

BSC 4934: Q'BIC Capstone Workshop

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http://www.cis.fiu.edu/~giri/teach/BSC4934_Su09.html

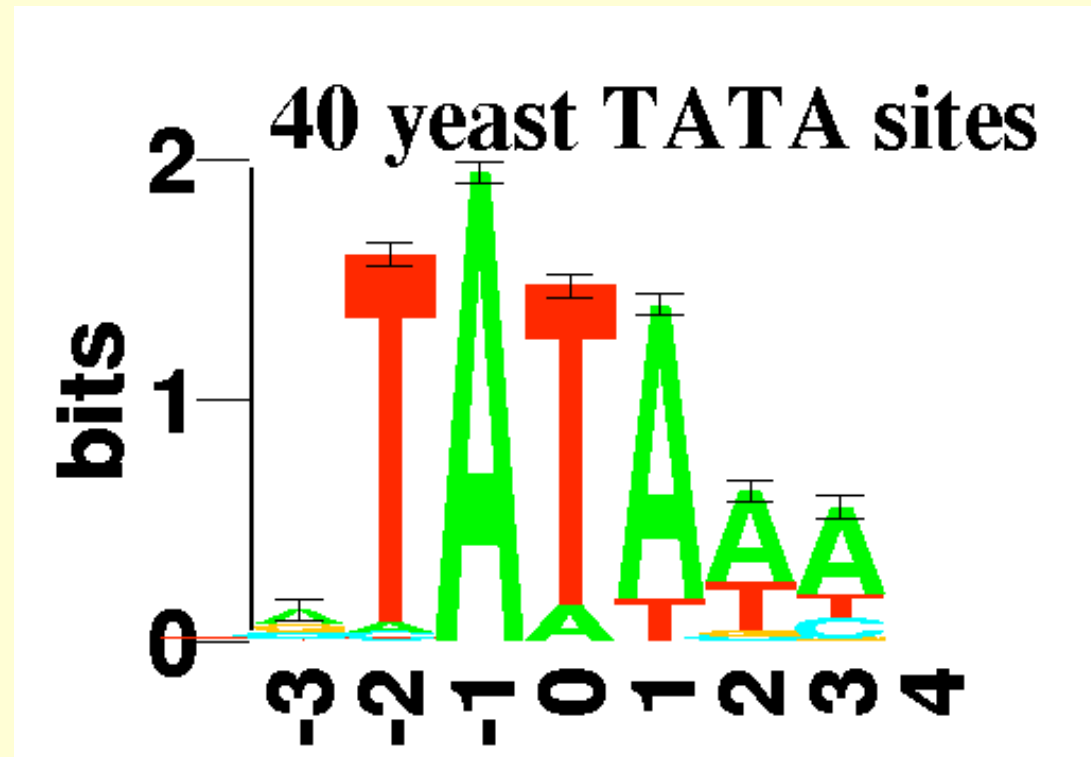
24 June through 7 July, 2009

Patterns in DNA Sequences

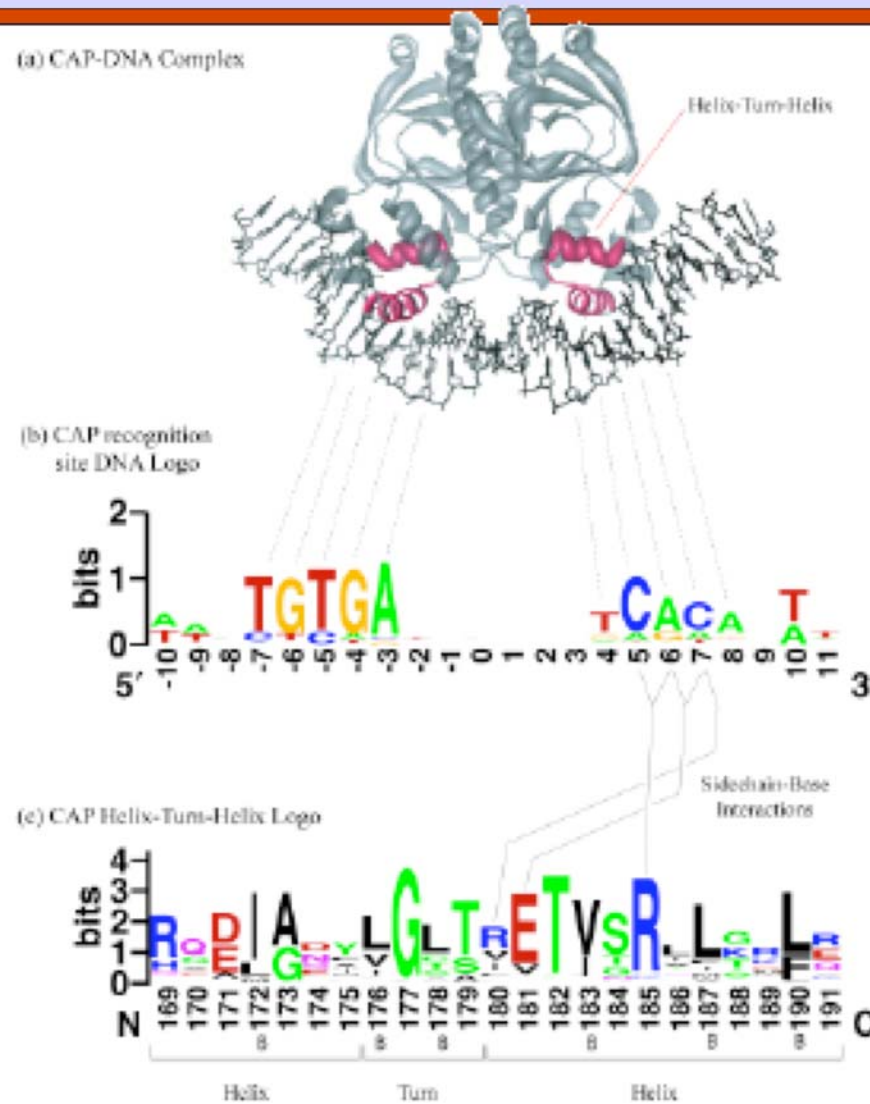
- Signals in DNA sequence control events
 - Start and end of genes
 - Start and end of introns
 - Transcription factor binding sites (regulatory elements)
 - Ribosome binding sites
- Detection of these patterns are useful for
 - Understanding gene structure
 - Understanding gene regulation

Motifs in DNA Sequences

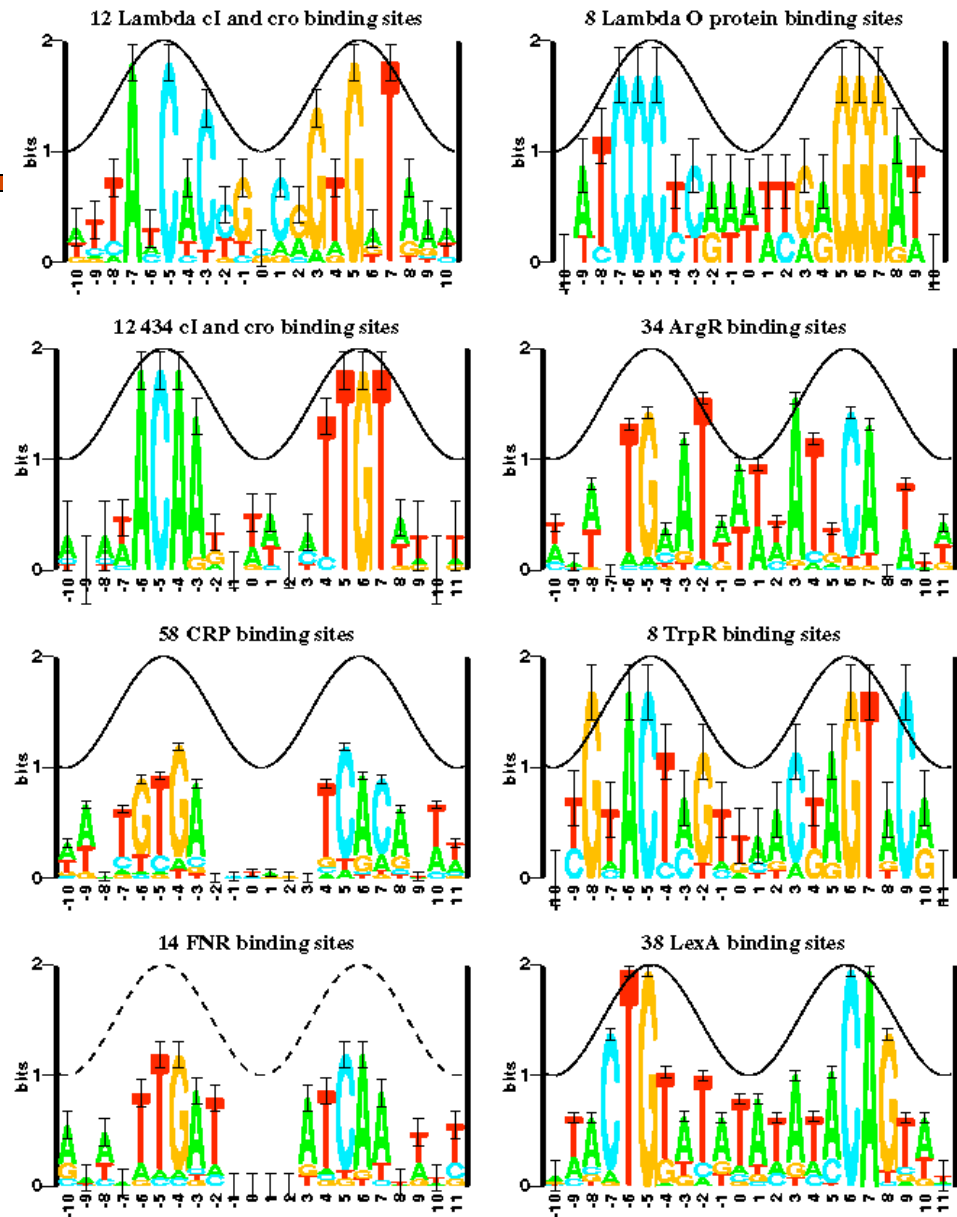
- Given a collection of DNA sequences of promoter regions, locate the transcription factor binding sites (also called regulatory elements)
 - Example:



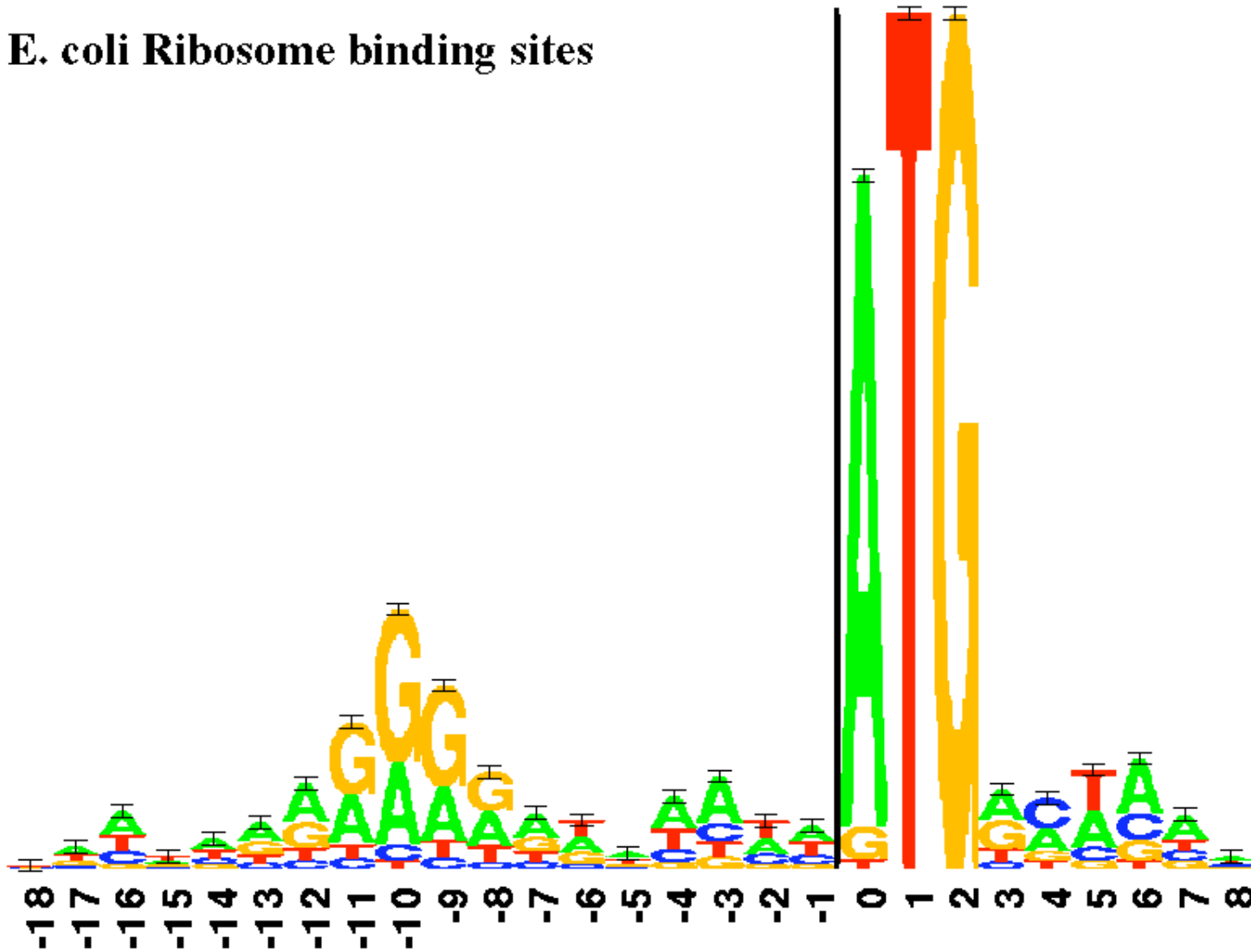
Motifs



More Motifs in *E. Coli* DNA Sequences

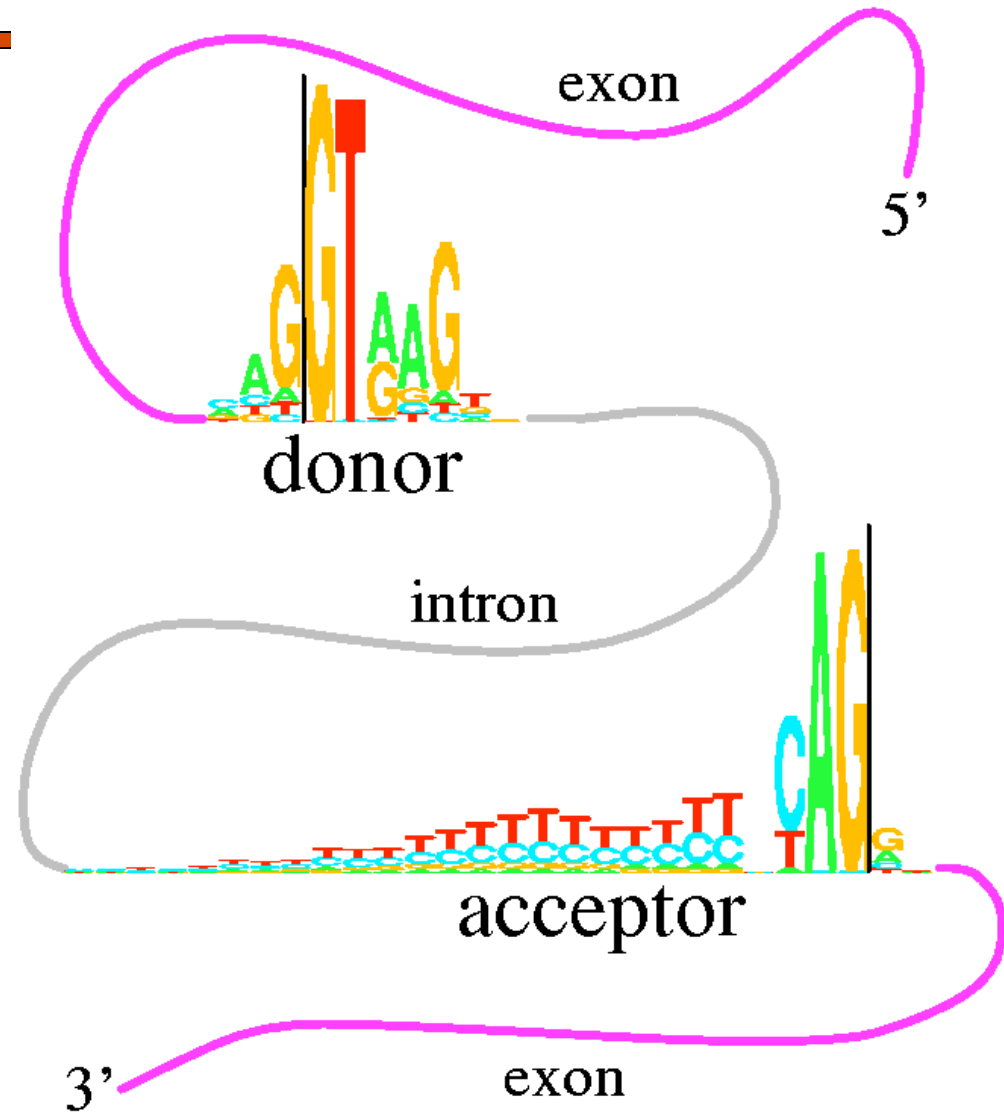


— **E. coli Ribosome binding sites**

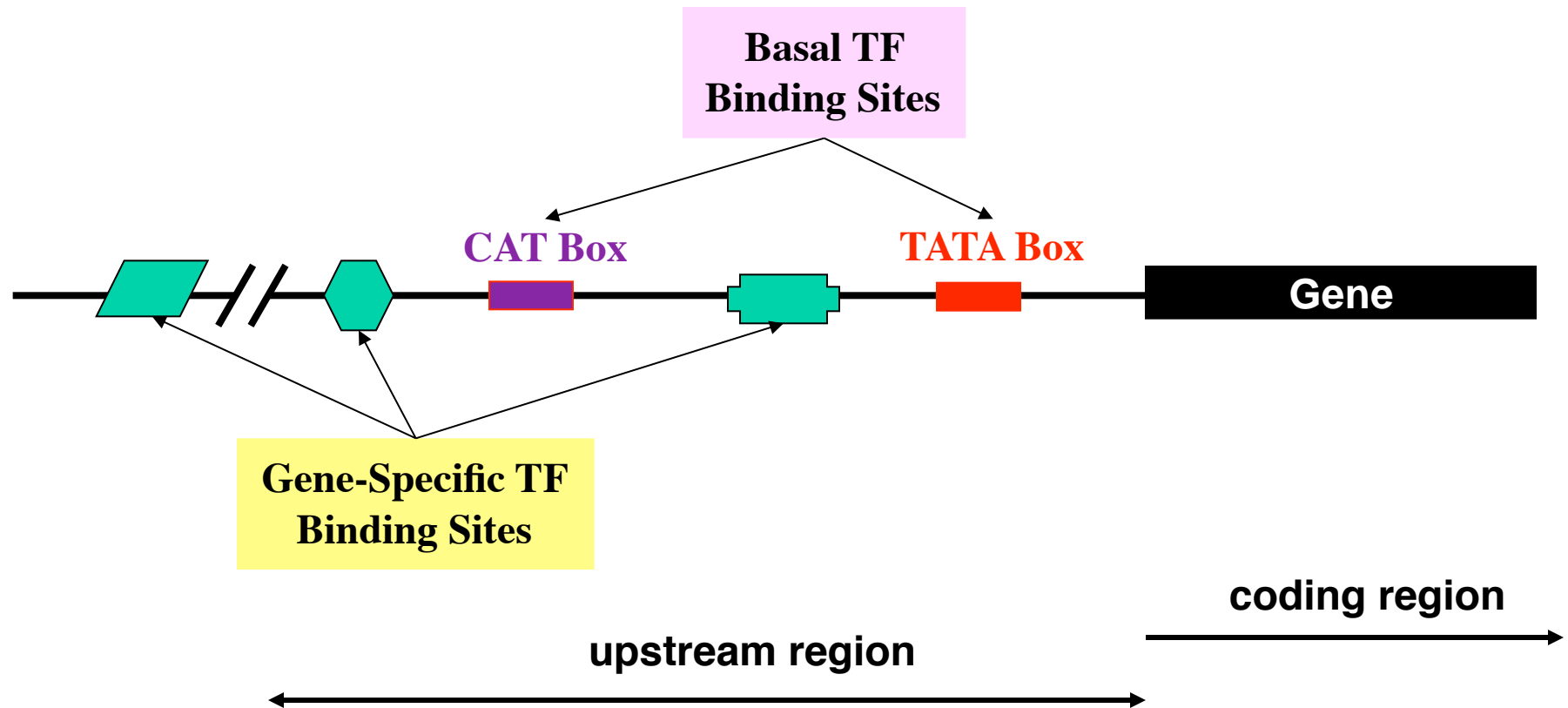


Other Motifs in DNA Sequences: Human Splice Junctions

This figure shows two "sequence logos" which represent sequence conservation at the 5' (donor) and 3' (acceptor) ends of human introns. The region between the black vertical bars is removed during mRNA splicing. The logos graphically demonstrate that most of the pattern for locating the intron ends resides on the intron. This allows more codon choices in the protein-coding exons. The logos also show a common pattern "CAGGT", which suggests that the mechanisms that recognize the two ends of the intron had a common ancestor. See R. M. Stephens and T. D. Schneider, "Features of spliceosome evolution and function inferred from an analysis of the information at human splice sites", *J. Mol. Biol.*, 228, 1124-1136, (1992)



Transcription Regulation



Prokaryotic Gene Characteristics

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

GENE SEQUENCE	PATTERN
1 GAATTCGATAAATCTCTGGTTTATTTGTGCAGTTTATGGTT	CTGNNNNNNNNNNCAG
41 CCAAATCGCCTTTTGTCTGTATATACTCACAGCATAAATCTG	TTGACA
81 TATAATACACCCAGGGGGCGGAATGAAAGCGTTAACGGCCA	CTGNNNNNNNNNNCAG
+10 GGGGG Ribosomal binding site	TATAAT, > mRNA start
121 GGCAACAAGAGGTGTTTGTATCTCATCCGTGATCACATCAG	GGAGG
161 CCAGACAGGTATGCGCGCGACGCGTGCAGAAATCGCCGAG	ATG
201 CGTTTGGGGTTCGGTTCCCAACGCGCGTGAAGAACATC	
241 TGAAGGCGCTGGCACGCAAAGGCGTTATTGAAATGTTTC	
281 CGCGCATCAGCGGGATTCGTCTGTGTGCAGGAAGAGGAA	
321 GAAGGGTTGCGCTGGTAGGTCTGTGTGGCTGCCGGTGAAC	
361 CACTTCTGGCGCAACAGCATATTGAAGGTCATTATCAGGT	OPEN READING FRAME
401 CGATCCTTCCTTATTCAGCCGAATGCTGATTTCTGCTG	
441 CGCGTCAGCGGGATGTCGATGAAAGATATCGGCATTTATGG	
481 ATGGTGAATCTGCTGGCAGTGCATAAACTCAGGATGTACG	
521 TAACGGTCAGGTCTGTGTCGCACTATTGATGACGAAGTT	
561 TTTTAAATTCCTTAAAAACAGGGCAATTAAGTCCGAACT	
601 TGTTGCCAGAAATAGCGAGTTTAAACCAATTTGTCGTTGA	
641 CCTTCGTCAGCAGAGCTTCACCATGAAAGGGCTGGCGGTT	TAA
681 GGGGTTATTCGCAACGGCGACTGGCTGTAACATATCTCTG	
721 AGACCGCATGCGCGCTTGGCGTCCGCGTTTGTTTTTCATC	
761 TCTCTTCATCAGGCTTGTCTGCATGGCATTCCTCACITCA	
801 TCTGATAAAGCACTCTGGCATCTCGCCTTACCCATGATTT	
841 TCTCCAAATATCACCGTTTCCGTTGCTGGGACTGGTTCGATAC	
881 GGCGGTAATTTGGTCACTTTGATAGCCCGTTTATTTGGGC	
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.

Motifs in DNA Sequences

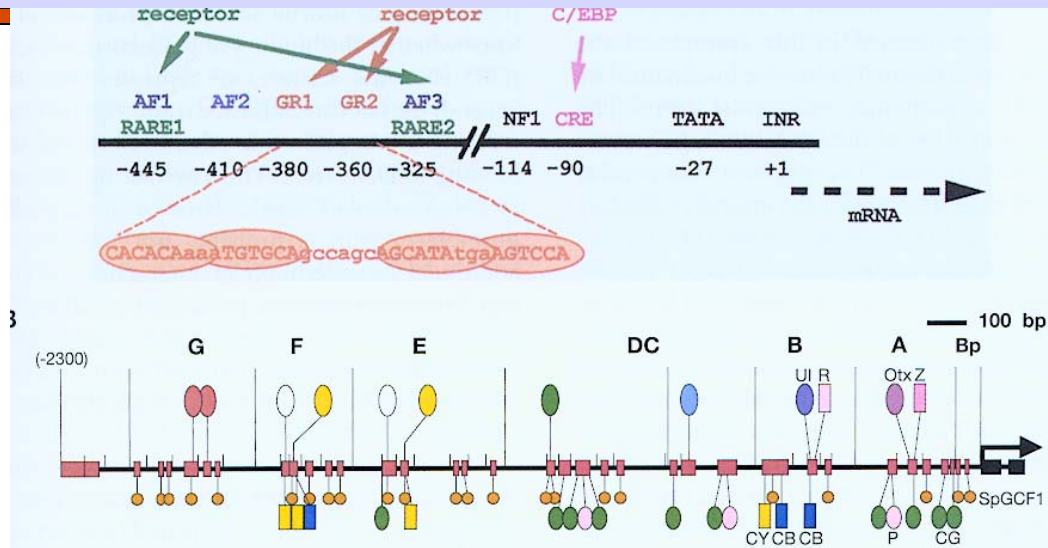
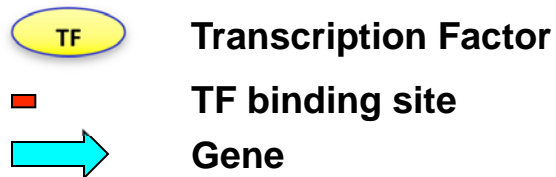
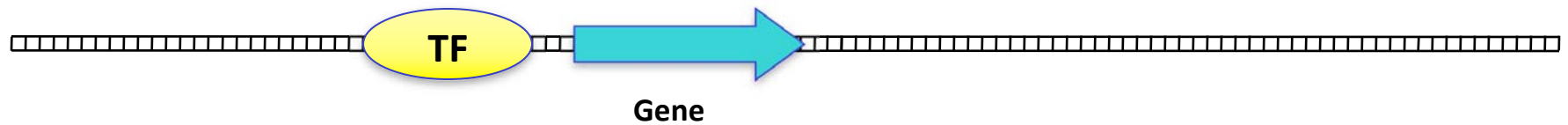
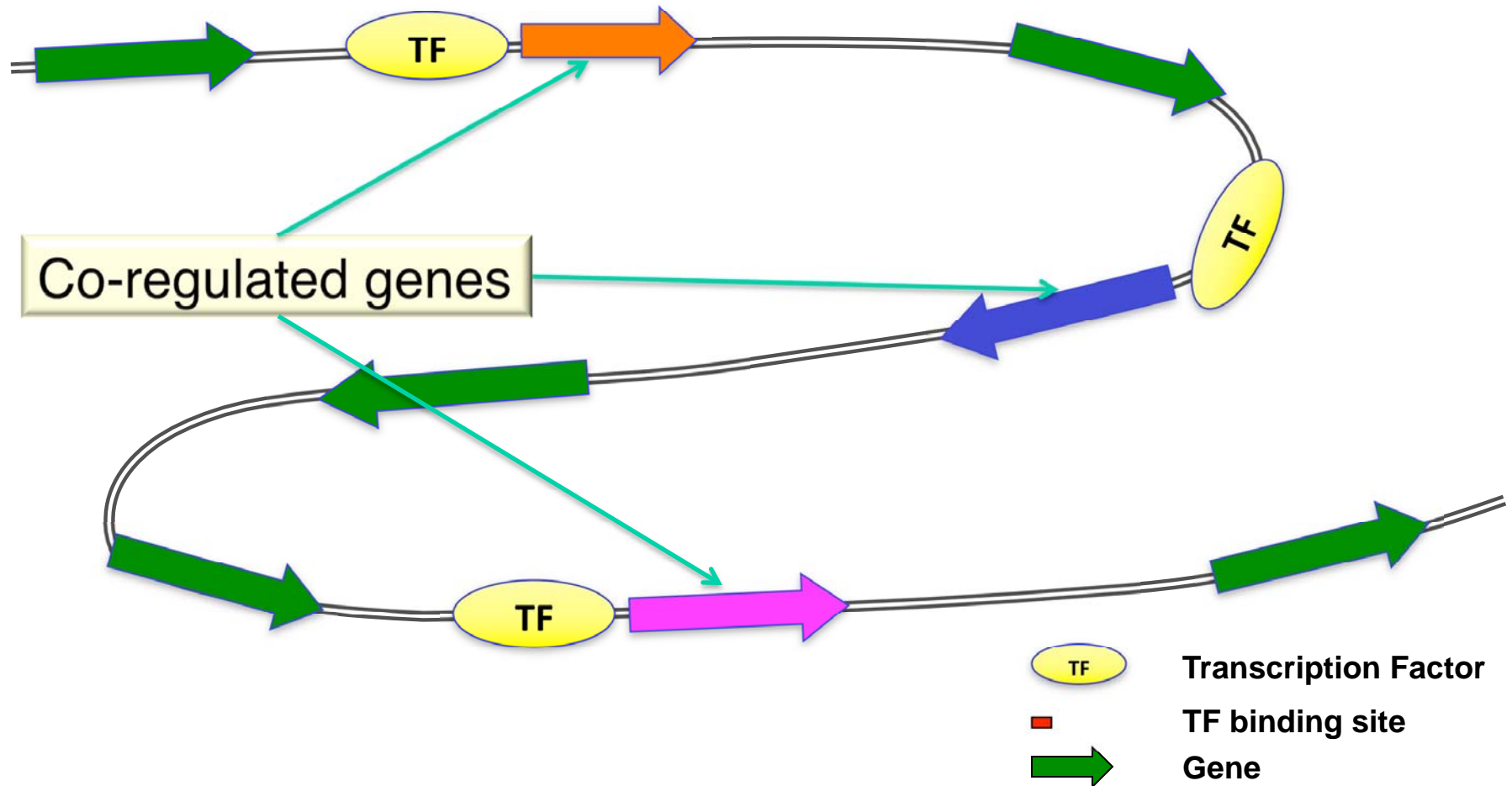


FIGURE 9.13. Regulatory elements of two promoters. (A) The rat *pepCK* gene. The relative positions of the TF-binding sites are illustrated (Yamada et al. 1999). The glucocorticoid response unit (GRU) includes three accessory factor-binding sites (AF1, AF2, and AF3), two glucocorticoid response elements (GR1 and GR2), and a cAMP response element (CRE). A dimer of glucocorticoid receptors bound to each GR element is depicted. The retinoic response unit (RAU) includes two retinoic acid response elements (RARE1 and RARE2) that coincide with the AF1 and AF3, respectively (Sugiyama et al. 1998). The sequences of the two GR sites and the binding of the receptor to these sites are shown. These sites deviate from the consensus sites and depend on their activity on accessory proteins bound to other sites in the GRU. This dependence on accessory proteins is reduced if a more consensus-like (canonical) GR element comprising the sequence TGTTCCT is present. The CRE that binds factor C/EBP is also shown. (B) The 2300-bp promoter of the developmentally regulated gene *endo16* of the sea urchin (Bolouri and Davidson 2002). Different colors indicate different binding sites for distinct proteins and proteins shown above the line bind at unique locations, below the line at several locations. The regions A–G are functional modules that determine the expression of the gene in a particular tissue at a particular time of development and may either serve to induce transcription of the gene as a necessary developmental step (A, B, and G) or repress transcription (C–F) in tissues when it is not appropriate. (Reprinted, with permission, from Bolouri and Davidson 2002 [©2002 Elsevier].)

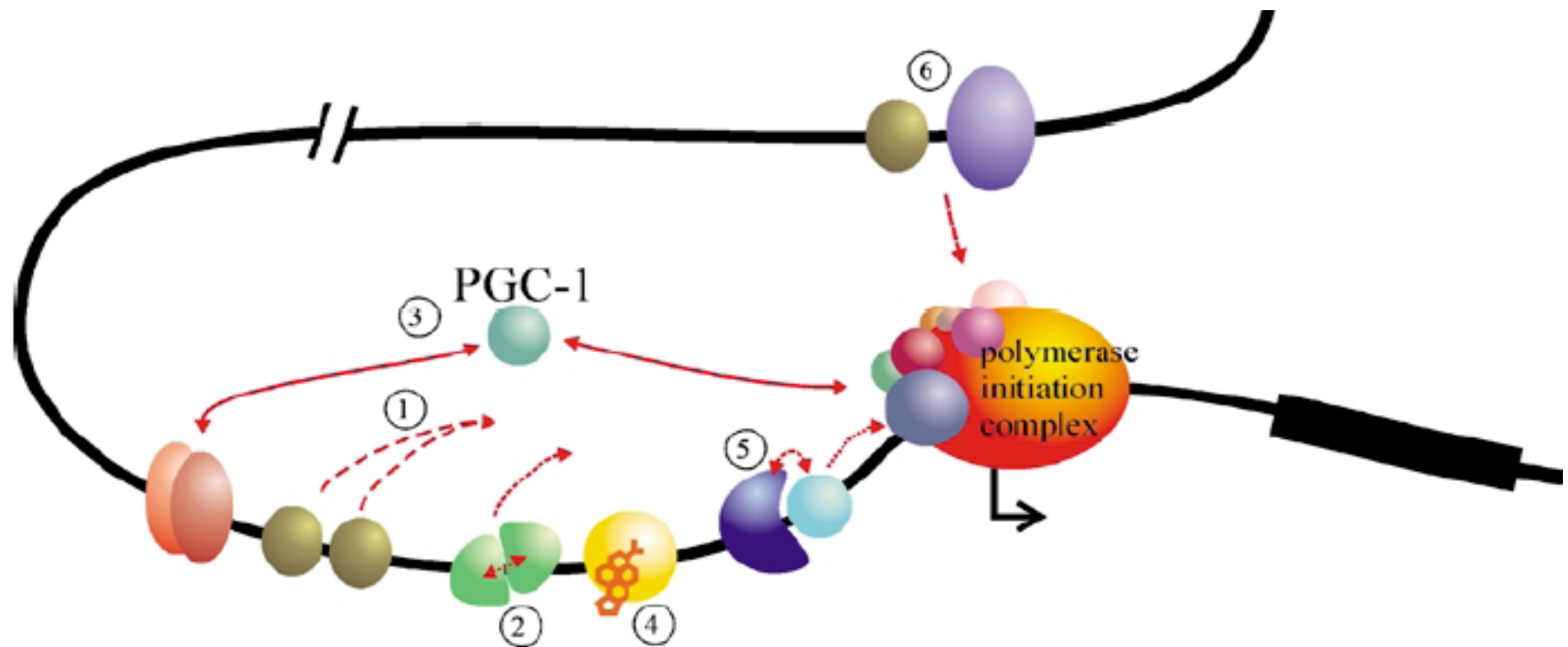
Single Gene Activation



Multiple Gene Activation



Transcription Regulation

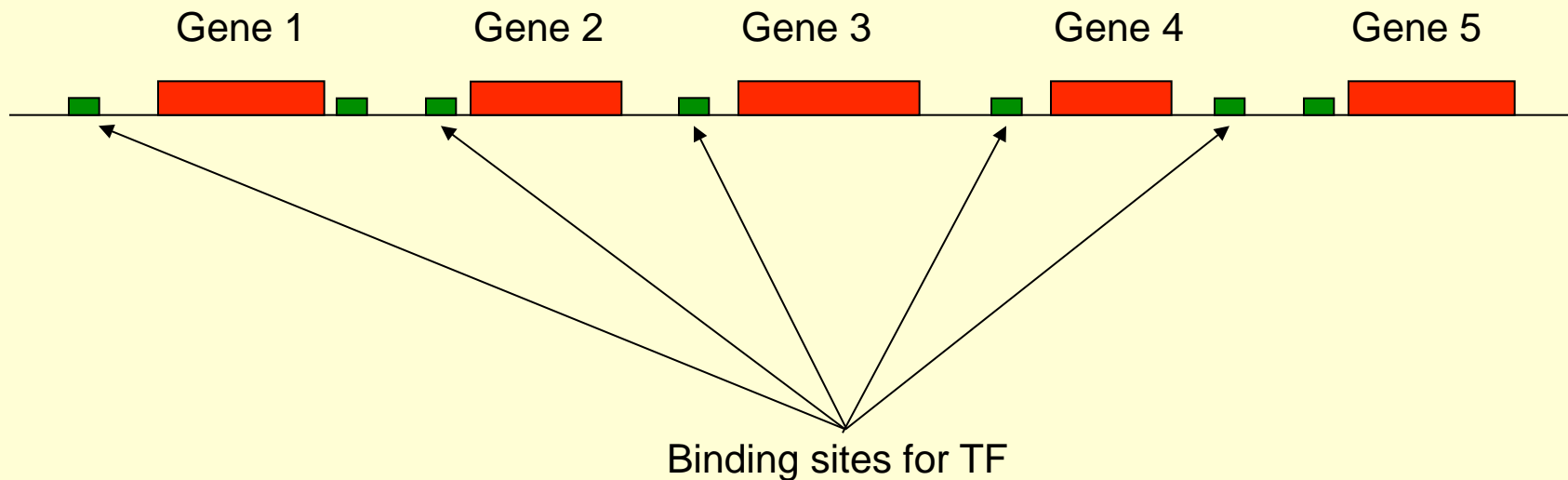


[Goffart *et al. Exp. Physiology* (2003)]

Motif-prediction: Whole genome

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

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

EM Algorithm

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

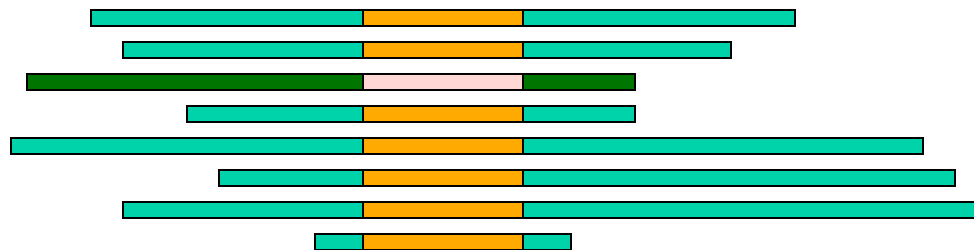
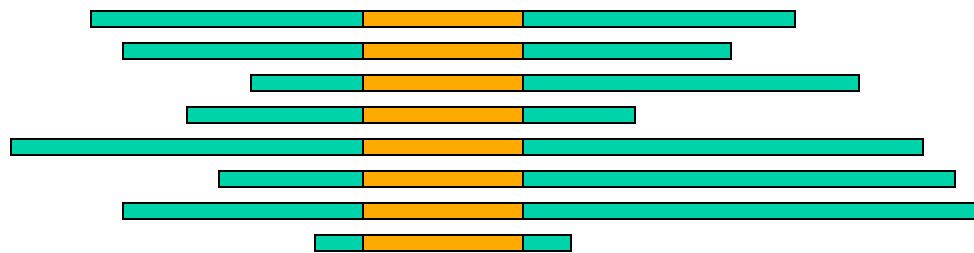
Initialize: random profile

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



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.

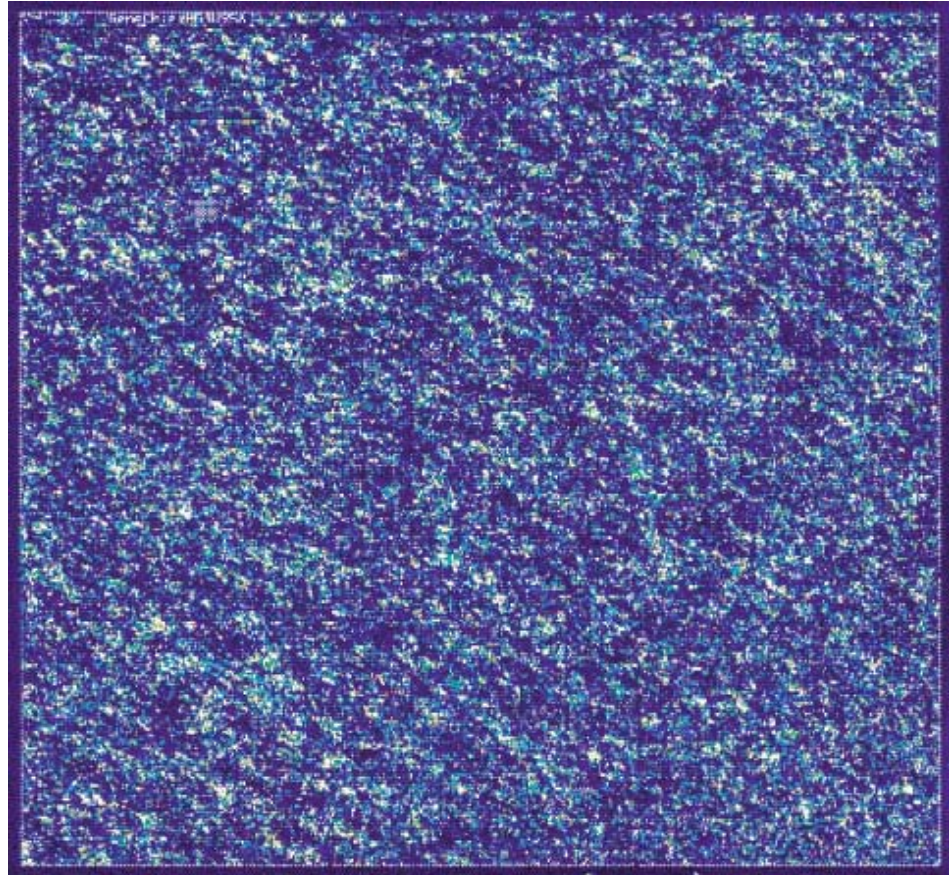
Microarray/DNA chip technology

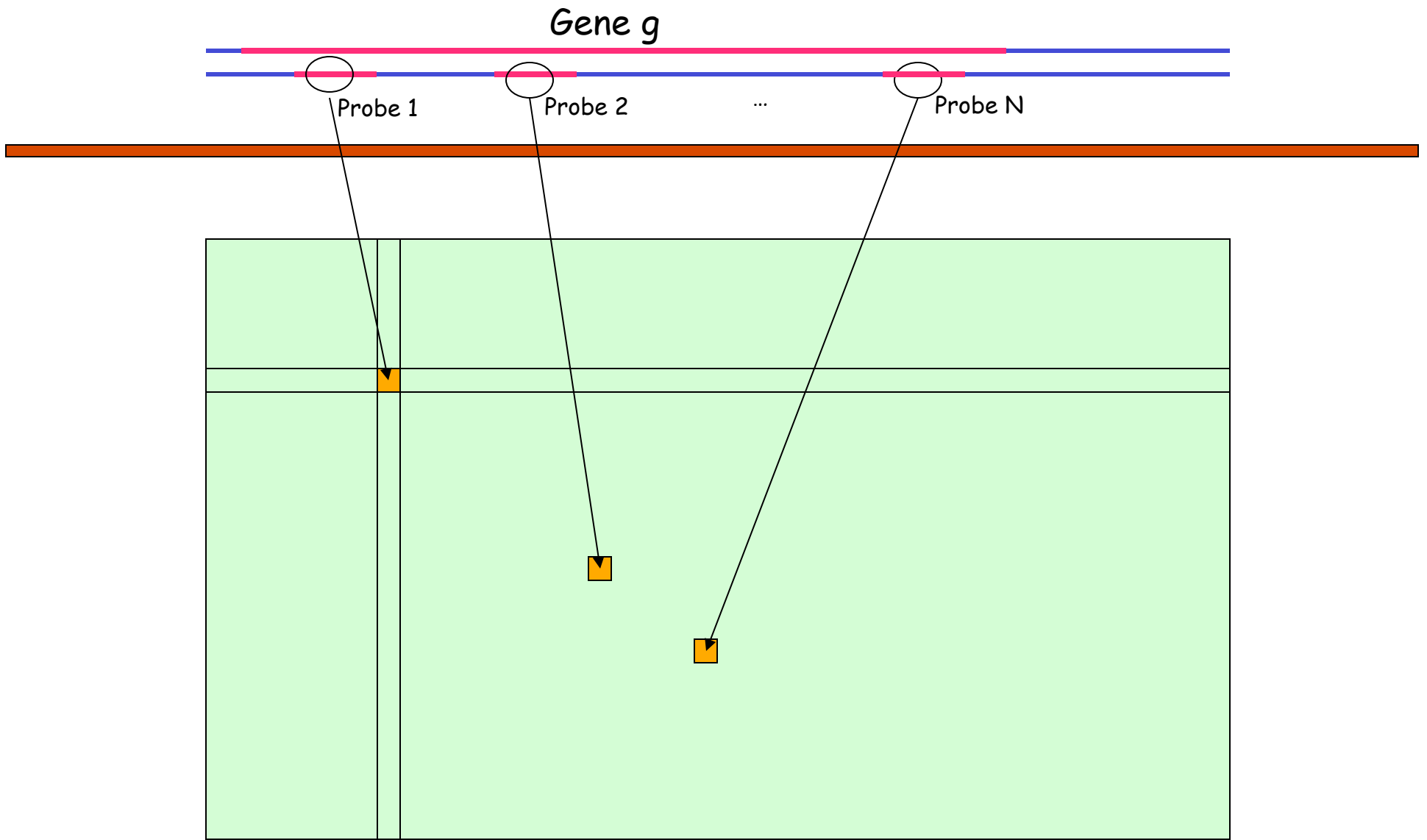
- High-throughput method to study gene expression of thousands of genes simultaneously.
- Many applications:
 - Genetic disorders & Mutation/polymorphism detection
 - Study of disease subtypes
 - Drug discovery & toxicology studies
 - Pathogen analysis
 - Differing expressions over time, between tissues,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

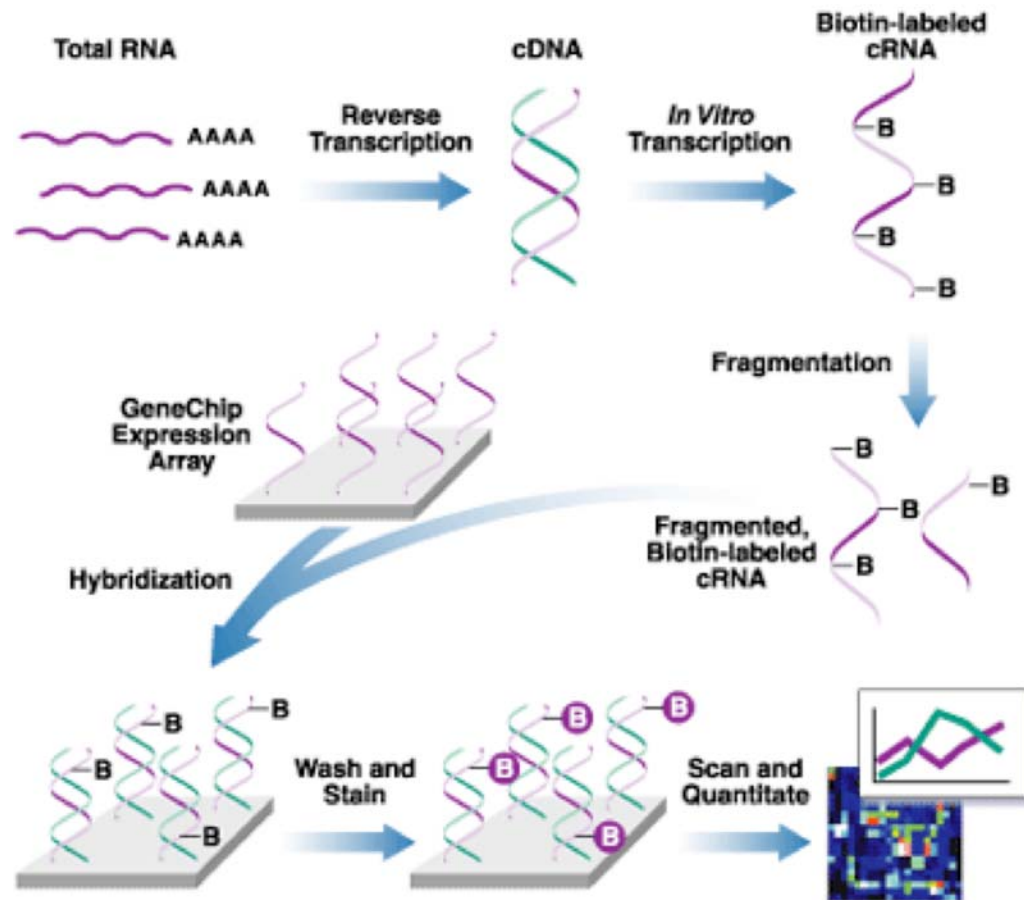




Microarray/DNA chips (Simplified)

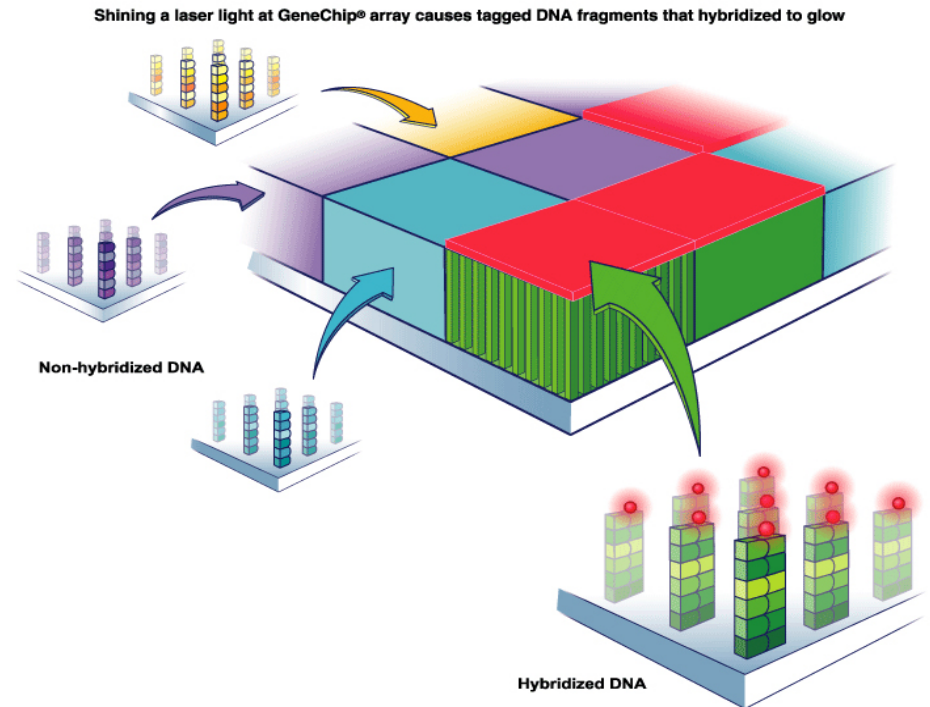
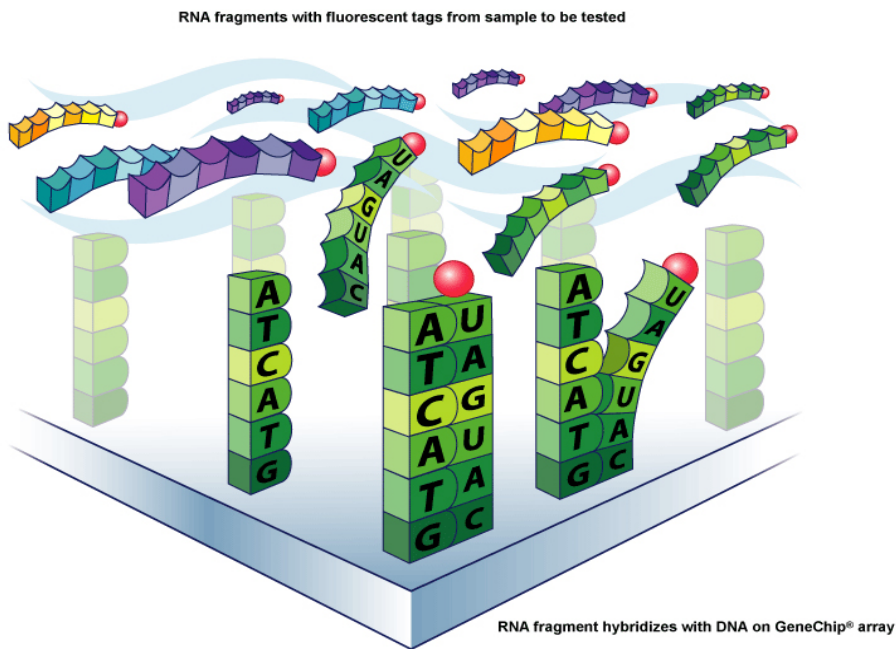
- ❑ Construct **probes** corresponding to reverse complements of genes of interest.
- ❑ Microscopic quantities of probes placed on solid surfaces at defined spots on the chip.
- ❑ Extract mRNA from sample cells and **label** them.
- ❑ Apply labeled sample (mRNA extracted from cells) to every spot, and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

Affymetrix DNA chip schematic

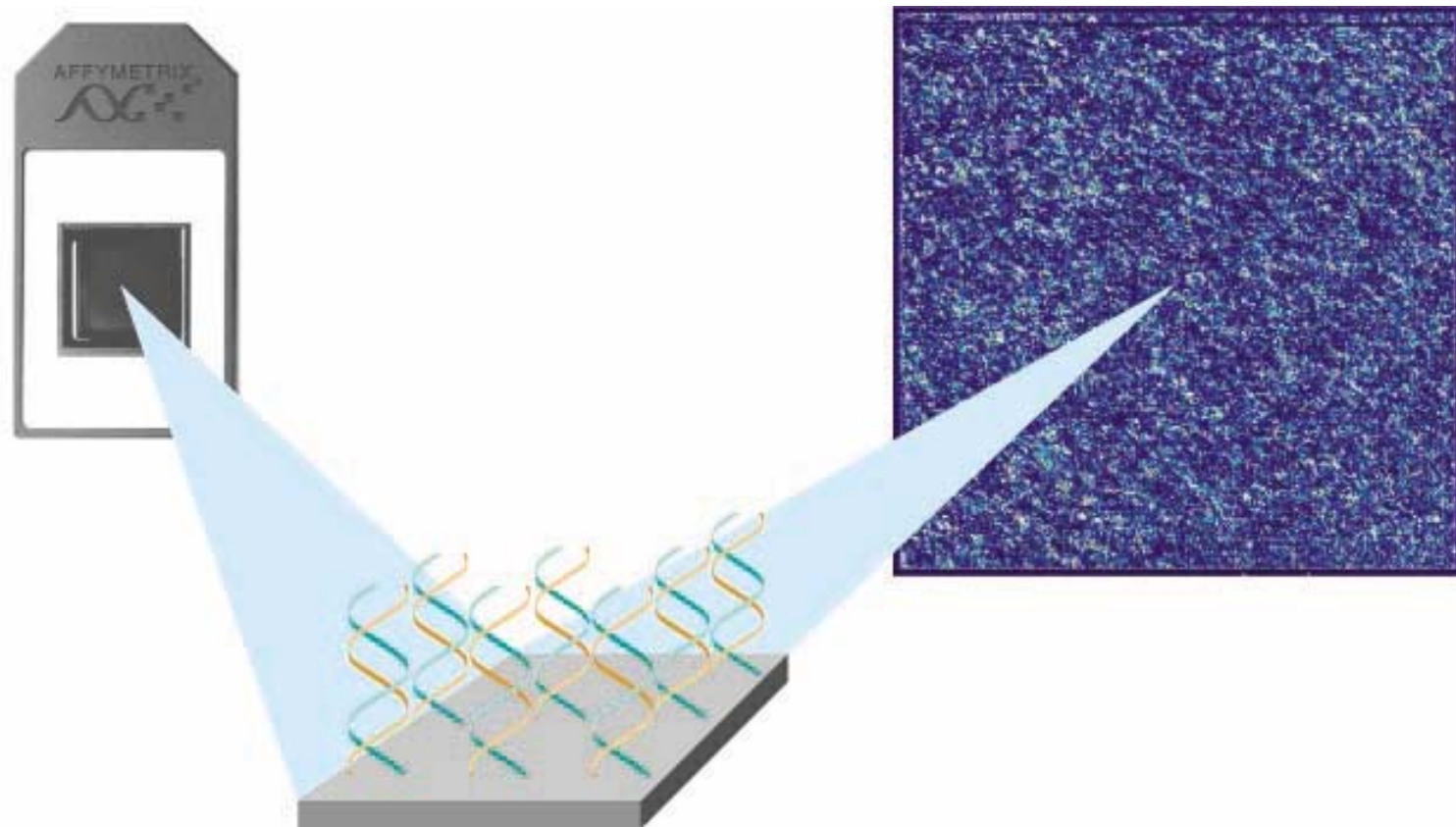


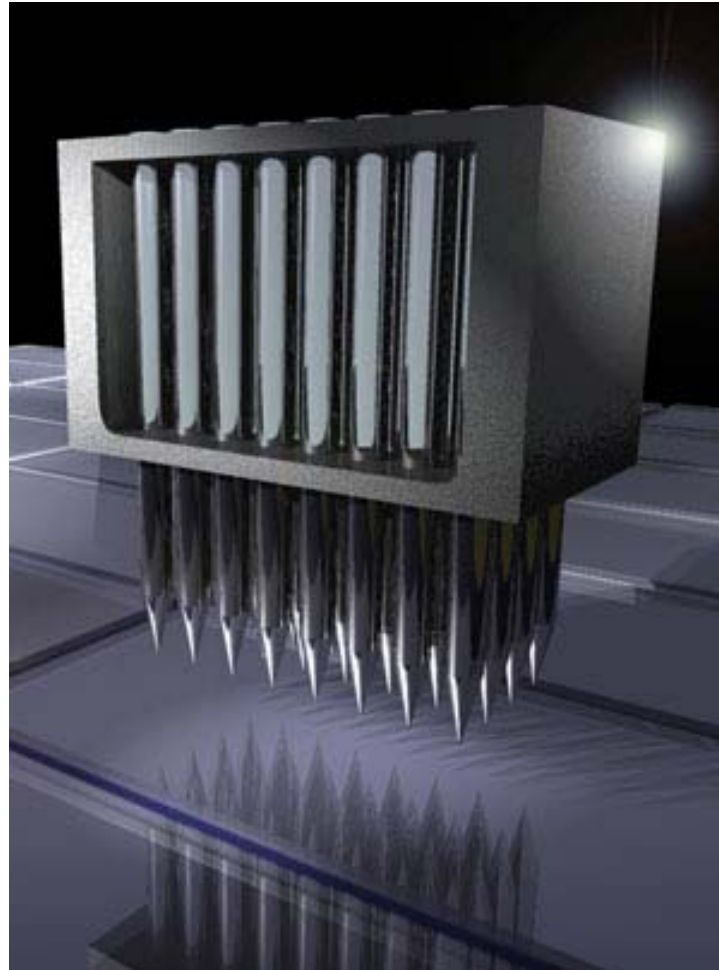
www.affymetrix.com

What's on the slide?



DNA Chips & Images

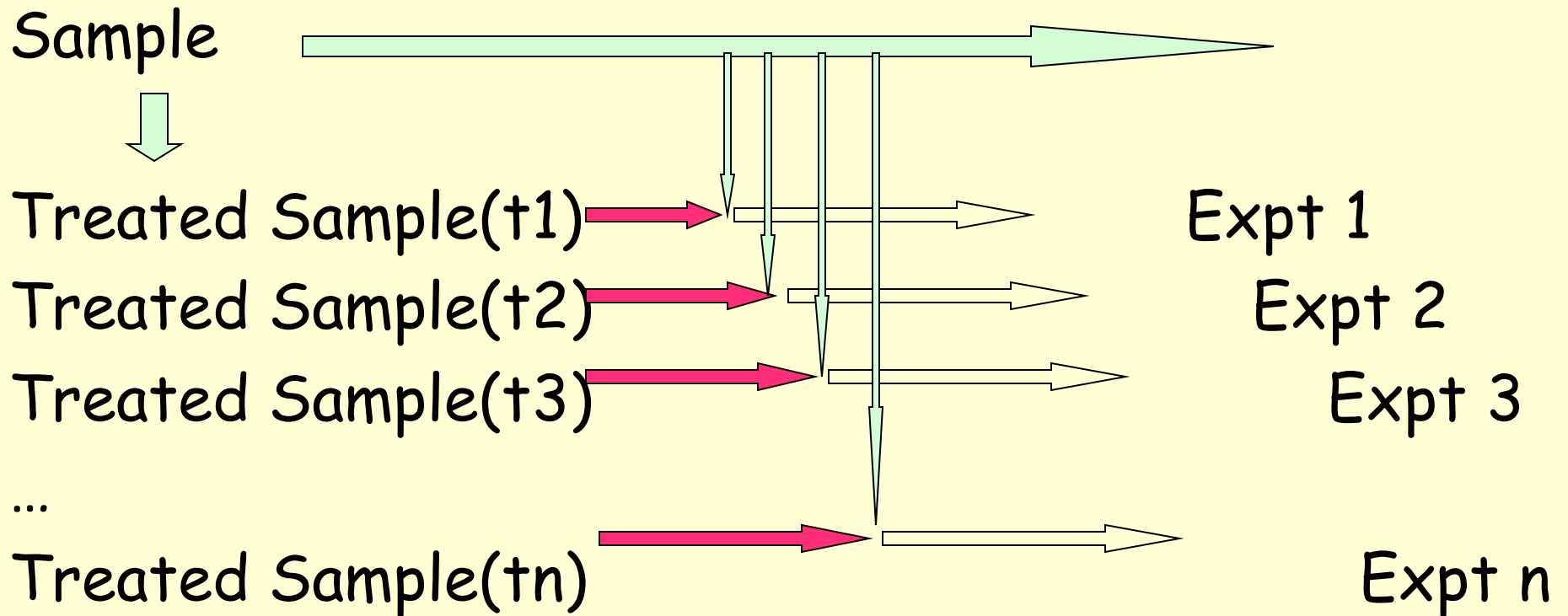




Microarrays: competing technologies

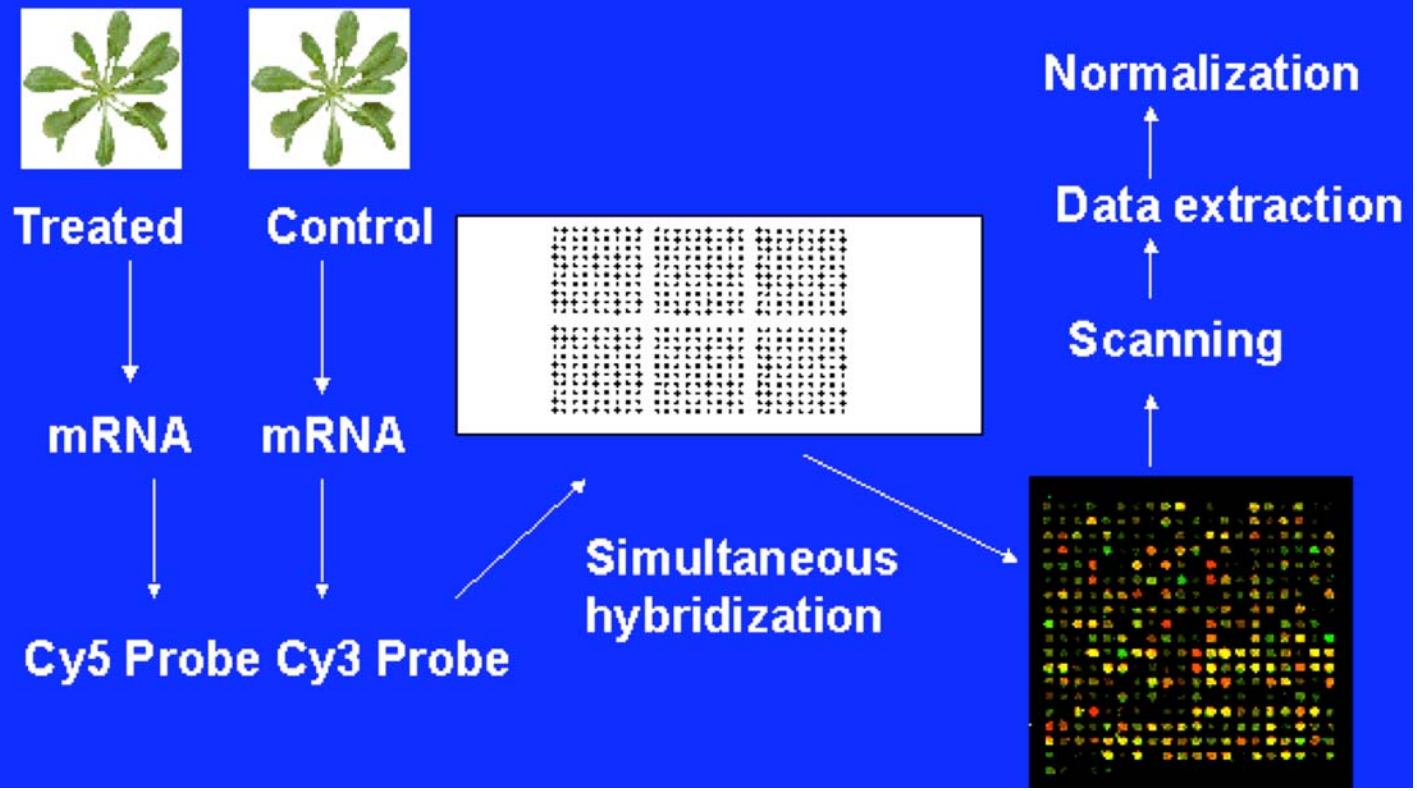
- ❑ Affymetrix & Agilent
- ❑ Differ in:
 - method to place DNA: Spotting vs. photolithography
 - Length of probe
 - Complete sequence vs. series of fragments

Study effect of treatment over time





2-color DNA microarray



How to compare 2 cell samples with Two-Color Microarrays?

- ❑ mRNA from sample 1 is extracted and labeled with a **red fluorescent** dye.
- ❑ mRNA from sample 2 is extracted and labeled with a **green fluorescent** dye.
- ❑ Mix the samples and apply it to every spot on the microarray. Hybridize sample mixture to probes.
- ❑ Use optical detector to measure the amount of **green** and **red** fluorescence at each spot.

Sources of Variations & Experimental Errors

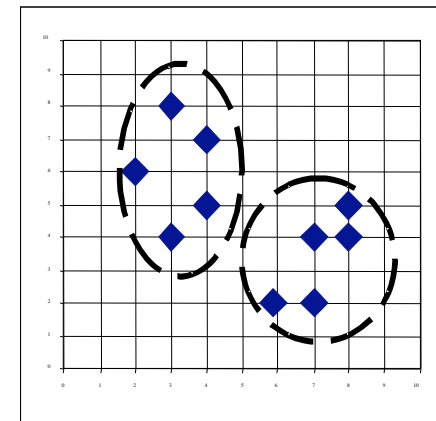
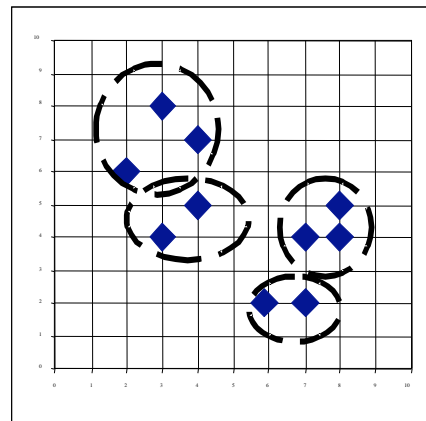
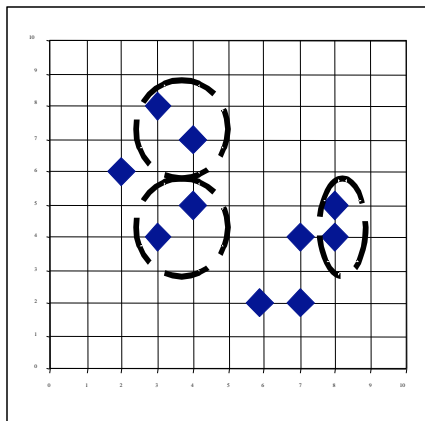
- ❑ Variations in cells/individuals
- ❑ Variations in mRNA extraction, isolation, introduction of dye, variation in dye incorporation, dye interference
- ❑ Variations in probe concentration, probe amounts, substrate surface characteristics
- ❑ Variations in hybridization conditions and kinetics
- ❑ Variations in optical measurements, spot misalignments, discretization effects, noise due to scanner lens and laser irregularities
- ❑ Cross-hybridization of sequences with high sequence identity
- ❑ Limit of factor 2 in precision of results
- ❑ Variation changes with intensity: larger variation at low or high expression levels

Need to Normalize data

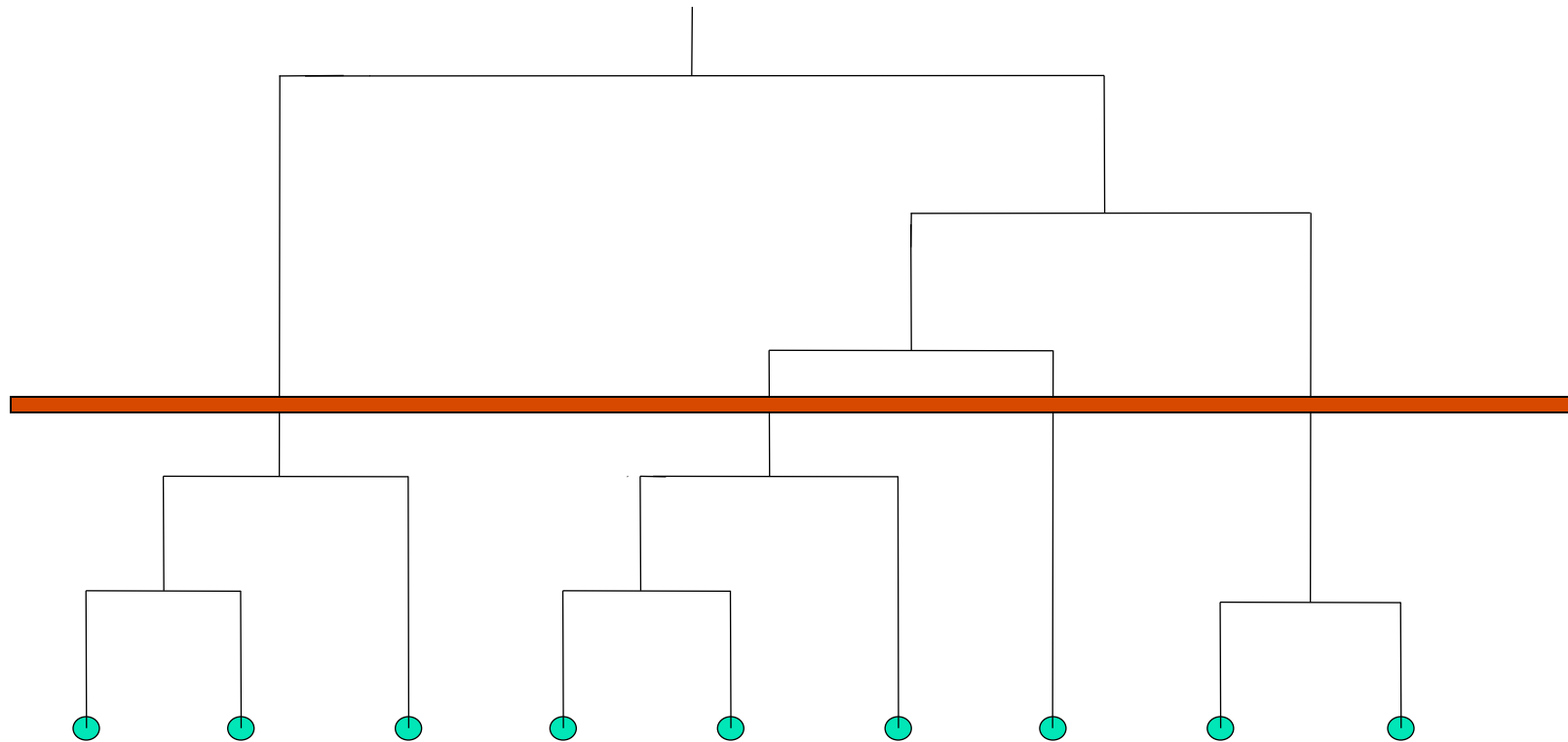
Clustering

- Clustering is a general method to study patterns in gene expressions.
- Several known methods:
 - Hierarchical Clustering (Bottom-Up Approach)
 - K-means Clustering (Top-Down Approach)
 - Self-Organizing Maps (SOM)

Hierarchical Clustering: Example



A Dendrogram



Hierarchical Clustering [Johnson, SC, 1967]

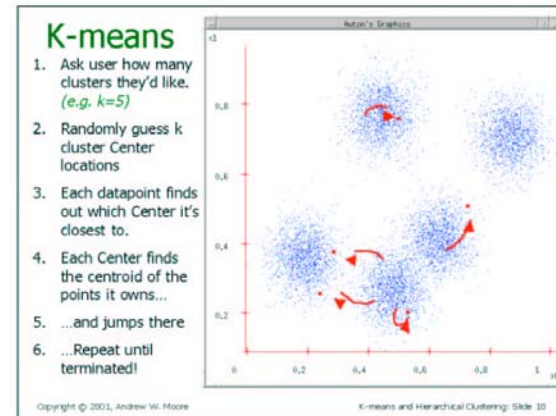
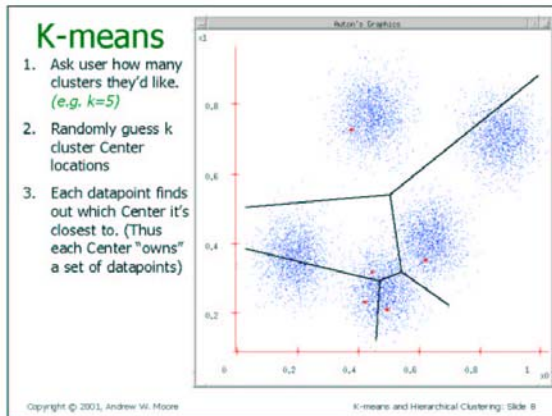
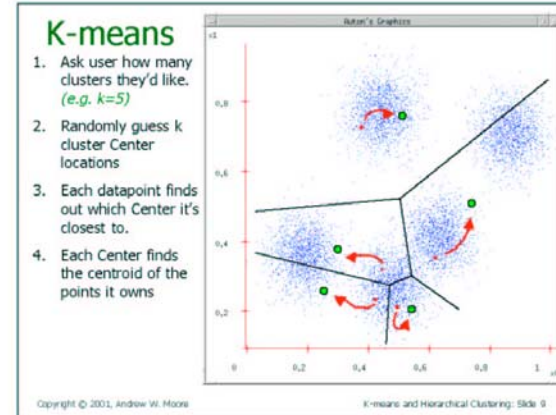
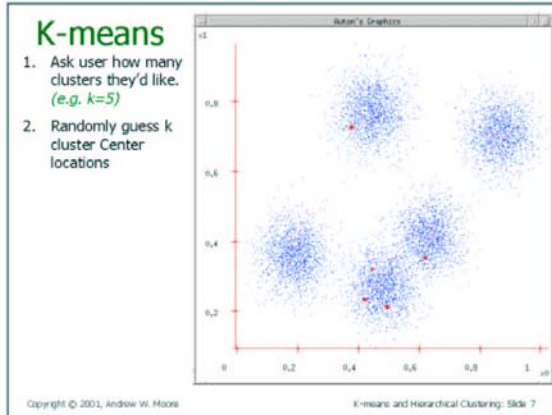
- Given n points in \mathbb{R}^d , compute the distance between every pair of points
- While (not done)
 - Pick closest pair of points s_i and s_j and make them part of the same cluster.
 - Replace the pair by an average of the two s_{ij}

Try the applet at: http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletH.html

K-Means Clustering: Example

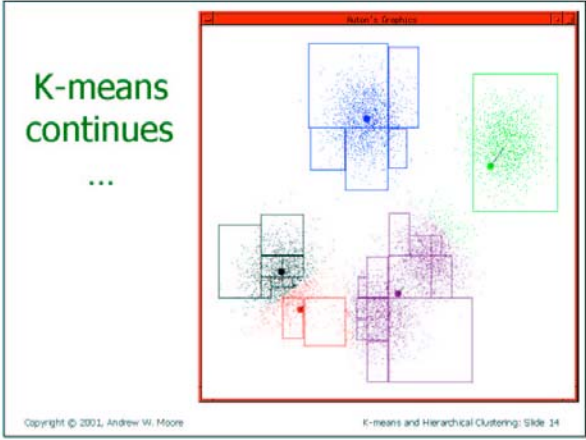
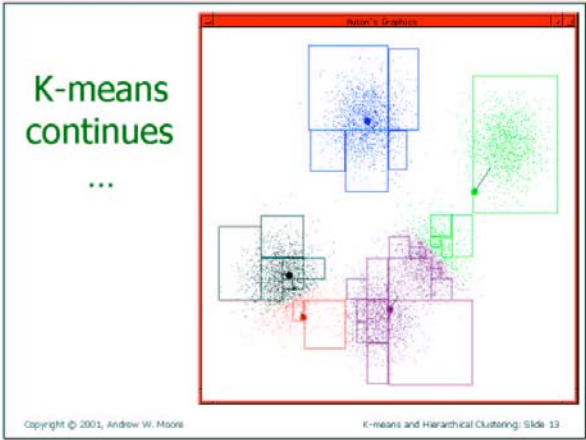
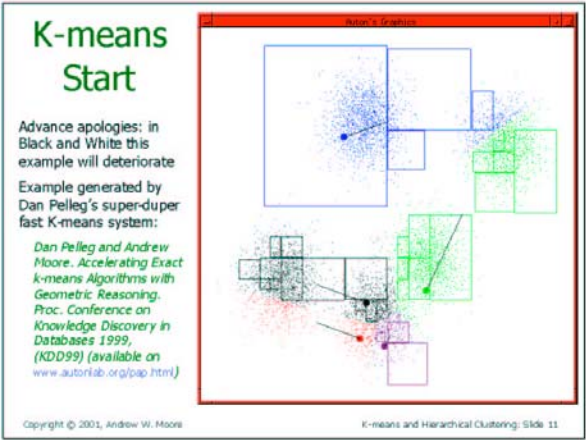
Example from Andrew Moore's tutorial on Clustering.

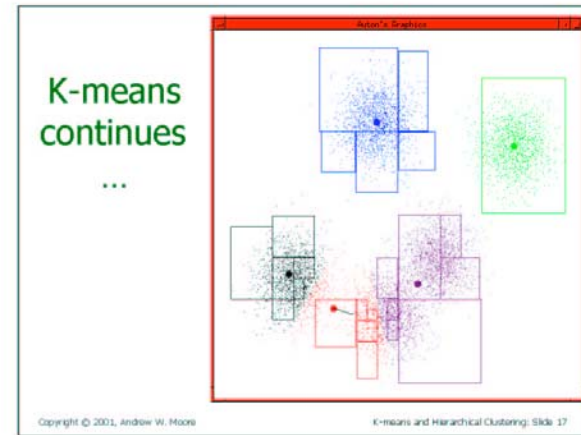
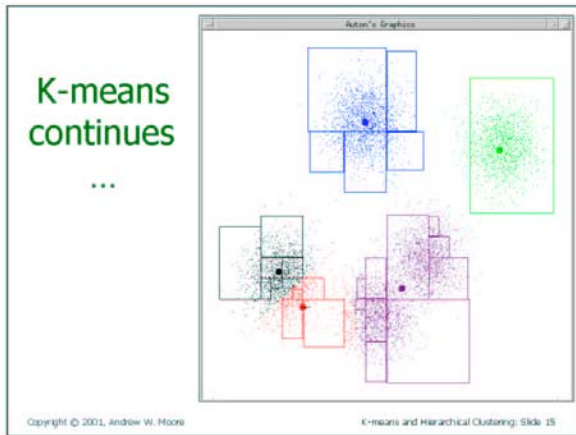
Start



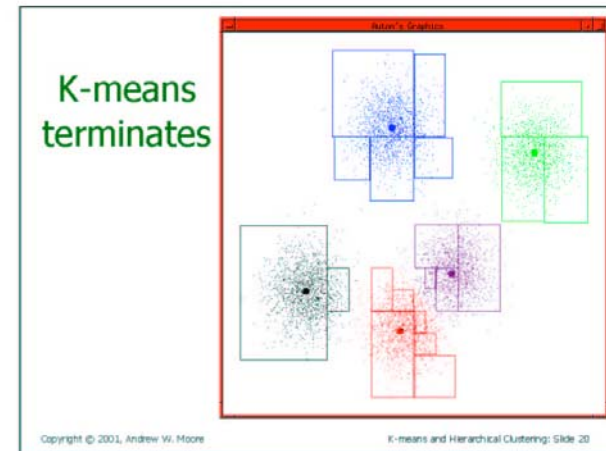
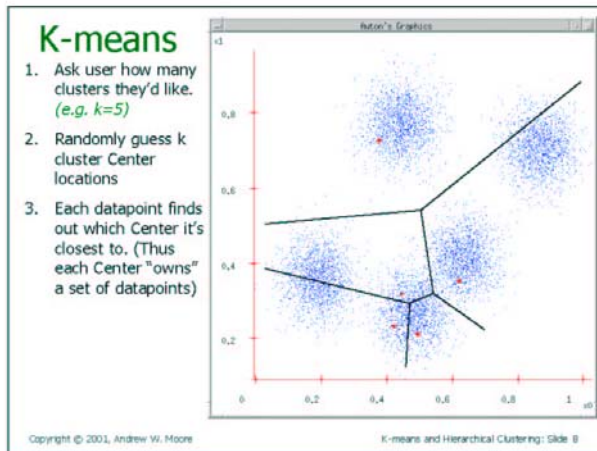
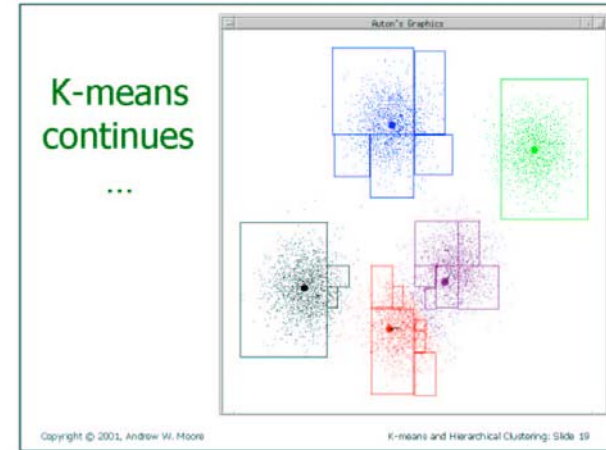
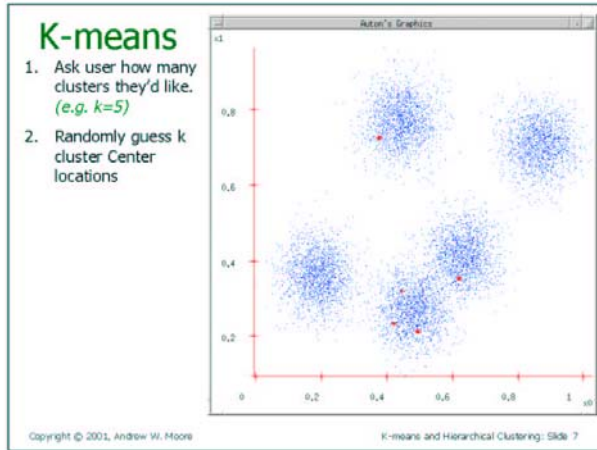
4

5





Start



End

K-Means Clustering [McQueen '67]

Repeat

- Start with randomly chosen cluster centers
- Assign points to give greatest increase in score
- Recompute cluster centers
- Reassign points

until (no changes)

Try the applet at: http://home.dei.polimi.it/matteucc/Clustering/tutorial_html/AppletH.html

Comparisons

Hierarchical clustering

- Number of clusters not preset.
- Complete hierarchy of clusters
- Not very robust, not very efficient.

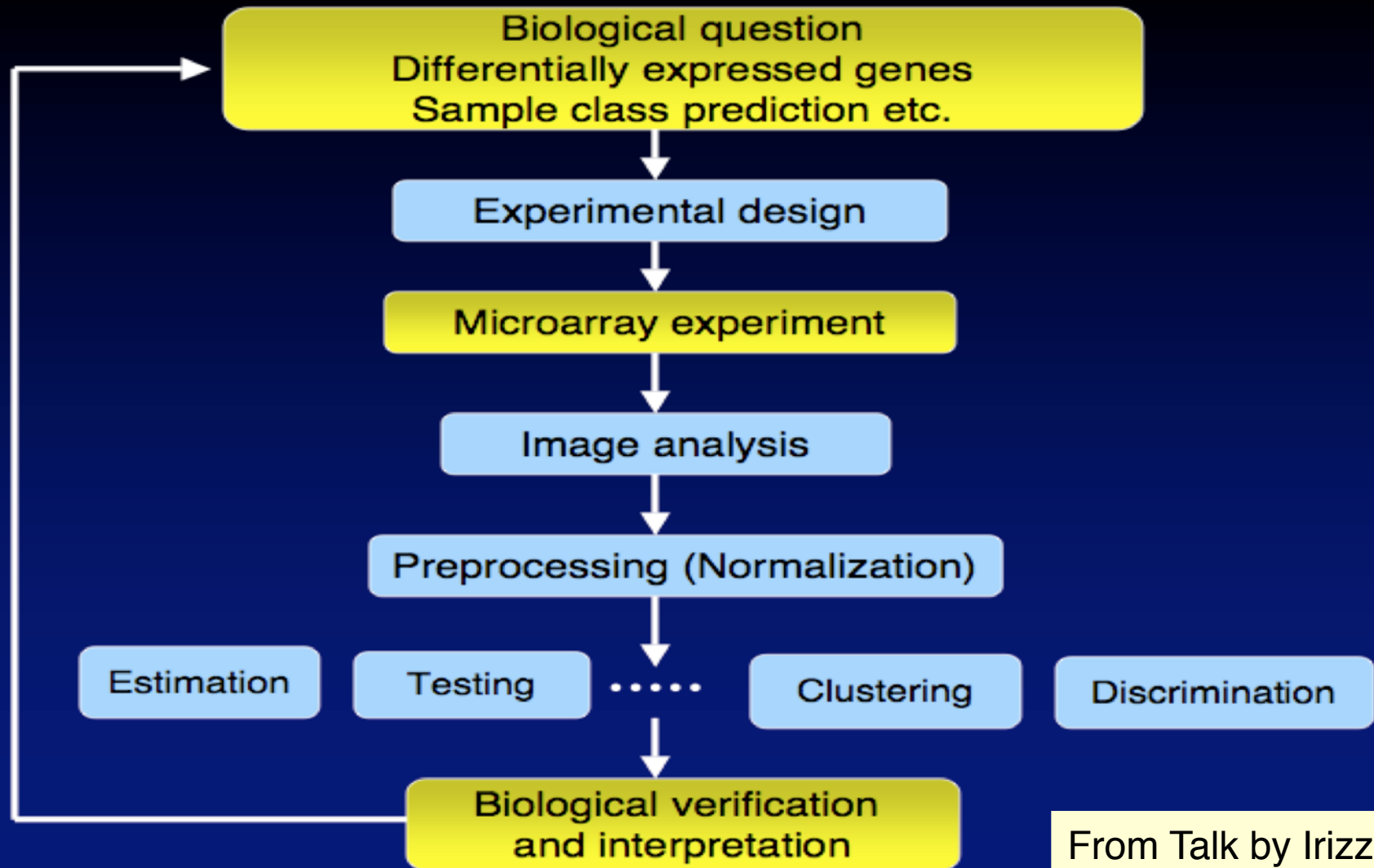
K-Means

- Need definition of a **mean**. Categorical data?
- More efficient and often finds optimum clustering.

Reading

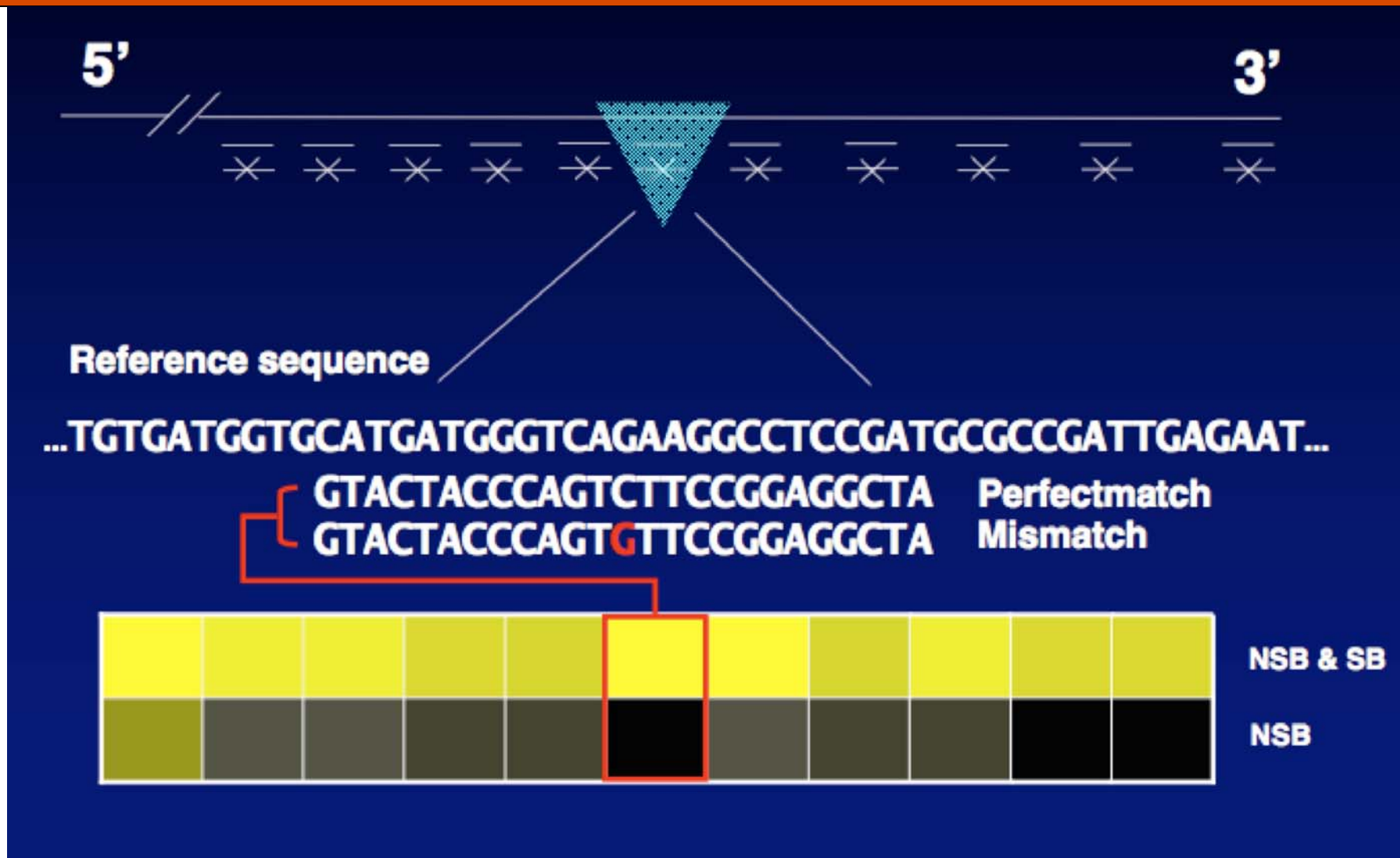
- The following slides come from a series of talks by Rafael Irizzary from Johns Hopkins
- Much of the material can be found in detail in the following papers from [<http://www.biostat.jhsph.edu/~ririzarr/papers/>]
 - Irizarry, RA, Hobbs, B, Collin, F, Beazer-Barclay, YD, Antonellis, KJ, Scherf, U, Speed, TP (2003) Exploration, Normalization, and Summaries of High Density Oligonucleotide Array Probe Level Data. *Biostatistics*. Vol. 4, Number 2: 249-264.
 - Bolstad, B.M., Irizarry RA, Astrand, M, and Speed, TP (2003), A Comparison of Normalization Methods for High Density Oligonucleotide Array Data Based on Bias and Variance. *Bioinformatics*. 19(2):185-193.

Inference Process

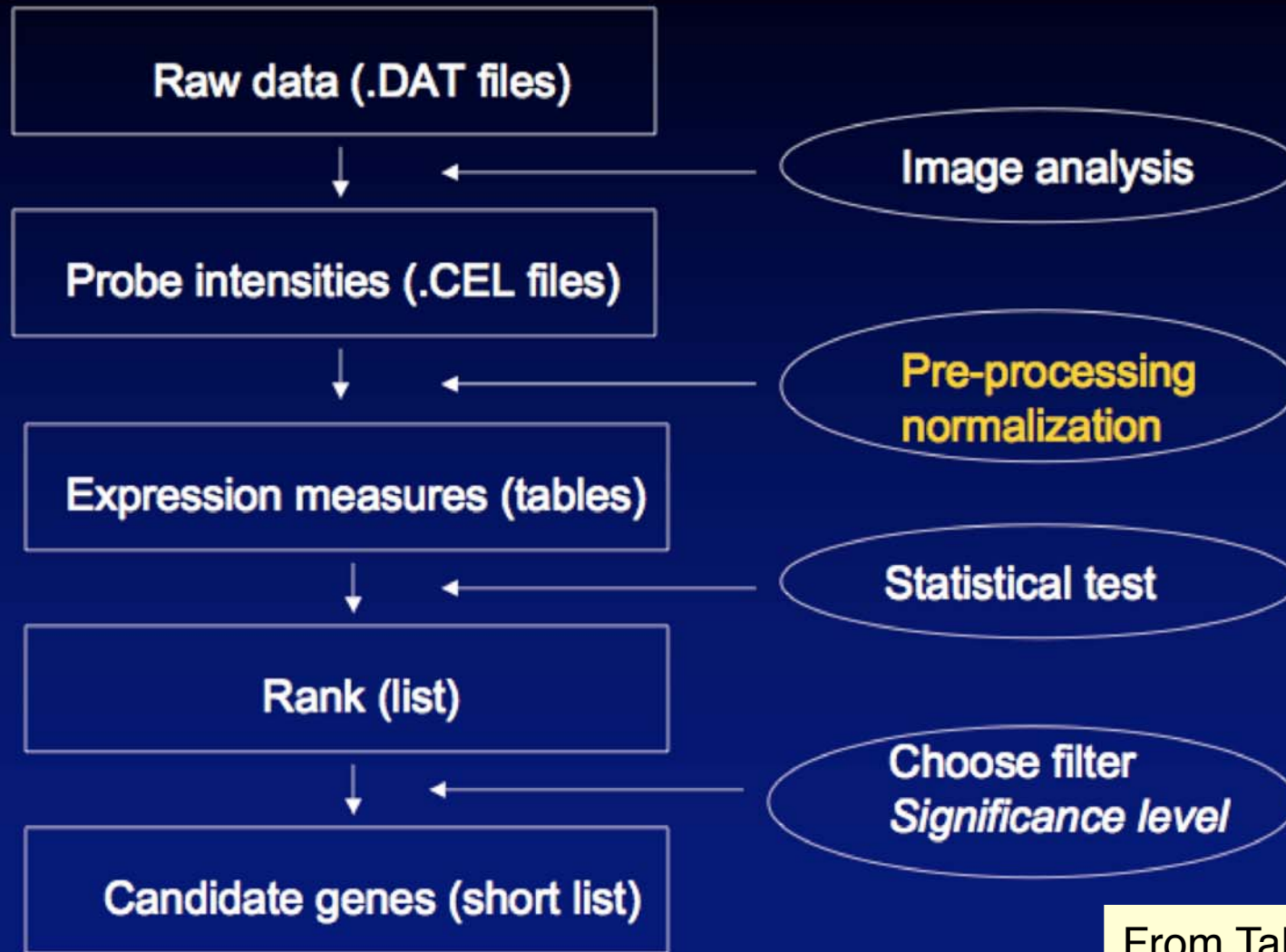


From Talk by Irizzary

Affymetrix Genechip Design



Workflow: Analyzing Affy data



From Talk by Irizzary

Affy Files

- **DAT** file: image file, about 10 million pixels, 30-50 MB
- **CEL** file: cell intensity file with probe level PM and MM values
- **CDF** file: chip description file describing which probes go in which probe sets and the location of probe-pair sets (genes, gene fragments, ESTs)

From Talk by Irizzary

Image analysis & Background Correction

- ❑ Each probe cell: 10 X 10 pixels
- ❑ Gridding estimates location of probe cell centers
- ❑ Signal is computed by
 - Ignoring outer 36 pixels leaving a 8 X 8 pixel area
 - Taking the 75 percentile of the signal from the 8 X 8 pixel area
- ❑ Background signal is computed as the average of the lowest 2% probe cell values, which is then subtracted from the individual signals

From Talk by Irizzary

Standard Normalization Procedure

- ❑ Log-transform the data
- ❑ Ensure that the average intensity and the standard deviation are the same across all arrays.
- ❑ This requires the choice of a baseline array, which may or may not be obvious.

Analyzing Affy data

□ MAS 4.0

- Works with PM-MM
- Negative values result very often
- Very noisy for low expressed genes
- Averages without log-transformation

□ dChip [Li & Wong, PNAS 98(1):31-36]

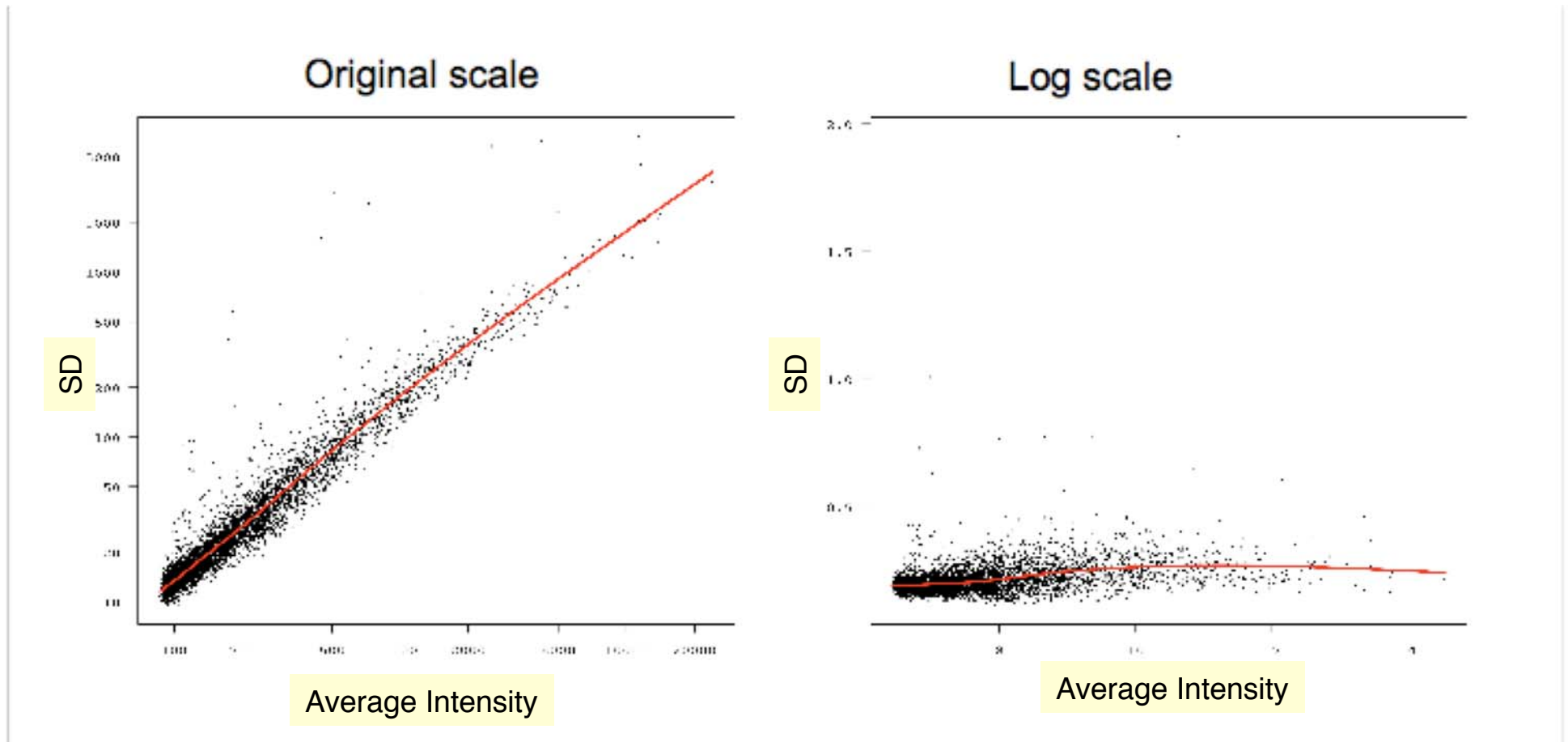
- Accounts for probe effect
- Uses non-linear normalization
- Multi-chip analysis reveals outliers

□ MAS 5.0

- Improves on problems with MAS 4.0

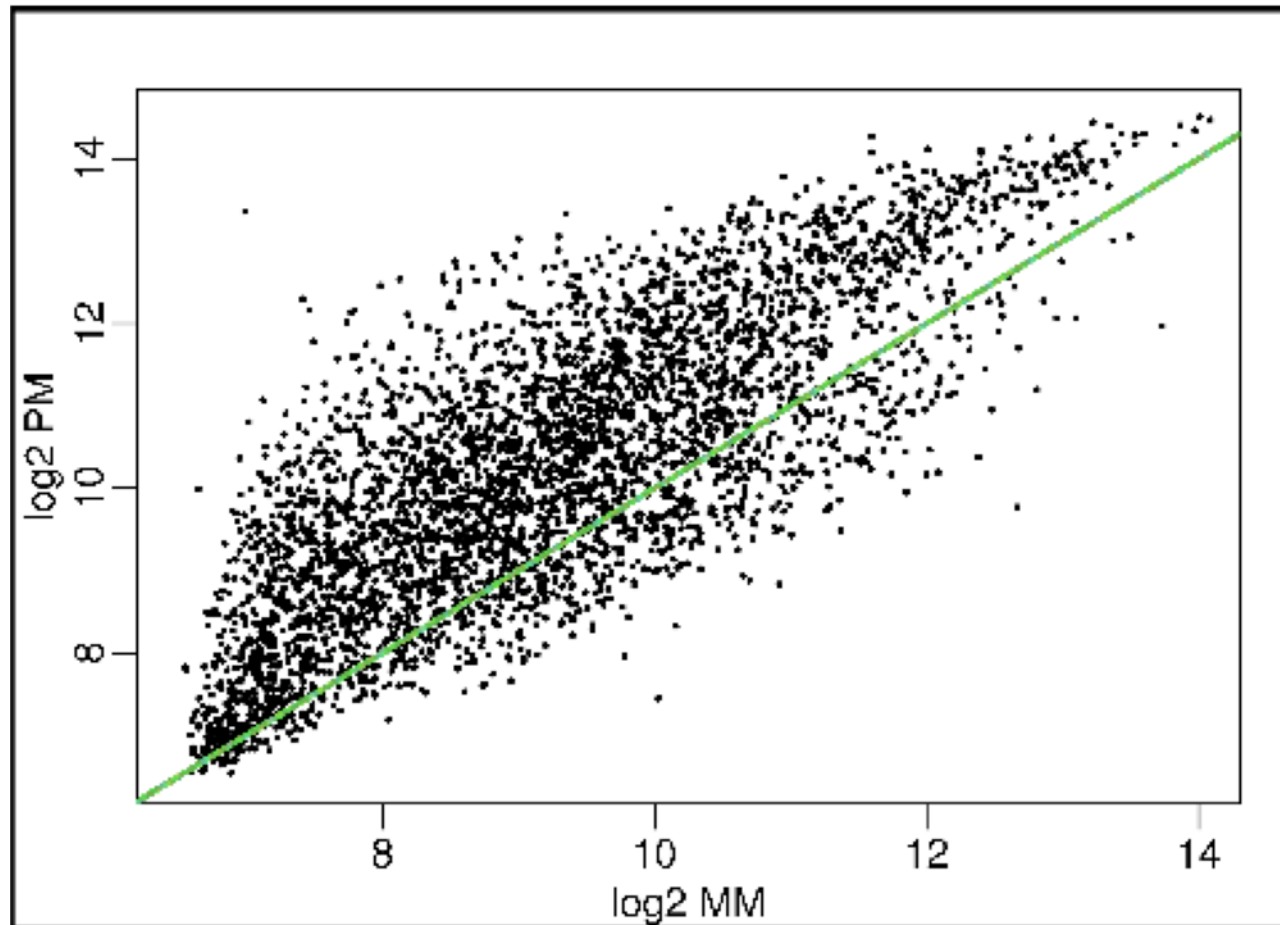
From Talk by Irizzary

Why you use log-transforms?



From Talk by Irizzary

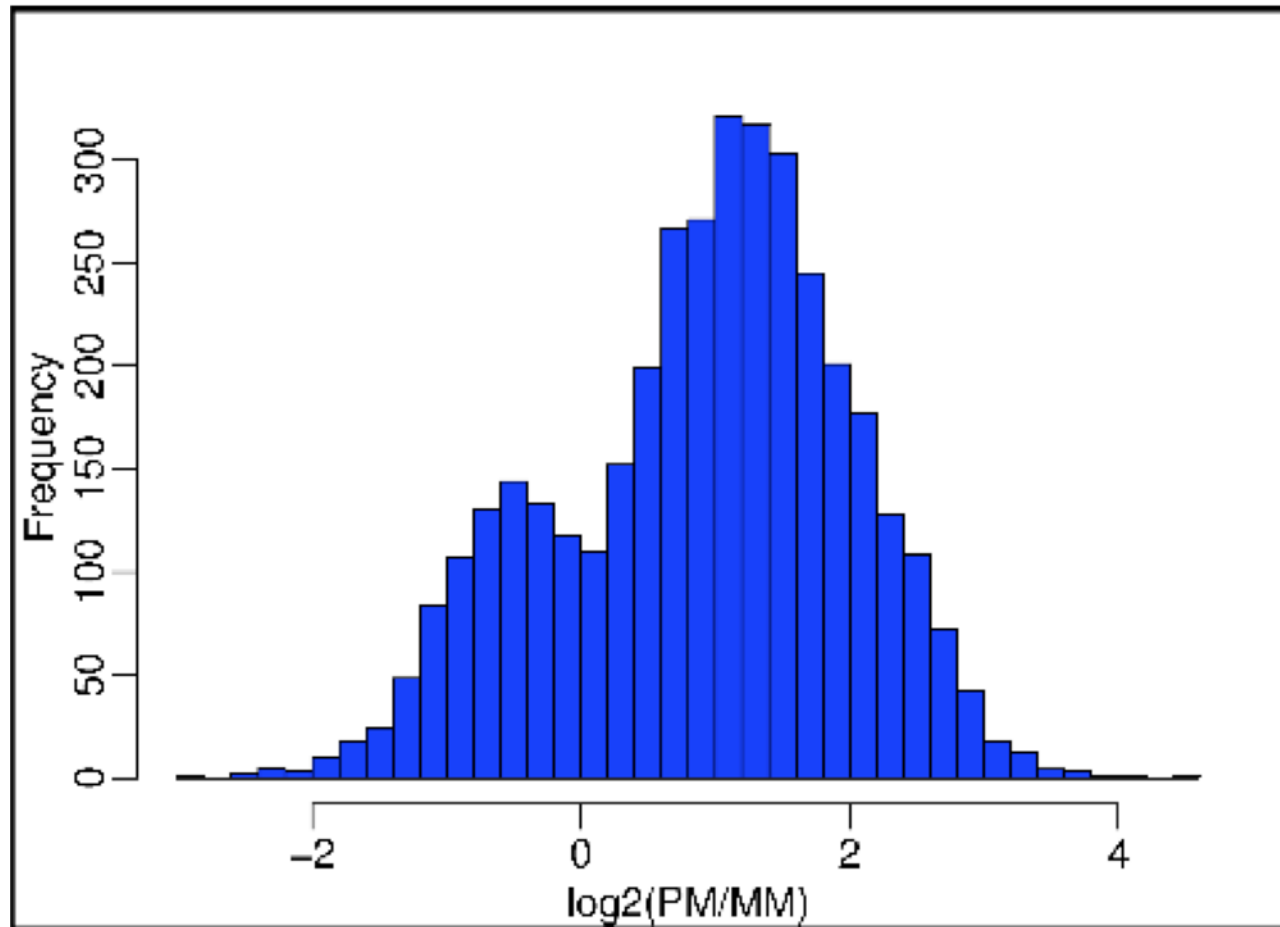
Problem with using (transformed) PM-MM



Sometimes MM is larger than PM!

From Talk by Irizzary

Bimodality for large expression values

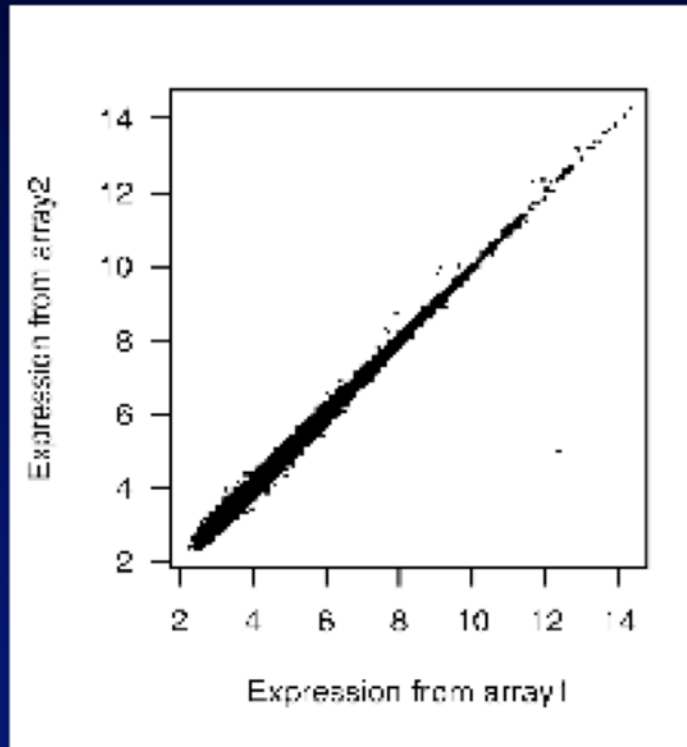


From Talk by Irizzary

MAS 5.0

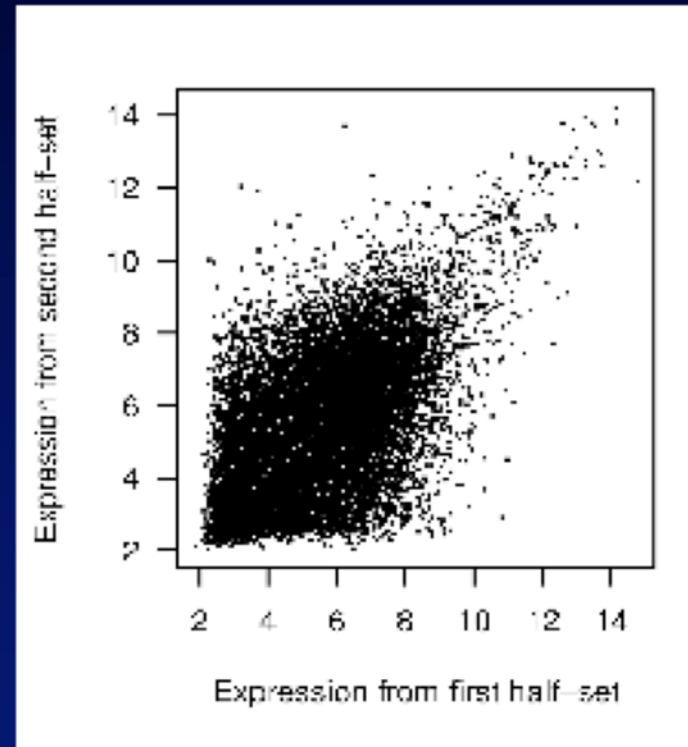
- ❑ **MAS 5.0** is Affymetrix software for microarray data analysis.
- ❑ Ad hoc background procedure used
- ❑ For summarization, they use:
 - **Signal = TukeyBiweight{log(PM_j - MM_j*)}**
 - Tukey Biweight: $B(x) = (1 - (x/c)^2)^2$, if $x < c$
= 0 otherwise
- ❑ Ad hoc scale normalization used

2 replicate arrays



Expression from corresponding probes are highly correlated

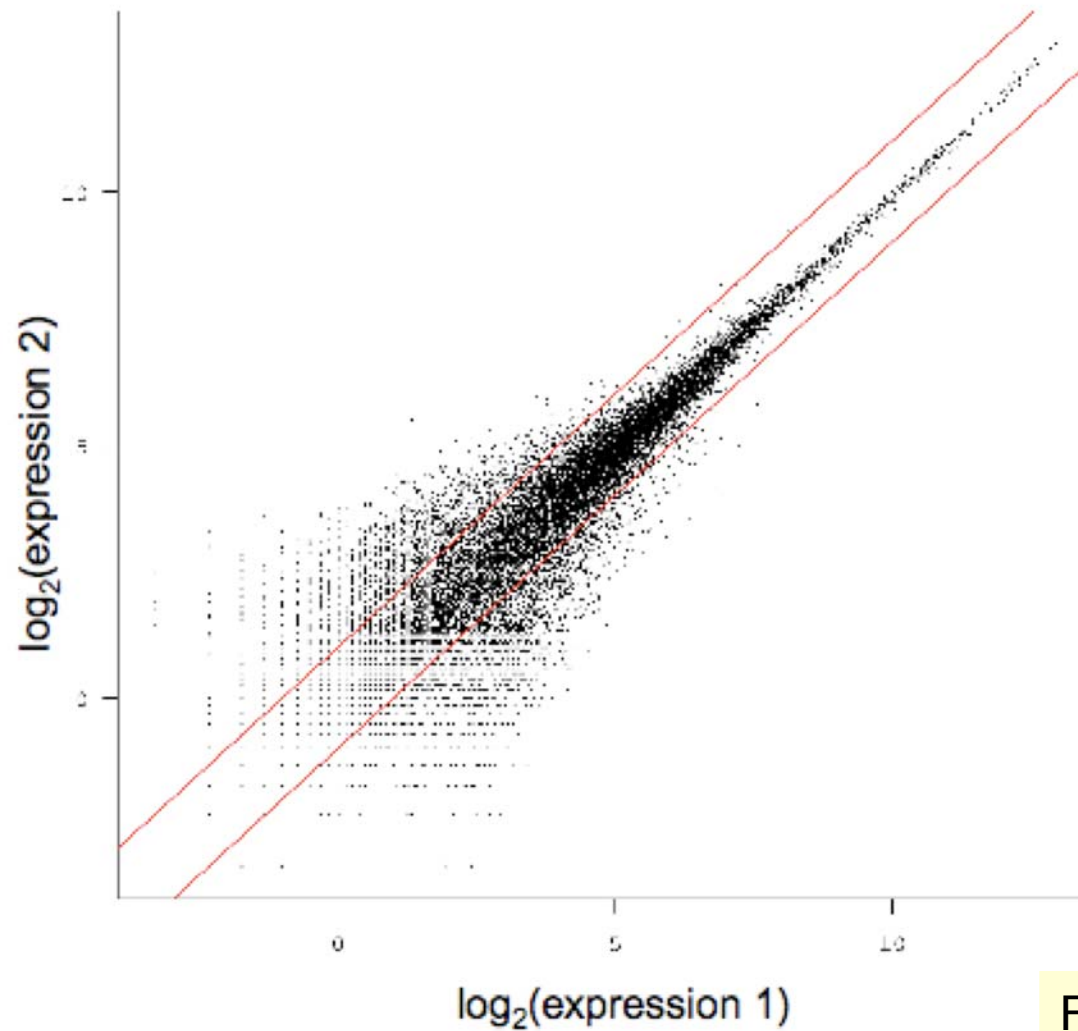
Correlation is higher than 0.99



Expression not correlated when probes randomly partitioned

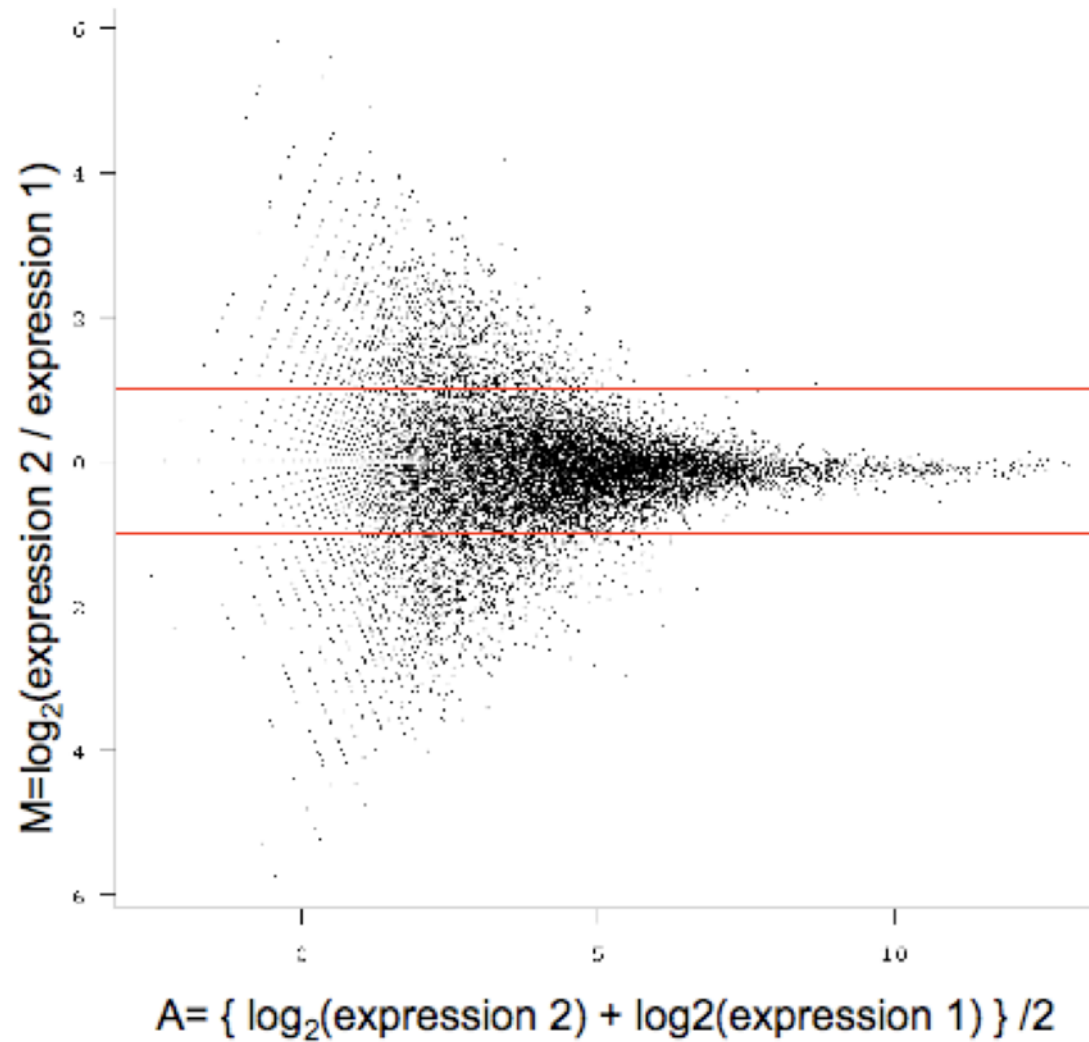
Correlation drops to 0.55

We have to deal with **variations!**



From Talk by Irizzary

MvA Plots

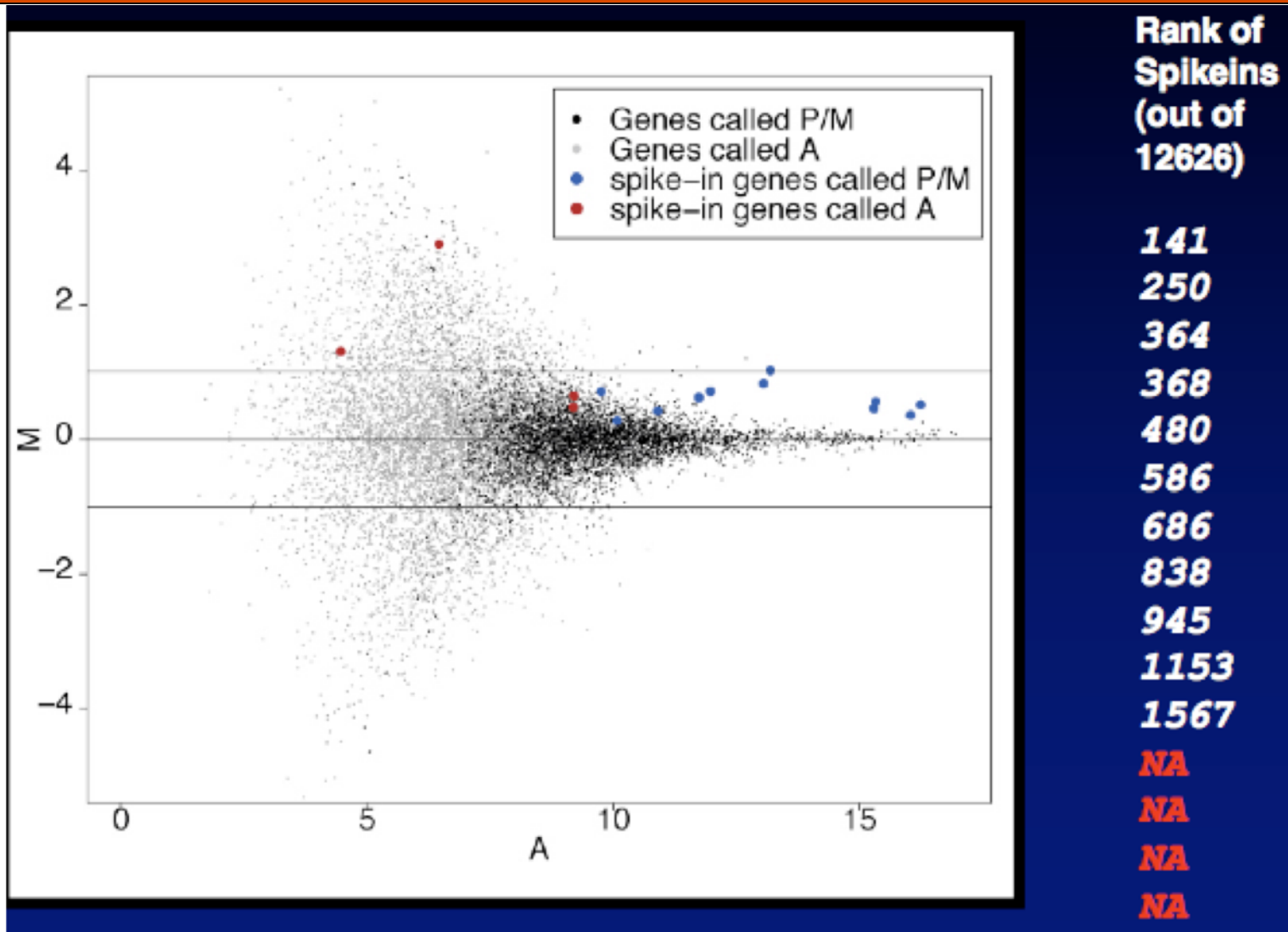


Spike-in Experiment

- ❑ Replicate RNA samples were hybridized to various arrays
- ❑ Some probe sets were spiked in at different concentrations across the different arrays
- ❑ Goal was to see if these spiked probe sets “stood out” as differentially expressed

From Talk by Irizzary

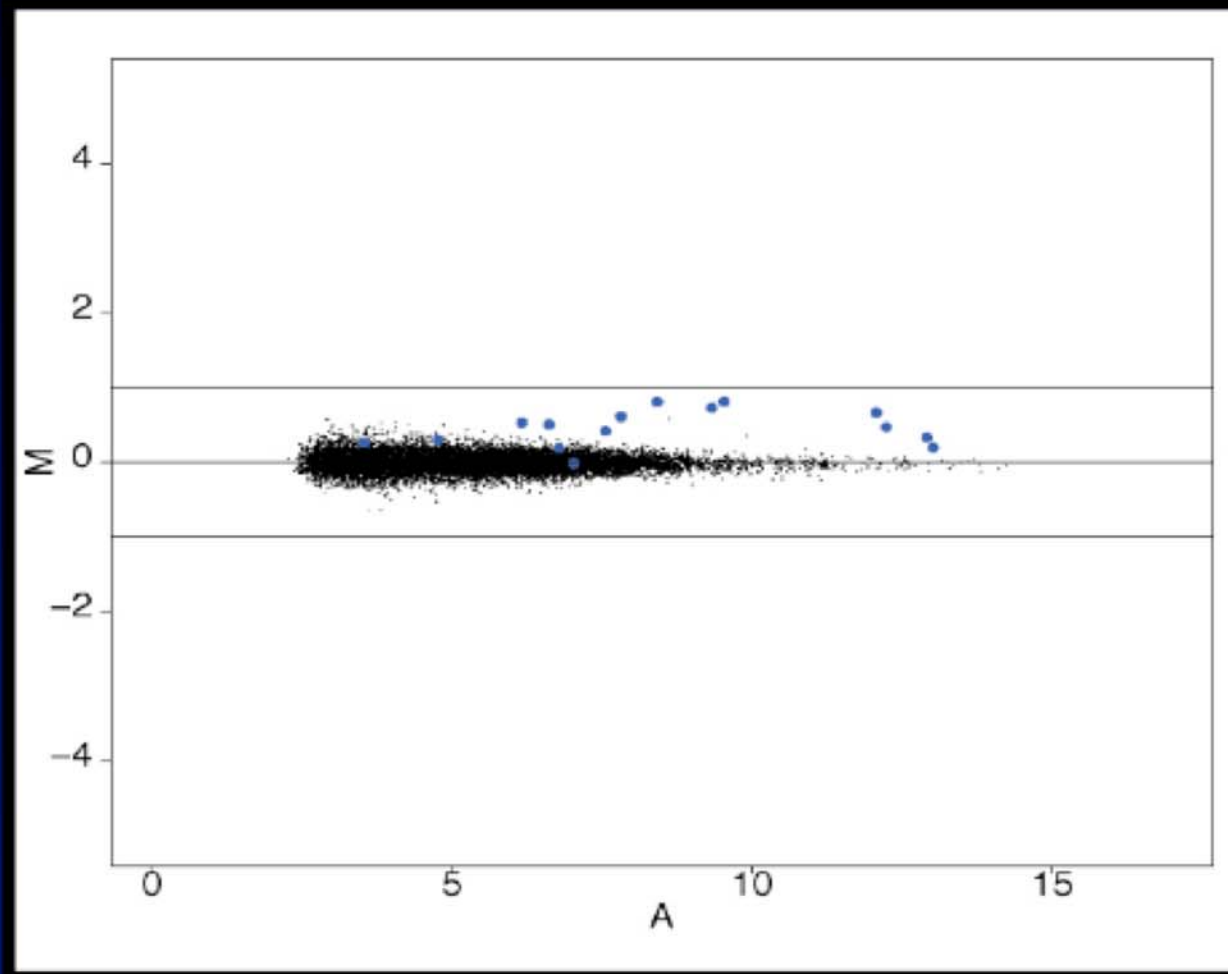
Analyzing Spike-in data with MAS 5.0



Robust Multiarray normalization (RMA)

- **Background correction** separately for each array
 - Find $E\{\text{Sig} \mid \text{Sig} + \text{Bgd} = \text{PM}\}$
 - Bgd is normal and Sig is exponential
- Uses **quantile normalization** to achieve "identical empirical distributions of intensities" on all arrays
- **Summarization**: Performed separately for each probe set by fitting probe level additive model
- Uses **median polish** algorithm to robustly estimate expression on a specific chip
- Also see **GCRMA** [Wu, Irizzary et al., 2004]

Analyzing Spike-in data with RMA

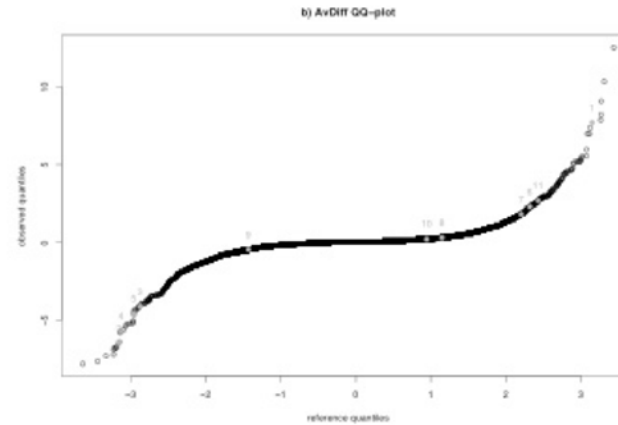
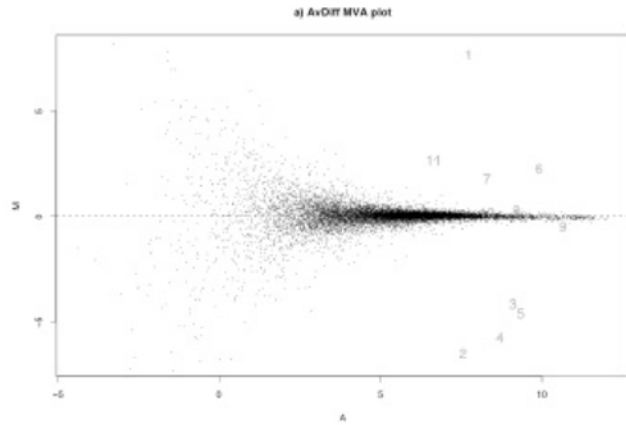


Rank of
Spikeins
(out of
12626)

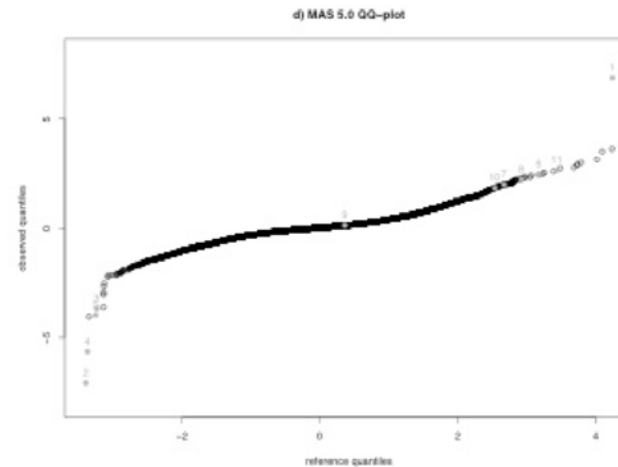
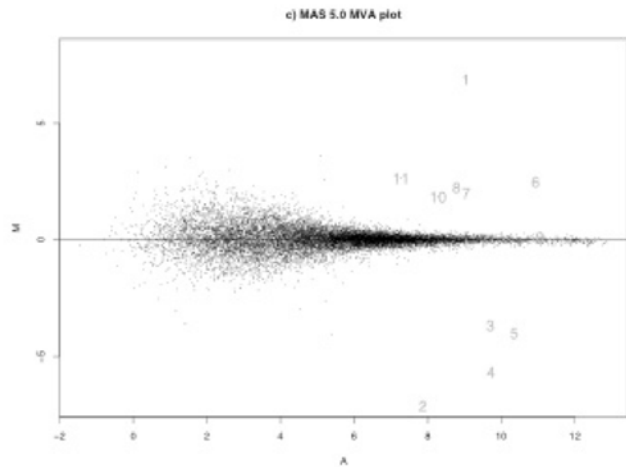
1
2
3
4
7
11
15
21
35
122
1182
230
450
1380
11700

Irizarry et al. (2003) *NAR* 31:e15

MvA and q-q plots



MAS 4.0

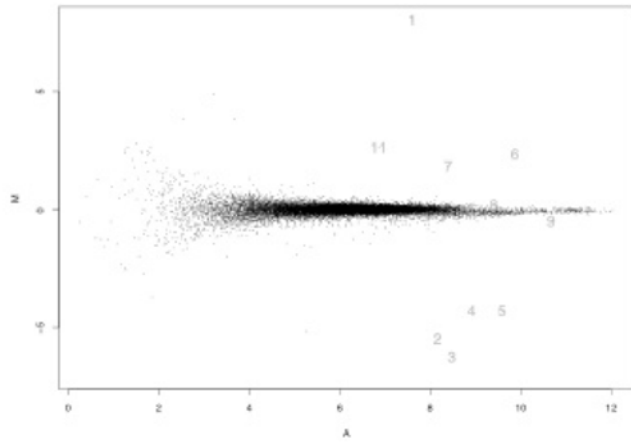


MAS 5.0

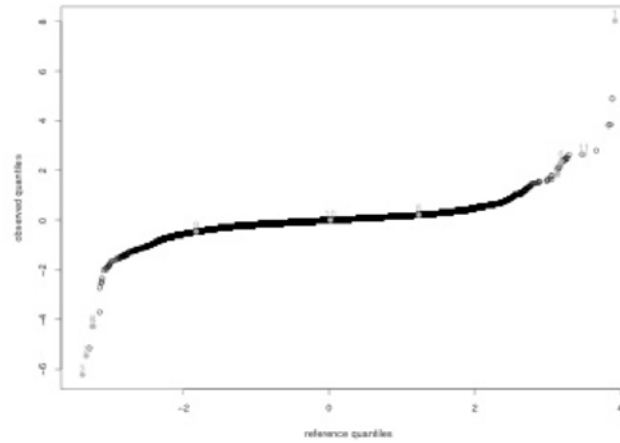
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MvA and q-q Plots

e) Li and Wong's β MVA plot

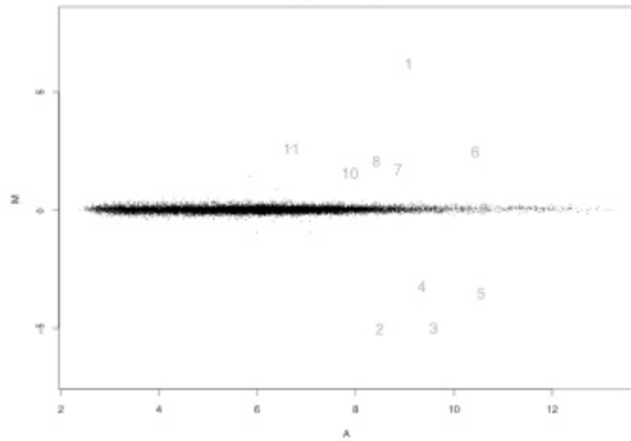


f) Li and Wong's β QQ-plot

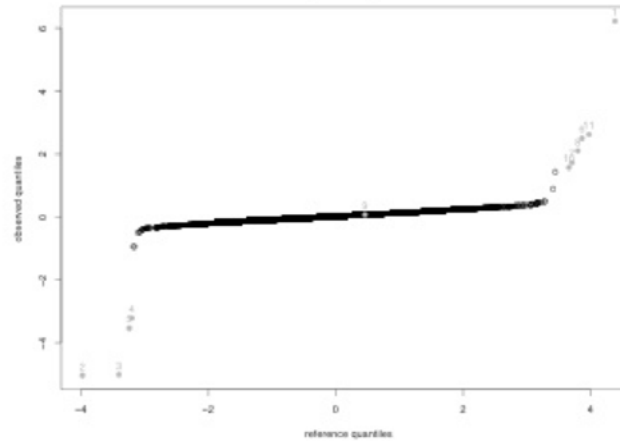


MBEI

g) RMA MVA plot



h) RMA QQ-plot



RMA

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Before and after quantile normalization

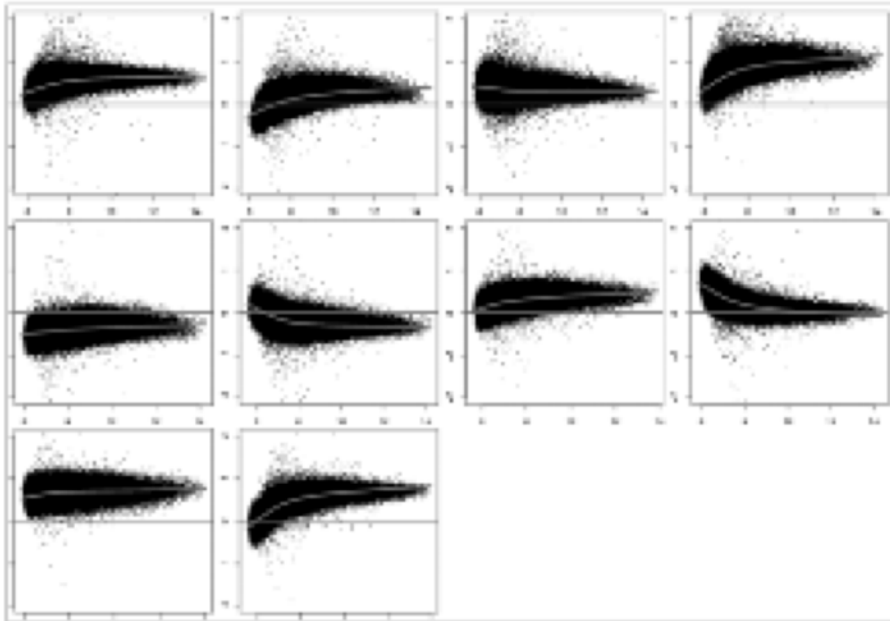


Fig. 2. 10 pairwise M versus A plots using liver (at concentration 10) dilution series data for unadjusted data.

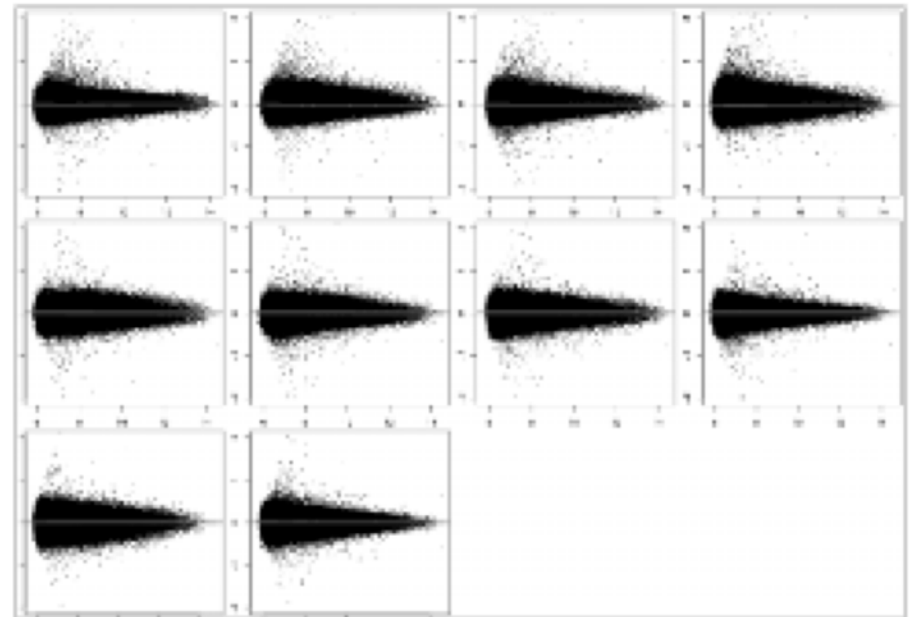


Fig. 3. 10 pairwise M versus A plots using liver (at concentration 10) dilution series data after quantile normalization.

From Talk by Irizzary

Bioconductor

- ❑ **Bioconductor** is an **open source** and open development software project for the analysis of biomedical and genomic data.
- ❑ World-wide project started in 2001
- ❑ **R** and the **R package system** are used to design and distribute software
- ❑ Commercial version of Bioconductor software called **ArrayAnalyzer**

From Talk by Irizzary

R: A Statistical Programming Language

- Try the tutorial at: [<http://www.cyclismo.org/tutorial/R/>]
- Also at: [<http://www.math.ilstu.edu/dhkim/Rstuff/Rtutor.html>]