

# Gene Regulation and Microarrays



# Overview

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- A. Gene Expression and Regulation
- B. Measuring Gene Expression: Microarrays
- C. Finding Regulatory Motifs

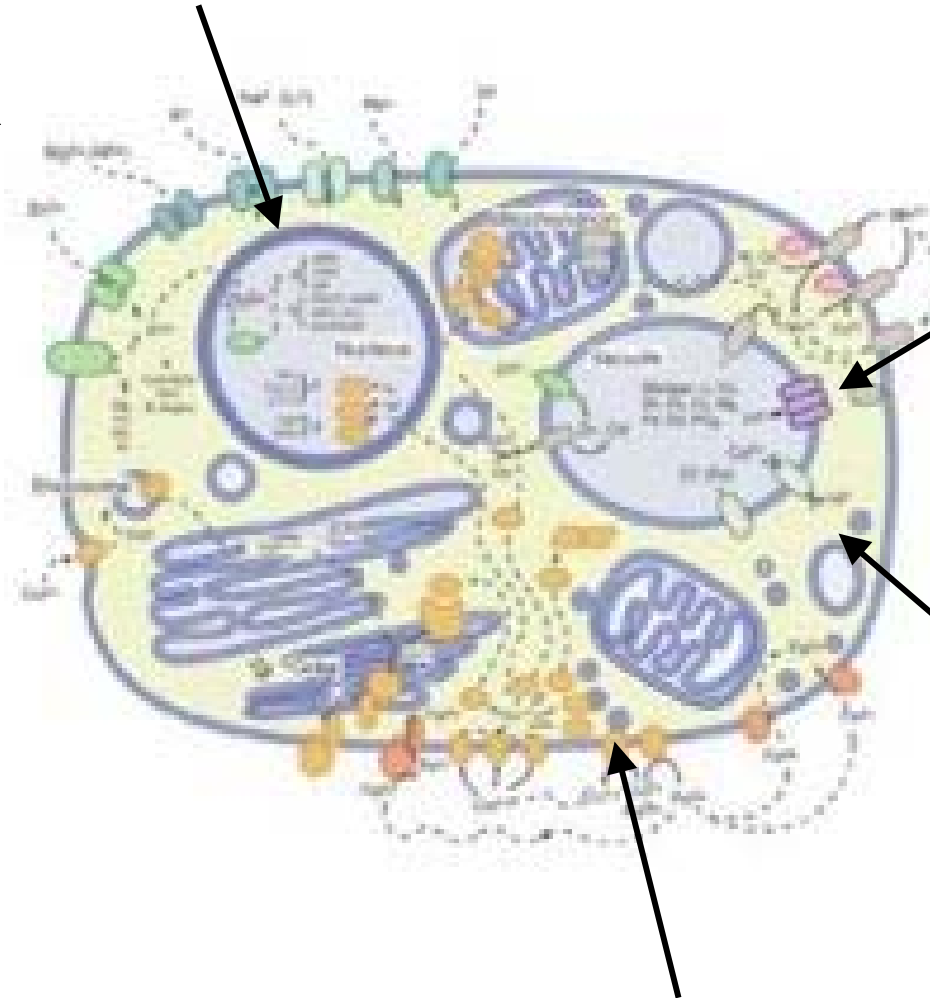


# A. Regulation of Gene Expression



# Cells respond to environment

Various external messages



Heat

Responds to environmental conditions

Food Supply



# Genome is fixed – Cells are dynamic

- A genome is static
  - Every cell in our body has a copy of same genome
- A cell is dynamic
  - Responds to external conditions
  - Most cells follow a **cell cycle** of division
- Cells differentiate during development

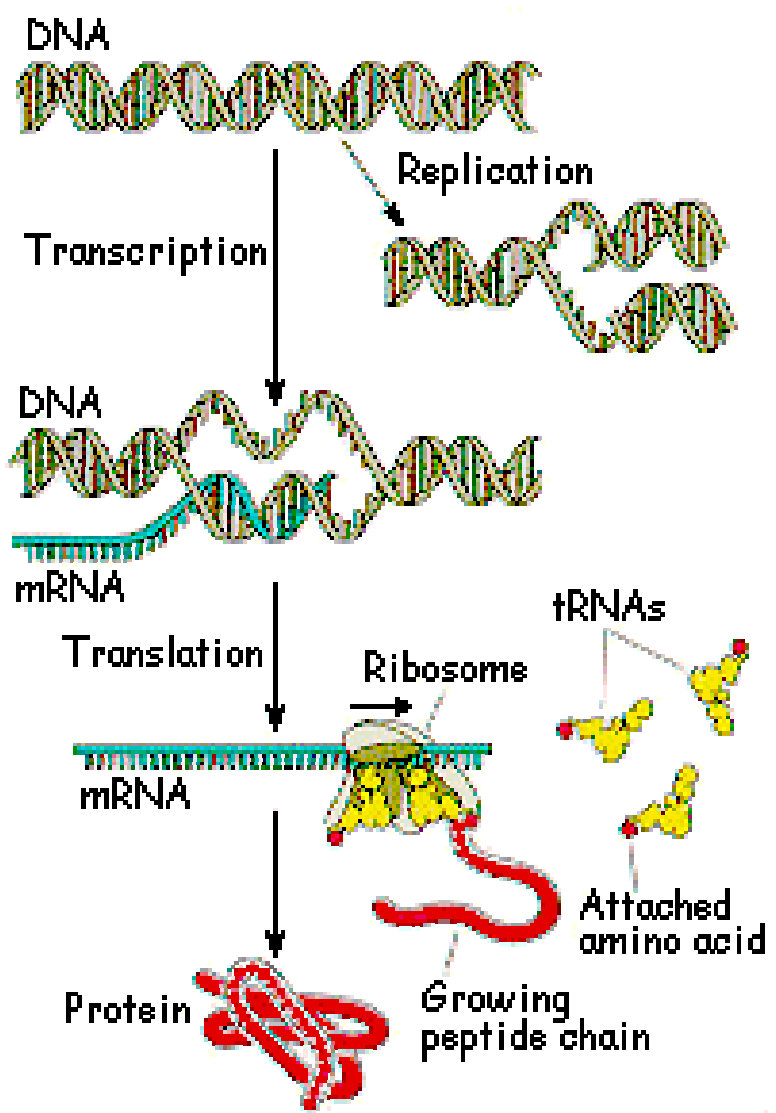


# Gene regulation

- Gene regulation is responsible for dynamic cell
- Gene expression varies according to:
  - Cell type
  - Cell cycle
  - External conditions
  - Location



# Where gene regulation takes place



- Opening of chromatin
- **Transcription**
- Translation
- Protein stability
- Protein modifications



# Transcriptional Regulation

- **Strongest** regulation happens during transcription
- **Best** place to regulate:  
No energy wasted making intermediate products
- However, **slowest** response time  
After a receptor notices a change:
  1. Cascade message to nucleus
  2. Open chromatin & bind transcription factors
  3. Recruit RNA polymerase and transcribe
  4. Splice mRNA and send to cytoplasm
  5. Translate into protein





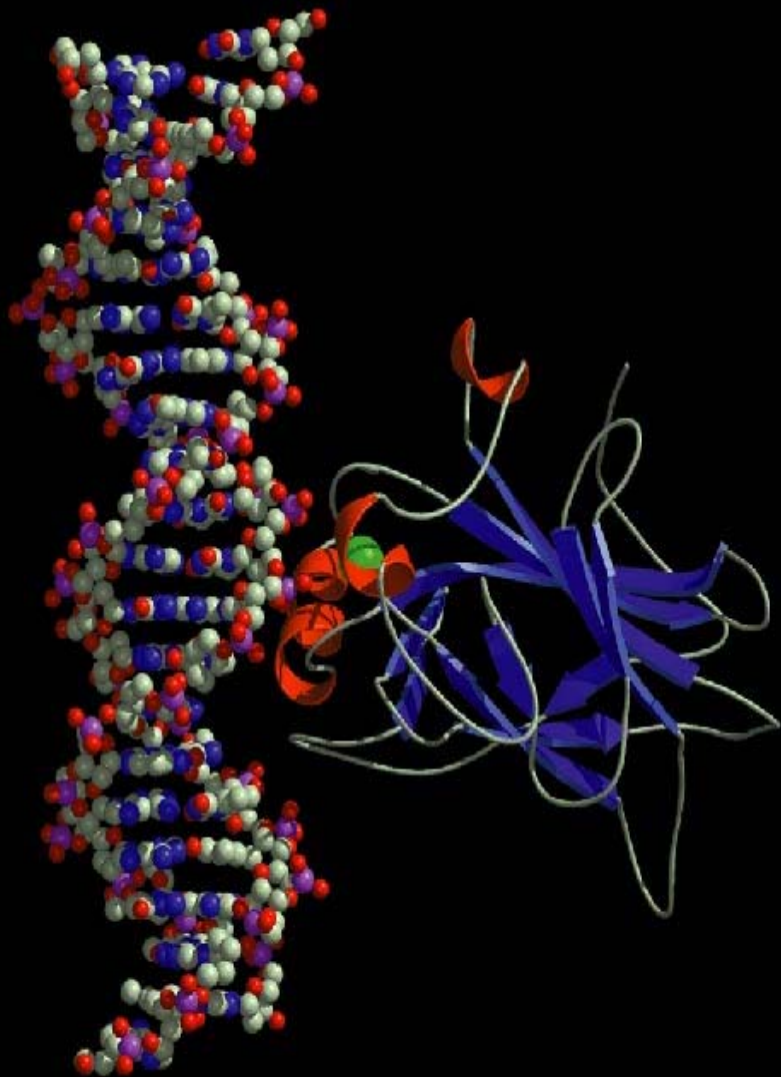
# Transcription Factors Binding to DNA

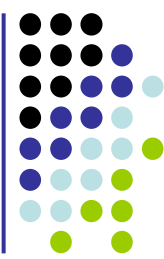
Transcription  
regulation:

Certain transcription  
factors bind DNA

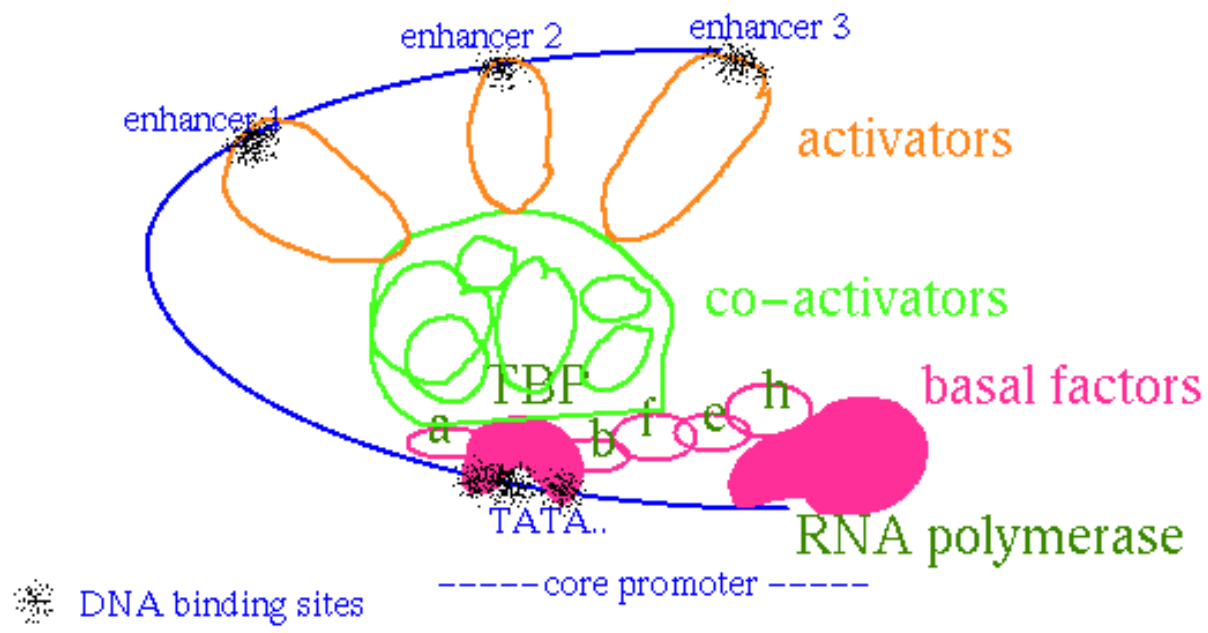
Binding recognizes  
DNA substrings:

Regulatory motifs





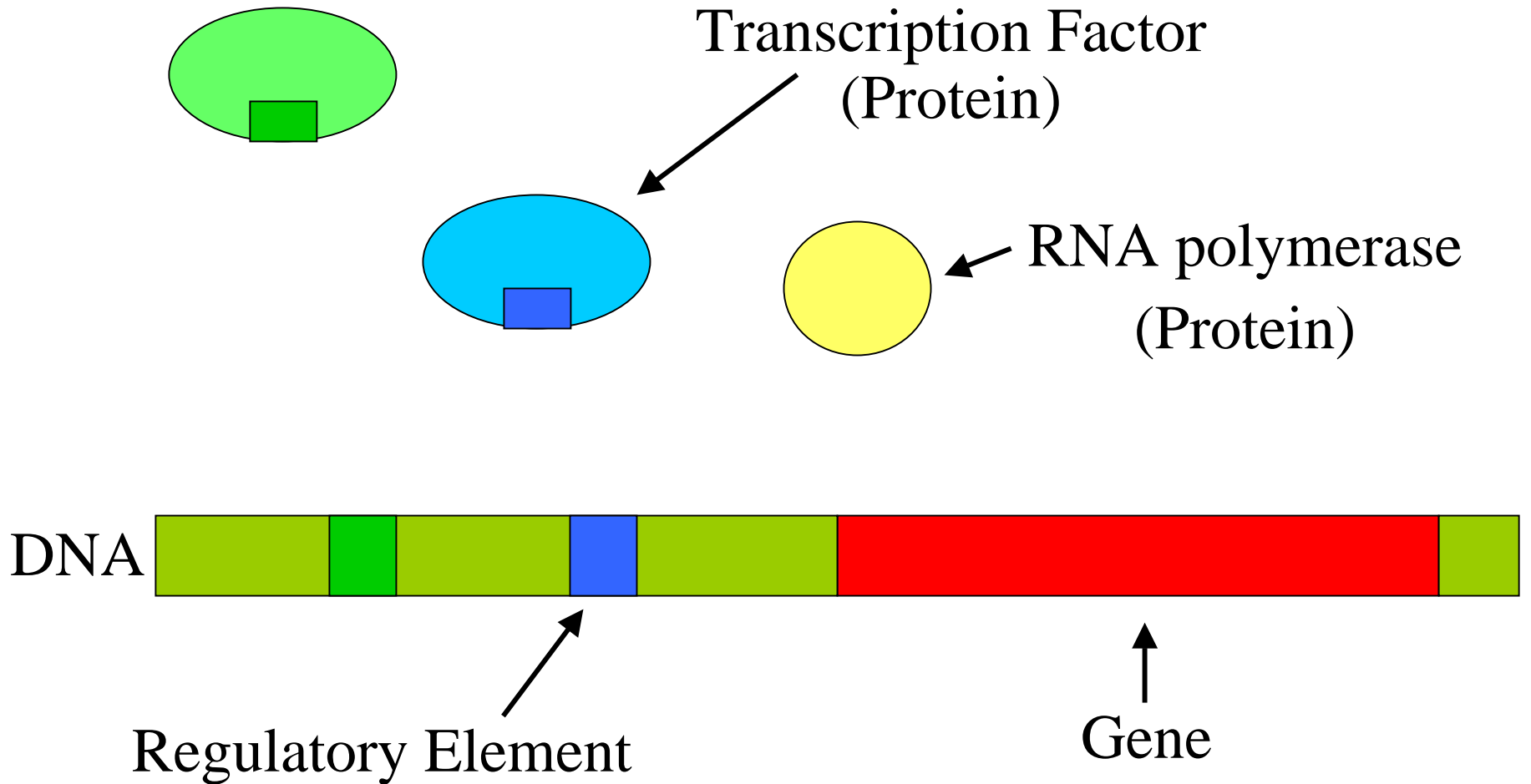
# Promoter and Enhancers



- Promoter necessary to start transcription
- Enhancers can affect transcription from afar

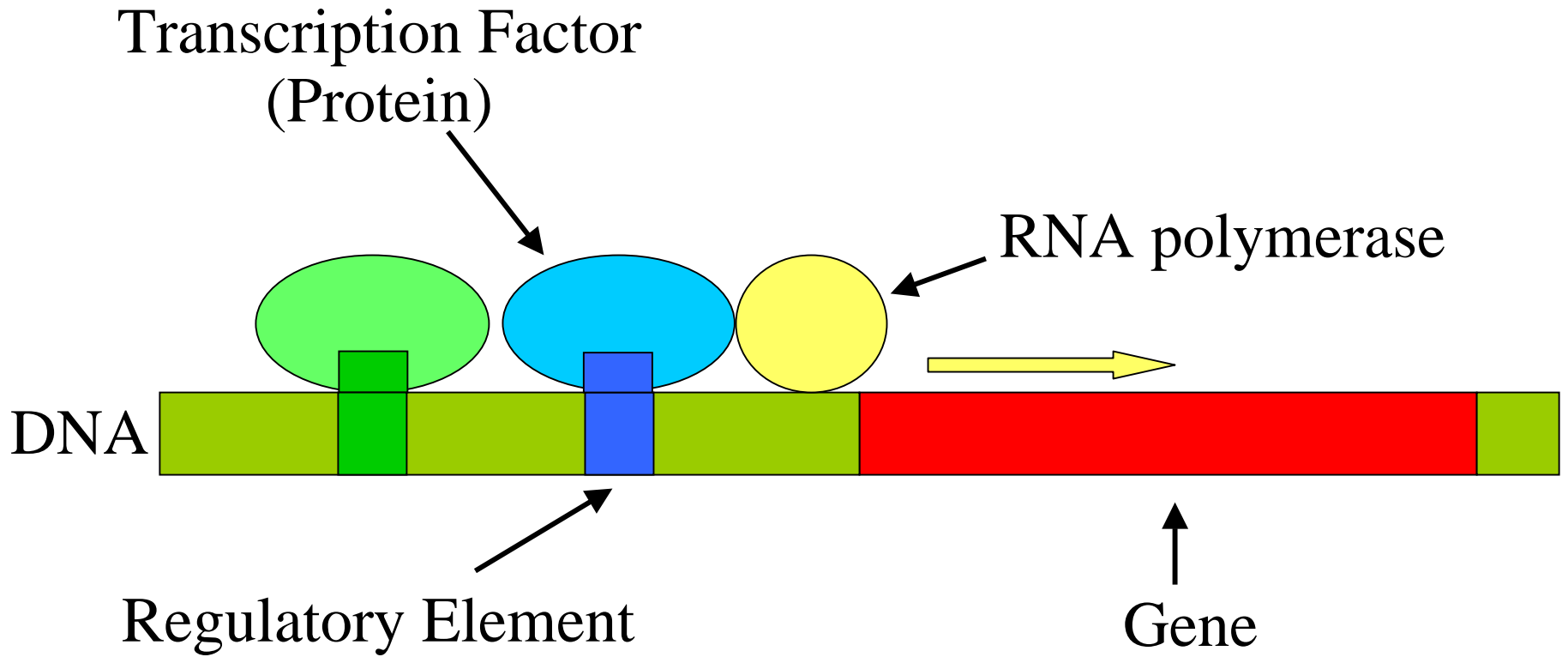


# Regulation of Genes



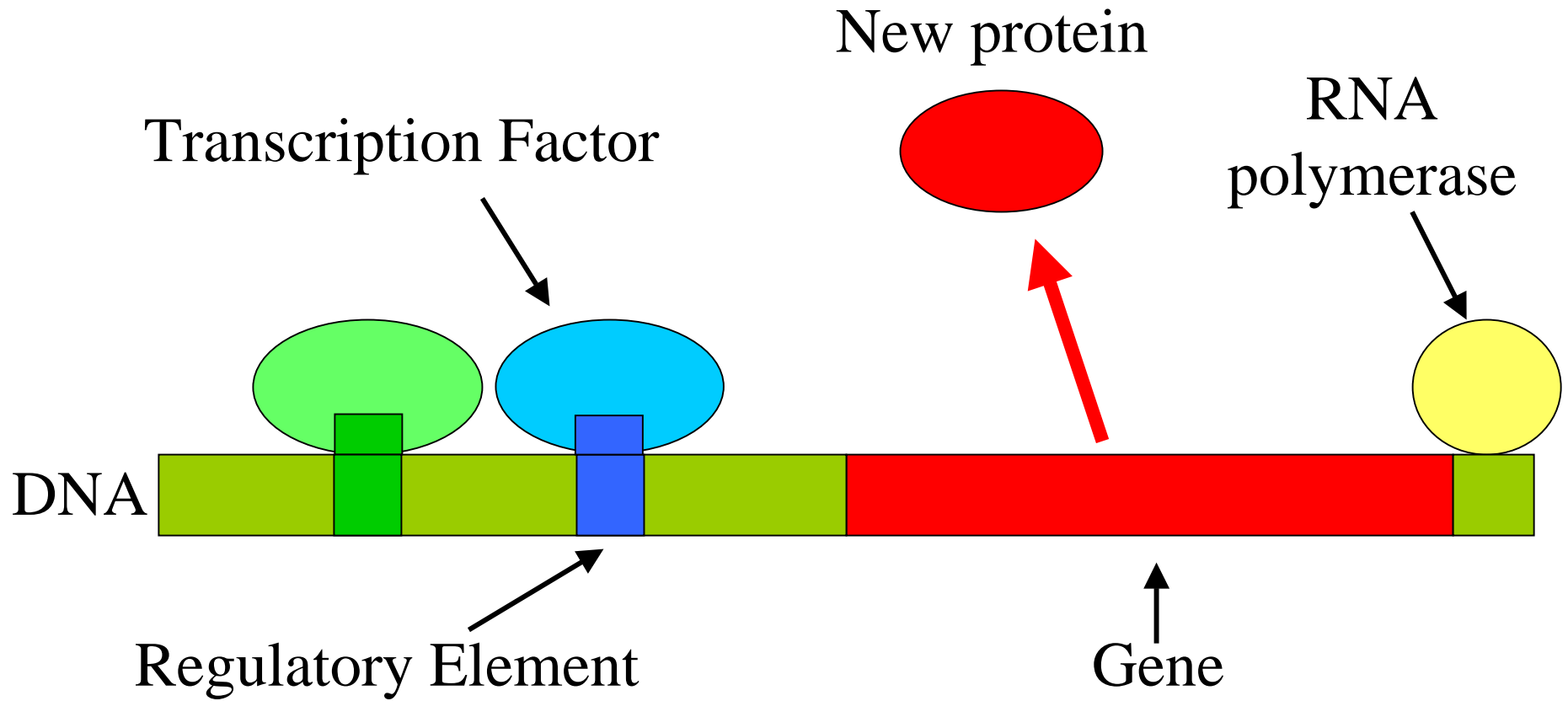


# Regulation of Genes



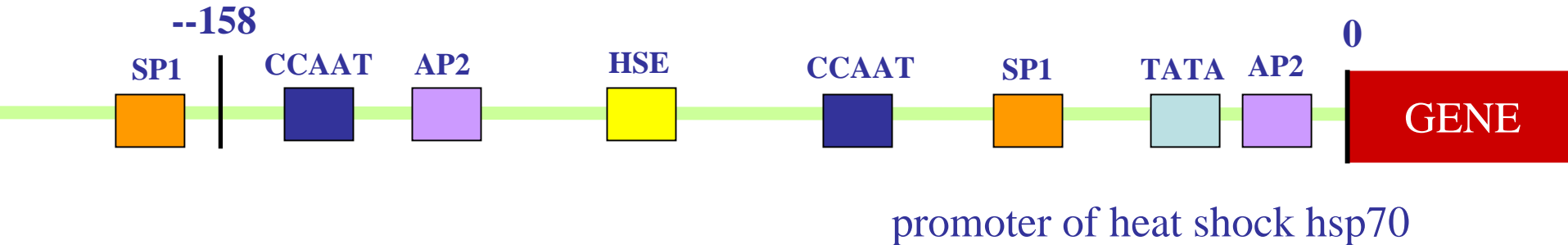


# Regulation of Genes





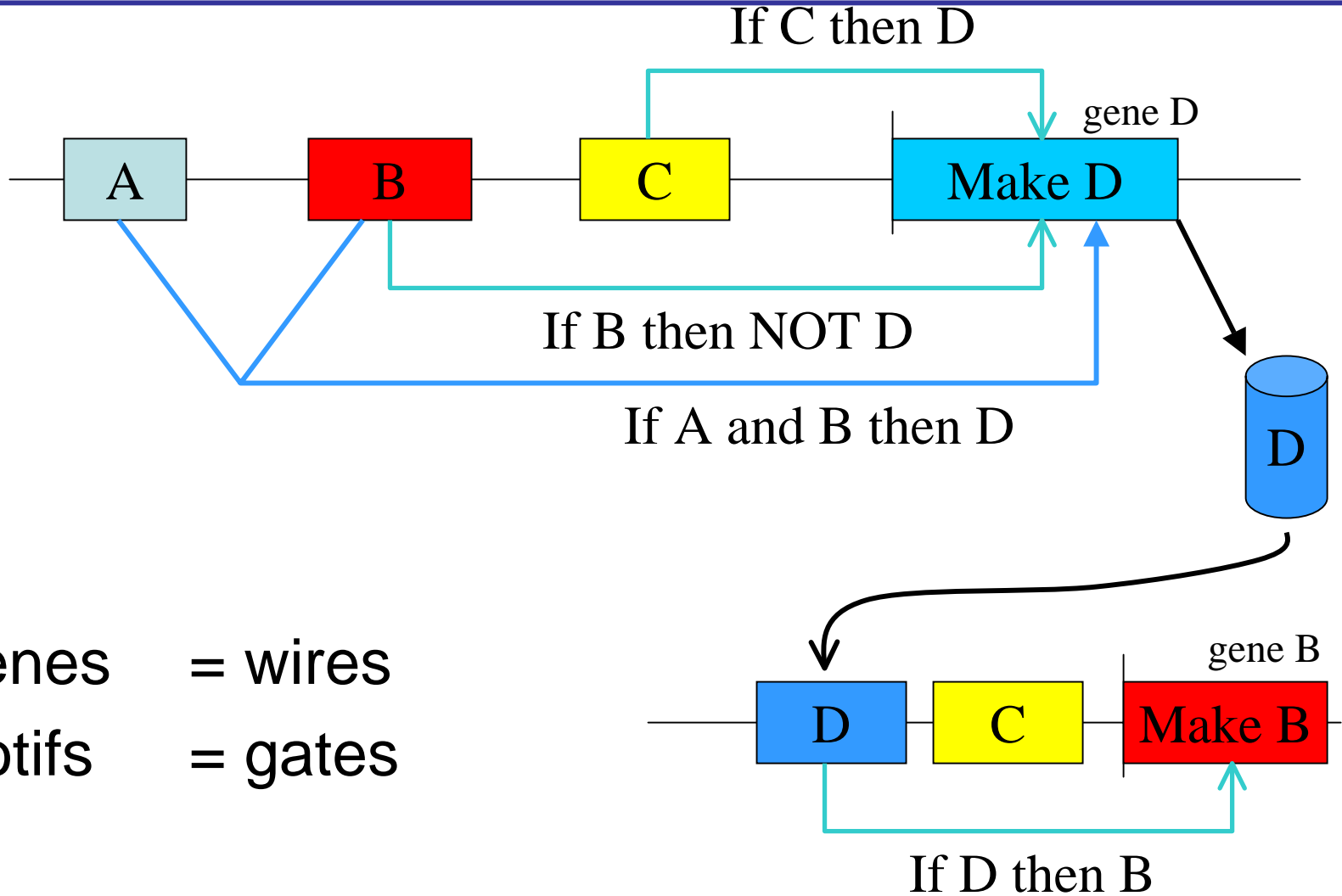
# Example: A Human heat shock protein



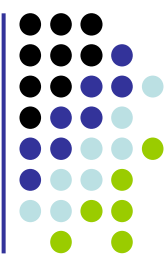
- TATA box: positioning transcription start
- TATA, CCAAT: constitutive transcription
- GRE: glucocorticoid response
- MRE: metal response
- HSE: heat shock element



# The Cell as a Regulatory Network



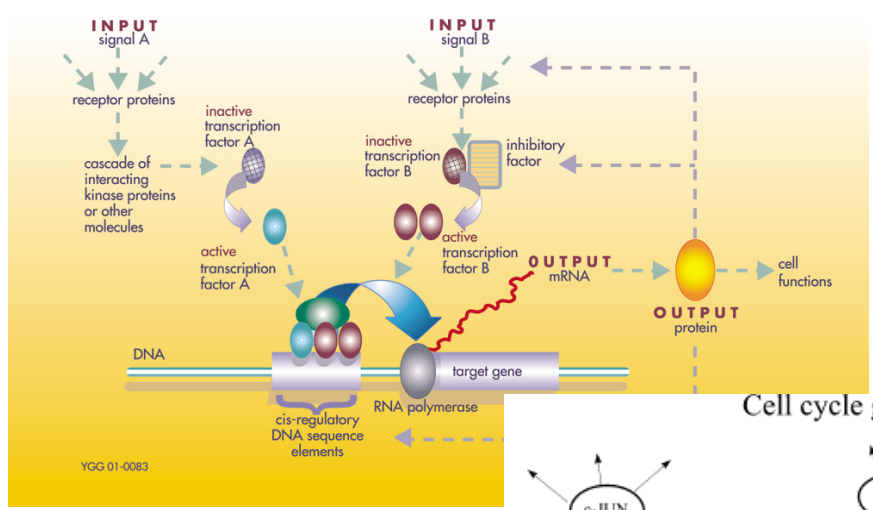
- Genes = wires
- Motifs = gates



# The Cell as a Regulatory Network (2)

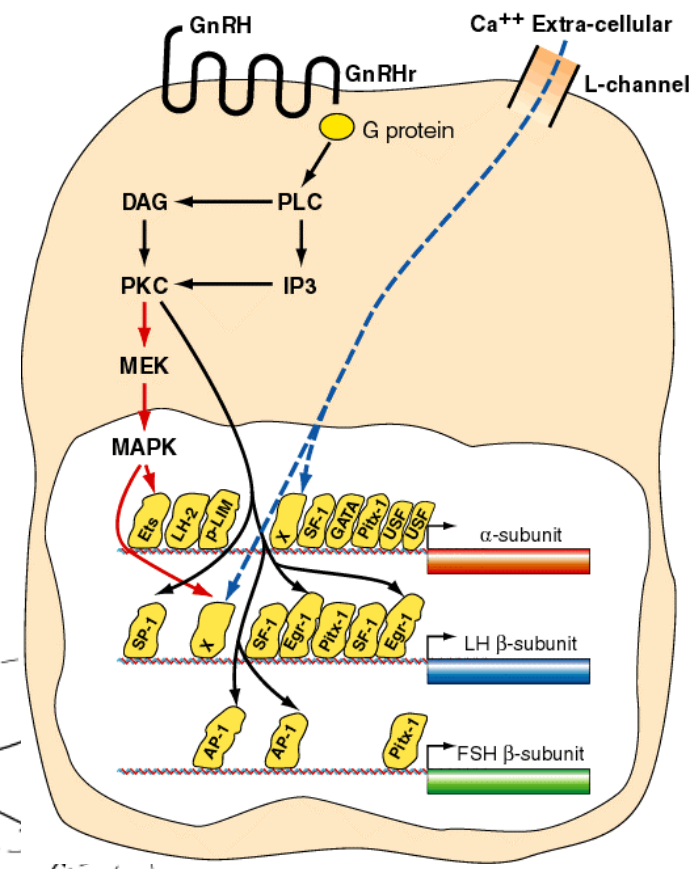
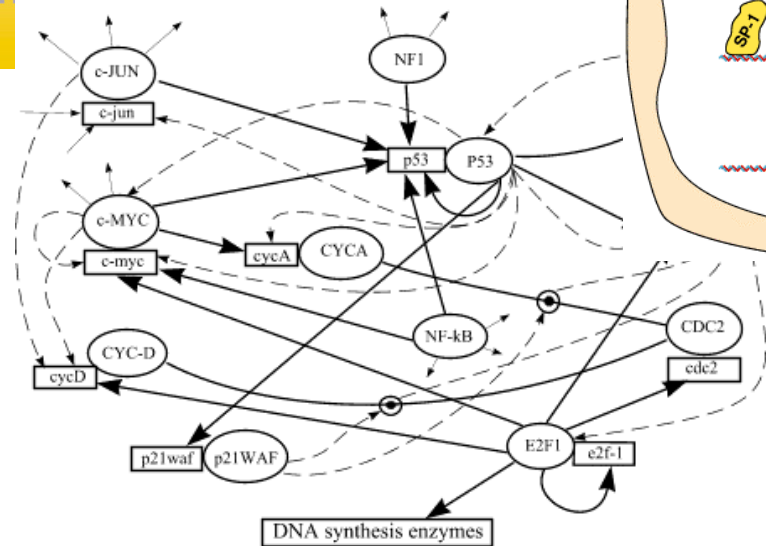
GENOMES to LIFE

## A GENE REGULATORY NETWORK

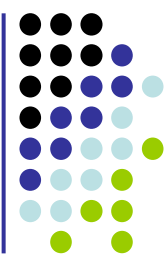


YGG 01-0083

## Cell cycle gene network

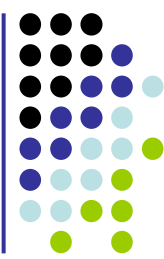






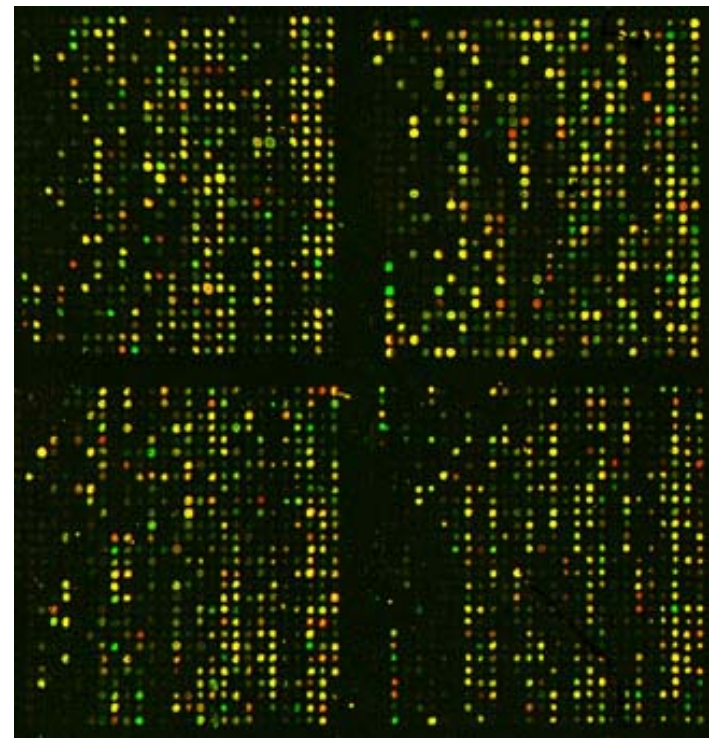
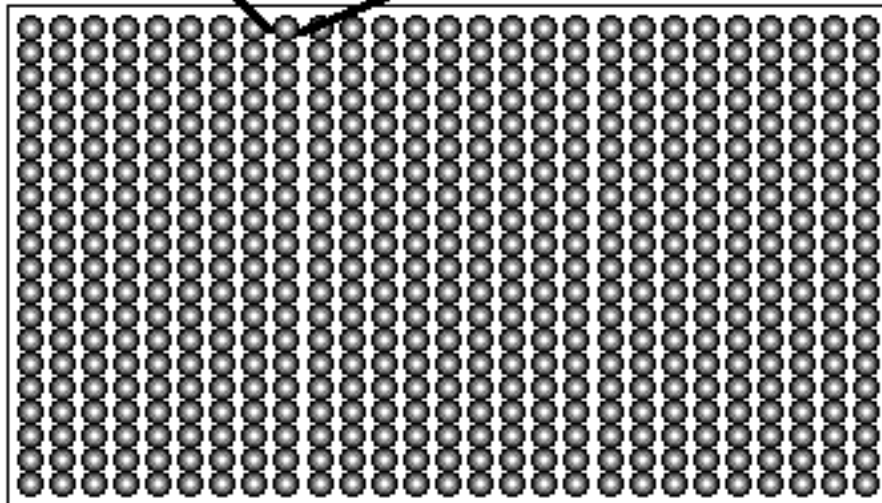
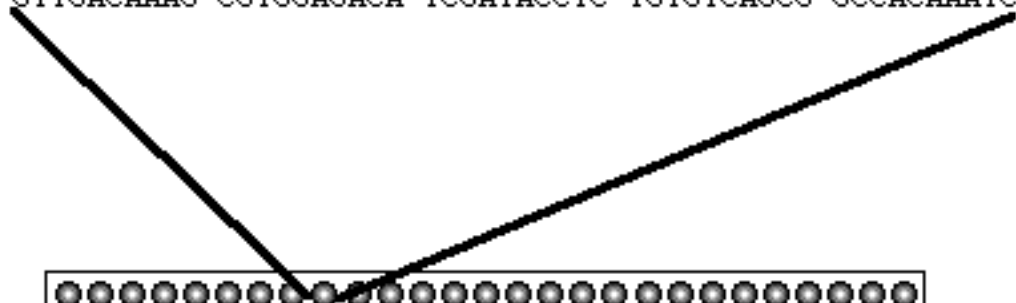
## B. DNA Microarrays

Measuring gene transcription in a high-throughput fashion



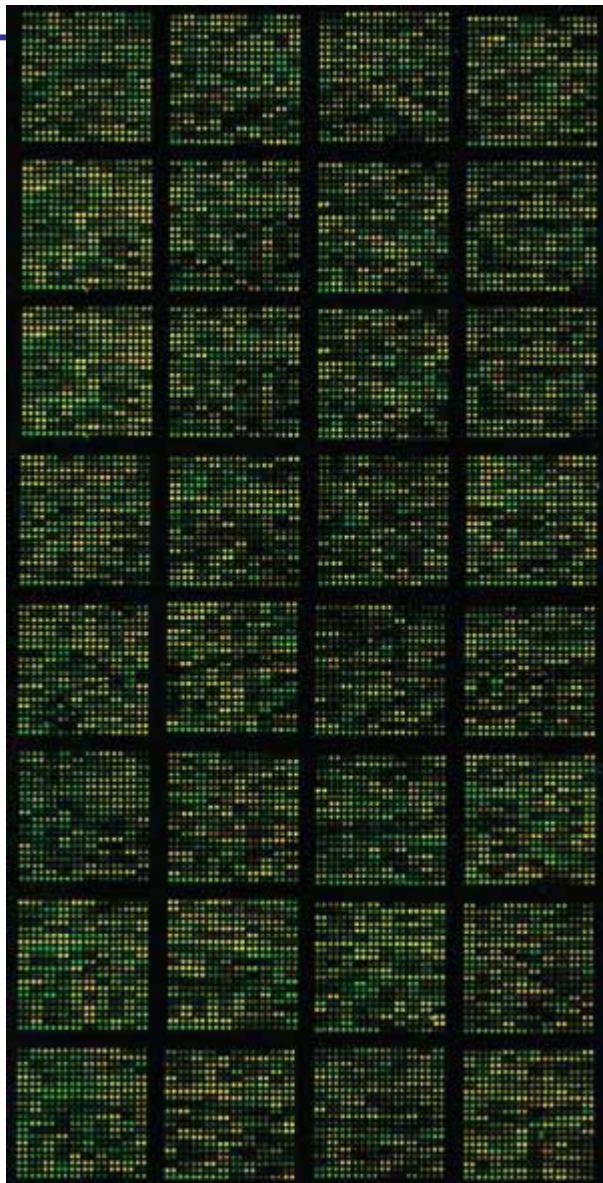
# What is a microarray

TCCTTTCGG	AACGGTTGGC	GTCTGCGCAC	GGCGGTGTGG	GGCATGACAT
GCCGCCCCAG	GAACAACCCC	GACACGGCTT	TAAGCCTCTC	AAATCGCTGT
AGACATCATC	TITACGTGCT	TGGCTTGCCC	TGCCACCATT	AGGGCTGTTC
CCGCGACGAC	TCGCCATPCA	ACCTCAGTCC	TTCGGGTGGA	GCGAGTGGGT
CGCGCGCAAG	GTGCGAATGG	GTGCGCGCA	AAGTGTTGCG	CTGGCTGTAT
TATATGCTGC	CTATAGCGAG	ACTAACGACC	CACACTTTCA	CACAAGGATT
TCCCGCTAAT	GGGTACCTCG	CGTCAGGACC	TTGACGCAAG	CGCGCCTTCG
GTTGGCCCA	AGCTTGCTAG	GACTACTTAT	CTTGAGCTCA	TTTAACATCC
CGGCGCCTCT	CCGGGAGCGG	TCGTGCGGAA	GAAGTCAAAC	CCGGAACGGC
GTTGACAAAAG	CGTGGAGACA	TCGATACCTC	TGTGTCAGCG	GCCACAAATC





## What is a microarray (2)



- A 2D array of DNA sequences from thousands of genes
- Each spot has many copies of same gene
- Allow mRNAs from a sample to hybridize
- Measure number of hybridizations per spot



# How to make a microarray

- Method 1: *DNA microarray* (Stanford)
  - Use PCR to amplify a 1Kb portion of each gene
  - Apply each sample on glass slide
- Method 2: *DNA Chip* (Affymetrix)
  - Grow oligonucleotides (25bp) on glass
  - Several words per gene (choose unique words)

If we know the gene sequences,

Can sample all genes in one experiment!





# Visualization Tools





# Goal of Microarray Experiments

- Measure level of gene expression across many different conditions:
  - Expression Matrix  $M$ :  $\{\text{genes}\} \times \{\text{conditions}\}$ :  
 $M_{ij} = |\text{gene}_i| \text{ in condition}_j$
- Deduce gene function
  - Genes with similar function are expressed under similar conditions
- Deduce gene regulatory networks – **parts and connections**-level description of biology



# Analysis of Microarray Data

- Clustering
  - **Idea:** Groups of genes that share similar function have similar expression patterns
    - Hierarchical clustering
    - k-means
    - Bayesian approaches
    - Projection techniques
      - Principal Component Analysis
      - Independent Component Analysis
- Classification
  - **Idea:** A cell can be in one of several states
    - (Diseased vs. Healthy, Cancer X vs. Cancer Y vs. Normal)
  - Can we train an algorithm to use the gene expression patterns to determine which state a cell is in?
    - Support Vector Machines
    - Decision Trees
    - Neural Networks
    - K-Nearest Neighbors





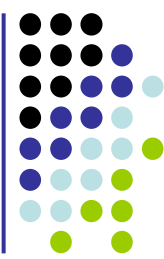
# Hierarchical Agglomerative Clustering

Michael Eisen, 1998

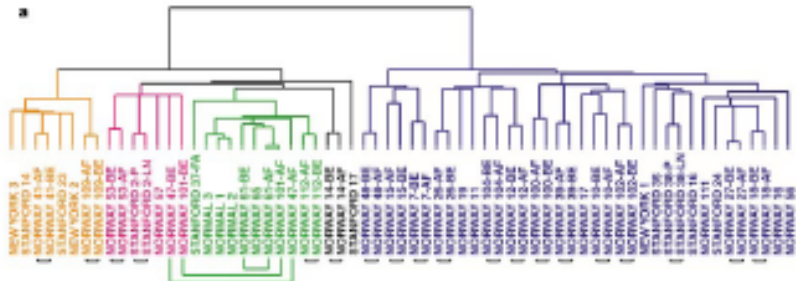
- Hierarchical Agglomerative Clustering
  - Step 1: Similarity score between all pairs of genes
    - Pearson Correlation

$$r = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)S_X S_Y}$$

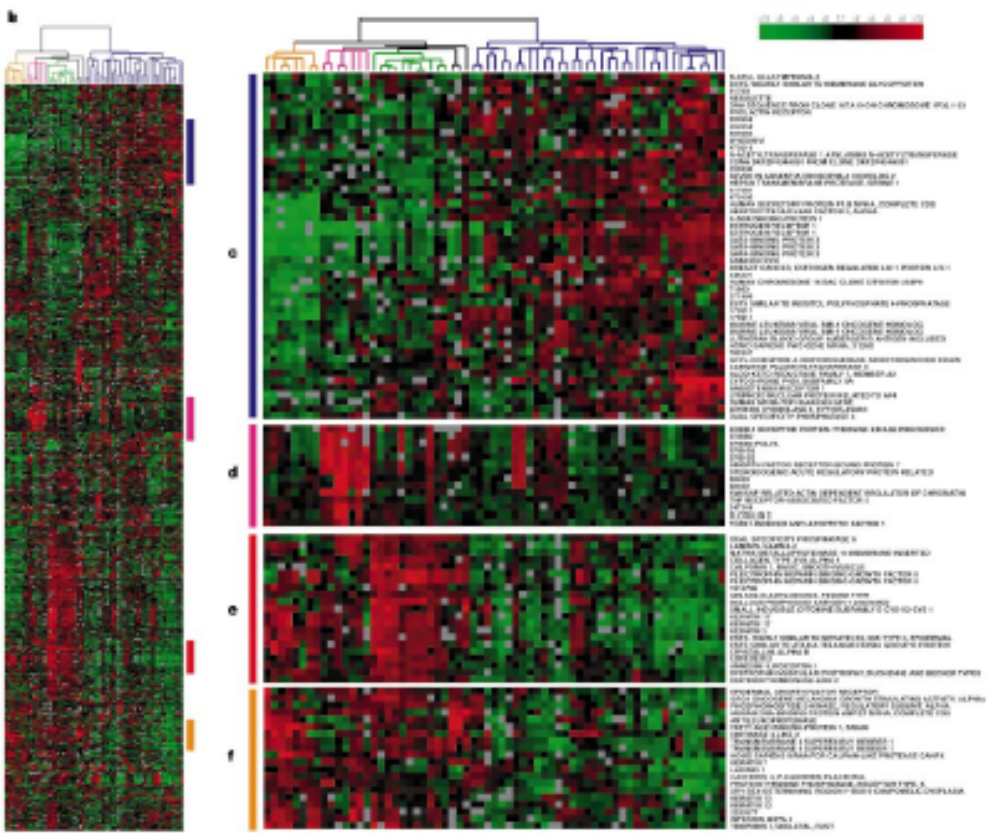
- Step 2: Find the two most similar genes, replace with a node that contains the average
  - Builds a tree of genes
- Step 3: Repeat.
- Can do the same with experiments



# Results of Clustering Gene Expression



- CLUSTER is simple and easy to use
- De facto standard for microarray analysis



Time:  $O(N^2M)$

N: #genes

M: #conditions



# K-Means Clustering Algorithm

- Randomly initialize  $k$  cluster means
- Iterate:
  - Assign each genes to the nearest cluster mean
  - Recompute cluster means
- Stop when clustering converges

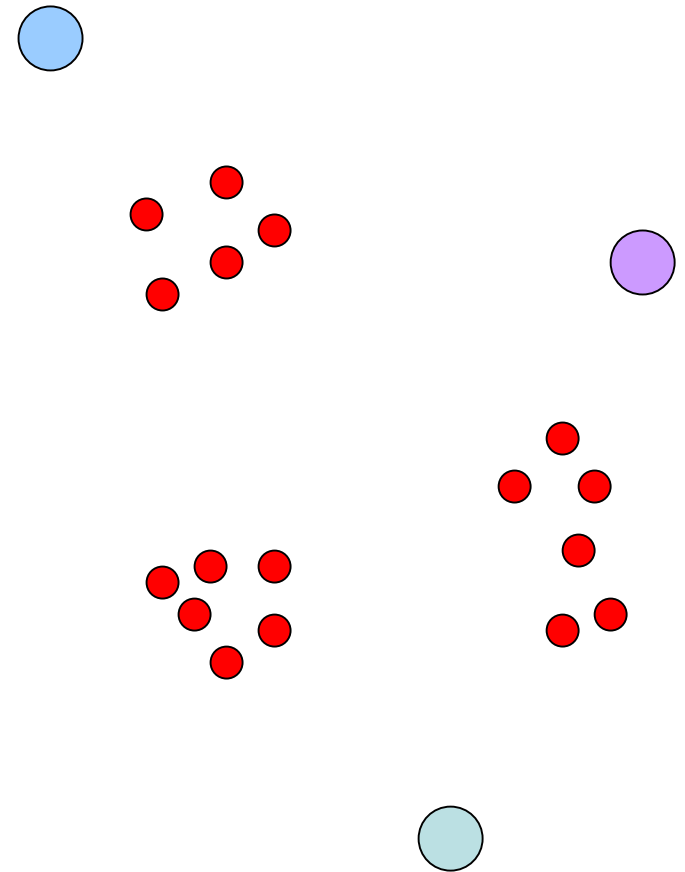
## Notes:

- Really fast
- Genes are partitioned into clusters
- How do we select  $k$ ?



# K-Means Algorithm

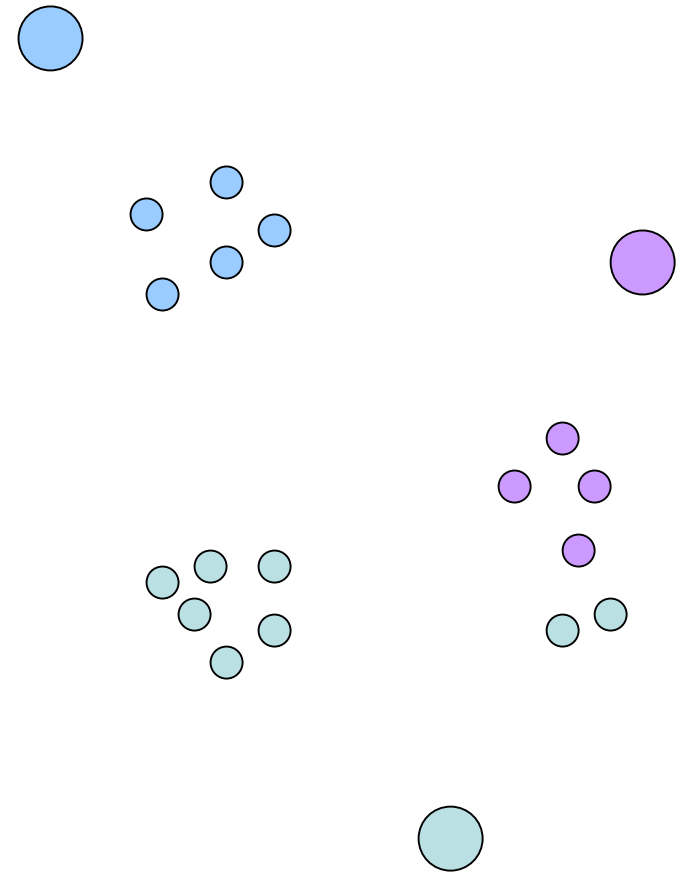
- Randomly Initialize Clusters





# K-Means Algorithm

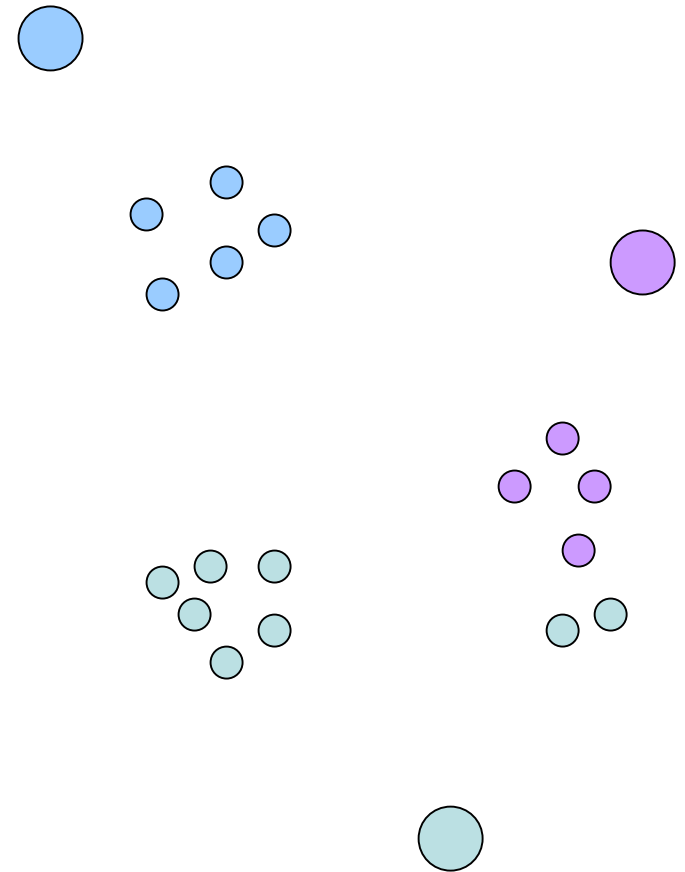
- Assign data points to nearest clusters





# K-Means Algorithm

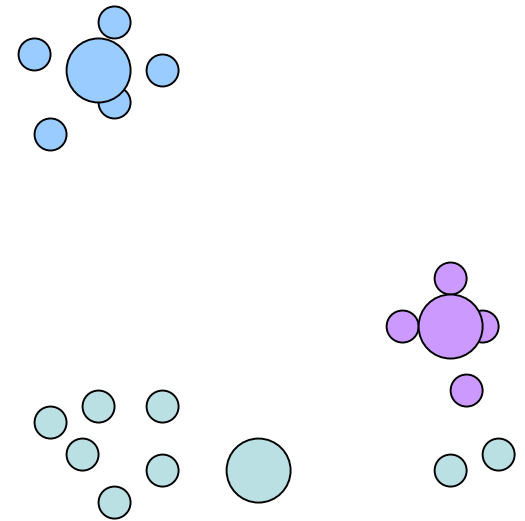
- Recalculate Clusters





# K-Means Algorithm

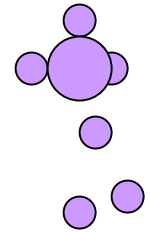
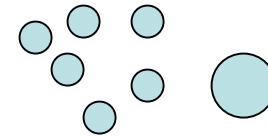
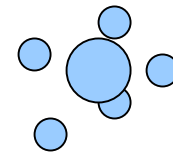
- Recalculate Clusters



# K-Means Algorithm



- Repeat

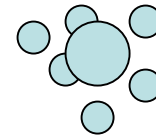
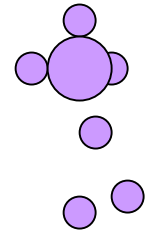
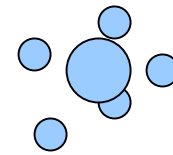




# K-Means Algorithm



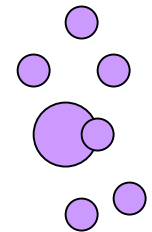
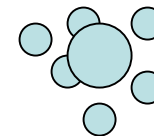
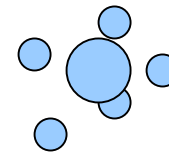
- Repeat





# K-Means Algorithm

- Repeat ... until convergence



Time:  $O(KNM)$   
per iteration

N: #genes  
M: #conditions



# Multiple-pass K-Means clustering

(A Gasch, MB Eisen 2002)

- Each gene can belong to many clusters
- Soft (fuzzy) assignment of genes to clusters
  - Each gene has 1.0 membership units, allocated amongst clusters based on correlation with means
- Cluster means are calculated by taking the weighted average of all the genes in the cluster

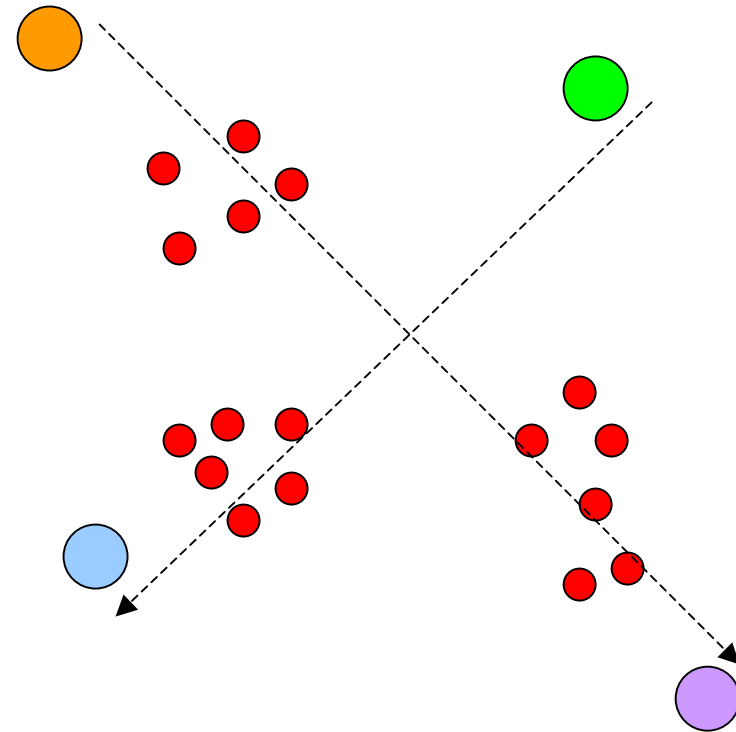
Algorithm:

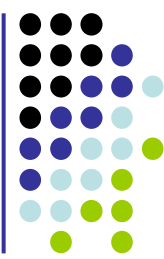
- Use PCA to initialize cluster means
- 3 applications of k-means clustering, find  $k/3$  clusters per application
  - In each application, start with brand new clusters and initializations
- And a few more heuristic tricks



# Initialization

- Use PCA to find a few eigenvectors for initialization
- These features capture the directions of maximum variance
- Must be orthonormal

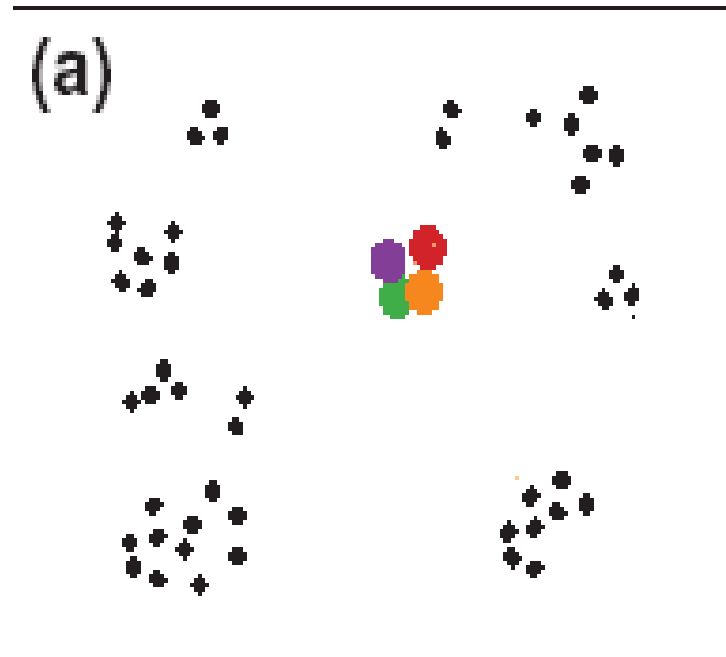


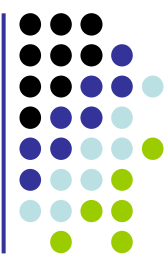


# Example

## Initialization

- $k/3$  centroids defined from  $k/3$  first eigenvectors





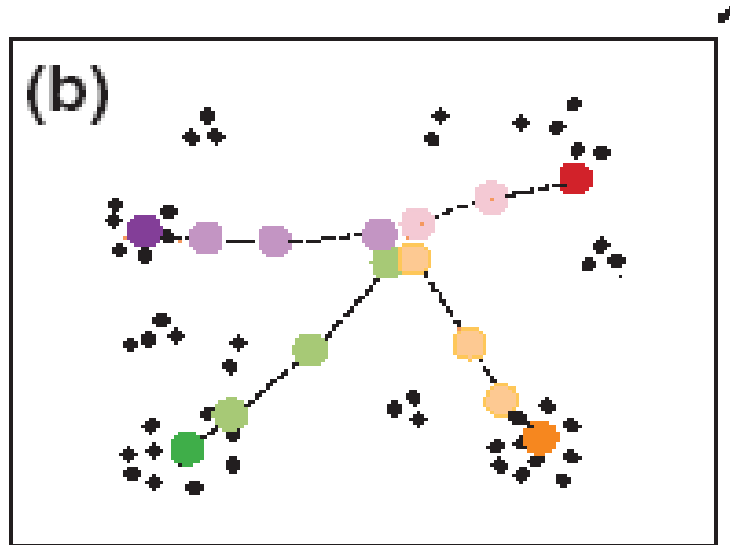
# Example

- First application of clustering

$$J(\mathbf{F}, \mathbf{V}) = \sum_{i=1}^N \sum_{j=1}^K m_{X_i V_j}^2 d_{X_i V_j}^2$$

Objective function to minimize,  $J(\mathbf{F}, \mathbf{V})$

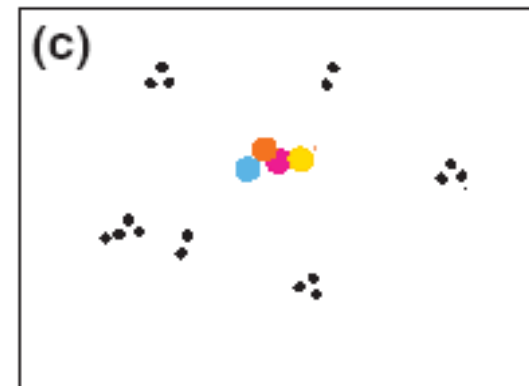
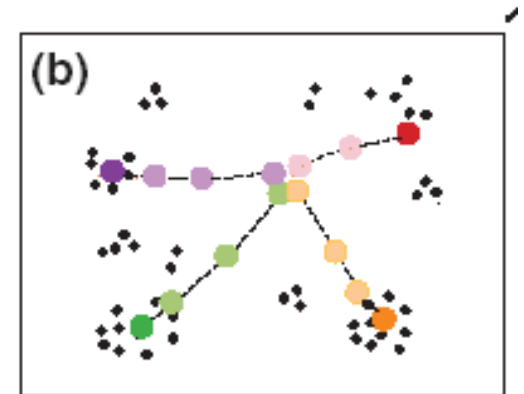
- $\mathbf{X}$  genes
- $\mathbf{F}$  assignment of genes to clusters
- $m_{X_i V_j}$  assign. coeff. of gene  $X_i$  to cluster  $V_j$
- $d_{X_i V_j}$  distance of gene  $X_i$  with centroid  $V_j$





# Iteration of the approach

- Remove genes that have a Pearson Correlation with a particular cluster greater than .7
  - Intuition: These strong signal from these genes has been accounted for
- Repeat

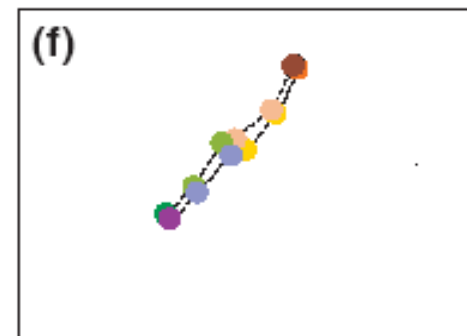
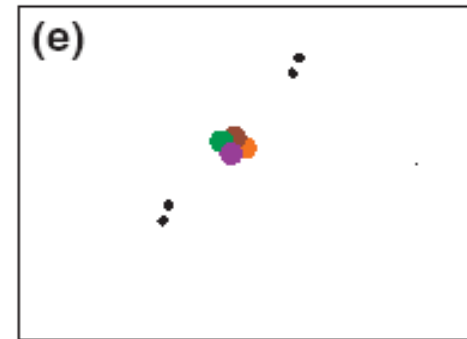




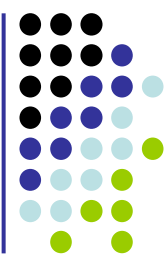
# Removing Duplicate Centroids

- Remove centroids with Pearson correlation  $> 0.9$
- Allows selecting a large initial number of clusters, since duplicates will be removed

3rd clustering cycle



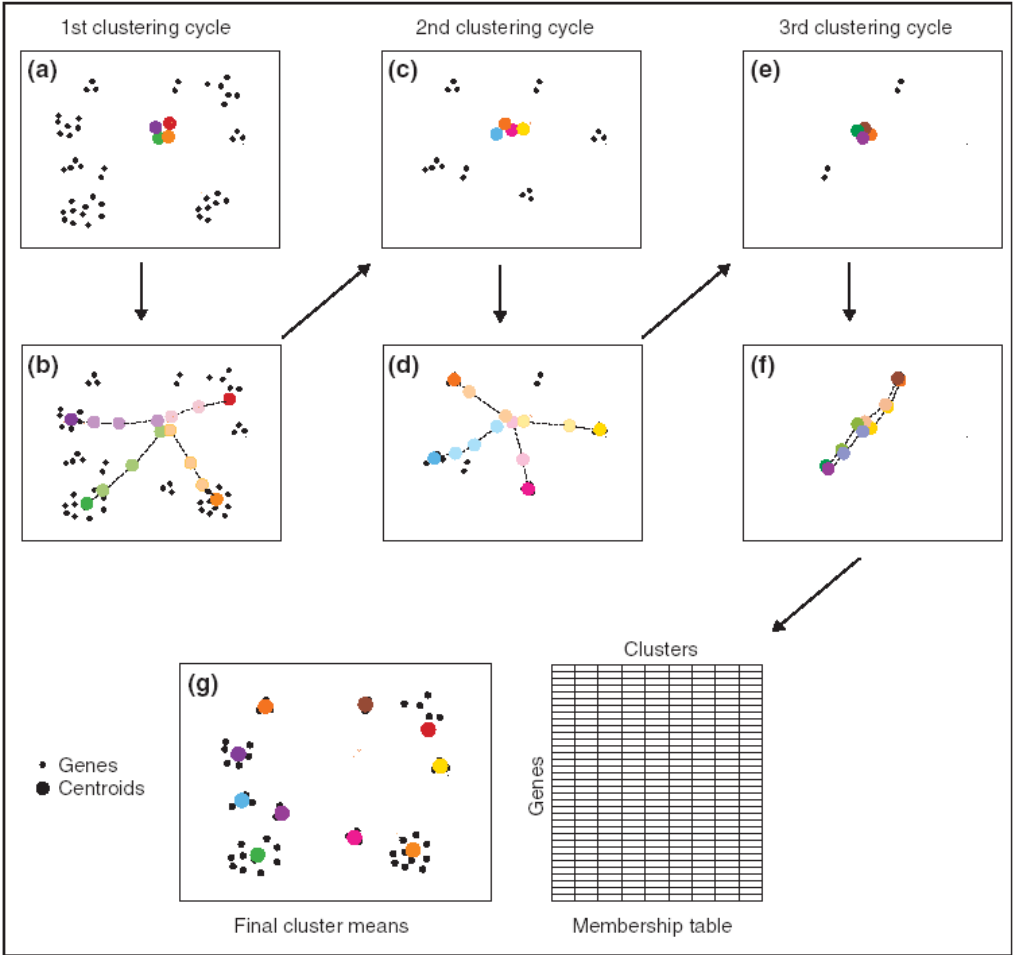




# Repeat 3 times

Output

- 1) Cluster means
- 2) Gene assignments to clusters





## 4. Analysis of Clustered Data

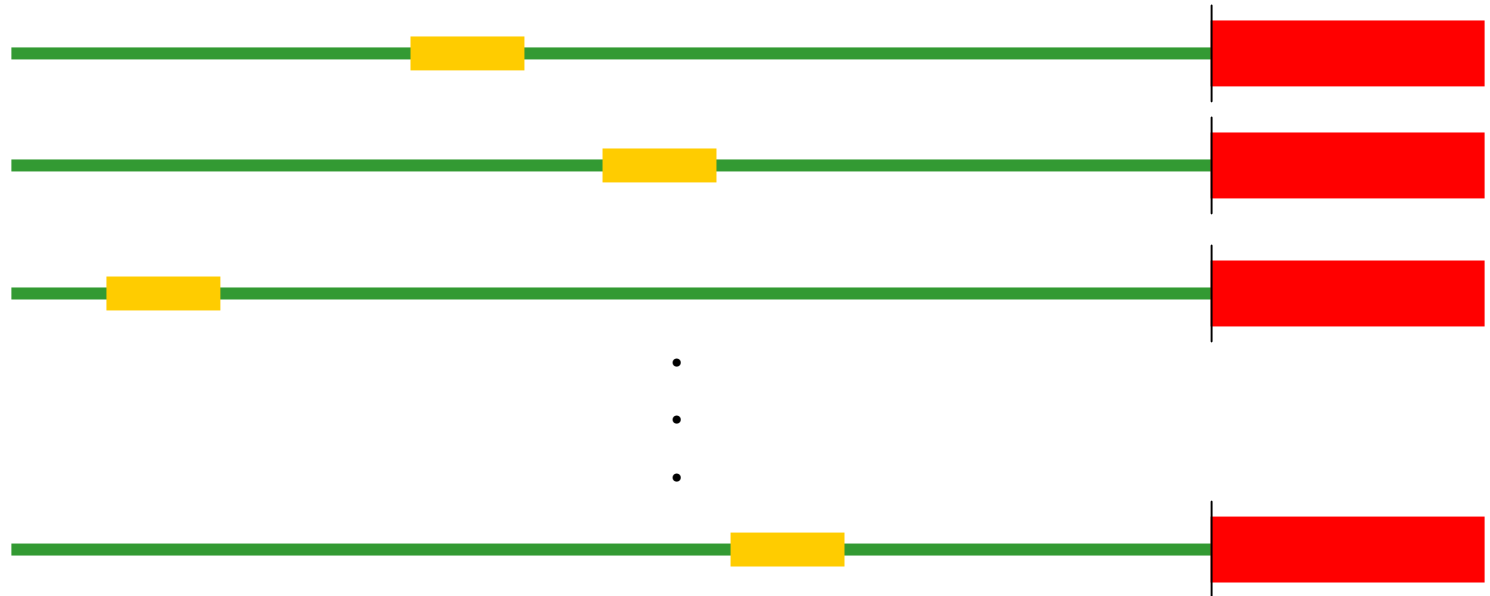
- Statistical Significance of Clusters
  - Gene Ontology/ KEGG databases
- **Regulatory motifs** responsible for common expression
- Regulatory Networks
- Experimental Verification



## C. Finding Regulatory Motifs



# Finding Regulatory Motifs



**Given** a collection of genes with common expression,

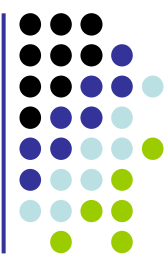
**Find** the TF-binding motif in common



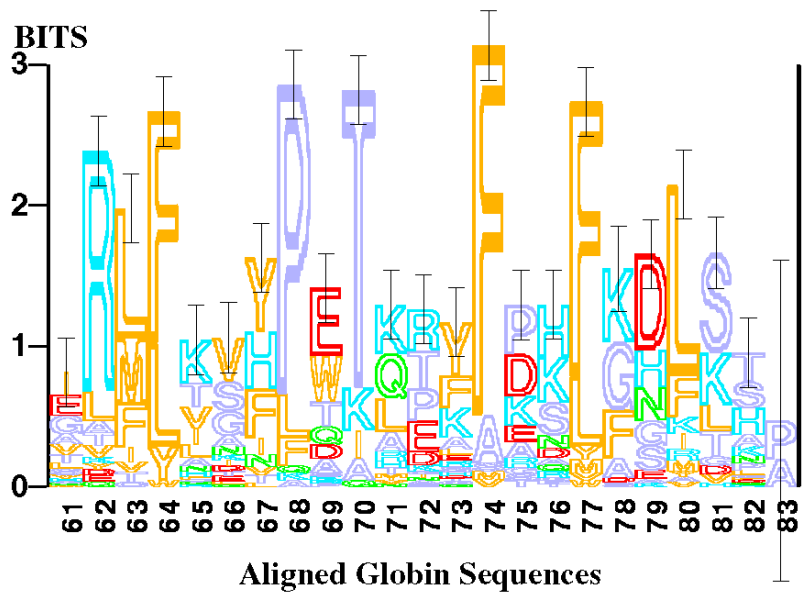
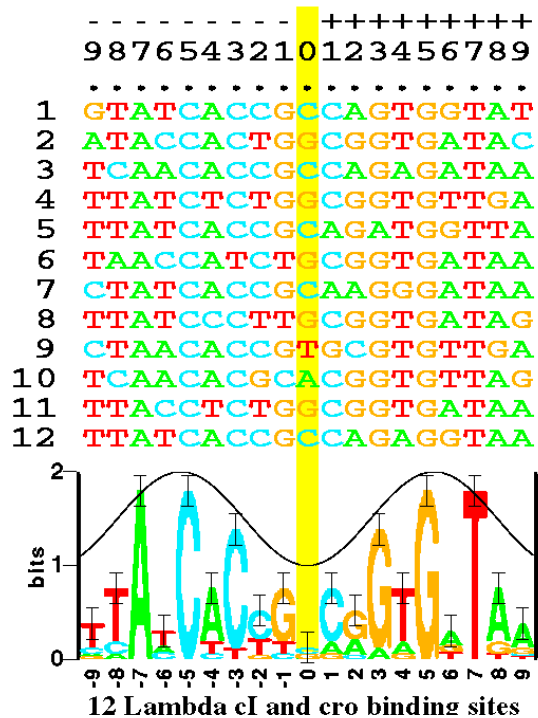
# Characteristics of Regulatory Motifs

ATATAAA TT T  
CTGATA A CAG  
GTGA TCA CA  
AGGGGG ACG CG  
AA AA AA  
TTTAAAT AA AA  
GAAACGTTGCG  
AA TTA A TA  
TTTAA T AA  
GGGACGAG  
AAAATAATTT  
A GA AAAA AA  
T TAA IT  
AA AA AAAAA  
TTT AA AA  
T T T IA AAA  
ATAAT ATTA  
ATTA AAAA TT

- Tiny
- Highly Variable
- ~Constant Size
  - Because a constant-size transcription factor binds
- Often repeated
- Low-complexity-ish



# Sequence Logos



- Information at pos'n  $i$ ,  $H(i)$
- Height of  $x$  at pos'n  $i$ ,  $L(a, i)$ 
  - Examples:
    - $\text{Prob}(A, i) = 1$ ;
    - $A: \frac{1}{2}; C: \frac{1}{4}; G: \frac{1}{4}$ ;

$$= - \sum_{\{\text{letter } a\}} \text{Prob}(a, i) \log_2 \text{Prob}(a, i)$$

$$= \text{Prob}(a, i) (2 - H(i))$$

$$H(i) = 0; L(A, i) = 2$$

$$H(i) = 1.5; L(A, i) = \frac{1}{4}; L(\text{not } T, i) = \frac{1}{4}$$



# Problem Definition

**Given** a collection of promoter sequences  $s_1, \dots, s_N$  of genes with common expression

## Probabilistic

Motif:  $M_{ij}; \quad 1 \leq i \leq W$   
 $1 \leq j \leq 4$

$M_{ij} = \text{Prob}[\text{letter } j, \text{ pos } i]$

**Find** best  $M$ , and positions  $p_1, \dots, p_N$  in sequences

## Combinatorial

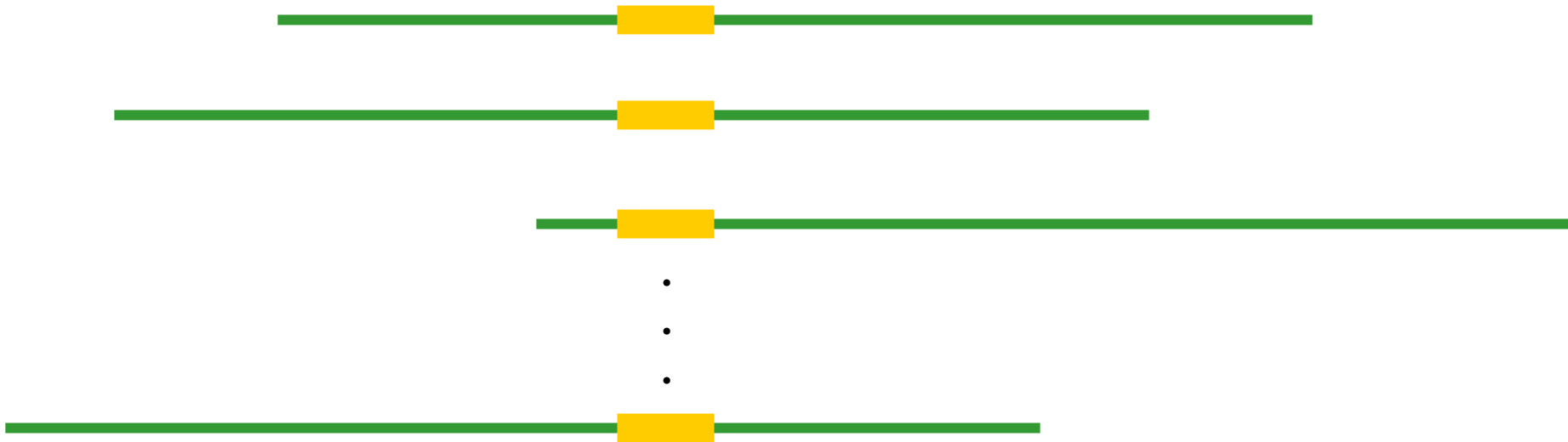
Motif  $M: m_1 \dots m_W$

Some of the  $m_i$ 's blank

**Find**  $M$  that occurs in all  $s_i$  with  $\leq k$  differences



# Essentially a Multiple Local Alignment



- Find “best” multiple local alignment

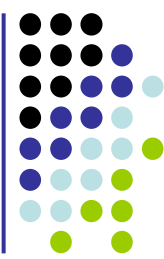
Alignment score defined differently in  
probabilistic/combinatorial cases





# Algorithms

- Probabilistic
  1. Expectation Maximization:  
MEME
  2. Gibbs Sampling:  
AlignACE, BioProspector
- Exhaustive  
CONSENSUS, TEIRESIAS, SP-STAR, MDscan



# Discrete Approaches to Motif Finding



# Discrete Formulations

Given sequences  $S = \{x^1, \dots, x^n\}$

- A motif  $W$  is a consensus string  $w_1 \dots w_K$
- **Find** motif  $W^*$  with “best” match to  $x^1, \dots, x^n$

Definition of “best”:

$d(W, x^i) = \min$  hamming dist. between  $W$  and a word in  $x^i$

$$d(W, S) = \sum_i d(W, x^i)$$