

CAP 5510: Introduction to Bioinformatics

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How to Represent Patterns

- Consensus sequence
- Alignments
- LOGO format
- Frequency Matrices
- Weight Matrices (Profiles, PSSMs, PWMs)

Pattern Representations

□ Consensus sequences

[Pribnow, 1975]

TACGAT

TATAAT

TATAAT

GATACT

TATGAT

TATGTT

TATAAT Consensus

TATRNT Consensus
w/ IUPAC

TATAAT Multi-level
G CGC Consensus
T

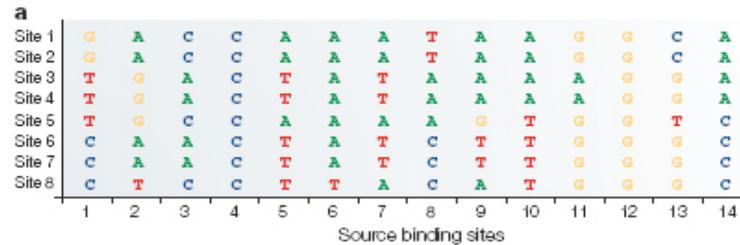
Needs Alignment

Pattern Representations

- Consensus sequences
- Weight Matrices (Profiles, PSSMs)
 - Frequency Counts
 - Relative Frequency Measures
 - Normalized Measures
 - Log-transformed Measures
 - Information content
 - "Logo" technique
 - HMMs

Pattern Representation: Weight Matrix

Alignment



Consensus



Frequencies

c Position frequency matrix (PFM)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
A	0	4	4	0	3	7	4	3	5	4	2	0	0	4
C	3	0	4	8	0	0	0	3	0	0	0	0	2	4
G	2	3	0	0	0	0	0	0	1	0	6	8	5	0
T	3	1	0	0	5	1	4	2	2	4	0	0	1	0

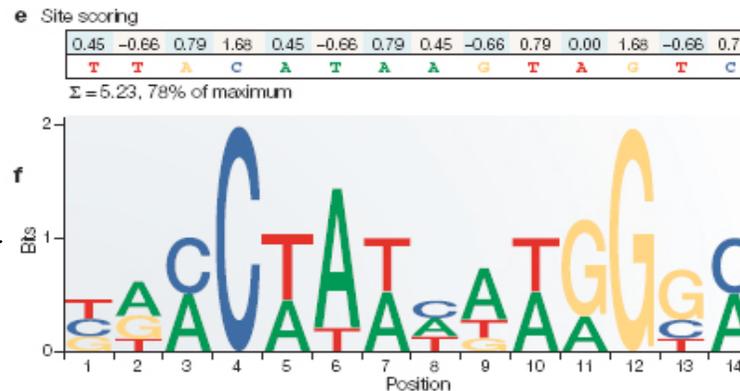
Scoring a sequence against a profile

Profile/
PSSM/PWM

d Position weight matrix (PWM)

A	-1.93	0.79	0.79	-1.93	0.45	1.50	0.79	0.45	1.07	0.79	0.00	-1.93	-1.93	0.79	
C	0.45	-1.93	0.79	1.68	-1.93	-1.93	-1.93	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	0.00	0.79
G	0.00	0.45	-1.93	-1.93	-1.93	-1.93	-1.93	-1.93	0.66	-1.93	1.30	1.68	1.07	-1.93	
T	0.15	0.66	-1.93	-1.93	1.07	0.66	0.79	0.00	0.00	0.79	-1.93	-1.93	-0.66	-1.93	

Visualizing a profile



[Wasserman, Sandelin, Nat Genet, 2004]

Formulae

- Prob of char **b** in position **i**:

$$p(b, i) = \frac{f_{b,i}}{N}$$

Frequency

Sequences

- Corrected prob:

$$P(b, i) = \frac{f_{b,i} + s(b)}{N + \sum_{a \in \mathbf{A}} s(a)}$$

PseudoCount

- Weight matrix entry:

- Information content of position of **i**:

$$W_{b,i} = \log_2 \frac{P(b, i)}{BP(b)}$$

Background Frequency

$$D_i = 2 + \sum_b P(b, i) \log_2 P(b, i)$$

[Wasserman, Sandelin, Nat Genet, 2004]

Statistical Evaluation Fundamentals

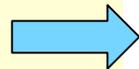
- Probability of finding a sequence w in some position of a DNA/protein sequence (assuming independence at each position)

- $\Pr(w_i) = \text{BP}(b)$ [Background Frequency]

$$\Pr(w) = \prod_{i=1}^m \Pr(w_i)$$

Statistical Evaluation

- **Z-score** of a motif with a certain frequency:

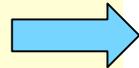


$$z(w) = \frac{Obs(w) - Exp(w)}{\sqrt{Var(w)}}$$

- **Information Content** or Relative Entropy of an alignment or profile:

- **Maximum a Posteriori (MAP) Score:**

- **Model Vs Background Score:**



$$IC(M) = \sum_{i=1}^4 \sum_{j=1}^m m_{i,j} \log \frac{m_{i,j}}{b_i}$$



$$MAP(M) = - \sum_{i=1}^4 \sum_{j=1}^m n_{i,j} \log \frac{m_{i,j}}{b_i}$$



$$L(w) = \frac{\Pr(w | M)}{\Pr(w | Bg)} = \prod_{j=1}^m \frac{m_{i,j}}{b_i}$$

Pattern Discovery in Protein Sequences

Motifs are combinations of secondary structures in proteins with a specific **structure** and a specific **function**. They are also called **super-secondary structures**.

Examples: Helix-Turn-Helix, Zinc-finger, Homeobox domain, Hairpin-beta motif, Calcium-binding motif, Beta-alpha-beta motif, Coiled-coil motifs.

Several motifs may combine to form **domains**.

- Serine proteinase domain, Kringle domain, calcium-binding domain, homeobox domain.

Motif Detection

Profile Method

- If many examples of the motif are known, then

- **Training**: build a **Profile** and compute a **threshold**

- **Testing**: **score** against profile

Combinatorial Pattern Discovery Methods

Gibbs Sampling

Expectation Method

HMM

How to evaluate these methods?

- ❑ Calculate TP, FP, TN, FN
- ❑ Compute **sensitivity** fraction of known sites predicted, **specificity**, and more.
 - **Sensitivity** = $TP / (TP + FN)$
 - **Specificity** = $TN / (TN + FN)$
 - Positive Predictive Value = $TP / (TP + FP)$
 - Performance Coefficient = $TP / (TP + FN + FP)$
 - Correlation Coefficient =

Motif Detection Problem

Input:

Set, S , of known (aligned) examples of a motif M ,
A new protein sequence, P .

Output:

Does P have a copy of the motif M ?

Example: Zinc Finger Motif

...**YK**₃**CGL**₆**CERS****F**VEKSAL**S**R**H**ORV**H**KN...

Input:

Database, D , of known protein sequences,
A new protein sequence, P .

Output:

What interesting patterns from D
are present in P ?

Supervised Pattern Discovery

□ Input: Alignment of known motifs, and
Query sequence

Output: Is the query sequence a motif?

● Profile Method [Gribskov et al., 1996]

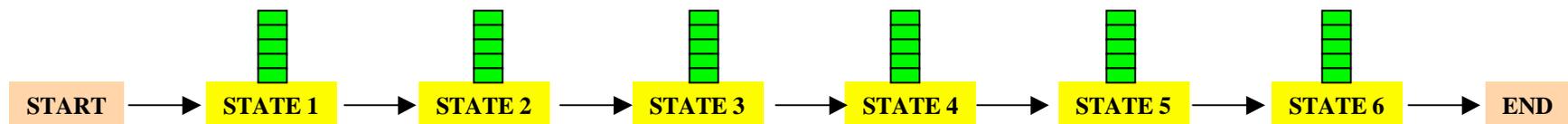
- Build a **profile** from the alignment and **score** query sequence against the profile to decide if it "fits the profile".
- Need to pick a **threshold** score.

● Enumerative/Combinatorial Methods

Profile HMMs

PROFILE METHOD, [M. Gribskov et al., '90]

Location in Seq.	Sequence						Protein Name
	1	2	3	4	5	6	
14	G	V	S	A	S	A	Ka RbtR
32	G	V	S	E	M	T	Ec DeoR
33	G	V	S	P	G	T	Ec RpoD
76	G	A	G	I	A	T	Ec TrpR
178	G	C	S	R	E	T	Ec CAP
205	C	L	S	P	S	R	Ec AraC
210	C	L	S	P	S	R	St AraC
13	G	V	N	K	E	T	Br MerR



Combinatorial Method: GYM

Pattern Generation:

Aligned Motif
Examples

Pattern Generator

Motif Detection:

New Protein
Sequence

Motif Detector

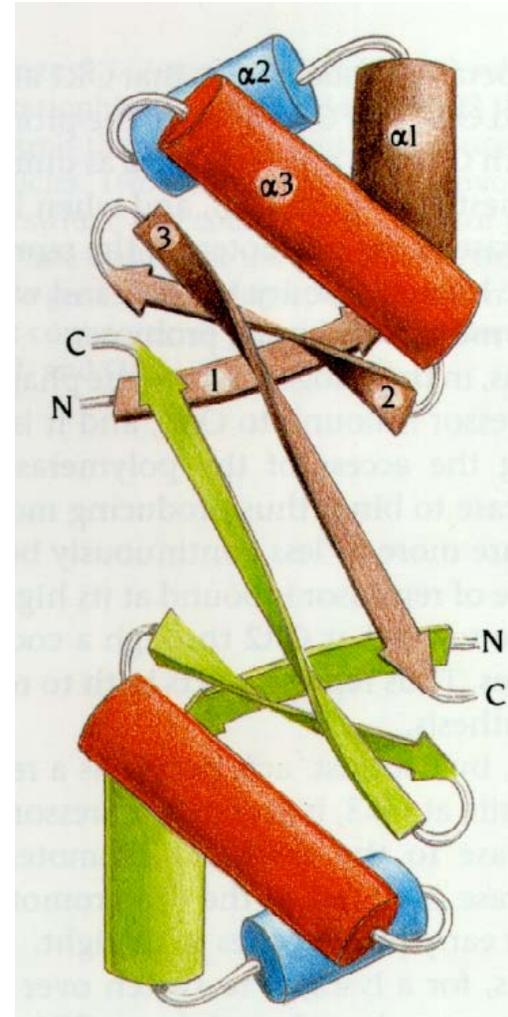
Detection
Results

Pattern
Dictionary

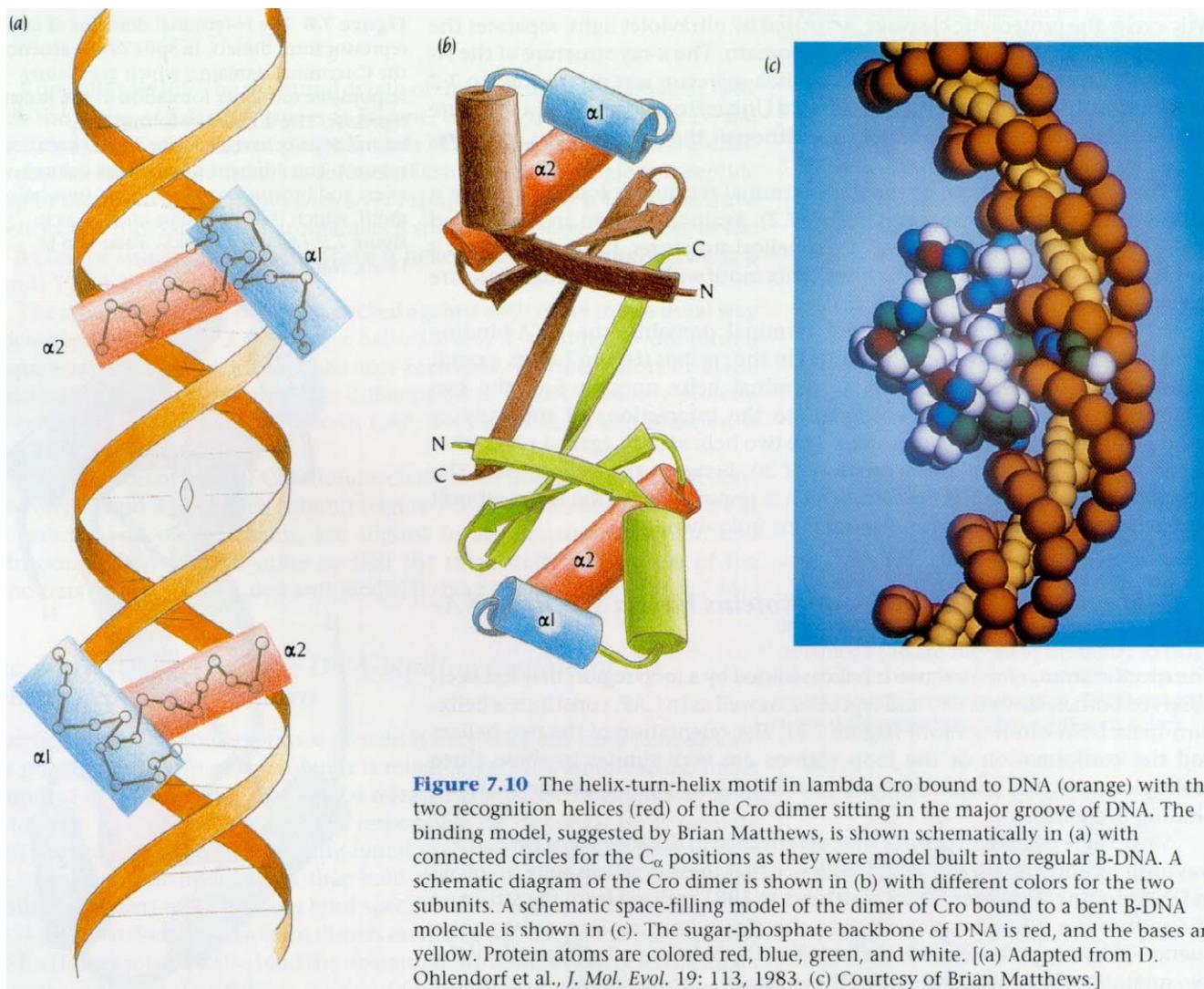
[Narasimhan, Bu, Wang, Xu, Yang, Mathee, J Comput Biol, 2002]

Helix-Turn-Helix Motifs

- Structure
 - 3-helix complex
 - Length: 22 amino acids
 - Turn angle
- Function
 - Gene regulation by binding to DNA



DNA Binding at HTH Motif



2/26/08

17

HTH Motifs: Examples

<i>Loc</i>	<i>Protein Name</i>	<i>Helix 2</i>									<i>Turn</i>				<i>Helix 3</i>								
		-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
14	Cro	F	G	Q	E	K	T	A	K	D	L	G	V	Y	Q	S	A	I	N	K	A	I	H
16	434 Cro	M	T	Q	T	E	L	A	T	K	A	G	V	K	Q	Q	S	I	Q	L	I	E	A
11	P22 Cro	G	T	Q	R	A	V	A	K	A	L	G	I	S	D	A	A	V	S	Q	W	K	E
31	Rep	L	S	Q	E	S	V	A	D	K	M	G	M	G	Q	S	G	V	G	A	L	F	N
16	434 Rep	L	N	Q	A	E	L	A	Q	K	V	G	T	T	Q	Q	S	I	E	Q	L	E	N
19	P22 Rep	I	R	Q	A	A	L	G	K	M	V	G	V	S	N	V	A	I	S	Q	W	E	R
24	CII	L	G	T	E	K	T	A	E	A	V	G	V	D	K	S	Q	I	S	R	W	K	R
4	LacR	V	T	L	Y	D	V	A	E	Y	A	G	V	S	Y	Q	T	V	S	R	V	V	N
167	CAP	I	T	R	Q	E	I	G	Q	I	V	G	C	S	R	E	T	V	G	R	I	L	K
66	TrpR	M	S	Q	R	E	L	K	N	E	L	G	A	G	I	A	T	I	T	R	G	S	N
22	BlaA Pv	L	N	F	T	K	A	A	L	E	L	Y	V	T	Q	G	A	V	S	Q	Q	V	R
23	TrpI Ps	N	S	V	S	Q	A	A	E	Q	L	H	V	T	H	G	A	V	S	R	Q	L	K

Combinatorial Method: GYM

- ❑ **Combinations of residues** in specific locations (may not be contiguous) contribute towards stabilizing a structure.
- ❑ Some **reinforcing** combinations are relatively rare.
- ❑ GYM algorithm is inspired by the APriori algorithm [**Agrawal et al., 1996**]

[Narasimhan, Bu, Wang, Xu, Yang, Mathee, J Comput Biol, 2002]

Patterns

Loc	Protein Name	Helix 2									Turn				Helix 3								
		-1	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
14	Cro	F	G	Q	E	K	T	A	K	D	L	G	V	Y	Q	S	A	I	N	K	A	I	H
16	434 Cro	M	T	Q	T	E	L	A	T	K	A	G	V	K	Q	Q	S	I	Q	L	I	E	A
11	P22 Cro	G	T	Q	R	A	V	A	K	A	L	G	I	S	D	A	A	V	S	Q	W	K	E
31	Rep	L	S	Q	E	S	V	A	D	K	M	G	M	G	Q	S	G	V	G	A	L	F	N
16	434 Rep	L	N	Q	A	E	L	A	Q	K	V	G	T	T	Q	Q	S	I	E	Q	L	E	N
19	P22 Rep	I	R	Q	A	A	L	G	K	M	V	G	V	S	N	V	A	I	S	Q	W	E	R
24	CII	L	G	T	E	K	T	A	E	A	V	G	V	D	K	S	Q	I	S	R	W	K	R
4	LacR	V	T	L	Y	D	V	A	E	Y	A	G	V	S	Y	Q	T	V	S	R	V	V	N
167	CAP	I	T	R	Q	E	I	G	Q	I	V	G	C	S	R	E	T	V	G	R	I	L	K
66	TrpR	M	S	Q	R	E	L	K	N	E	L	G	A	G	I	A	T	I	T	R	G	S	N
22	BlaA Pv	L	N	F	T	K	A	A	L	E	L	Y	V	T	Q	G	A	V	S	Q	Q	V	R
23	TrpI Ps	N	S	V	S	Q	A	A	E	Q	L	H	V	T	H	G	A	V	S	R	Q	L	K

● Q1 G9 N20

● A5 G9 V10 I15

Pattern Mining Algorithm

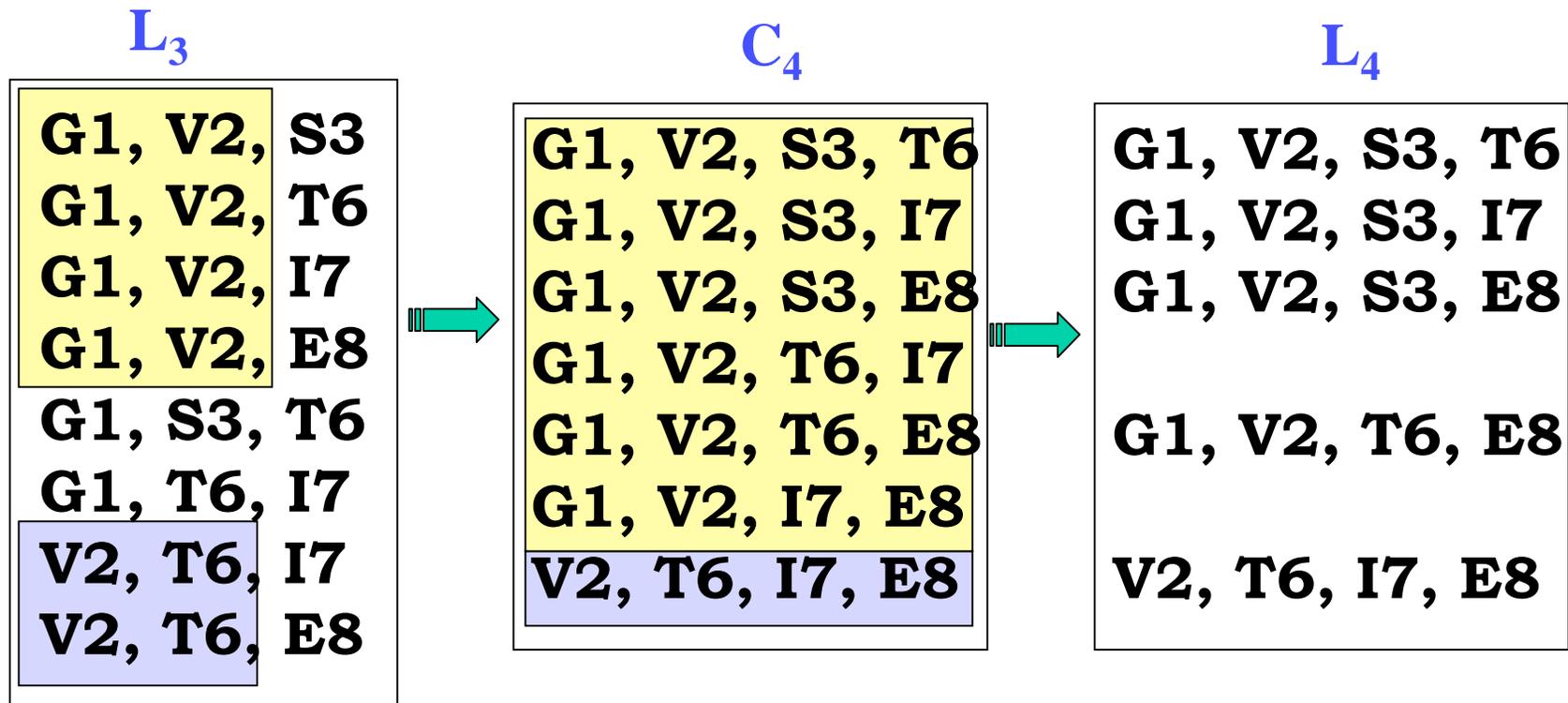
Algorithm **Pattern-Mining**

Input: Motif length m , support threshold T ,
list of aligned motifs M .

Output: Dictionary L of frequent patterns.

1. $L_1 :=$ All frequent patterns of length 1
2. **for** $i = 2$ **to** m **do**
3. $C_i :=$ **Candidates**(L_{i-1})
4. $L_i :=$ Frequent candidates from C_i
5. **if** ($|L_i| \leq 1$) **then**
6. **return** L as the union of all L_j , $j \leq i$.

Candidates Function



Motif Detection Algorithm

Algorithm **Motif-Detection**

Input : Motif length m ,
threshold score T ,
pattern dictionary L ,
and input protein sequence $P[1..n]$.

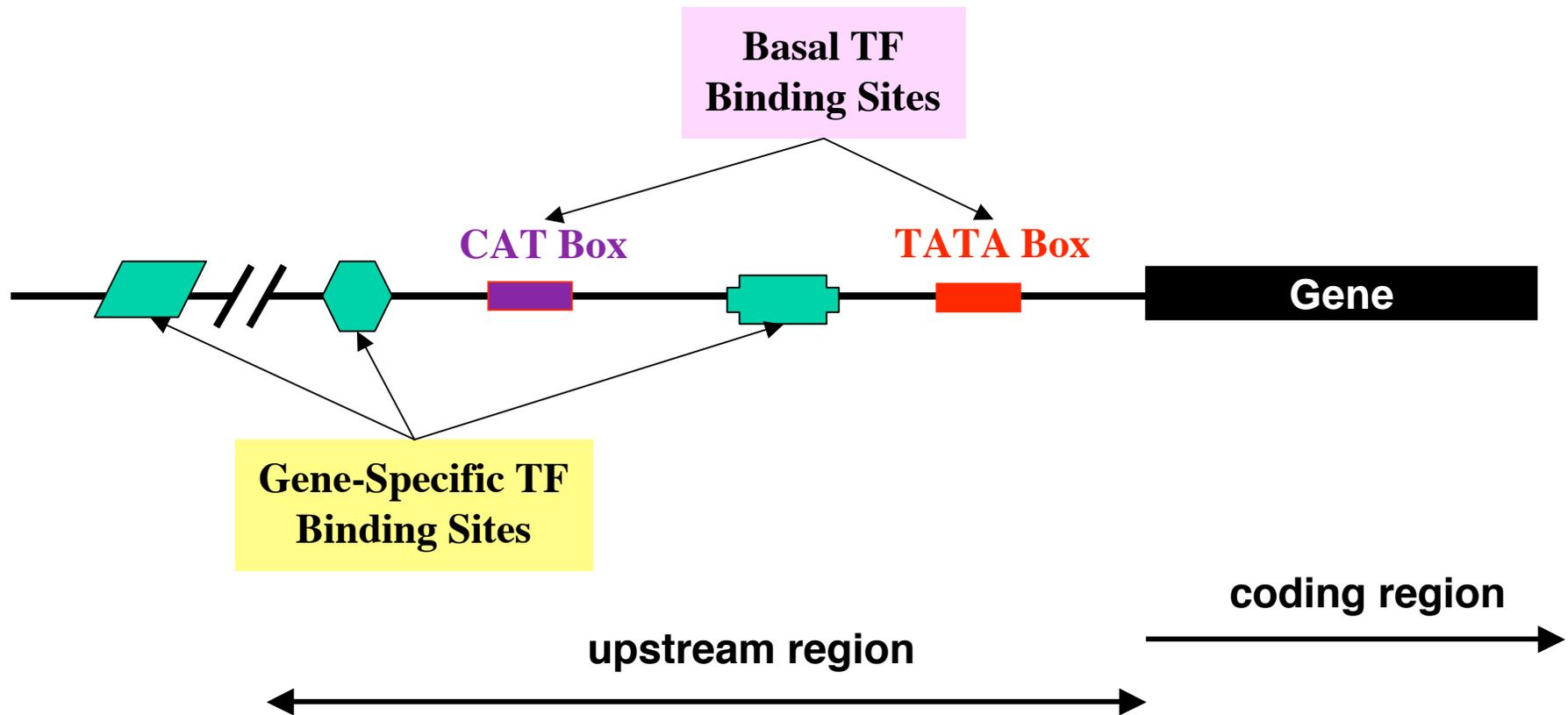
Output : Detected motif(s).

1. **for** each location i **do**
2. $S := \text{MatchScore}(P[i..i+m-1], L)$.
3. **if** $(S > T)$ **then**
4. Report it as a possible motif

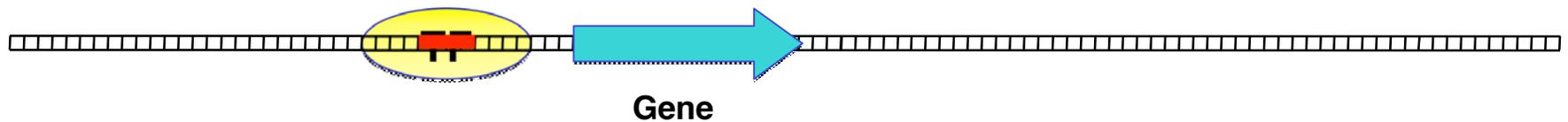
Experimental Results: GYM 2.0

<i>Motif</i>	<i>Protein Family</i>	<i>Number Tested</i>	<i>GYM = DE Agree</i>	<i>Number Annotated</i>	<i>GYM = Annot.</i>
<i>HTH Motif (22)</i>	Master	88	88 (100 %)	13	13
	Sigma	314	284 + 23 (98 %)	96	82
	Negates	93	86 (92 %)	0	0
	LysR	130	127 (98 %)	95	93
	AraC	68	57 (84 %)	41	34
	Rreg	116	99 (85 %)	57	46
	Total	675	653 + 23 (94 %)	289	255 (88 %)

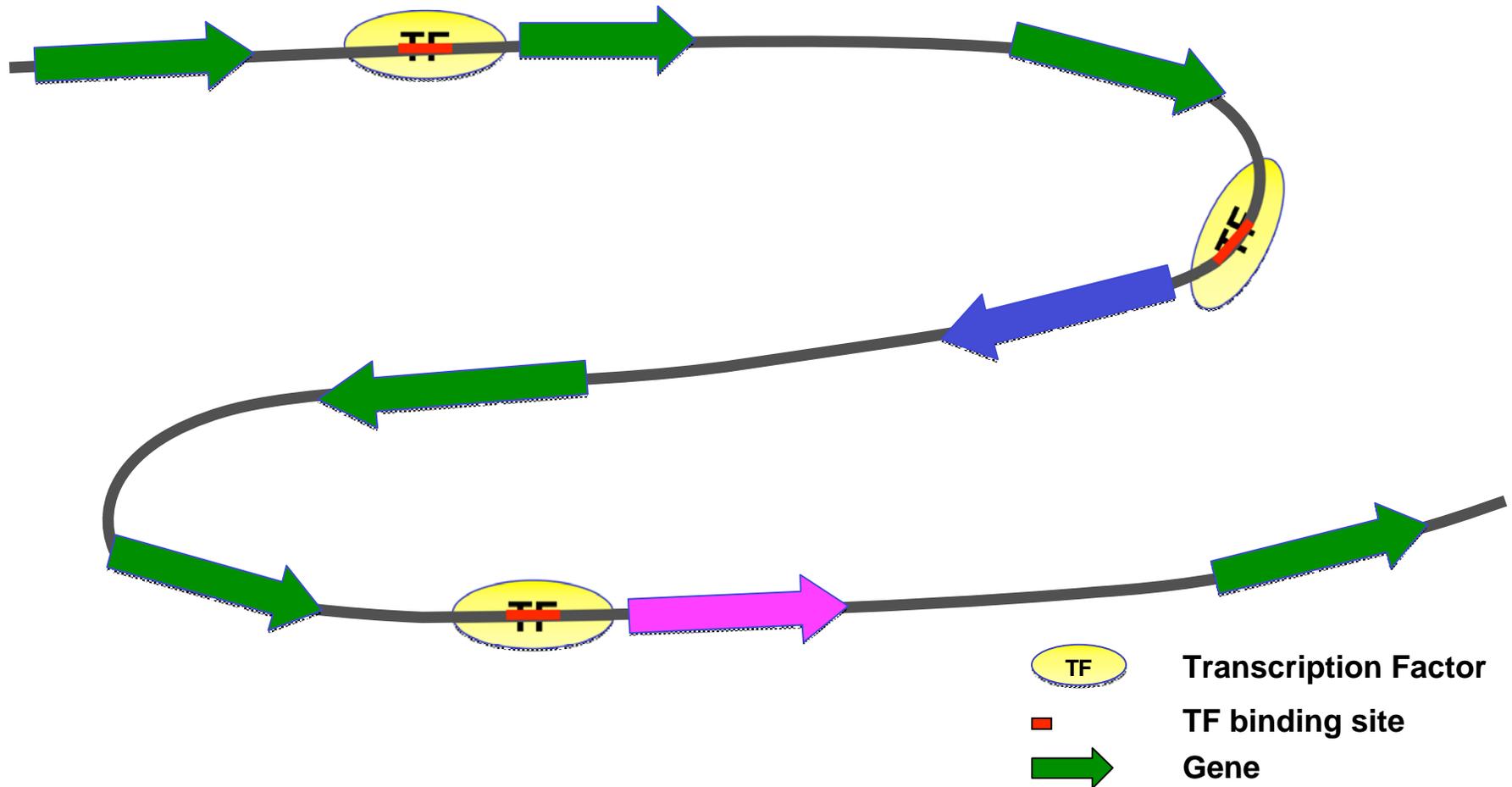
Transcription Regulation



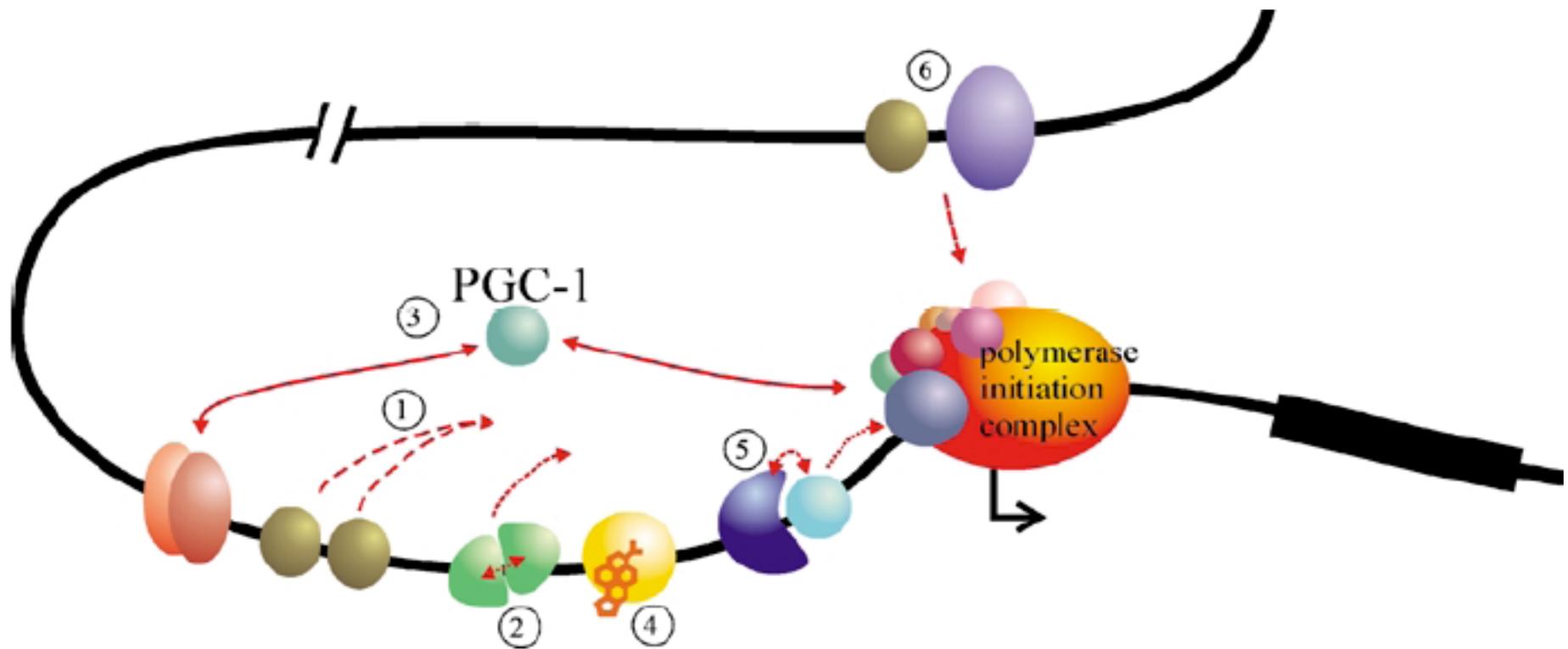
Single Gene Activation



Multiple Gene Activation



Transcription Regulation



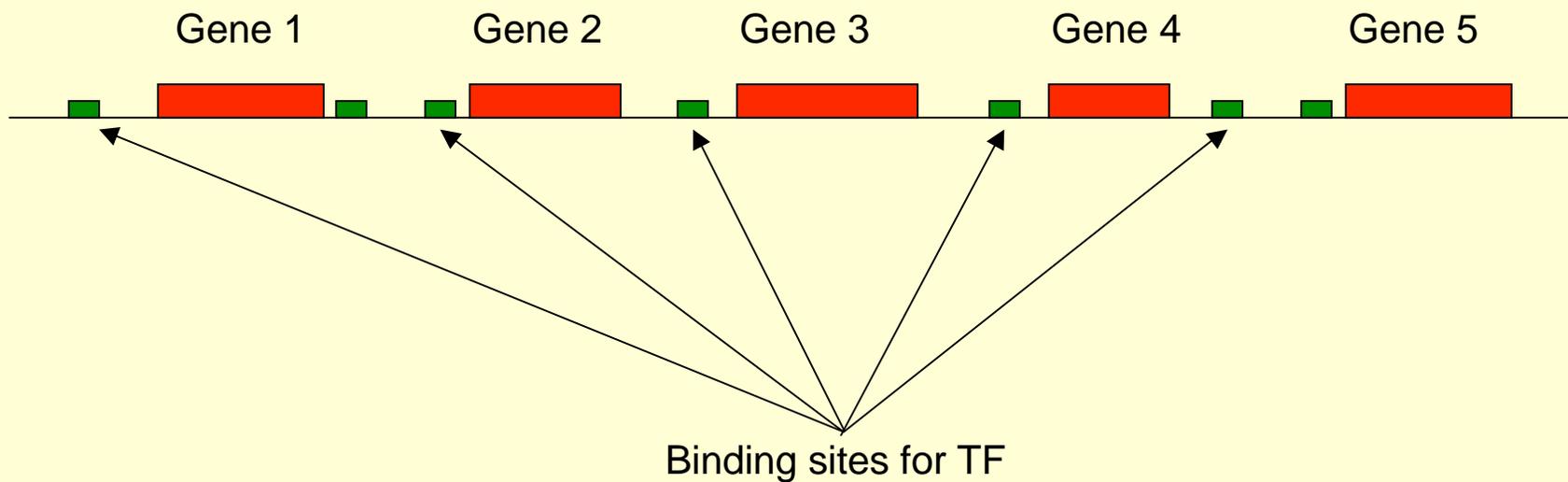
[Goffart *et al.* *Exp. Physiology* (2003)]

Motif-prediction: Whole genome

Problem: Given the upstream regions of all genes in the genome, find all **over-represented** sequence signatures.

Motif-prediction: Whole genome

Basic Principle: If a TF co-regulates many genes, then all these genes should have at least 1 binding site for it in their upstream region.



Motif Detection (TFBMs)

- ❑ See evaluation by Tompa et al.
 - [bio.cs.washington.edu/assessment]
- ❑ *Gibbs Sampling Methods*: AlignACE, GLAM, SeSiMCMC, MotifSampler
- ❑ *Weight Matrix Methods*: ANN-Spec, Consensus,
- ❑ *EM*: Improbizer, MEME
- ❑ *Combinatorial & Misc.*: MITRA, oligo/dyad, QuickScore, Weeder, YMF

Predicting Motifs in Whole Genome

- ❑ **MEME**: EM algorithm [Bailey *et al.*, 1994]
- ❑ **AlignACE**: Gibbs Sampling Approach [Hughes *et al.*, 2000]
- ❑ **Consensus**: Greedy Algorithm Based [Hertz *et al.*, 1990]
- ❑ **ANN-Spec**: Artificial Neural Network and a Gibbs sampling method [Workman *et al.*, 2000]
- ❑ **YMF**: Enumerative search [Sinha *et al.*, 2003]
- ❑ ...

EM Method: Model Parameters

- Input: upstream sequences

- $X = \{X_1, X_2, \dots, X_n\}$,

- Motif profile: $4^{\circ}k$ matrix $\mathbb{P} = (\mathbb{P}_{rp})$,

- $r \in \{A, C, G, T\}$

- $1 \leq p \leq k$

- $\mathbb{P}_{rp} = \text{Pr}(\text{residue } r \text{ in position } p \text{ of motif})$

- Background distribution:

- $\mathbb{P}_{r0} = \text{Pr}(\text{residue } r \text{ in background})$

EM Method: Hidden Information

□ $Z = \{Z_{ij}\}$, where

$$Z_{ij} = \begin{cases} 1, & \text{if motif instance starts at} \\ & \text{position } i \text{ of } X_j \\ 0, & \text{otherwise} \end{cases}$$

□ Iterate over probabilistic models that could generate X and Z , trying to converge on this solution

Statistical Evaluation

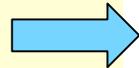
□ **Z-score** of a motif with a certain frequency:



$$z(w) = \frac{Obs(w) - Exp(w)}{\sqrt{Var(w)}}$$

□ **Information Content** or Relative Entropy of an alignment or profile:

□ **Maximum a Posteriori (MAP) Score:**



$$IC(M) = \sum_{i=1}^4 \sum_{j=1}^m m_{i,j} \log \frac{m_{i,j}}{b_i}$$

□ **Model Vs Background Score:**



$$MAP(M) = - \sum_{i=1}^4 \sum_{j=1}^m n_{i,j} \log \frac{m_{i,j}}{b_i}$$



$$L(w) = \frac{\Pr(w | M)}{\Pr(w | Bg)} = \prod_{j=1}^m \frac{m_{i,j}}{b_i}$$

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Counts

Frequencies

35

EM Algorithm

Goal: Find θ, Z that maximize $\Pr(X, Z | \theta)$

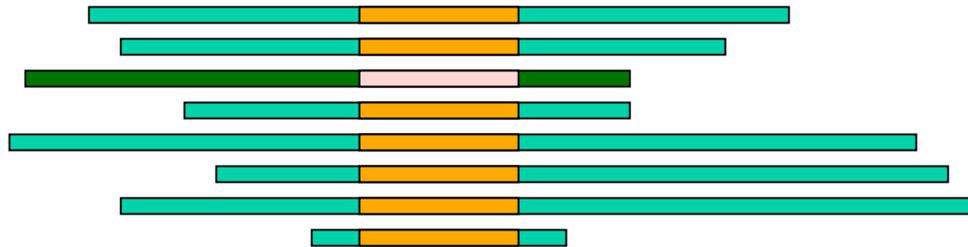
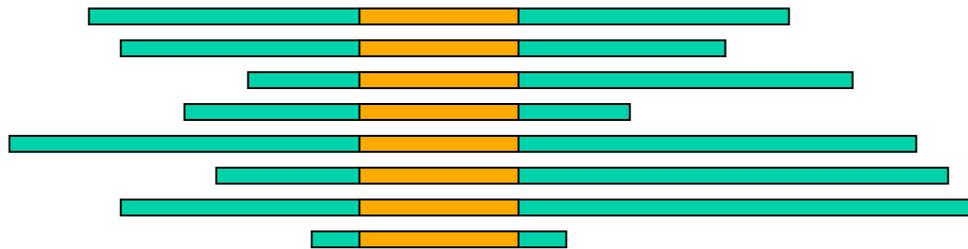
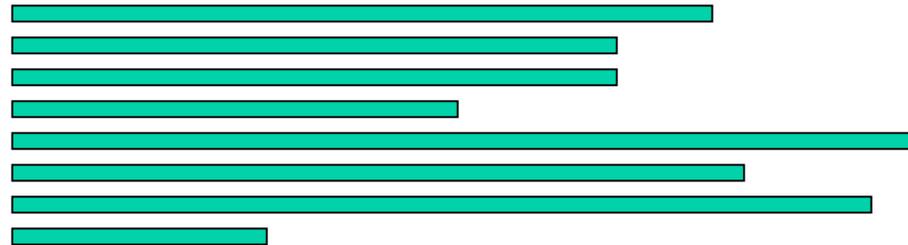
Initialize: random *profile*

E-step: Using *profile*, compute a likelihood value z_{ij} for each m -window at position i in input sequence j .

M-step: Build a new *profile* by using every m -window, but weighting each one with value z_{ij} .

Stop if converged

Gibbs Sampling for Motif Detection



Prokaryotic Gene Characteristics

DNA PATTERNS IN THE *E. coli* *lexA* GENE

GENE SEQUENCE	PATTERN
1 GAATTCGATAAATCTCTGGTTTTATTTGTGCAGTTTATGGTT TT	CTGNNNNNNNNNNCAG TTGACA
41 CCAAATCGCCTTTTTCCTGTATATACTCACAGCATAAATCTG CCAA -35 -10 TATACT >	CTGNNNNNNNNNNCAG TATAAT, > mRNA start
81 TATA TACAC CCAGGGGGCGGAATGAAAGCGTTAACGGCCA +10 GGGGG Ribosomal binding site	CTGNNNNNNNNNNCAG GGAGG
121 GGCAACAAGAGGTGTTTGATCTTCATCCGTGATCACATCAG	
161 CCAGACAGGTATGCGCGACGCGTGCAGAAATCGCGCAG	ATG
201 CGTTTGGGGTTCGGTTCCCAAACGCGCTGAAGAACATC	
241 TGAAGGCGCTGGCACGCAAAGGCGTTATTGAAATGTTTC	
281 CGCGCATCAGCGGGATTTCGTCTGTGTCAGGAAGAGGAA	
321 GAAGGGTTGCGCTGGTAGGTCGTGTGGCTGCCGGTGAAC	
361 CACTTCTGGCGCAACAGCATATTGAAGGTCATTATCAGGT	OPEN READING FRAME
401 CGATCCTTCCTTATTCAGCCGAATGCTGATTTCTGCTG	
441 CGCGTCAGCGGGATGTCGATGAAAGATATCGGCATTATGG	
481 ATGGTGACTTGCTGGCAGTGCATAAACTCAGGATGTACG	
521 TAACGGTCAGGTCGTGTCGCAAGTATTGATGACGAAGTT	
561 TCCCTTTCAGCCCTTAAAAACAGGGCAATTAAGTCCGAAAC	
601 TGTTGCCAGAAATAGCGAGTTTAAACCAATTTGTCGTTGA	
641 CCTTCGTCAGCAGAGCTTCACCATGAAAGGGCTGGCGGTT	TAA
681 GGGGTTATTTCGCAACGGCGACTGGCTGTAACATATCTCTG	
721 AGACCGCGATGCGCCTTGGCGTCCGCGTTTGTGTTTTCATC	
761 TCTCTTCATCAGGCTTGTCTGCATGGCATTCCTCACITCA	
801 TCTGATAAAGCACTCTGGCATCTCGCCTTACCCATGATTT	
841 TCTCCAAATACACC GTTCC GTTGC TGGGACTGGTTCGATAAC	
881 GGCGTAAATGGTCACTTTGATAGCCCGTTTATTGTTGGC	
921 GGCGTGGCGTTGGCGCAACGGCGGACCAAGCT	

Shown are matches to approximate consensus binding sites for LexA repressor (CTGNNNNNNNNNNCAG), the -10 and -35 promoter regions relative to the start of the mRNA (TTGACA and TATAAT), the ribosomal binding site on the mRNA (GGAGG), and the open reading frame (ATG...TAA). Only the second two of the predicted LexA binding sites actually bind the repressor.

FIGURE 9.6. The promoter and open reading frame of the *E. coli* *lexA* gene.

Gene Expression

- ❑ Process of transcription and/or translation of a gene is called **gene expression**.
- ❑ Every cell of an organism has the same genetic material, but different genes are **expressed** at different times.
- ❑ Patterns of gene expression in a cell is indicative of its state.

Hybridization

- ❑ If two complementary strands of DNA or mRNA are brought together under the right experimental conditions they will hybridize.
- ❑ A hybridizes to $B \Rightarrow$
 - A is reverse complementary to B , or
 - A is reverse complementary to a subsequence of B .
- ❑ It is possible to experimentally verify whether A hybridizes to B , by labeling A or B with a radioactive or fluorescent tag, followed by excitation by laser.

Measuring gene expression

- ❑ Gene expression for a single gene can be measured by extracting mRNA from the cell and doing a simple **hybridization** experiment.
- ❑ Given a sample of cells, gene expression for every gene can be measured using a single **microarray** experiment.

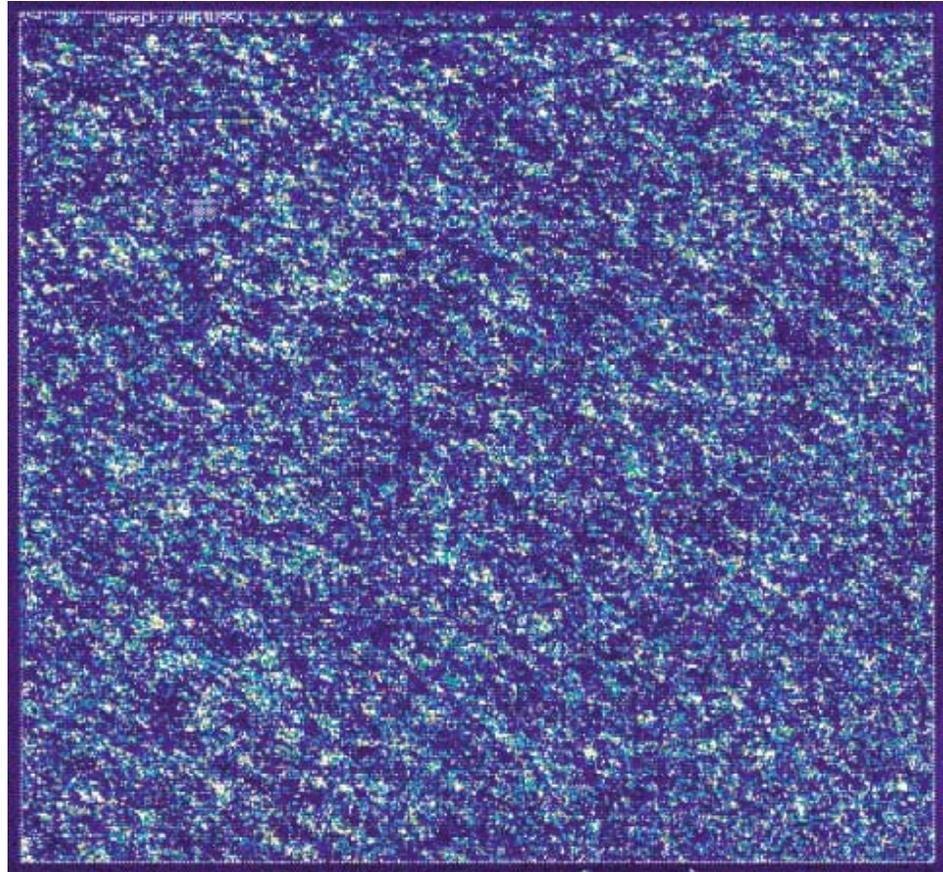
Microarray/DNA chip technology

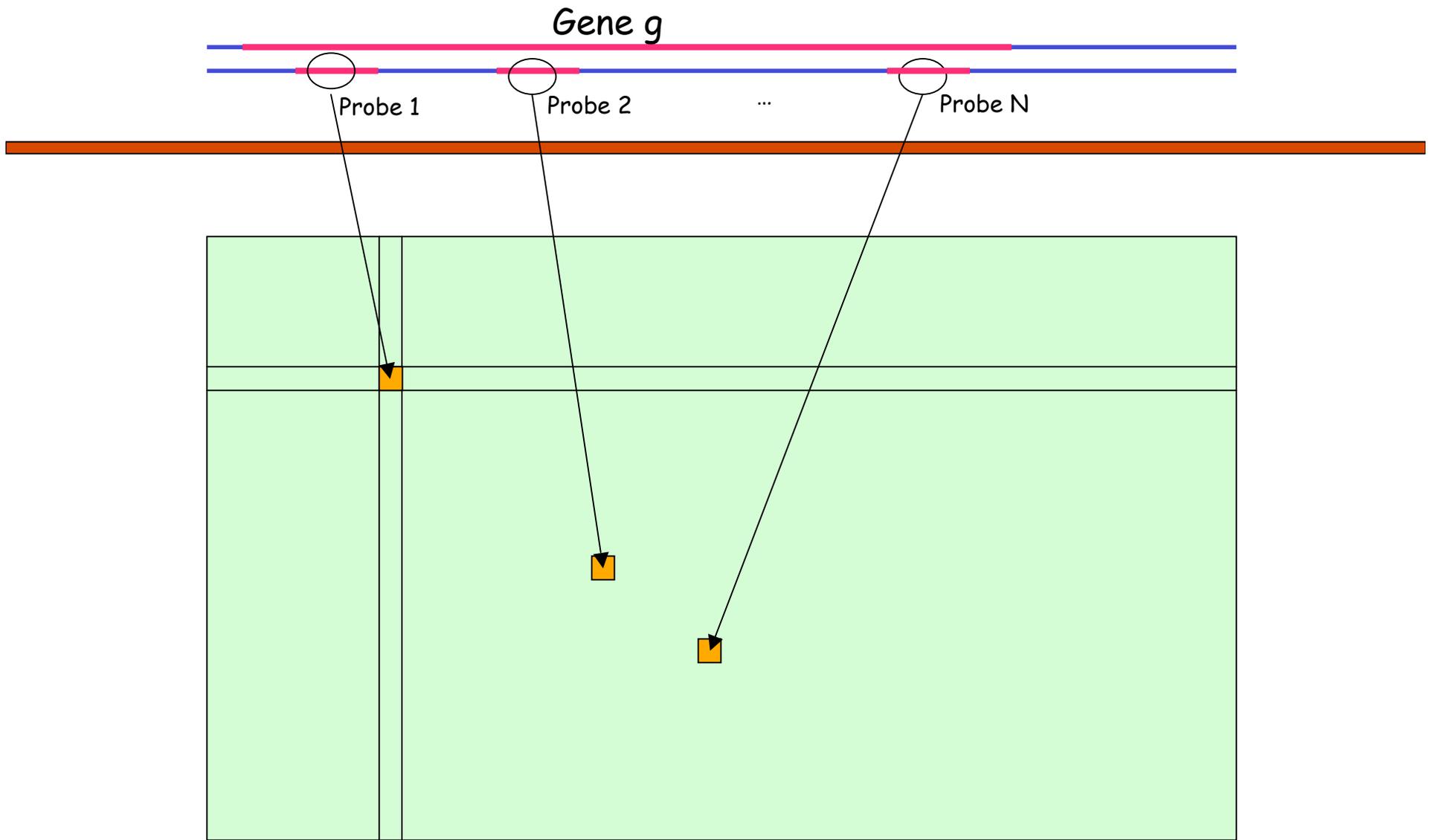
- High-throughput method to study gene expression of thousands of genes simultaneously.
- Many applications:
 - Genetic disorders & Mutation/polymorphism detection
 - Study of disease subtypes
 - Drug discovery & toxicology studies
 - Pathogen analysis
 - Differing expressions over time, between tissues, between drugs, across disease states

Microarray Data

<i>Gene</i>	<i>Expression Level</i>
<i>Gene1</i>	
<i>Gene2</i>	
<i>Gene3</i>	
...	

Gene Chips

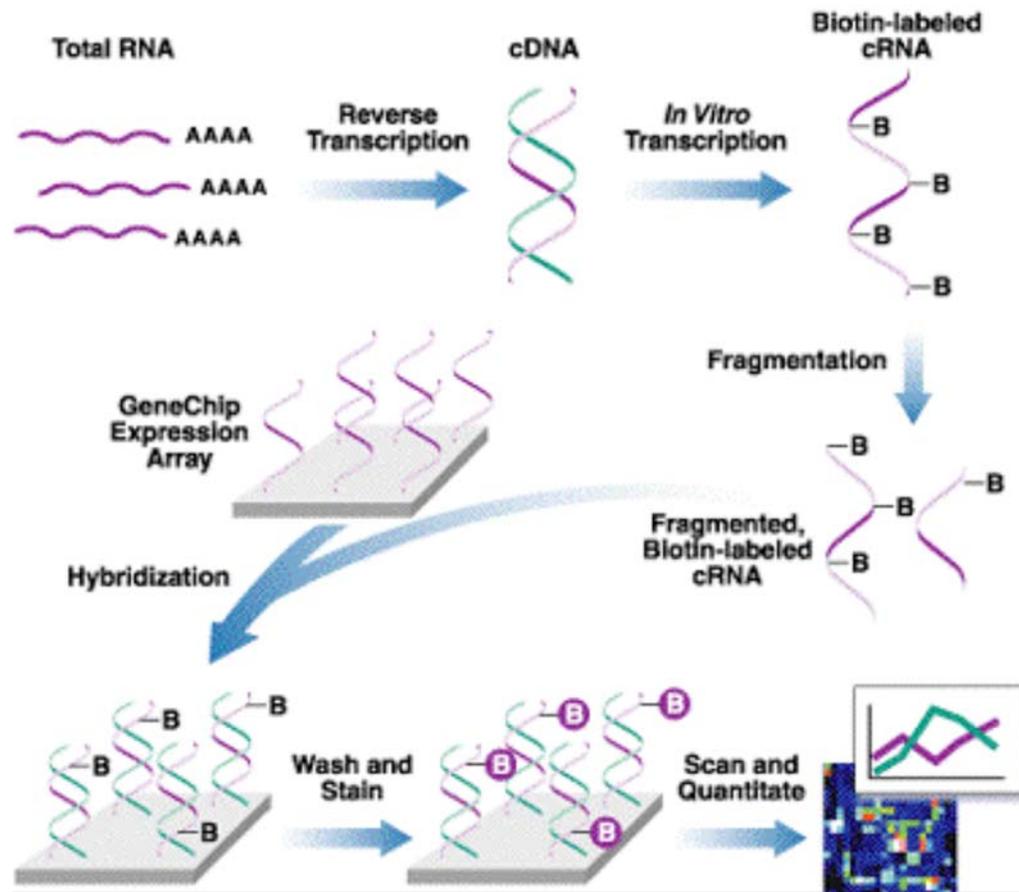




Microarray/DNA chips (Simplified)

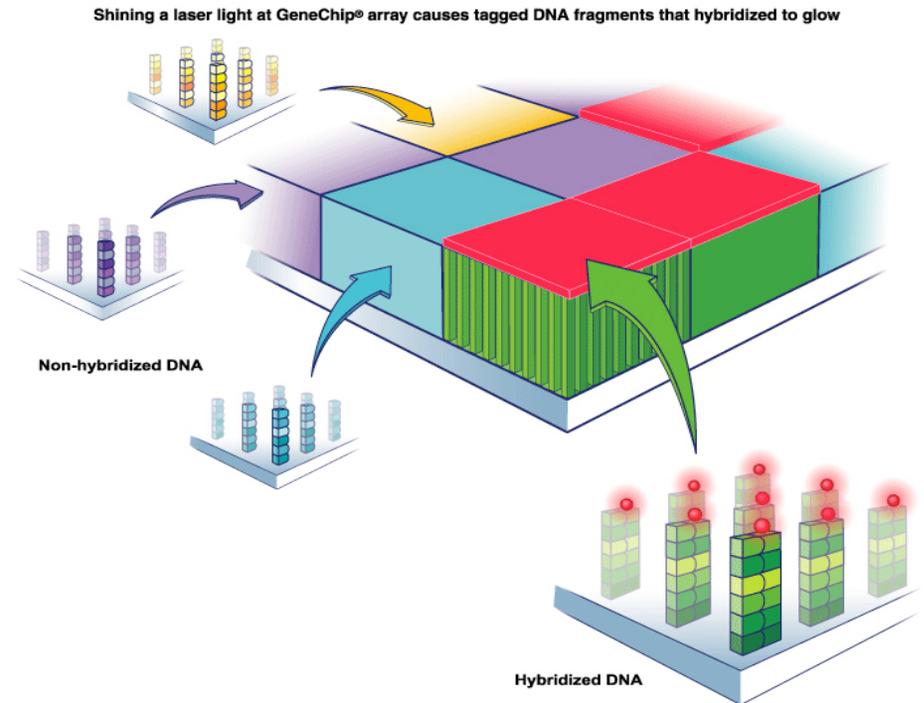
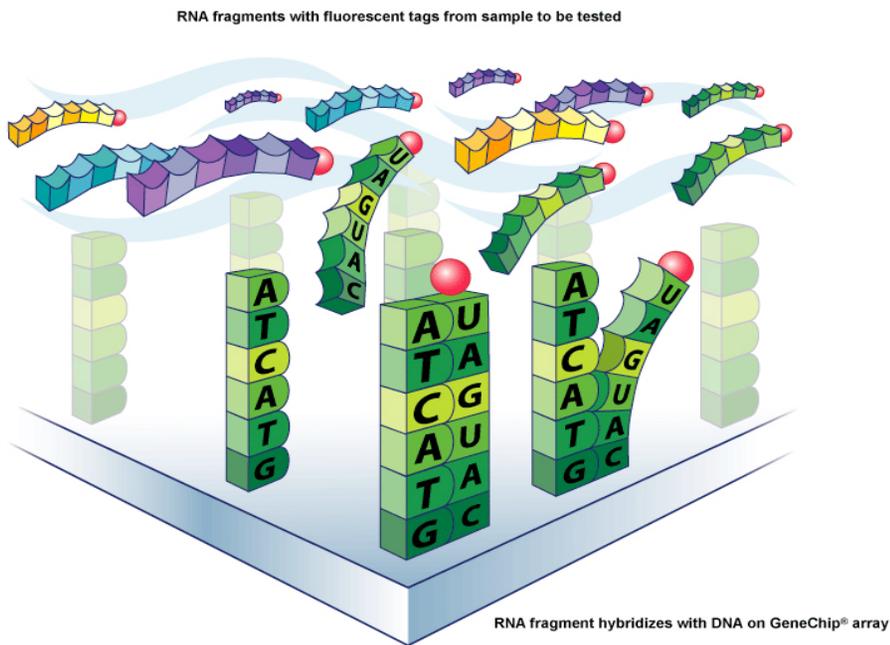
- ❑ Construct **probes** corresponding to reverse complements of genes of interest.
- ❑ Microscopic quantities of probes placed on solid surfaces at defined spots on the chip.
- ❑ Extract mRNA from sample cells and **label** them.
- ❑ Apply labeled sample (mRNA extracted from cells) to every spot, and allow hybridization.
- ❑ Wash off unhybridized material.
- ❑ Use optical detector to measure amount of fluorescence from each spot.

Affymetrix DNA chip schematic

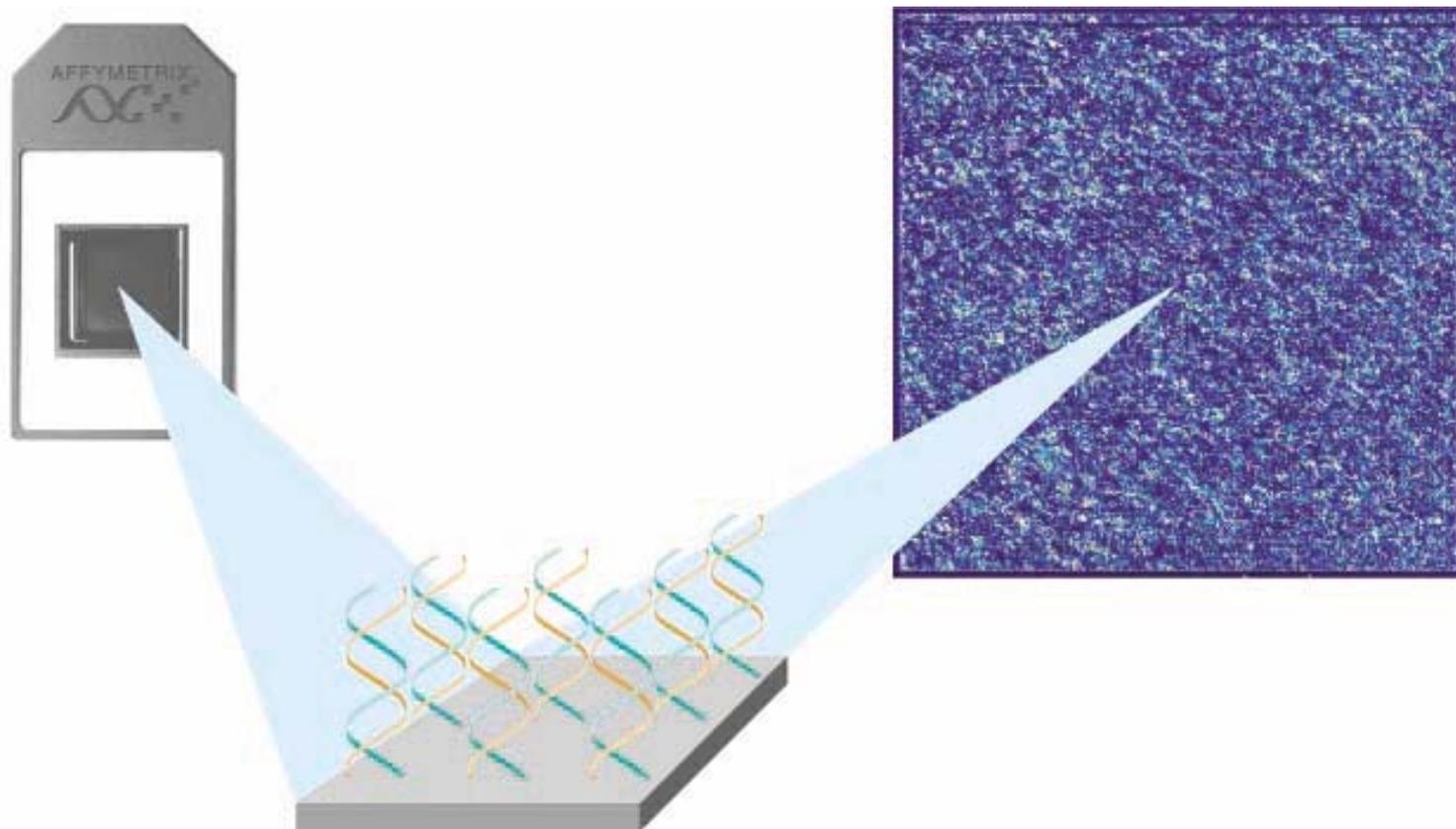


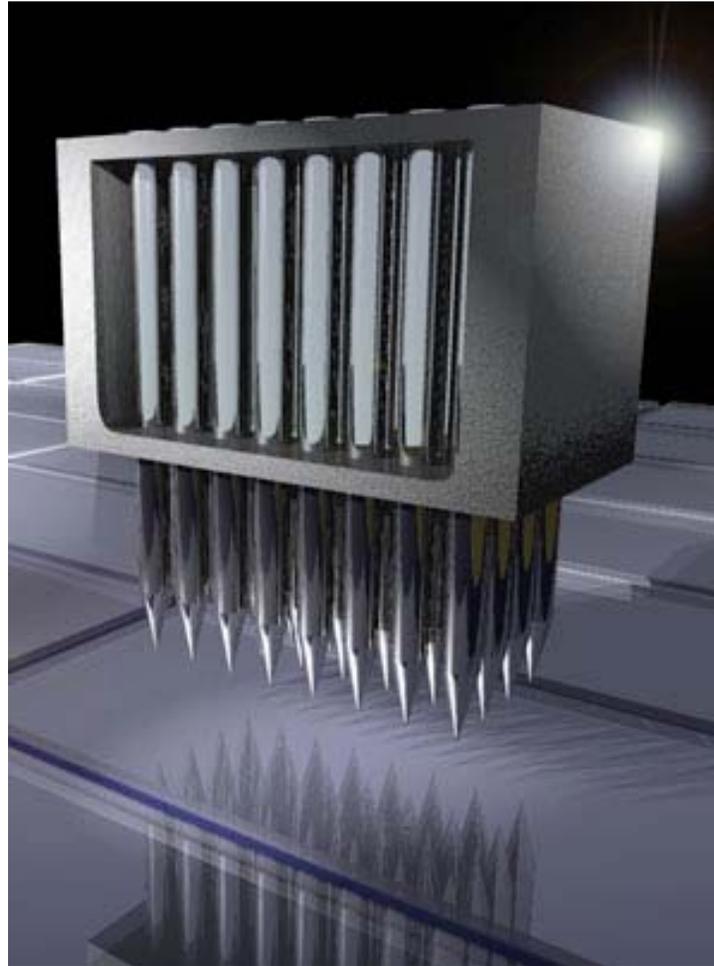
www.affymetrix.com

What's on the slide?



DNA Chips & Images





Microarrays: competing technologies

- ❑ Affymetrix & Agilent
- ❑ Differ in:
 - method to place DNA: Spotting vs. photolithography
 - Length of probe
 - Complete sequence vs. series of fragments