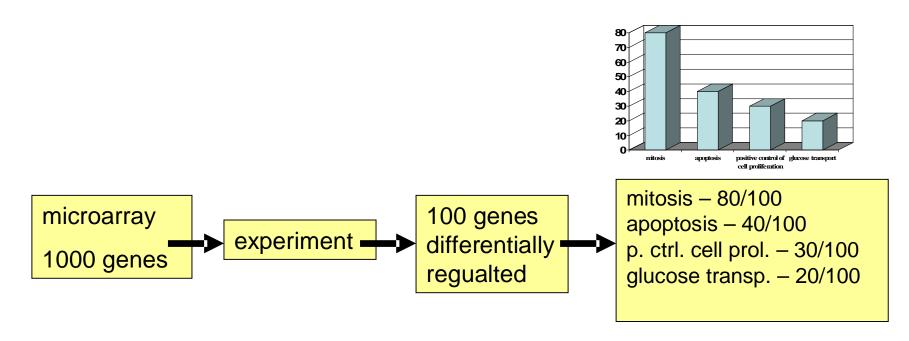


GO for microarray analysis

- Annotations give 'function' label to genes
- Ask meaningful questions of microarray data e.g.
 - genes involved in the same process, same/different expression patterns?

Using GO in practice

- statistical measure
 - how likely your differentially regulated genes fall into that category by chance

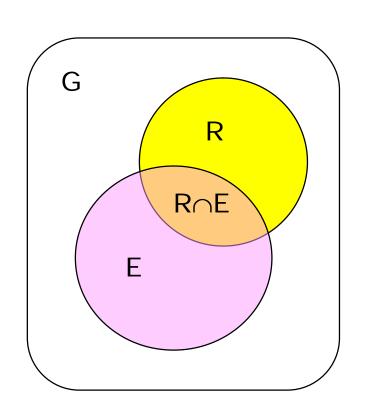


Using GO in practice

 However, when you look at the distribution of all genes on the microarray:

Process	Genes on array	# genes expected in 100 random genes	occurred
mitosis	800/1000	80	80
apoptosis	400/1000	40	40
p. ctrl. cell prol.	100/1000	10	30
glucose transp.	50/1000	5	20

How to estimate that the overlap is more than expected by random?

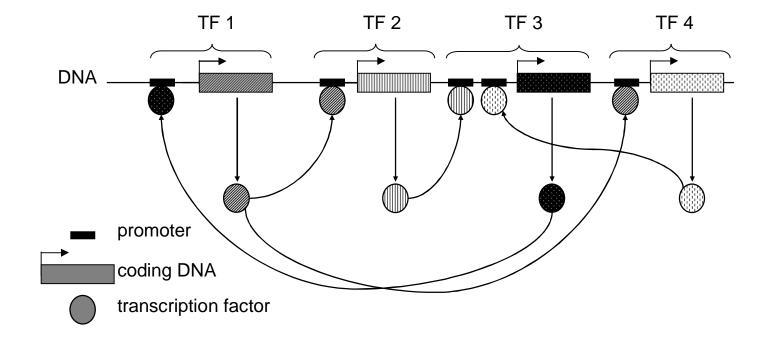


We assume that the elements of the set E are marked, and pick the set of size |R| at random. Then the size $x=|R\cap E|$ of the intersection are distributed according to *hypergeometric* distribution. The probability of observing an intersection of size k or larger can be computed according to formula:

$$P(x \ge k) = 1 - \sum_{i=0}^{k} \frac{\binom{|E|}{i} \binom{|G| - |E|}{|R| - i}}{\binom{|G|}{|R|}}$$

Parts list - number of transcription factors

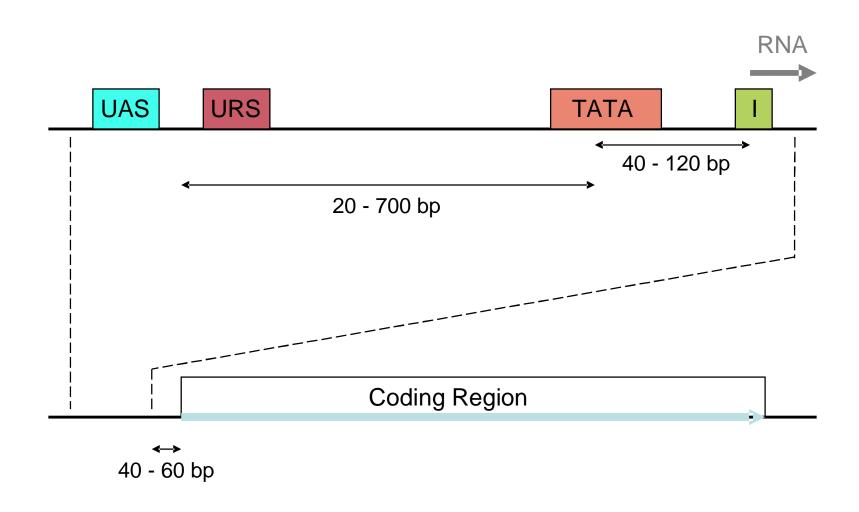
Organism	Number of	Number of
	genes	transcription
		regulators
		(GO:0030528)
Yeast	6682	312 (4.7%)
Fly	13525	492 (3.6%)
Human	22287	1034 (4.6%)



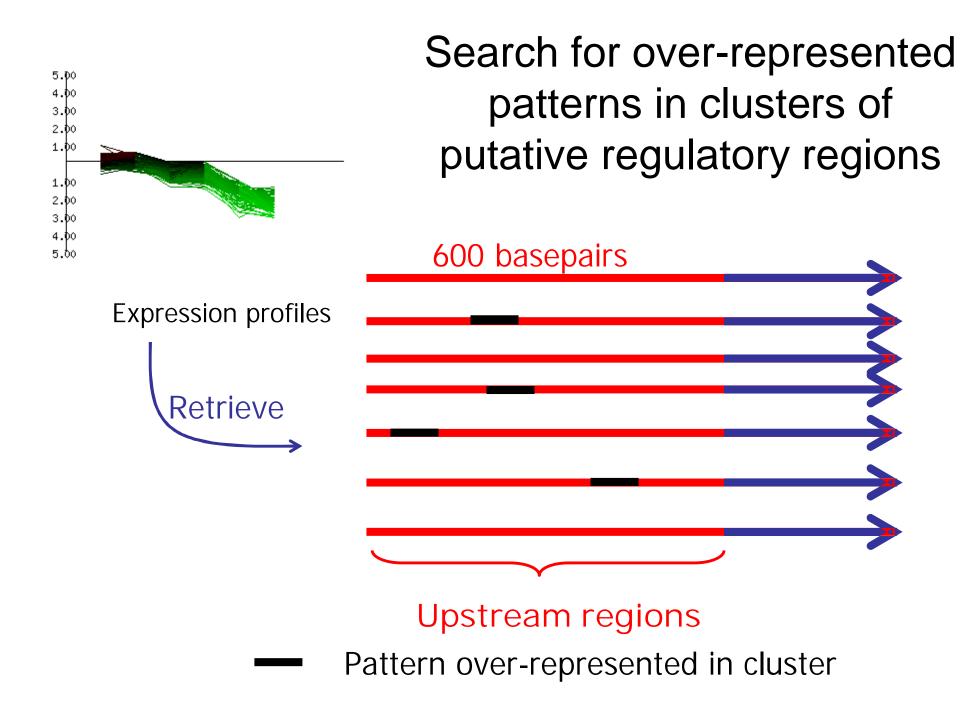
Transcription factor binding sites and promoters

 Binding site identification is much more elusive than gene identification

Organization of a typical yeast promoter

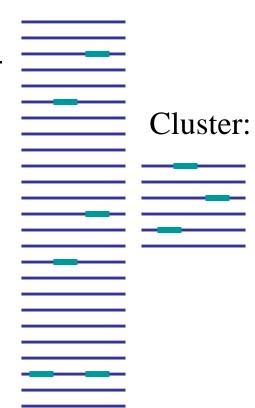


Computational identification of TF binding sites



Pattern selection criteria Binomial distribution

Background ALL
upstream
sequences



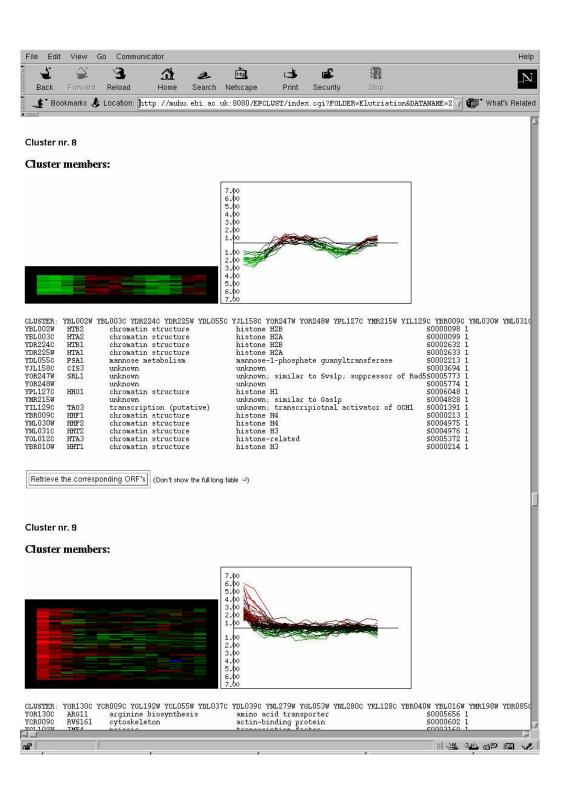
 π occurs 3 times

 $P(\pi,6)$ is probability of having 3 or more matches in 6 sequences

5 out of 25,
$$p = 0.2$$

$$P(\pi,6) = 0.0989$$

Clustering of gene expression data (K-means clustering)



1 mismatch

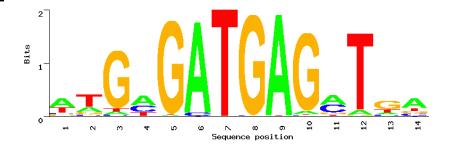
GATGAG.T

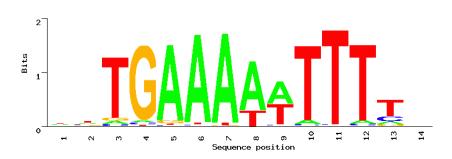
TGAAA..TTT

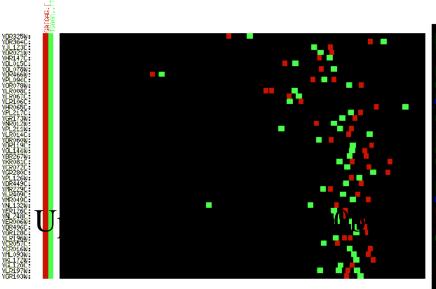


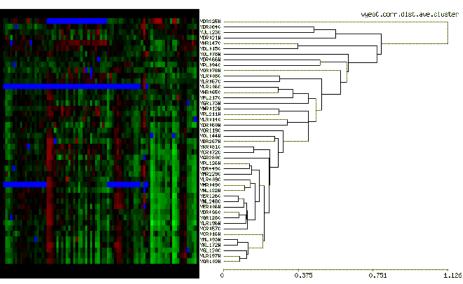
GATGAG.T W/30

TGAAA..TTT

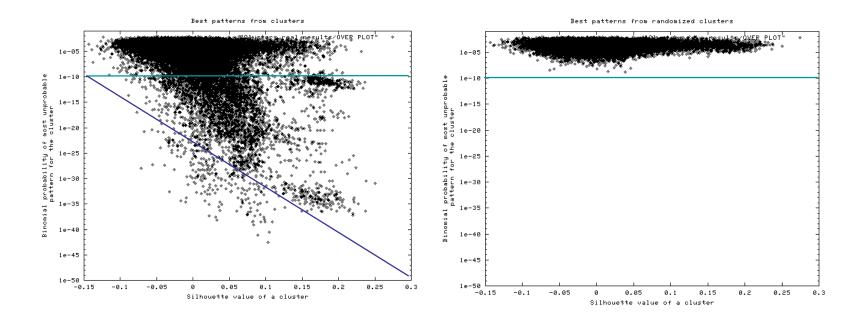








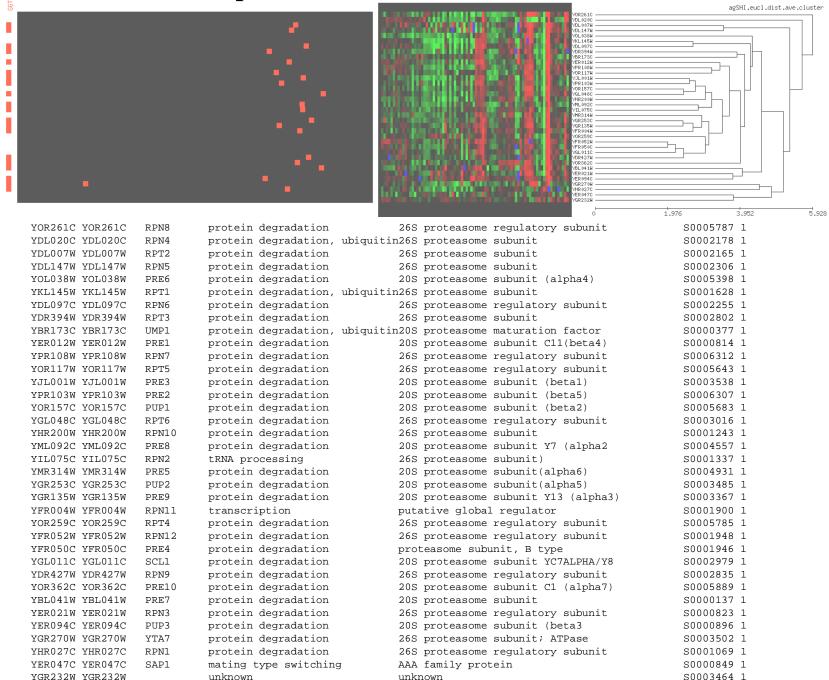
Pattern vs cluster "strength"



The pattern probability vs. the average silhouette for the cluster

The same for randomised clusters

GGTGGCAA - proteasome associated control element



GGTGGCAA is a binding site for RPN4

FEBS Lett 1999 Apr 30;450(1-2):27-34

Rpn4p acts as a transcription factor by binding to PACE, a nonamer box found upstream of 26S proteasomal and other genes in yeast.

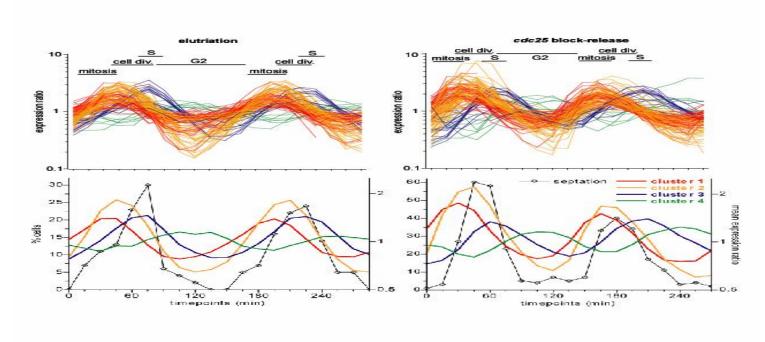
Mannhaupt G, Schnall R, Karpov V, Vetter I, Feldmann H Adolf-Butenandt-Institut der Ludwig-Maximilians-Universitat Munchen, Germany.

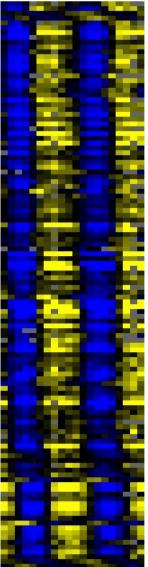
We identified a new, unique upstream activating sequence

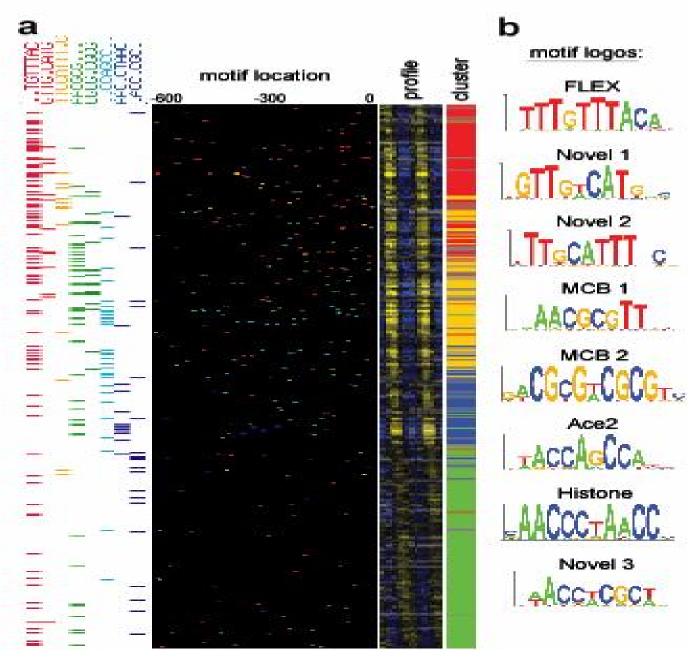
(5'-**GGTGGCAAA**-3') in the promoters of 26 out of the 32 proteasomal yeast genes characterized to date, which we propose to call proteasomeassociated control element. By using the one-hybrid method, we show that the factor binding to the proteasome-associated control element is Rpn4p, a protein

containing a C2H2-type finger motif and two acidic domains. ...

Microarray expression measurements in cell cycle for over 400 periodic genes in yeast







Kivinen at al

Computational TF binding site identification

- Works OK for yeasts, but even for S.
 Pombe difficult
- For human this type of strategy does not work – the putative promoter regions are too long
- The best that has been achieved for human is to use known binding site patterns, to try to find where they are in the genome

Known binding sites for S.pombe

CAGTCACA

ACCCTACCCT

ACGCGT

TTCTTTGTTY

ACAAT

TTTGTTTAC

GAAnnTTC

TGACGTCA

HomolD

HomolE

MCB

TR-box

M-box

FLEX

HSE

CRE

(translation)

(translation)

(cell cycle)

(mating)

(mating)

(meiosis)

(stress)

(stress)

Alternative methods for high throughput binding site identification

- ChIP-on-chip identify intragenic sequences of a few hundred base-pairs binding a particular transcription factor, then look for an overrepresented sequence elements
- Protein binding arrays hybridise the transcription factor directly on the array
- Phylogenetic foot printing or shadowing

ChIP-chip (Chromatin Immuno Precipitation on chip) experiments to identify TF binding sites

- The method
 - TF are cross-linked to genomic DNA with Chromatin IP
 - The DNA is fragmented and nonprotein binding bits washed away
 - The remaining DNA is labelled and hybridised on a microarray containing intragenic regions
 - The spot brightness now tells where TF were bound
- Problems
 - Binding is still condition specific
 - Are the binding functional?

Problems in binding site identification

- They are all based on the assumption that statistically overrepresented sequence elements are functional
- They are all based the assumption that the binding sites can be described by regular expressions or position weight matrices
- They work on yeasts around ~50% OK, but so far they have failed in higher organisms
- On the order of 4000 TF BS location for S. Cerevisiae

Parts list - conclusions

- Gene identification OK
- Gene function only 1/3 of the genes have known function
- Transcription Factors 1/3 2/3
- Transcription factor binding site identification – More or less OK for yeast, rather poor for higher organism

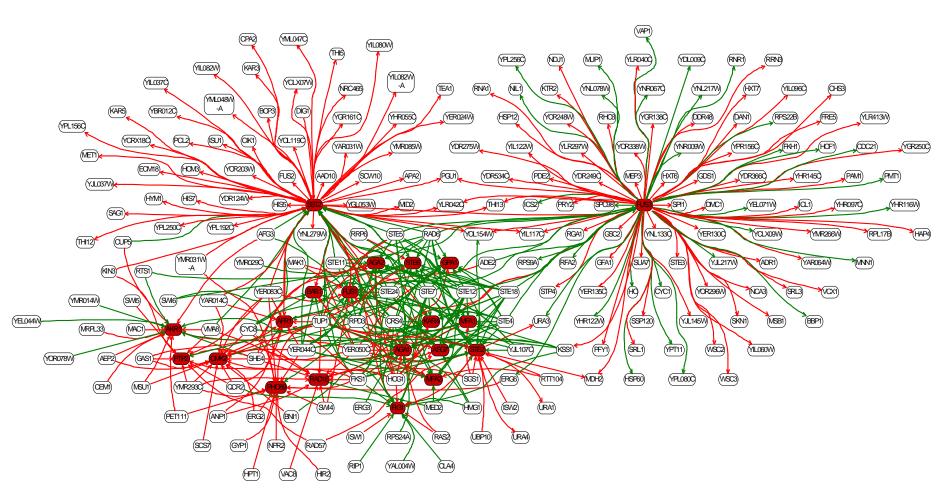
Gene Networks - four levels of hierarchical description

- Parts list genes, transcription factors, promoters, binding sites, ...
- Topology a graph describing the connections between the parts
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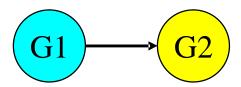
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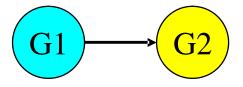
Topology – a graph where nodes represent genes and edges (arcs) represent relationships between genes



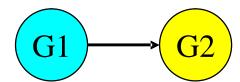
The arcs can have different meaning



- The product of gene G1 is a transcription factor, which binds to the promoter of gene G2 (in Chip-chip experiment) – physical interaction network (direct network)



- Gene G2 contains a binding site for gene G1 (in silico BS identification)



- The disruption of gene G1 changes the expression level of gene G2 – data interpretation network (indirect network)

What kind of things we can study on this level?

- Ideally this graph should tell us which gene can potentially regulate which others and which are independent
- How complex is this graph? What are the connectivity properties? Can we find modules?

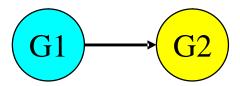
What kind of things we can study on this level

- Source genes and target genes nodes with outgoing arcs and nodes with incoming arcs respectively
- For every source gene we can define the set of target genes (target set of a gene)
- How graphs with different edges relate?
 How do target sets of the same gene compare in different networks?

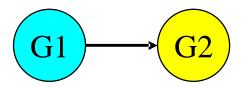
Data for S. cerevisiae

- ChIP network (Young lab, Science 2002, Nature 2004) – binding locations for 177 transcription factors (about 4500 locations in the genome) – direct network
- Mutation network (Hughes et al, Cell 2000)
 - 228 yeast mutant expression data for all genes – indirect network

The arcs can have different meaning

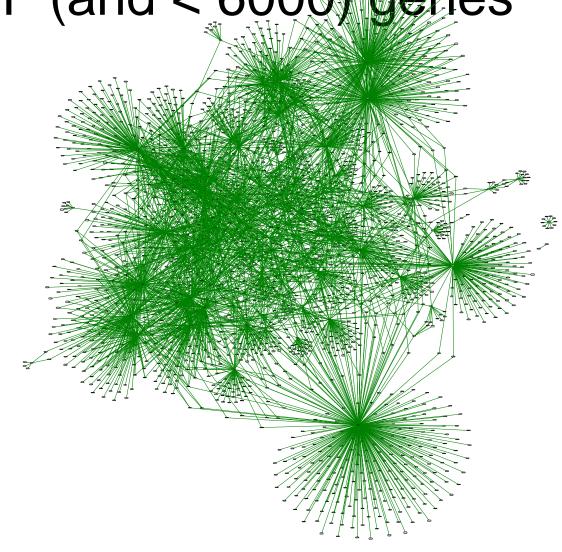


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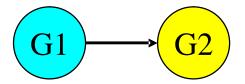
Transcription factor binding network in *S. cerevisiae* for ~100 TF (and < 6000) denes



Data for S. cerevisiae

- ChIP network (Young lab, Science 2002, Nature 2004) – binding locations for 177 transcription factors (about 4500 locations in the genome) – direct network
- The presence of derived transcription factor binding site data used to improve the networks

The arcs can have different meaning

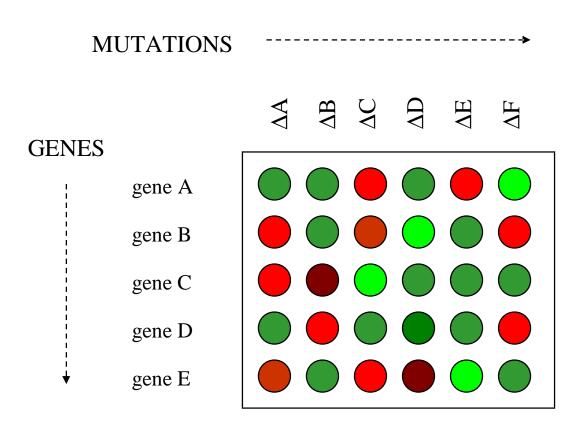


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Data for S. cerevisiae

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The mutation microarray data matrix



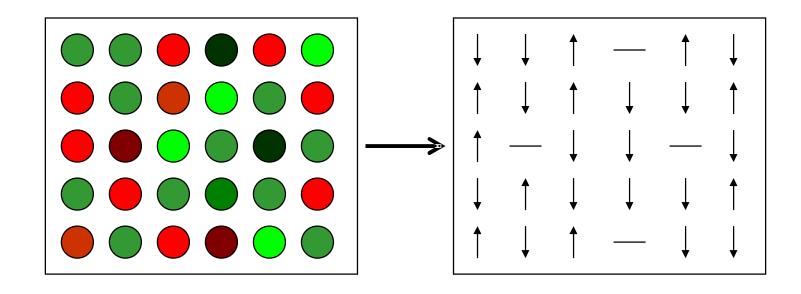
Discretization of the data

The normalized expression log(ratios) are discretized using two thresholds:

$$X \le C \Rightarrow X' = -1$$

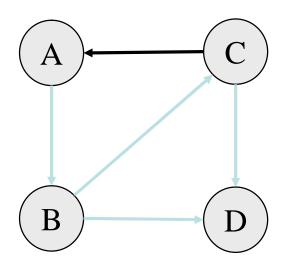
$$C \le X \le C \Rightarrow X' = 0$$

$$X \ge C \Rightarrow X' = 1$$



Gene disruption networks

	ΔA	$\Delta \mathbf{B}$	ΔC
gene A	-1	0	-1
gene B	1	-1	0
gene C	0	1	-1
gene D	0	1	1



Yeast mutation data

- Gene expression data for all ~6000 genes for ~300 systematic mutation experiments in yeast published by Rosetta (Gene Expression Compendium, Cell, 2000)
- Additionally ~60 replicates for the wildtype, and an error model, together allowing to discretize the data

Dataset

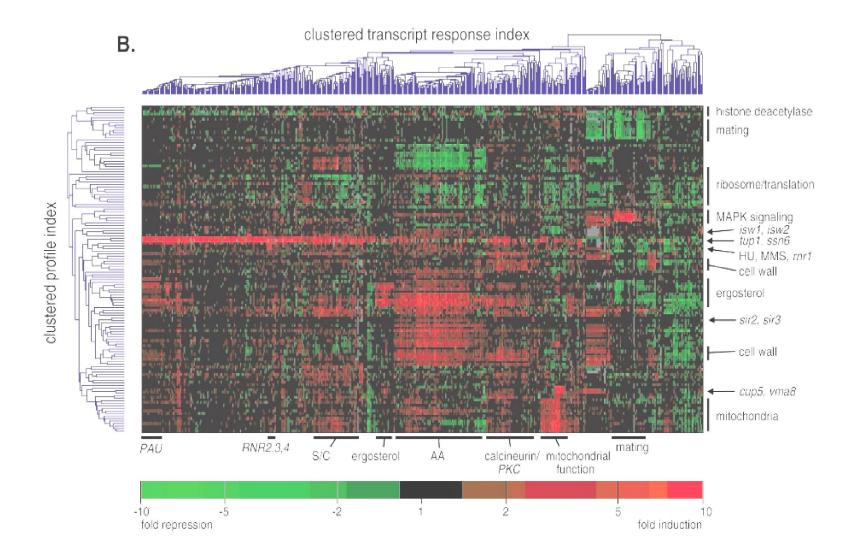
The dataset used is coming from Hughes *et al.*:

"Functional discovery via a compendium of expression profiles", Cell 102, 109-126 (2000)

- Yeast data, 6316 gene expression profiles over 300 experiments
- 276 deletion mutants (274 single, 2 double)
- 11 tet-promotor mutants
- 13 compound treatments

We have selected a subset of 207 experiments:

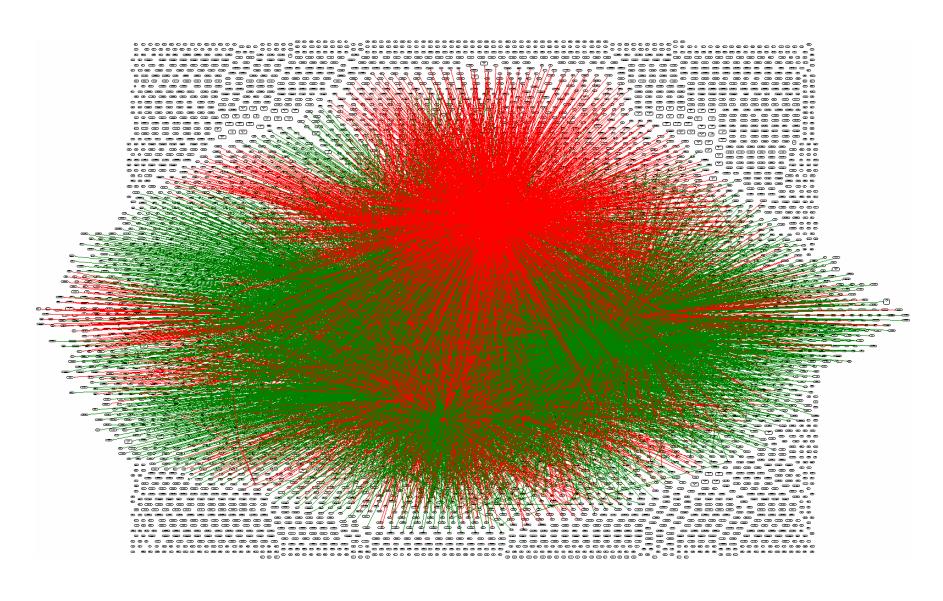
- Single deletion mutants
- Diploid cells only
- All chromosomes present



Gene specific thresholds

- ~ 80 experiments on 'wild-type' yeast were performed, revealing wide variation in gene expression dependent on particular gene
- Gene expression variation for each gene can be assumed to have normal distribution
- Standard deviation for each gene can be used therefore for assessing the threshold on gene by gene basis

Mutation network for S. Cerevisiae



Why topology is important?

- Reduce hypothesis space when analysing next layers of model complexity – instead of default – all genes depend on all, topology tells us which genes are independent
- What is the complexity of gene regulation
 - Given a transcription factor T how many genes does T regulate?
 - Given a gene A, how many transcription factors regulate A?
- Are networks modular?