

Microarray Data Preprocessing

Affymetrix GeneChip

國立臺灣大學 資訊所

Course: 生物資訊之統計與計算方法

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Outlines

■ Affymetrix GeneChip Technology

- GeneChip Photolithography, Array Design, Analysis Process

■ Comparison with cDNA Microarrays

■ Assay and Analysis Flow Chart

- Image Analysis, Affymetrix Data Files, from DAT to CEL.

■ Quality Assessment

- RNA Sample Quality Control
- Array Hybridization Quality Control
- Statistical Quality Control (Diagnostic Plots)

■ Low level Analysis

(from probe level data to expression value)

- Background Correction, Normalization, PM Correction, Expression Index

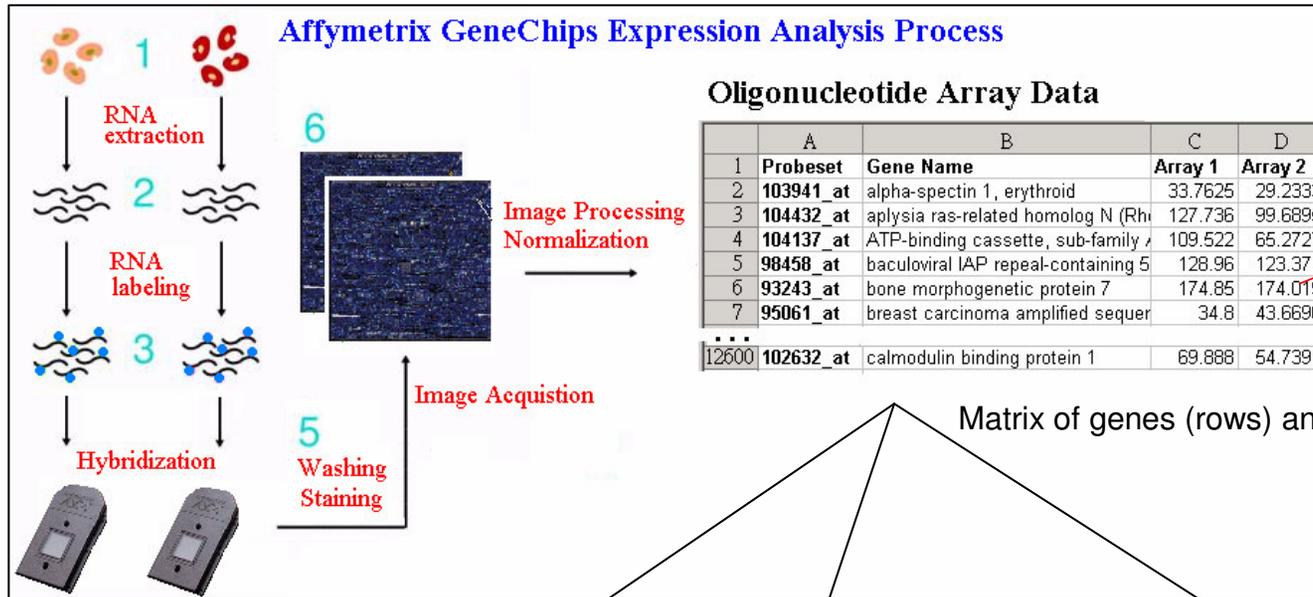
■ Software

- Freeware: BioConductor, dChip, RMAExpress
- Commercial: GCOS, GeneSpring

■ Useful Links and Reference

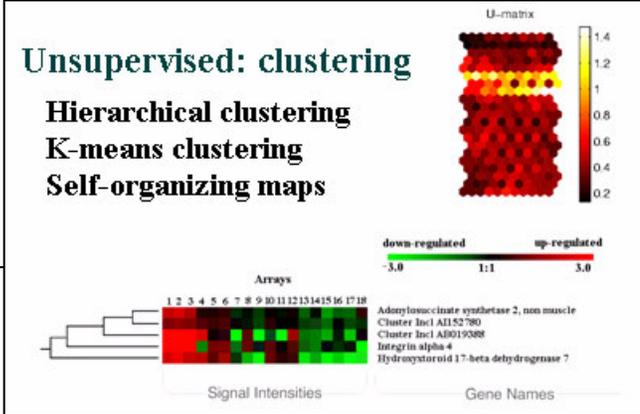
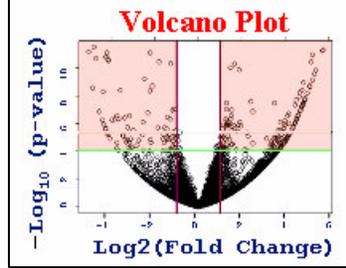


Overview



Expression Index

Discovery of differentially expressed genes
Parametric: t-test
Non-parametric: Wilcoxon, Mann-Whitney test



Supervised: classification

- Linear discriminants
- Decision trees
- Support vector machines

Support Vector Classifiers

input space

feature space

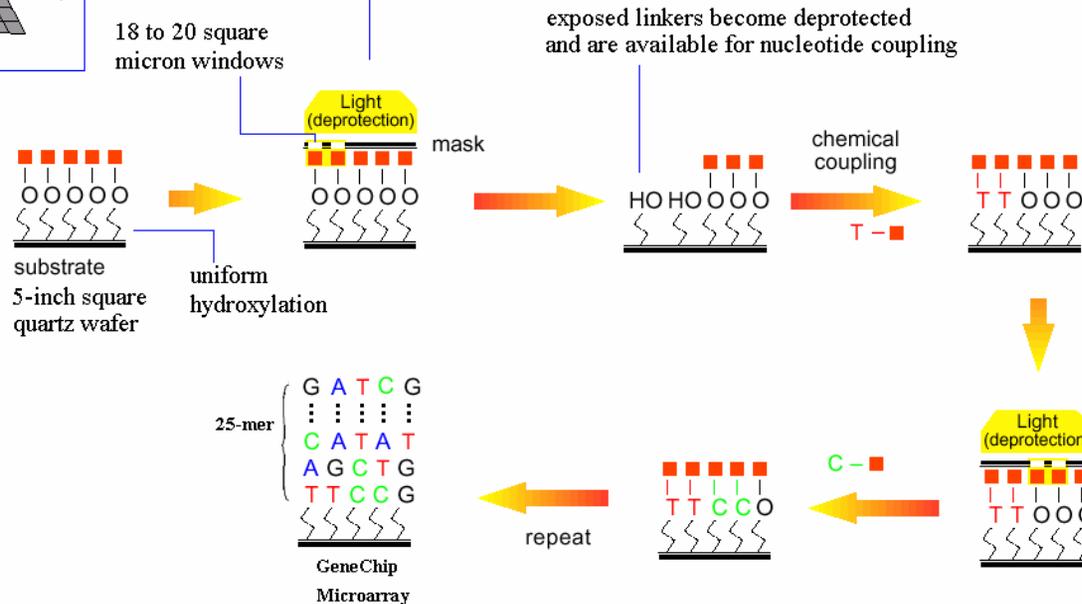
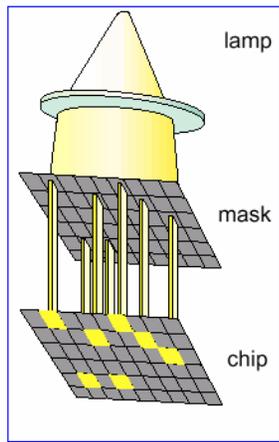
● normal

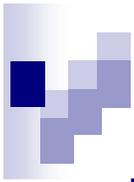
◆ diseased

Boser, Guyon, and Vapnik (1992)

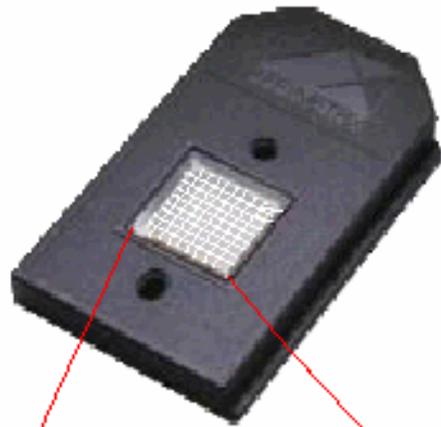
GeneChip Photolithography

1. 在要作為晶片的玻璃版上放一層對光敏感的標記分子 (X)
 - 將光當作合成反應中的活化物。
 - 這些標記分子經過光照後可以形成羥基 (-OH)。
 - 這些羥基可與核甘中的鹼基序列結合起來，合成一段DNA序列。
2. 藉由石版照明面罩(Photolithography Mask) 調控制照光與不照光的區域
 - 把不接上某個鹼基的部份蓋住。
 - 沒有蓋住的部份經光照後即可形成羥基。
3. 事先將核甘序列中的鹼基 (A、T、C、G) 經過修飾成 3-O-phosphoramidite-activated deoxynucleoside，並在其5'端的羥基處以光標記物質加以保護
 - 在此四個鹼基中選一個，令其流經玻璃表面，此鹼基會與羥基的部份結合起來。
 - 之後再蓋住其他部份，使其他未形成羥基的部份經過光照後產生羥基。
 - 再以另一個鹼基流過玻璃片，重複這些步驟，以接出含各種鹼基序列的核甘序列。





GeneChip Expression Array Design



1.28cm

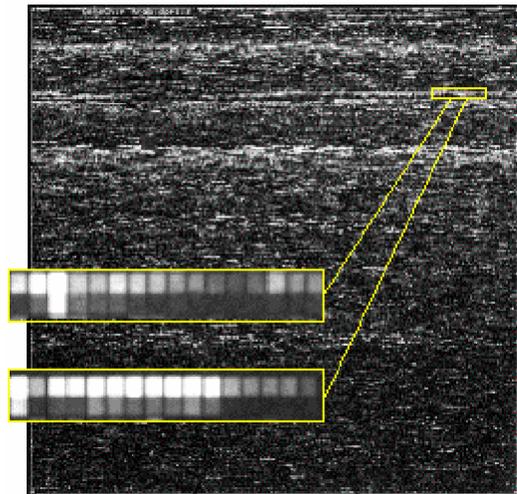
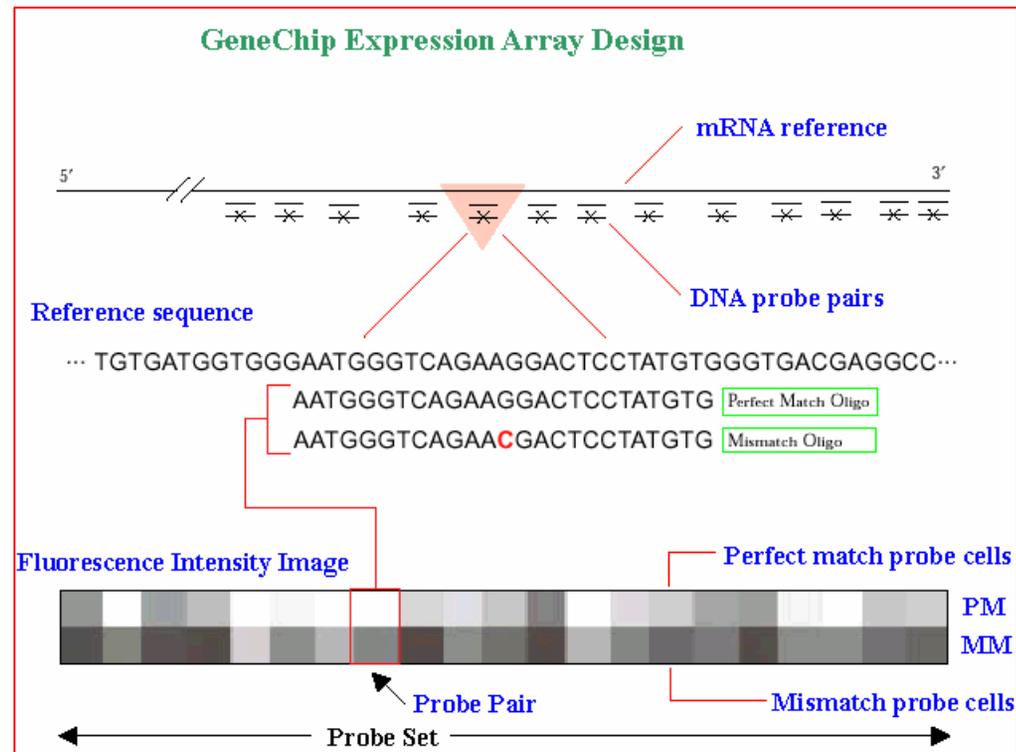
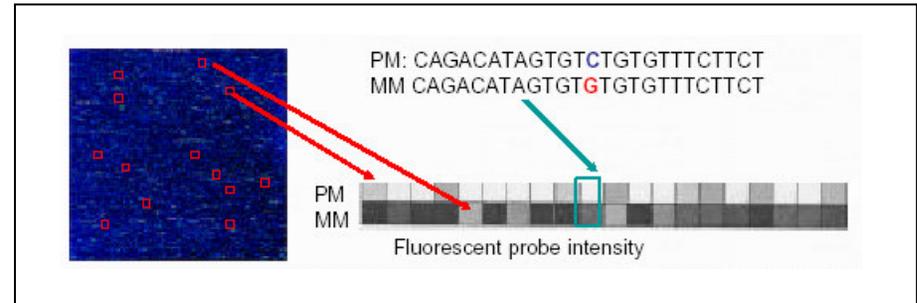
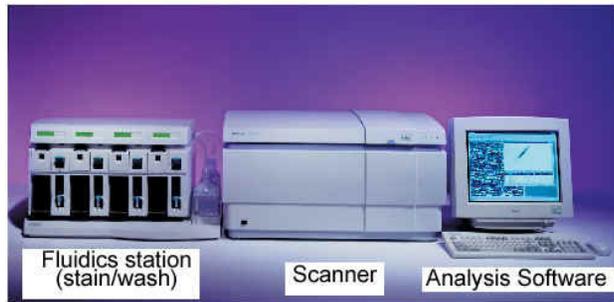


Image of hybridized probe array



GeneChip Expression Analysis Process

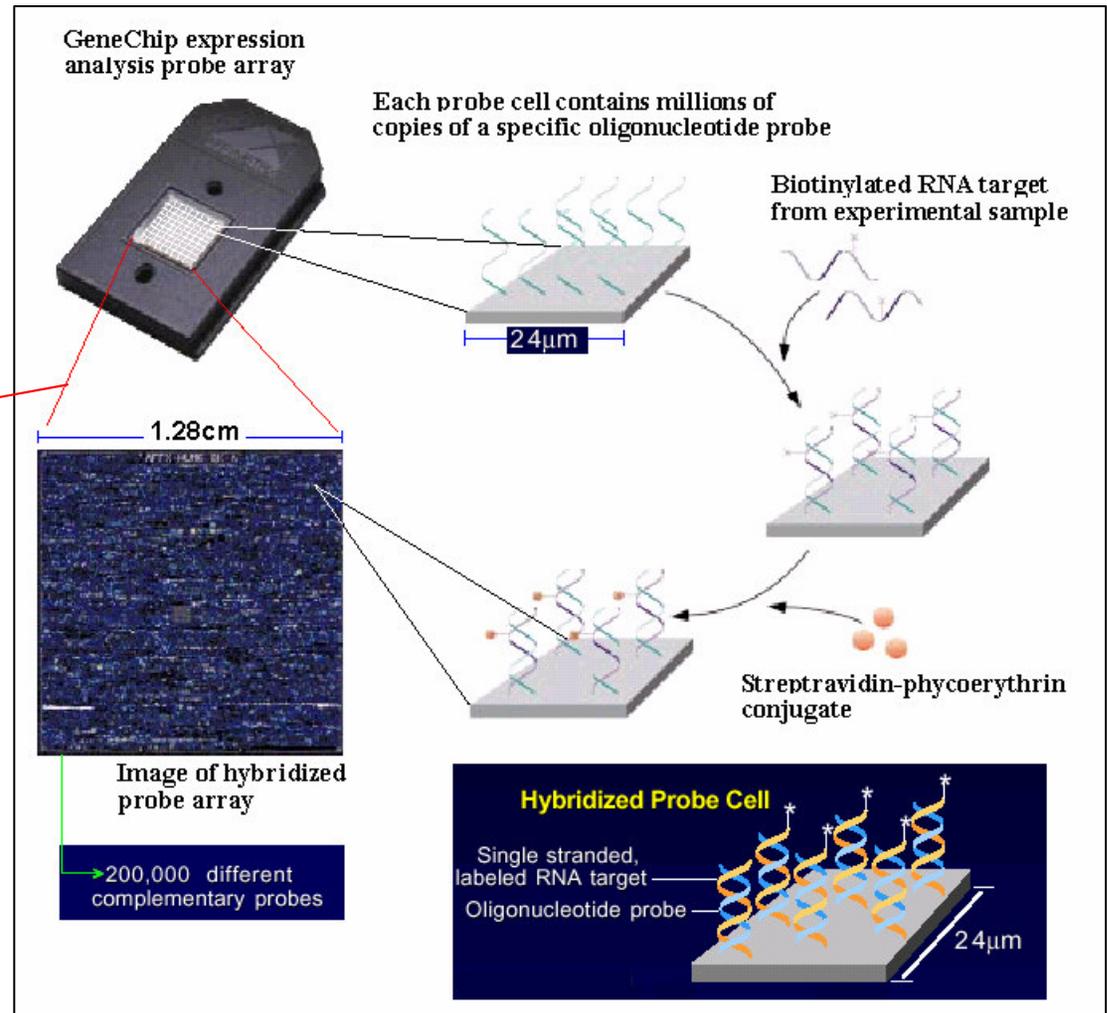
The GeneChip® Instrument System



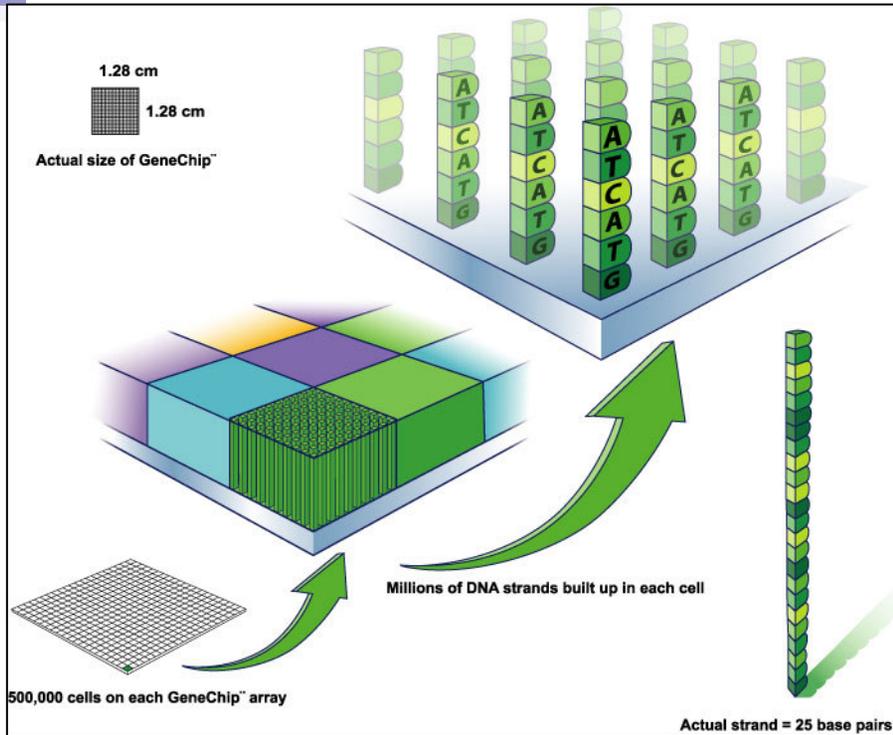
Scan and Quantitate



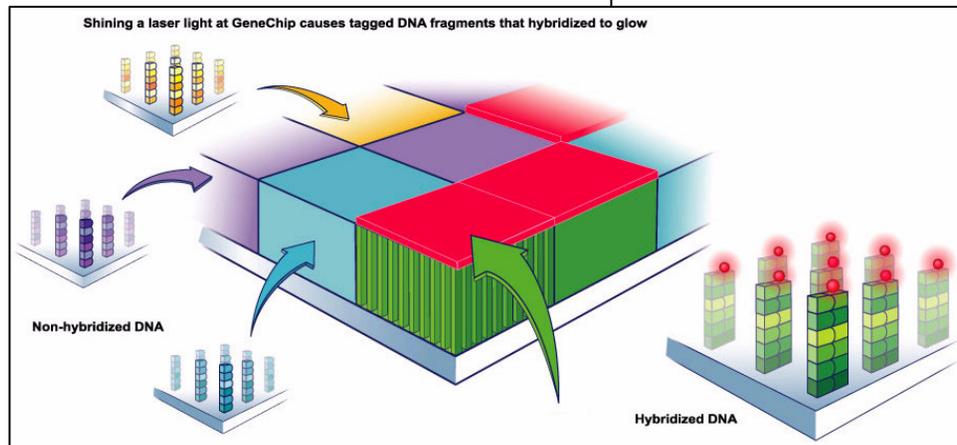
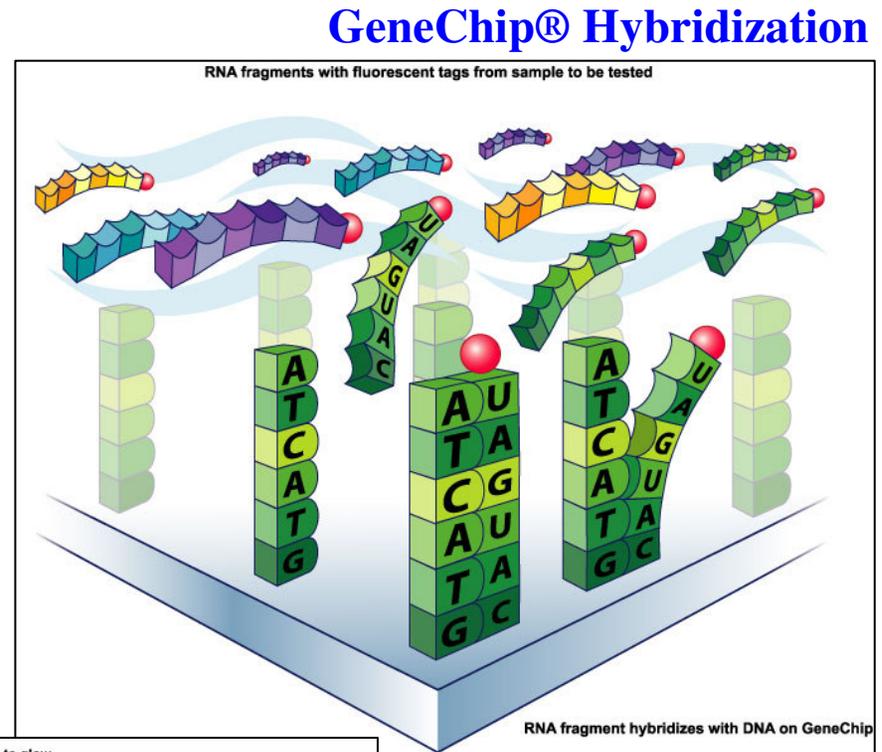
Affymetrix GeneChip®
Scanner 3000 with workstation.



More Figures on Affymetrix Web Site



GeneChip® Single Feature

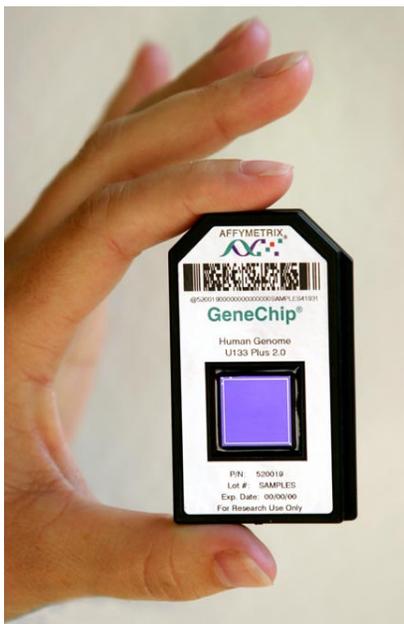
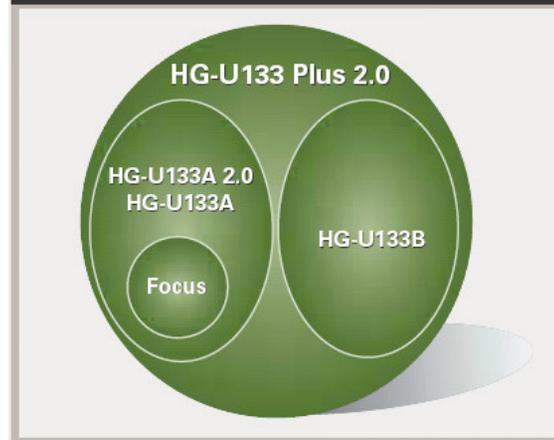


Hybridized GeneChip® Microarray

GeneChip® Human Genome Array

Arrays	Instrument / Software Compatibility
HG-U133 Plus 2.0	GeneChip® Scanner 3000, enabled for High-Resolution Scanning,* and GeneChip Operating Software (GCOS) with the GeneChip Scanner 3000 High-Resolution Scanning Patch
HG-U133A 2.0	GeneChip® Scanner 3000, enabled for High-Resolution Scanning,* and GeneChip Operating Software (GCOS) with the GeneChip Scanner 3000 High-Resolution Scanning Patch
HG-U133A	GeneArray® 2500 Scanner or newer and Affymetrix® Microarray Suite version 5.0 or newer
HG-U133B	GeneArray® 2500 Scanner or newer and Affymetrix® Microarray Suite version 5.0 or newer
Focus	GeneArray® 2500 Scanner or newer and Affymetrix® Microarray Suite version 5.0 or newer

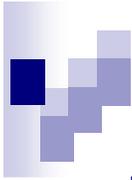
Figure 1. Relationship Among GeneChip® Human Genome Arrays



Critical Specifications for GeneChip® Human Genome Arrays

	Human Genome U133 Plus 2.0 Array	Human Genome U133A 2.0 Array	Human Genome U133 Set	Human Genome Focus Array
Number of arrays in set	1	1	2	1
Number of transcripts	~47,400	18,400	~39,000	~8,500
Number of genes	38,500	14,500	~33,000	~8,400
Number of probe sets	>54,000	>22,000	>45,000	>8,700
Feature size	11 µm	11 µm	18 µm	18 µm
Oligonucleotide probe length	25-mer	25-mer	25-mer	25-mer
Probe pairs/sequence	11	11	11	11
Control sequences included:				
Hybridization controls	<i>bioB, bioC, bioD, cre</i>			
Poly-A controls	<i>dap, lys, phe, thr</i>			
Normalization control set	100 probe sets	100 probe sets	100 probe sets	100 probe sets
Housekeeping/Control genes	GAPDH, beta-Actin, ISGF-3 (STAT1)			
Detection sensitivity	1:100,000*	1:100,000*	1:100,000*	1:100,000*

*As measured by detection of pre-labeled transcripts derived from human cDNA clones in a complex human background.



Comparison with Spotted cDNA Microarray

Spotted cDNA Microarray

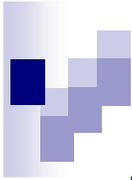
Probes are cDNA fragments, usually amplified by PCR.

- At least two samples are hybridized to chip.
- One probe one gene.
- Probes of varying length
- Fluorescence at different wavelengths measured by a scanner.
 - Samples (normally poly(A)+ RNA) are labelled using fluorescent dyes.
- Probes are deposited on a solid support, either positively charged nylon or glass slide.

Affymetrix GeneChips

Probes are oligos synthesized in situ using a photolithographic approach

- One target sample per array.
- 16-20 probe-pairs per gene.
- Probes are 25-mers.
- The apparatus requires a fluidics station for hybridization and a special scanner.
 - Only a single fluorochrome is used per hybridization.
- Oligonucleotides synthesized in situ on silica wafers.



Comparison with Spotted cDNA Microarray



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Advantages of Spotted Arrays

- Can choose the DNA on the array.
- Cheaper.
- Do not need to know the DNA sequence.
- Can hybridize closely related species.

Disadvantages of Spotted Arrays

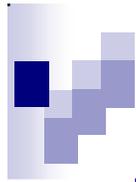
- More technically variable.
- Less specificity (will cross hybridize to genes ~80% homology).
- Cannot distinguish closely related gene families.
- May need to confirm DNA sequence.
- Repeated amplification and quality control.

Advantages of Affymetrix Chips

- High specificity (small probe length means gene family members can be differentiated.)
- Very well researched technology
- Very robust protocols and results are very reproducible.
- Can use small amount of RNA
- Widely used, so annotation of probe sets is of relatively high quality.

Disadvantages of Affymetrix Chips

- Very expensive to design (~US\$300,000).
- Expensive to perform experiments (~US\$400 + \$300 labeling/hybridization).
- Limited to the species for which there are chips available sequence required.
- No probe manipulation.
- Single target hybridization, so comparison always involves two experiments, and dye swaps are impossible.
- Match/mismatch technology has major limitations: mismatch signal often higher than match, and dose response curve is different for each pair.



Terms & Descriptions



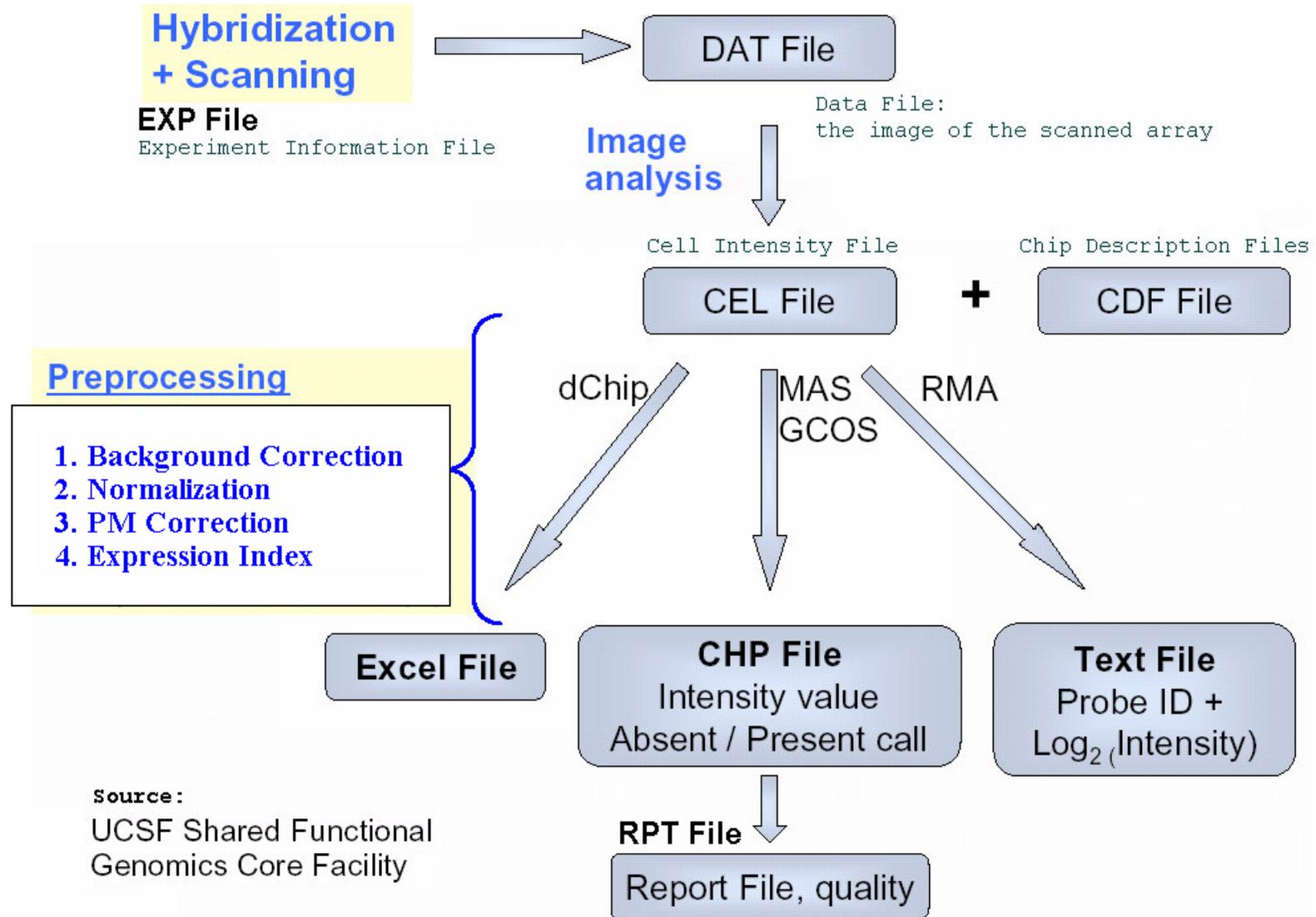
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- **Target:** the labeled sample applied to the array (consists of cRNA in vitro transcribed from cDNA which was in turn reverse transcribed from total mRNA extracted from the sample).
- **Background (BG):** a measure of the magnitude of background. For each of 16 sectors, the average intensity of features with intensities falling in the lowest 2% of features within the sector.
- **Noise:** a measure of the variance in background.

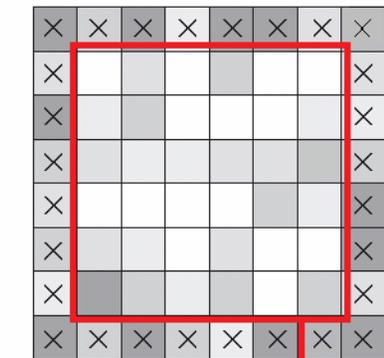
- **Feature (Probe):** a 24-50 nm portion of the array on which are synthesized ~10⁷ molecules of a single oligonucleotide (a.k.a. tile). A scan generates one pixel for every 3mm².
- **Perfect match (PM):** an oligonucleotide (~25bp) specific for a region of the cRNA of a gene.
- **Mismatch (MM):** an oligonucleotide (~25bp) specific for a region of the cRNA of a gene with a single mismatched nucleotide in the centre location - always paired with a PM.
- **Probe pair:** a pair of probes, one PM and its corresponding MM.
- **Probe set:** a set of 20 probe pairs designed to probe for the transcript of a single gene.
- **Probe Array Tiling** - The spatial organization of probe array features into probe pairs and sets.

- **Fold change (FC):** the magnitude of change observed in a gene's expression from one scan to another.
- **Metrics** - The calculated answer of mathematical equations used by the GeneChip® probe array algorithm software.

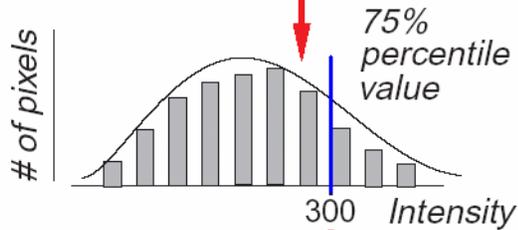
Assay and Analysis Flow Chart



From DAT to CEL

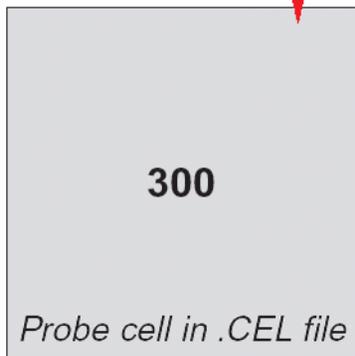


Probe cell in .DAT file

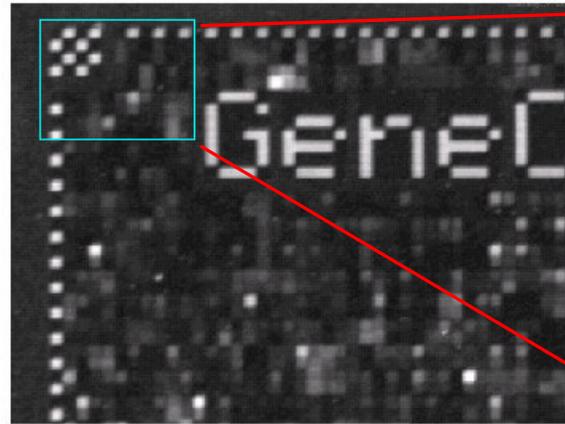


300

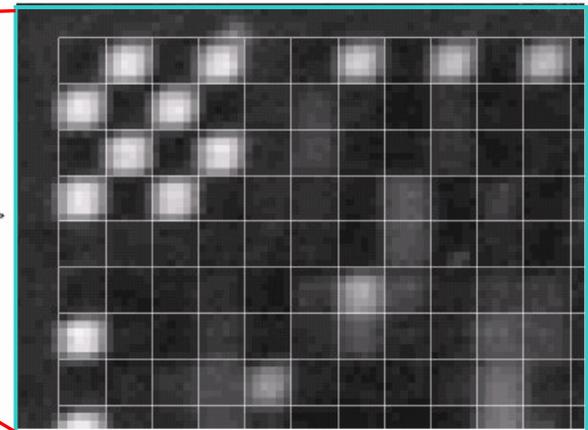
Intensity



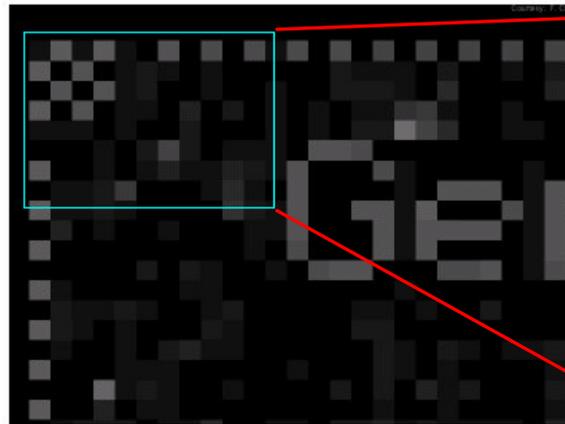
Probe cell in .CEL file



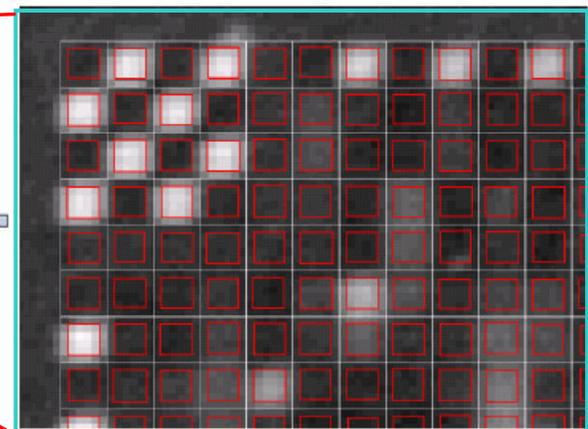
DAT



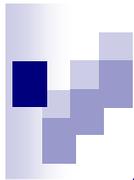
DAT + Grid



CEL



DAT + Grid - Outer Pixel



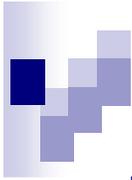
MAS5.0 Analysis Output File (*.CHP)

	Analysis Name	Probe Set Name	Stat Pairs	Stat Pairs Used	Signal	Detection	Detection p-value	Stat Comr
1	030606 En test3	Pae_16SrRNA_s_at	16	16	11.3	A	0.872355	
2	030606 En test3	Pae_23SrRNA_s_at	16	16	26.6	A	0.378184	
3	030606 En test3	PA1178_oprH_at	12	12	5.4	A	0.975070	
4	030606 En test3	PA1816_dnaQ_at	12	12	5.9	A	0.805907	
5	030606 En test3	PA3183_zwf_at	12	12	7.9	A	0.708540	
6	030606 En test3	PA3640_dnaE_at	12	12	10.8	A	0.964405	
7	030606 En test3	PA4407_ftsZ_at	12	12	9.5	A	0.921030	
8	030606 En test3	Pae_16SrRNA_s_st	16	16	8.9	A	0.660442	
9	030606 En test3	Pae_23SrRNA_s_st	16	16	22.0	A	0.561639	
10	030606 En test3	PA1178_oprH_st	12	12	35.1	P	0.024930	
11	030606 En test3	PA1816_dnaQ_st	12	12	34.7	A	0.240088	
12	030606 En test3	PA3183_zwf_st	12	12	6.5	A	0.985972	
13	030606 En test3	PA3640_dnaE_st	12	12	87.5	A	0.173261	
14	030606 En test3	PA4407_ftsZ_st	12	12	47.5	A	0.623158	
15	030606 En test3	AFFX-Athal-Actin_5_r_at	16	16	89.8	P	0.013092	

Metrics

	030606 En test3		Descriptions
	Signal	Detection	
Pae_16SrRNA_s_at	11.3	A	
Pae_23SrRNA_s_at	26.6	A	
PA1178_oprH_at	5.4	A	
PA1816_dnaQ_at	5.9	A	
PA3183_zwf_at	7.9	A	
PA3640_dnaE_at	10.8	A	
PA4407_ftsZ_at	9.5	A	
Pae_16SrRNA_s_st	8.9	A	
Pae_23SrRNA_s_st	22.0	A	
PA1178_oprH_st	35.1	P	
PA1816_dnaQ_st	34.7	A	
PA3183_zwf_st	6.5	A	
PA3640_dnaE_st	87.5	A	
PA4407_ftsZ_st	47.5	A	

Pivot



Quality Assessment



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■ RNA Sample Quality Control

- *Validation of total RNA*
- *Validation of cRNA*
- *Validation of fragmented cRNA*

Two aspects of quality control: detecting poor hybridization and outliers

■ Array Hybridization Quality Control

- Probe Array Image Inspection (DAT, CEL)
- B2 Oligo Performance
- MAS5.0 Expression Report Files (RPT)
 - Scaling and Normalization factors
 - Average Background and Noise Values
 - Percent Genes Present
 - Housekeeping Controls: Internal Control Genes
 - Spike Controls: Hybridization Controls: bioB, bioC, bioD, cre
 - Spike Controls: Poly-A Control: dap, lys, phe, thr, trp

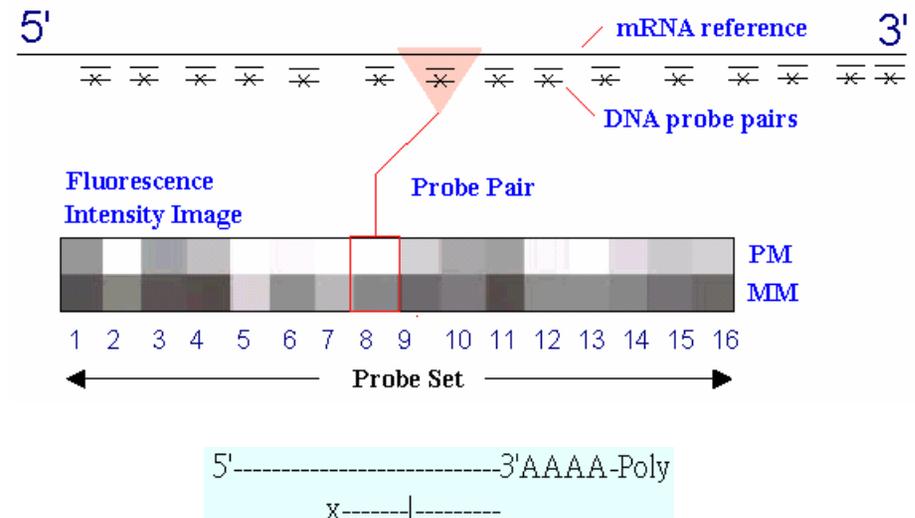
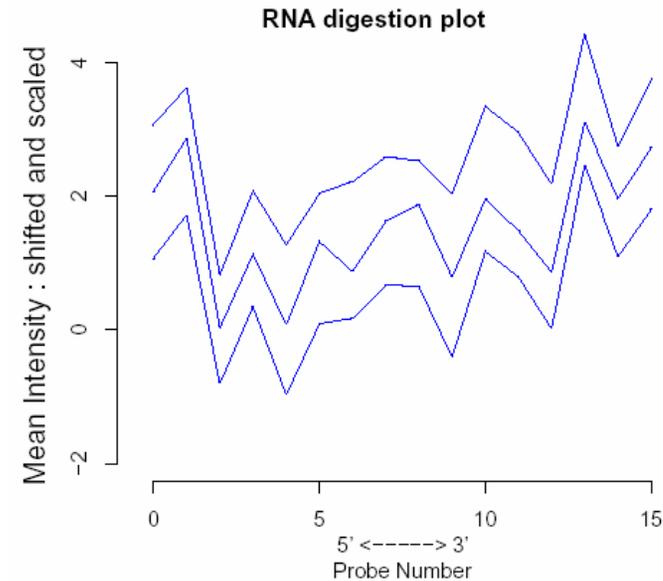
■ Statistical Quality Control (Diagnostic Plots)

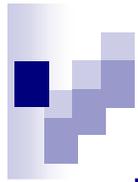
- ◆ Reasons for poor hybridizations
 - mRNA degenerated
 - one or more experimental steps failed
 - poor chip quality, ...
- ◆ reasons for (biological) outliers
 - infiltration with non-tumour tissue
 - wrong label
 - contamination, ...

RNA Degradation Plots

Assessment of RNA Quality:

- Individual probes in a probe set are ordered by location relative to the 5' end of the targeted RNA molecule.
- Since RNA degradation typically starts from the 5' end of the molecule, **we would expect probe intensities to be systematically lowered at that end of a probeset when compared to the 3' end.**
- On each chip, probe intensities are averaged by location in probeset, with the average taken over probesets.
- The RNA degradation plot produces a side-by-side plots of these means, making it easy to notice any 5' to 3' trend.





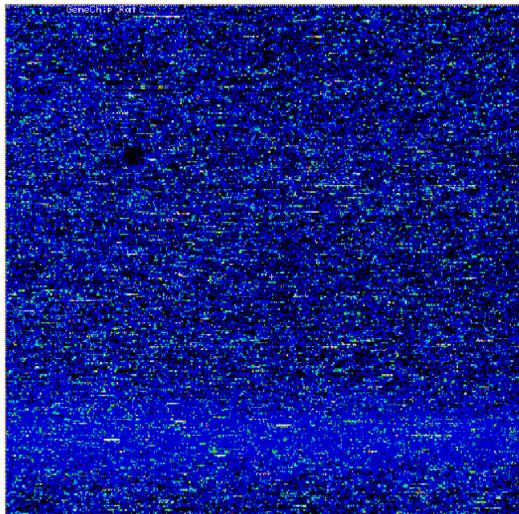
Probe Array Image Inspection



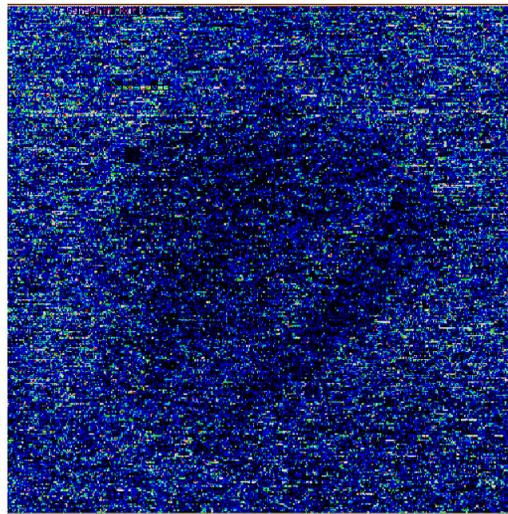
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- Saturation: PM or MM cells > 46000
- Defect Classes:
dimness/brightness, high Background, high/low intensity spots, scratches, high regional, overall background, unevenness, spots, Haze band, scratches, crop circle, cracked, snow, grid misalignment.
- As long as these areas do not represent more than 10% of the total probes for the chip, then the area **can be masked** and the data points thrown out as outliers.

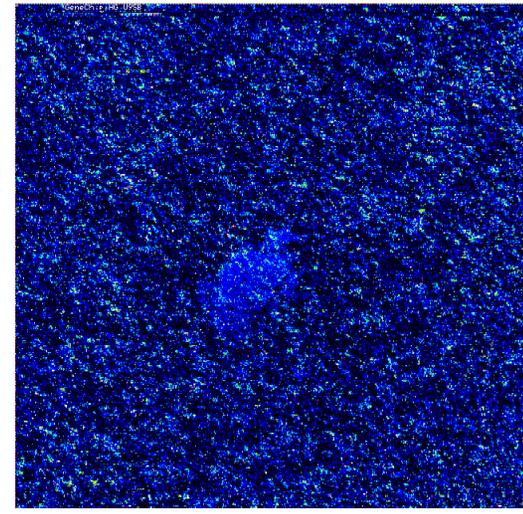
Haze Band



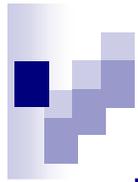
Crop Circles



Spots, Scratches, etc.



Source: Michael Elashoff (GLGC)



Probe Array Image Inspection (conti.)

Li, C. and Wong, W. H. (2001) Model-based analysis of oligonucleotide arrays: Expression index computation and outlier detection, Proc. Natl. Acad. Sci. Vol. 98, 31-36.



Fig. 1. A contaminated D array from the Murine 6500 Affymetrix GeneChip® set. Several particles are highlighted by arrows and are thought to be torn pieces of the chip cartridge septum, potentially resulting from repeatedly pipetting the target into the array.

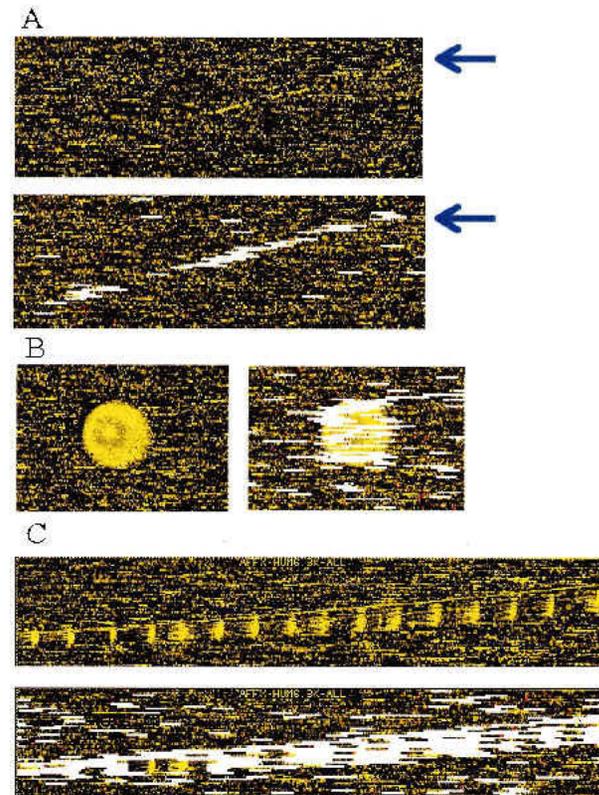
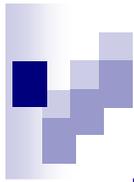


Fig. 5. (A) A long scratch contamination (indicated by arrow) is alleviated by automatic outlier exclusion along this scratch. (B and C) Regional clustering of array outliers (white bars) indicates contaminated regions in the original images. These outliers are automatically detected and accommodated in the analysis. Note that some probe sets in the contaminated region are not marked as array outliers, because contamination contributed additively to PM and MM in a similar magnitude and thus cancel in the PM-MM differences, preserving the correct signals and probe patterns.

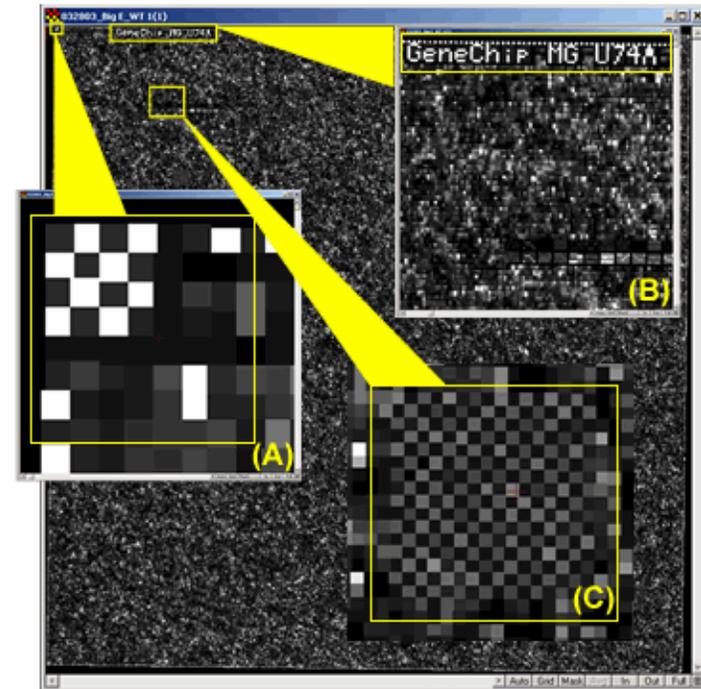


B2 Oligo Performance



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- Make sure the alignment of the grid was done appropriately.
- Look at the spiked in Oligo B2 control in order to check the hybridization uniformity.
- The border around the array, the corner region, the control regions in the center, are all checked to make sure the hybridization was successful.



Affymetrix CEL File Image- Yellow squares highlighting various Oligo B2 control regions: (A) one of the corner regions, (B) the name of the array, and (C) the "checkerboard" region.

Source: Baylor College of Medicine, Microarray Core Facility

MAS5.0 Expression Report File (*.RPT)

Report Type: Expression Report
Date: 04:42PM 02/24/2004

Filename: test.CHP
Probe Array Type: HG-U133A
Algorithm: Statistical
Probe Pair Thr: 8
Controls: Antisense

Alpha1: 0.05
Alpha2: 0.065
Tau: 0.015
Noise (RawQ): 2.250
Scale Factor (SF): 5.422
TGT Value: 500
Norm Factor (NF): 1.000

Background:				
Avg:	64.23	Std: 1.75	Min: 59.50	Max: 67.70
Noise:				
Avg:	2.54	Std: 0.14	Min: 2.10	Max: 3.00
Corner+				
Avg:	49	Count: 32		
Corner-				
Avg:	5377	Count: 32		
Central-				
Avg:	4845	Count: 9		

- The Scaling Factor- In general, the scaling factor should be around three, but as long as it is not greater than five, the chip should be okay.
- The scaling factor (SF) should remain consistent across the experiment.

- Average Background: 20-100
- Noise < 4

- The measure of Noise (RawQ), Average Background and Average Noise values should remain consistent across the experiment.

The following data represents probe sets that exceed the probe pair threshold and are not called "No Call".

Total Probe Sets: 22283
Number Present: 9132 41.0%
Number Absent: 12766 57.3%
Number Marginal: 385 1.7%

Average Signal (P): 1671.0
Average Signal (A): 119.6
Average Signal (M): 350.1
Average Signal (All): 759.3

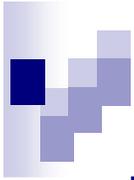
- Percent Present : 30~50%, 40~50%, 50~70%.
- Low percent present may also indicate degradation or incomplete synthesis.

MAS5.0 Expression Report File (*.RPT)

■ Sig (3'/5')- This is a ratio which tells us how well the labeling reaction went. The two to really look at are your 3'/5' ratio for GAPDH and B-ACTIN. In general, they should be less than three.

■ Spike-In Controls (BioB, BioC, BioD, Cre)- These spike in controls also tell how well your labelling reaction went. BioB is only Present half of the time, but BioC, BioD, & Cre should always have a present (P) call.

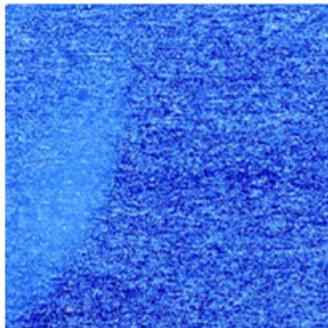
Housekeeping Controls:								
Probe Set	Sig(5')	Det(5')	Sig(M')	Det(M')	Sig(3')	Det(3')	Sig(all)	Sig(3'/5')
AFFX-HUMISGF3A/M97935	272.8	P	856.8	P	1274.5	P	801.36	4.67
AFFX-HUMRGE/M10098	340.6	M	181.3	A	632.6	P	384.80	1.86
AFFX-HUMGAPDH/M33197	13890.6	P	15366.6	P	14060.7	P	14439.32	1.01
AFFX-HSAC07/X00351	35496.8	P	39138.0	P	31375.0	P	35336.61	0.88
AFFX-M27830	469.2	P	2206.1	A	114.3	A	929.86	0.24
Spike Controls:								
Probe Set	Sig(5')	Det(5')	Sig(M')	Det(M')	Sig(3')	Det(3')	Sig(all)	Sig(3'/5')
AFFX-BIOB	559.0	P	801.6	P	385.8	P	582.14	0.69
AFFX-BIOC	1132.9	P			818.0	P	975.47	0.72
AFFX-BIOD	874.7	P			6918.1	P	3896.42	7.91
AFFX-CRE	10070.5	P			16198.0	P	13134.27	1.61
AFFX-DAP	10.9	A	60.9	A	8.5	A	26.75	0.78
AFFX-LYS	51.5	A	86.2	A	14.1	A	50.62	0.27
AFFX-PHE	4.9	A	4.0	A	40.0	A	16.30	8.20
AFFX-THR	20.3	A	53.2	A	18.7	A	30.77	0.92
AFFX-TRP	9.8	A	11.1	A	2.7	A	7.86	0.28
AFFX-R2-EC-BIOB	497.6	P	928.0	P	479.4	P	634.98	0.96
AFFX-R2-EC-BIOC	1319.9	P			1705.0	P	1512.50	1.29
AFFX-R2-EC-BIOD	4744.0	P			4865.7	P	4804.82	1.03
AFFX-R2-P1-CRE	25429.2	P			30469.5	P	27949.37	1.20
AFFX-R2-BS-DAP	5.9	A	1.6	A	3.3	A	3.58	0.55
AFFX-R2-BS-LYS	32.2	A	43.7	M	74.7	P	50.18	2.32
AFFX-R2-BS-PHE	14.8	A	27.5	A	146.5	A	62.91	9.93
AFFX-R2-BS-THR	209.5	P	152.9	A	15.8	A	126.08	0.08



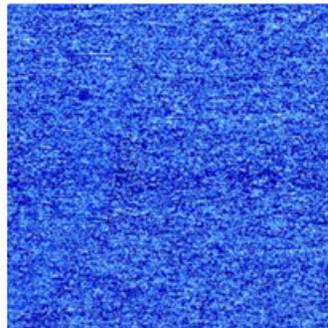
Statistical Plots

Image

Gradient Correction



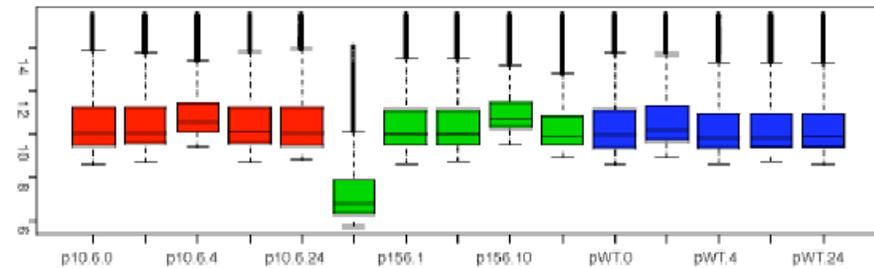
Before



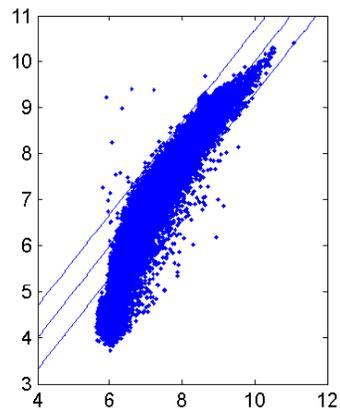
After

Box Plots

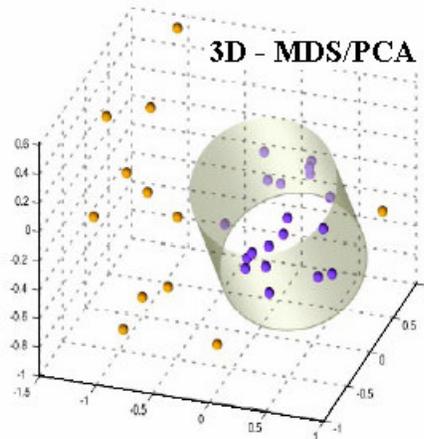
Arabidopsis-Cell/AG.CDF : PM



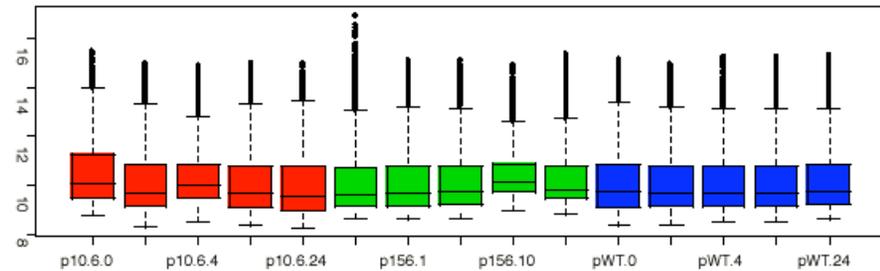
Scatterplot

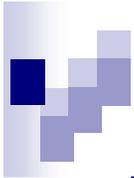


3D - MDS/PCA



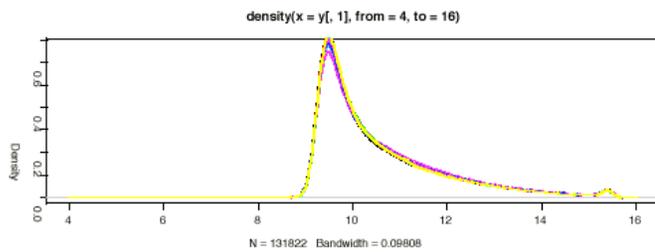
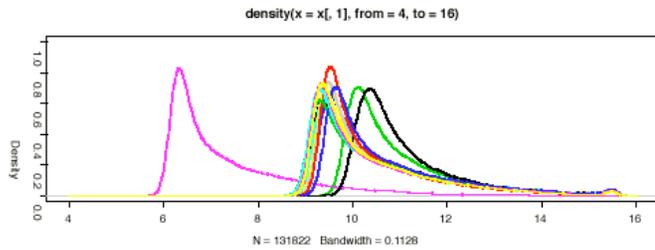
Arabidopsis-Cell/AG.CDF : PM



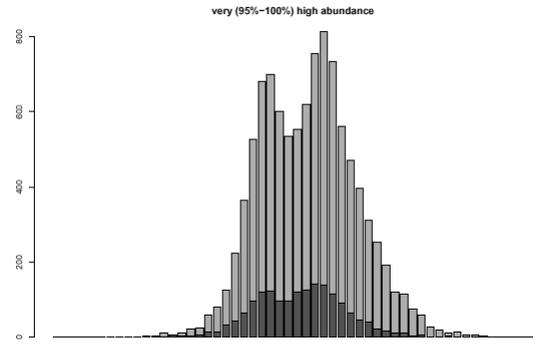


Statistical Plots (conti.)

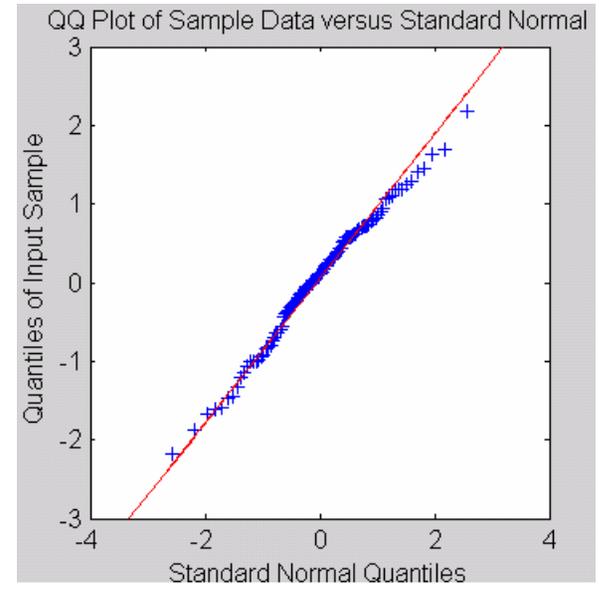
Density Plots



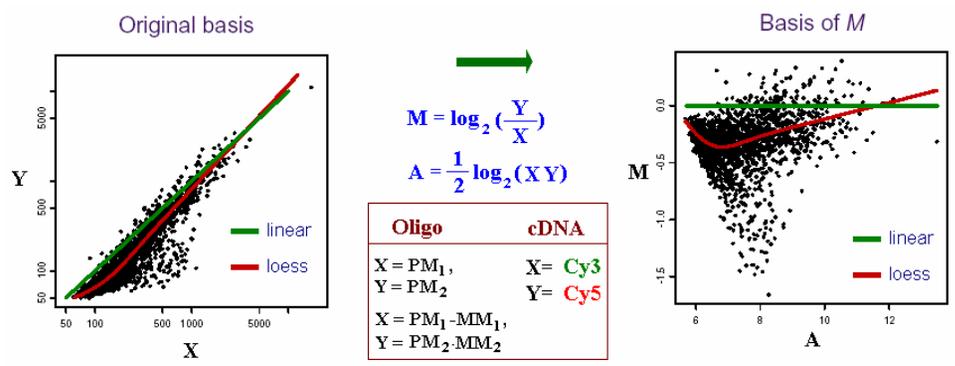
Histogram

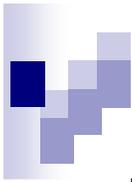


QQ-Plot



MA Plot

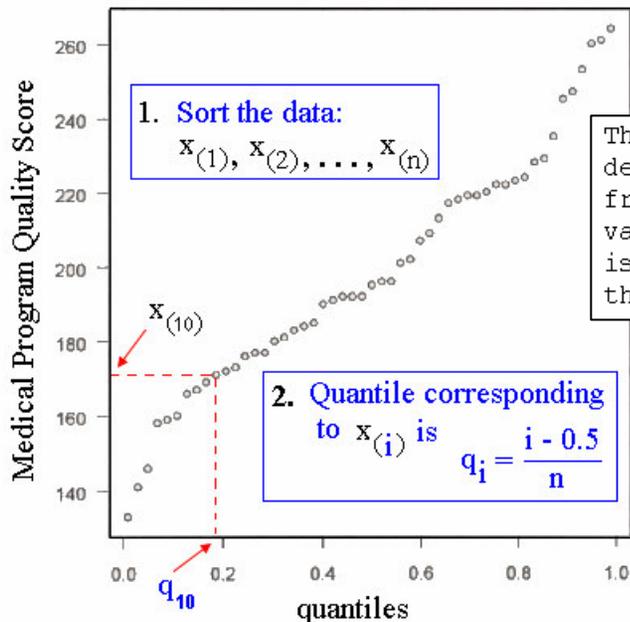




Quantile Plots



The empirical quantiles



1. Sort the data:
 $X_{(1)}, X_{(2)}, \dots, X_{(n)}$

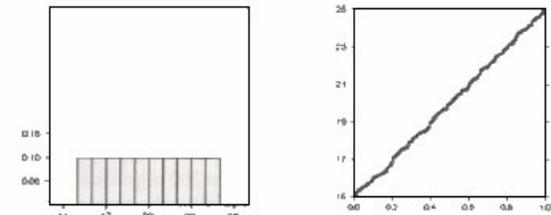
The q th quantile of a data set is defined as that value where a q fraction of the data is below that value and $(1-q)$ fraction of the data is above that value. For example, the 0.5 quantile is the median.

2. Quantile corresponding to $X_{(i)}$ is
$$q_i = \frac{i - 0.5}{n}$$

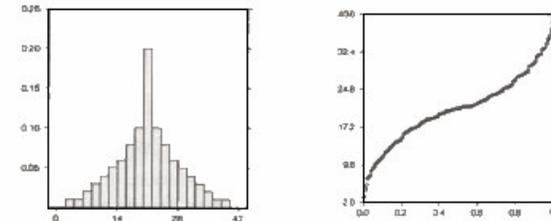
- 0.5 is subtracted from each i value to avoid extreme quantiles of exactly 0 or 1.
- The latter would cause problems if empirical quantiles were to be compared against quantiles derived from a theoretical, asymptotic distribution such as the normal.
- This adjustment has no effect on the shape of any graphical display.

Comparison of histogram and Quantile plots for differently shaped data distribution

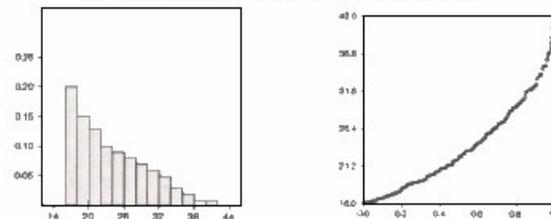
Uniform distribution



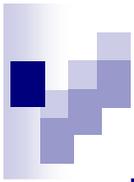
Symmetric, bell-shaped distribution



Positively skewed distribution



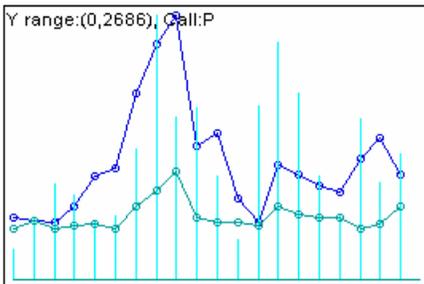
Figures modified from Jacoby (1997)



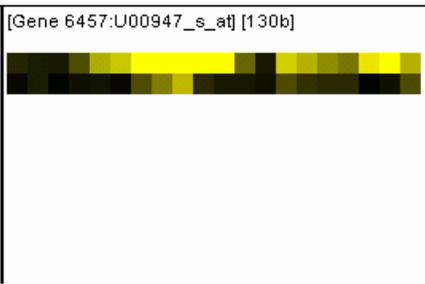
Statistical Plots (conti.)

Heatmap with Dendrogram

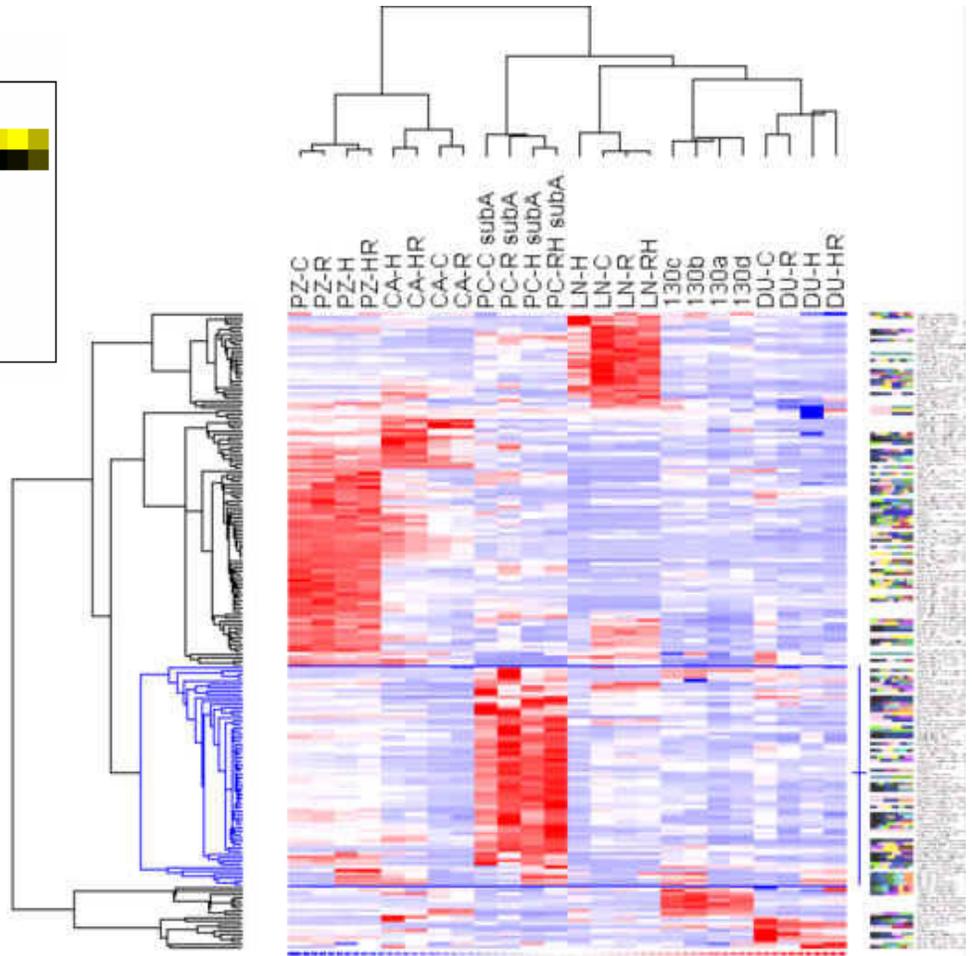
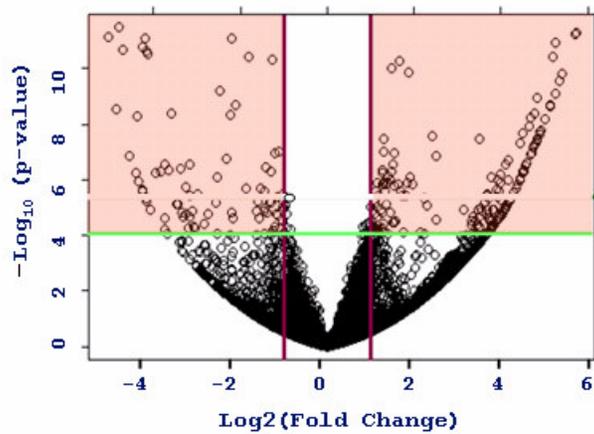
Line Plots

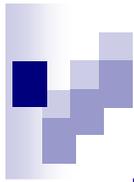


Profiles Plots



Volcano Plot





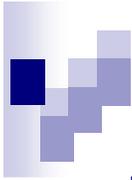
Background Correction/Adjustment

What is background?

- A measurement of signal intensity caused by auto fluorescence of the array surface and non-specific binding.
- Since probes are so densely packed on chip must use probes themselves rather than regions adjacent to probe as in cDNA arrays to calculate the background.
- In theory, the MM should serve as a biological background correction for the PM.

What is background correction?

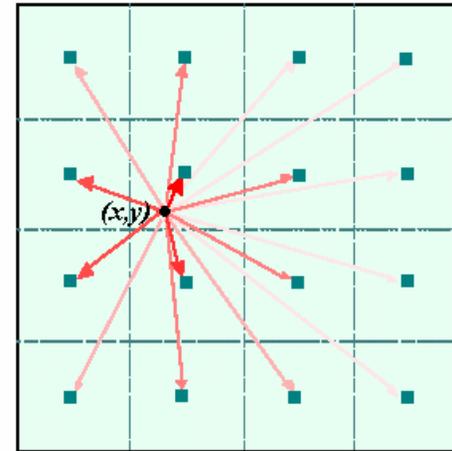
- A method for removing background noise from signal intensities using information from only one chip.



Background Methods: MAS5

Zone Values

- For purposes of calculating background values, the array is split up into K rectangular zones Z_k ($k = 1, \dots, K$, default $K = 16$).
- Control cells and masked cells are not used in the calculation.
- The cells are ranked and the lowest 2% is chosen as the background b for that zone (bZ_k).
- The standard deviation of the lowest 2% cell intensities is calculated as an estimate of the background variability n for each zone (nZ_k).



Smoothing Adjustment

weights

$$w_k(x, y) = \frac{1}{d_k^2(x, y) + \text{smooth}}$$

background

$$b(x, y) = \frac{1}{\sum_{k=1}^K w_k(x, y)} \sum_{k=1}^K w_k(x, y) bZ_k$$

Noise Correction

noise

$$n(x, y) = \frac{1}{\sum_{k=1}^K w_k(x, y)} \sum_{k=1}^K w_k(x, y) nZ_k$$

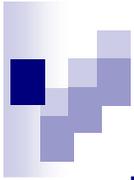
adjusted intensity

$$A(x, y) = \max(I'(x, y) - b(x, y), \text{NoiseFrac} * n(x, y))$$

where $I'(x, y) = \max(I(x, y), 0.5)$

- MAS method corrects both PM and MM probes.

Affymetrix: Statistical Algorithm Description Document



Background Methods: RMA

RMA: Robust Multichip Average (Irizarry and Speed, 2003)

- Assumes PM probes are a convolution of normal and exponential.
- Observed PM = Signal + Noise, ($O = S + N$).
- **Assume**
 - Signal is exponential (alpha)
 - Noise (background) is Normal (mu, sigma).
- Use $E[S|O=o, S>0]$ as the background corrected PM.
- MM probe intensities are not corrected by RMA/RMA2.

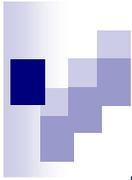
$$E(s|O = o) = a + b \frac{\phi\left(\frac{a}{b}\right) - \phi\left(\frac{o-a}{b}\right)}{\Phi\left(\frac{a}{b}\right) + \Phi\left(\frac{o-a}{b}\right) - 1}$$

$$a = s - \mu - \sigma^2 \alpha$$

$$b = \sigma$$

ϕ : standard normal density function

Φ : standard normal distribution function



Normalization



31/52

Sources of Variation

amount of RNA in the biopsy
efficiencies of

- RNA extraction
- reverse transcription
- labeling
- photodetection

PCR yield
DNA quality
Spotting efficiency, spot size
cross- or unspecific-hybridization
stray signal

Systematic → Normalization

- similar effect on many measurements
- corrections can be estimated from data

Stochastic → Error Model

- too random to be explicitly accounted for
- noise

What is normalization?

- Non-biological factor can contribute to the variability of data, in order to reliably compare data from multiple probe arrays, differences of non-biological origin must be minimized.
- Normalization is a process of reducing unwanted variation across chips. It may use information from multiple chips.

Why normalization?

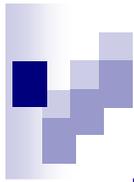
Normalization corrects for overall chip brightness and other factors that may influence the numerical value of expression intensity, enabling the user to more confidently compare gene expression estimates between samples.

Main idea

Remove the systematic bias in the data as completely possible while preserving the variation in the gene expression that occurs because of biologically relevant changes in transcription.

Assumption

- The average gene does not change in its expression level in the biological sample being tested.
- Most genes are not differentially expressed or up- and down-regulated genes roughly cancel out the expression effect.



The Options on Normalization

■ Levels

- PM&MM, PM-MM, Expression indexes

■ Features

- All, Rank invariant set, Spike-ins, housekeeping genes.

■ Methods

- Complete data: no reference chip, information from all arrays used: Quantiles Normalization, MVA Plot + Loess
- Baseline: normalized using reference chip: MAS 4.0, MAS 5.0, Li-Wong's Model-Based, Qspline

Normalization Methods: constant

Normalization and Scaling

- The data can be normalized from:
 - a limited group of probe sets.
 - all probe sets.

Global Scaling

the average intensities of all the arrays that are going to be compared are multiplied by scaling factors so that all average intensities are made to be numerically equivalent to a preset amount (termed target intensity).

$$SF = \frac{TGT}{TrimMean(2^{SignalLogValue_i}, 0.02, 0.98)}$$

$$A \times SF = TGT$$

$$\Rightarrow SF = \frac{TGT}{A}$$

Global Normalization

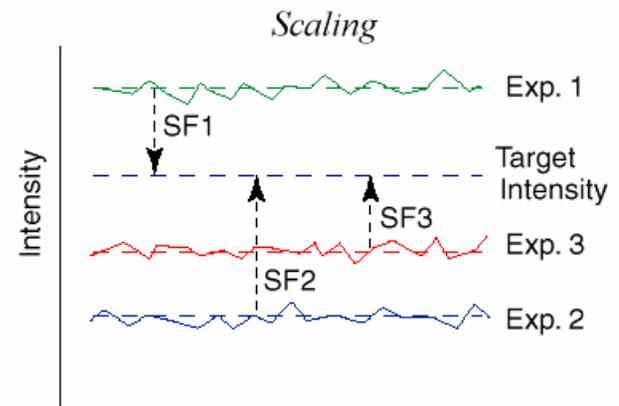
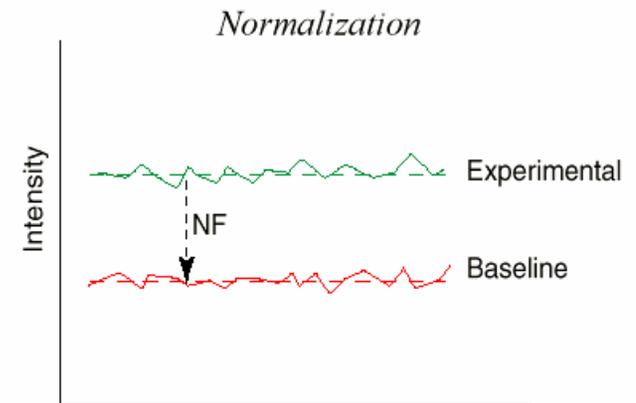
the normalization of the array is multiplied by a Normalization Factor (NF) to make its Average Intensity equivalent to the Average Intensity of the baseline array.

$$A_{exp} \times NF = A_{base}$$

$$\Rightarrow NF = \frac{A_{base}}{A_{exp}}$$

$$nf = \frac{TrimMean(SPVB_i, 0.02, 0.98)}{TrimMean(SPVE_i, 0.02, 0.98)}$$

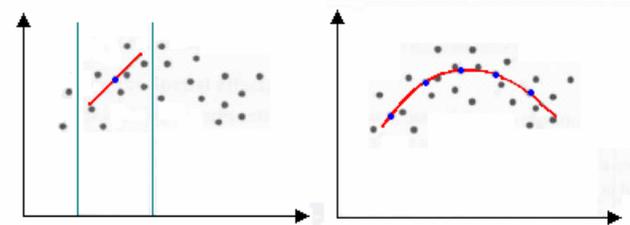
Average intensity of an array is calculated by averaging all the Average Difference values of every probe set on the array, excluding the highest 2% and lowest 2% of the values.



Normalization Methods: loess

- Loess normalization (Bolstad *et al.*, 2003) is based on **MA plots**. Two arrays are normalized by using a loess smoother.
- Skewing** reflects experimental artifacts such as the
 - contamination of one RNA source with genomic DNA or rRNA,
 - the use of unequal amounts of radioactive or fluorescent probes on the microarray.
- Skewing can be corrected with local normalization: fitting a local regression curve to the data.

Loess regression
(locally weighted polynomial regression)



1. For any two arrays i, j with probe intensities x_{ki} and x_{kj} where $k = 1, \dots, p$ represents the probe

2. we calculate

$$M_k = \log_2(x_{ki}/x_{kj}) \text{ and } A_k = \frac{1}{2} \log_2(x_{ki}x_{kj}).$$

3. A normalization curve is fitted to this M versus A plot using loess.

Loess is a method of local regression
(see Cleveland and Devlin (1988) for details).

4. The fits based on the normalization curve are \hat{M}_k

5. the normalization adjustment is $M'_k = M_k - \hat{M}_k$.

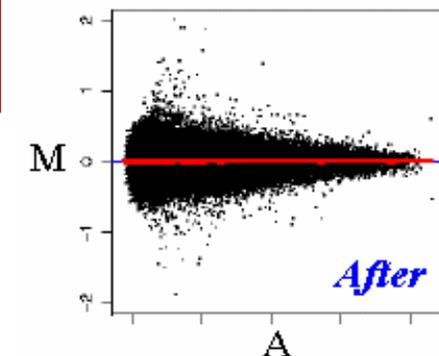
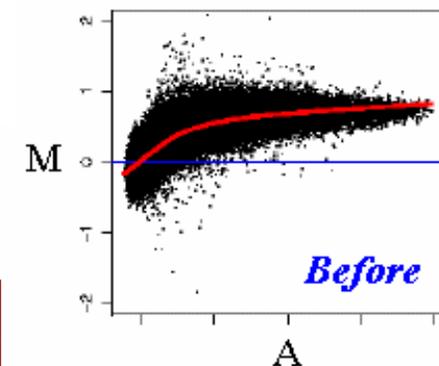
6. Adjusted probe intensities

$$\text{are given by } x'_{ki} = 2^{A_k + \frac{M'_k}{2}} \text{ and } x'_{kj} = 2^{A_k - \frac{M'_k}{2}}.$$

$$M = \log_2\left(\frac{Y}{X}\right)$$

$$A = \frac{1}{2} \log_2(XY)$$

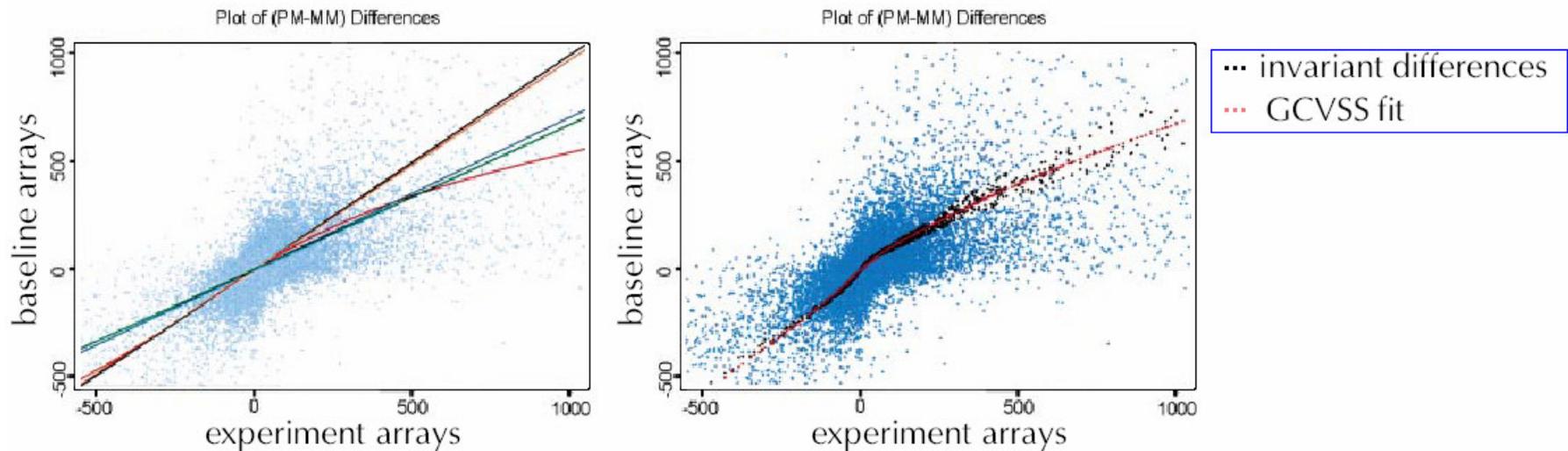
Oligo	cDNA
X = PM ₁ ,	X = Cy3
Y = PM ₂	Y = Cy5
X = PM ₁ · MM ₁ ,	
Y = PM ₂ · MM ₂	

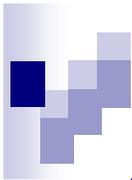


Normalization Methods: invariant set

(Li and Wong, 2001)

- Using a baseline array, arrays are normalized by selecting invariant sets of genes (or probes) then using them to fit a non-linear relationship between the "treatment" and "baseline" arrays.
- The non-linear relationship is used to carry out the normalization.
- A set of probe is said to be invariant if ordering of probe in one chip is same in other set.
- Fit the non-linear relation using cross validated smoothing splines (GCVSS).

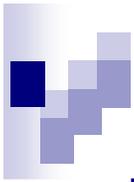




Invariant Set Algorithm

(Li and Wong, 2001)

- Invariant difference selection algorithm (IDS) chooses a subset of PM/MM intensity differences to serve as the basis for fitting a normalization relation.
- A set of probes are said to be invariant if the ordering of these probes according to the PM/MM differences in the experiment array, is the same as that in the baseline array.
- Intuitively, if a gene is truly differentially expressed, then the PM/MM differences for this gene are more likely to have different ranks relative to the other probes, and hence they are not likely to be included in a large invariant set.
- IDS algorithm uses the following expressions to determine the approximately invariant set:
$$R_i = \frac{[L(B_i + E_i) + H(2N - B_i - E_i)]}{2N}$$
$$D_i = \frac{2|B_i - E_i|}{(B_i + E_i)}$$
- L and H are the rank difference thresholds for the low and high ends of the difference intensity range.
- B_i and E_i are the ranks for the i th difference of the baseline and experiment arrays
- N is the total number of differences that were ordered in the current iteration of the algorithm.
- R_i defines the threshold for difference intensity i by linearly interpolating the threshold between a low difference intensity threshold, given by L , and a high difference intensity threshold, given by H .
- D_i is the rank difference test statistic used to determine if the i th difference should be included in the invariant set
- The i th difference is considered approximately invariant if $D_i < R_i$
- Once the approximately invariant set of differences has been selected, the normalization curve is constructed by applying the GCVSS technique to the invariant set



Normalization Methods: qspline

- Qspline normalization (Workman *et al.*, 2002) uses a target array (either one of the arrays or a synthetic target), arrays are normalized by fitting splines to the quantiles, then using the splines to perform the normalization.

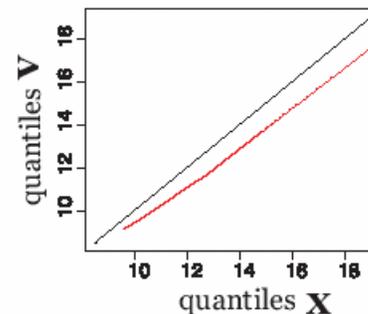
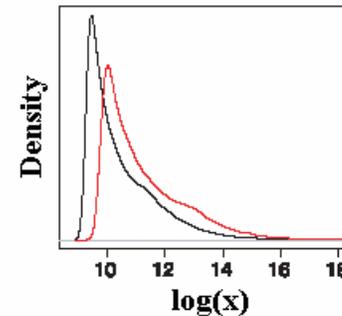
The q th quantile of a data set is defined as that value where a q fraction of the data is below that value and $(1-q)$ fraction of the data is above that value. For example, the 0.5 quantile is the median.

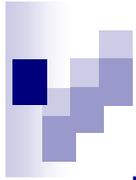
Qspline normalization

uses quantiles from array signals \mathbf{x} and target signals \mathbf{v} , to fit smoothing B-splines.

The splines are then used as signal-dependent normalization functions on the signals of \mathbf{x} .

The target signals can be from another array or could be means calculated from multiple arrays





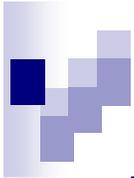
PM Correction Methods

- **PM only**

make no adjustment to the PM values.

- **Subtract MM from PM**

This would be the approach taken in MAS 4.0 Affymetrix (1999). It could also be used in conjunction with the liwong model.



PM Correction Methods: MAS 5.0

- An **ideal mismatch** is subtracted from PM. The ideal mismatch is documented by Affymetrix (2002).
- The Ideal Mismatch will always be less than the corresponding PM and thus we can safely subtract it without risk of negative values.

To calculate a specific background ratio representative for the probe set, we use the **one-step biweight algorithm (T_{bi})**.

The biweight specific background (SB) for probe pair j in probe set i is:

$$SB_i = T_{bi} \left(\log_2(PM_{i,j}) - \log_2(MM_{i,j}) : j = 1, \dots, n_i \right)$$

$$IM_{i,j} = \begin{cases} MM_{i,j}, & MM_{i,j} < PM_{i,j} \\ \frac{PM_{i,j}}{2^{(SB_i)}}, & MM_{i,j} \geq PM_{i,j} \text{ and } SB_i > \text{contrast}\tau \\ \frac{PM_{i,j}}{2^{\left(\frac{\text{contrast}\tau}{1 + \left(\frac{\text{contrast}\tau - SB_i}{\text{scale}\tau} \right)^2} \right)}}, & MM_{i,j} \geq PM_{i,j} \text{ and } SB_i \leq \text{contrast}\tau \end{cases}$$

default $\text{contrast}\tau = 0.03$, default $\text{scale}\tau = 10$

Probe Value

the probe value PV for every probe pair j in probeset i .

n is the number of probe pairs in the probeset.

$$V_{i,j} = \max(PM_{i,j} - IM_{i,j}, d)$$

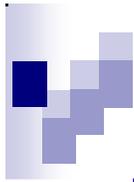
default $\delta = 2^{(-20)}$

$$PV_{i,j} = \log_2(V_{i,j}), j = 1, \dots, n_i$$

[Affymetrix: Statistical Algorithm Description Document](#)

One-Step Tukey's Biweight Algorithm **Purpose**

There are several stages in the algorithms in which we want to calculate an average. The biweight algorithm is a method to determine a robust average unaffected by outliers.

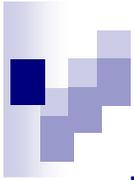


Expression Index Estimates

Summarization

- Reduce the 11-20 probe intensities on each array to a single number for gene expression.
- The goal is to produce a measure that will serve as an indicator of the level of expression of a transcript using the PM (and possibly MM values).
- The values of the PM and MM probes for a probeset will be combined to produce this measure.

- **Single Chip**
 - avgDiff : no longer recommended for use due to many flaws.
 - **Signal** (MAS5.0): use One-Step Tukey biweight to combine the probe intensities in log scale
 - average log 2 (PM - BG)
- **Multiple Chip**
 - **MBEI** (li-wong): a multiplicative model
 - **RMA**: a robust multi-chip linear model fit on the log scale



Summarization Methods: avgdiff (MAS4.0)

- **Average Difference**

The mean intensity of a particular probe set after control correction (perfect match minus mismatch for each probe pair).

- **Absolute Expression Value**

A value derived by certain statistical methods (depending on the array type and other factors) that is representative of the amount of RNA hybridised to the array for a particular gene. The statistical algorithms are usually provided with the scanning software.

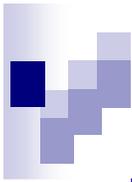
- The average difference for a particular probe set is then defined as the mean of all the (PM-MM) differences. The resulting value, or absolute expression value, is then taken as proportional to the actual amount of RNA of the corresponding gene in the sample.

- No longer recommended for use due to many flaws.

$$\text{Difference}_{\text{probe pair}} = PM - MM$$

$$\text{Average Difference}_{\text{probe set}} = \sum_{i=1}^n \frac{(PM_i - MM_i)}{n}$$

(Where: n = number of probe pairs for gene X)



Summarization Methods: MAS5

Signal is calculated as follows:

1. Cell intensities are preprocessed for global background.
2. An ideal mismatch value is calculated and subtracted to adjust the PM intensity.
3. The adjusted PM intensities are log-transformed to stabilize the variance.
4. The biweight estimator is used to provide a robust mean of the resulting values. Signal is output as the antilog of the resulting value.
5. Finally, Signal is scaled using a trimmed mean.

Probe Value

the probe value PV for every probe pair j in probeset i .
 n is the number of probe pairs in the probeset.

$$V_{i,j} = \max(PM_{i,j} - IM_{i,j}, d) \quad \text{default } \delta = 2^{(-20)}$$

$$PV_{i,j} = \log_2(V_{i,j}), j=1, \dots, n_i$$

Signal Log Value

$$SignalLogValue_i = T_{bi}(PV_{i,1}, \dots, PV_{i,n_i})$$

$$sf = \frac{\text{target signal}}{\text{TrimMean}(2^{SignalLogValue_i}, 0.02, 0.98)}$$

$$nf = \frac{\text{TrimMean}(SPVb_i, 0.02, 0.98)}{\text{TrimMean}(SPVe_i, 0.02, 0.98)}$$

The reported value of probe set i is: **Signal**

$$ReportedValue(i) = nf * sf * 2^{(SignalLogValue_i)}$$

Summarization Methods: Iwong

(Model-Based Expression Index, MBEI)

- If there are multiple arrays from the same experiment available, this model provides an intuitive estimate of the mean and standard error of the θ s and ϕ s.
 - The standard error estimates of the θ s and ϕ s can be used to identify outlier arrays and probes that will consequently be excluded from the final estimation of the probe response pattern. For each array, this model computes an expression level on the i th array θ_i .
 - If a specific array has a large standard error relative to other arrays, possibly due to external factors like the imaging process, then this is called an **outlier array**.
 - Similarly, if the estimate of ϕ_j for the j th probe has a large standard error, possibly due to non-specific cross-hybridization, it is called an **outlier probe**.
 - Individual PM-MM differences might also be identified by large residuals compared with the fit; these **single outliers** are regarded as missing values in the model-fitting algorithm.
- Cross-hybridization is more likely to occur at the MM probes, rather than the PM probes, and so a PM-only model exists that calculates expression values that are always positive (Li and Wong 2001). Studies suggest that the PM-only model is more robust to cross-hybridization than the PM-MM

For a gene

$$y_{ij} = \phi_i \theta_j + \epsilon_{ij}$$

y_{ij} is PM_{ij} or the difference between $PM_{ij} - MM_{ij}$.

ϕ_i is a probe response parameter

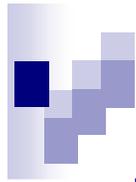
θ_j is the expression on array j .

$$\sum_j \phi_j^2 = J$$

$$\epsilon_{ij} \sim N(0, \sigma^2)$$

$i = 1, \dots, I$ the number of chips

$j = 1, \dots, J$ number of probe pairs



Other Summarization Methods

Medianpolish

- This is the summarization used in the RMA expression summary Irizarry et al. (2003).
- A multichip linear model is fit to data from each probeset.
- The medianpolish is an algorithm (see Tukey (1977)) for fitting this model robustly.
- Please note that expression values you get using this summary measure will be in log₂ scale.

for a probeset k with $i = 1, \dots, I_k$ probes and data from $j = 1, \dots, J$ arrays

fit the following model

$$\log_2 \left(PM_{ij}^{(k)} \right) = \alpha_i^{(k)} + \beta_j^{(k)} + \epsilon_{ij}^{(k)}$$

where α_i is a probe effect and

β_j is the log₂ expression value.

Playerout

- This method is described in Lazaridis et al. (2002).
- A non parameteric method is used to determine weights.
- The expression value is then the weighted average.

Emmanuel. N. Lazaridis, Dominic. Sinibaldi, Gregory. Bloom, Shrikant. Mane, and Richard. Jove. A simple method to improve probe set estimates from oligonucleotide arrays. *Math Biosci*, 176(1):53–58, Mar 2002.

Image Analysis/Normalization

Shareware/Freeware

- **Bioconductor** (R, Gentleman)
- DNA-Chip Analyzer (**dChip** v1.3) (Li and Wong)
- **RMExpress**: a simple standalone GUI program for windows for computing the RMA expression measure.

Commercial

- Affymetrix GeneChip Operating Software (**GCOS** v1.0)
- GeneSpring GX v7.3

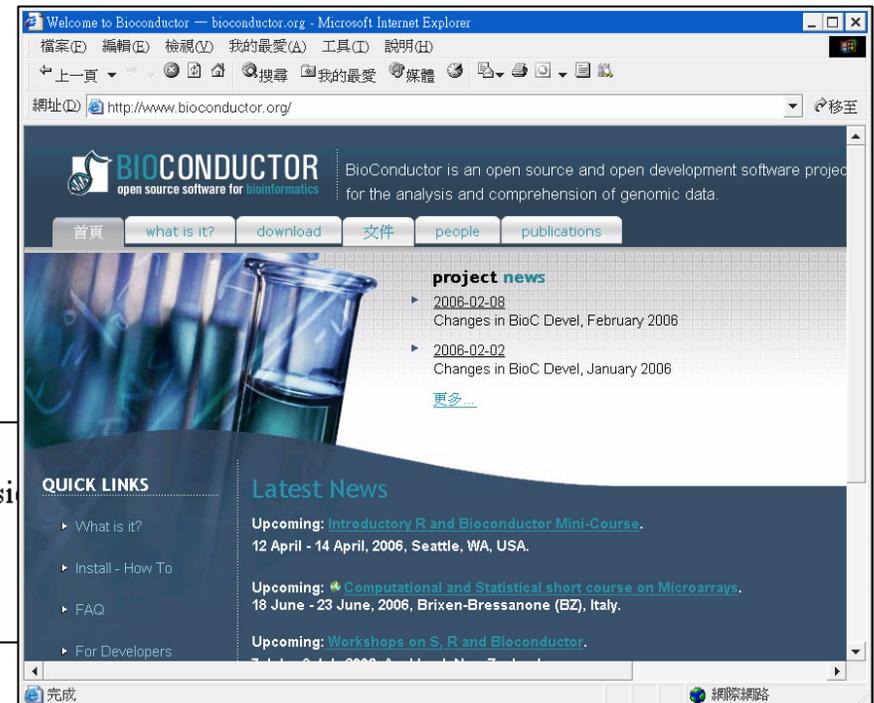
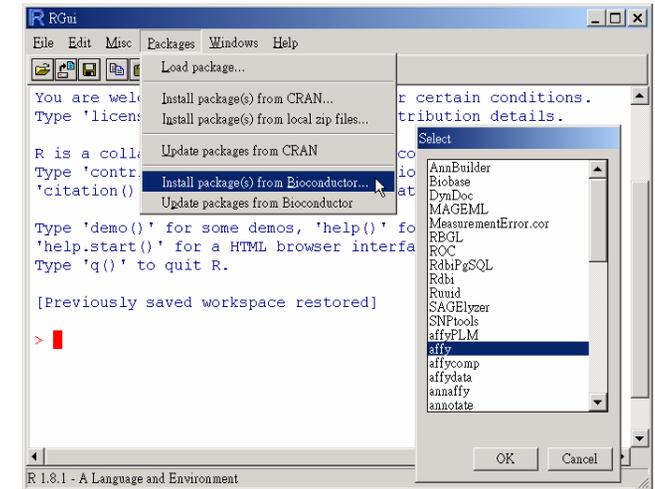
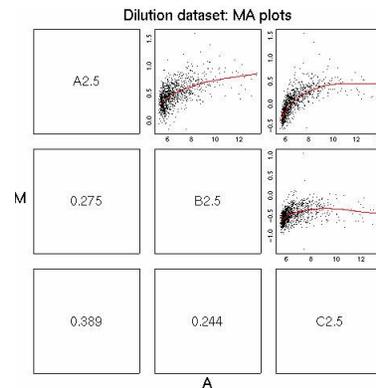
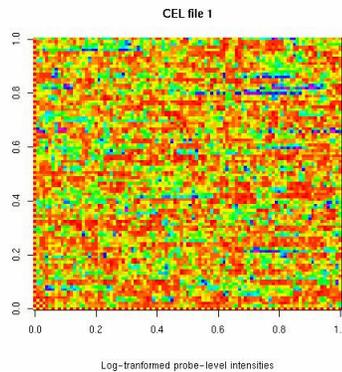
The Bioconductor: affy

The Bioconductor Project
Release 1.7

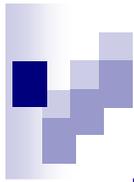
<http://www.bioconductor.org/>



affypdnn
affyPLM
gcrma
makecdfenv



[affy](#) Methods for Affymetrix Oligonucleotide Arrays
[affycomp](#) Graphics Toolbox for Assessment of Affymetrix Expression
[affydata](#) Affymetrix Data for Demonstration Purpose
[annaffy](#) Annotation tools for Affymetrix biological metadata
[AffyExtensions](#) For fitting more general probe level models



The Bioconductor: affy



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Quick Start: probe level data (*.cel) to expression measure.

```
> library(affy)
> getwd()
> list.celfiles()
> setwd("myaffy")
> getwd()
> list.celfiles()
> Data <- ReadAffy()

> eset.rma <- rma(Data)
> eset.mas <- expresso(Data,
                       normalize= FALSE,
                       bgcorrect.method="mas",
                       pmcorrect.method="mas",
                       summary.method="mas")

> eset.liwong <- expresso(Data,
                         normalize.method="invariantset",
                         bg.correct=FALSE,
                         pmcorrect.method="pmonly",
                         summary.method="liwong")

> eset.myfun <- express(Data,
                       summary.method=function(x)
                           apply(x, 2, median))

> write(eset.rma, file="mydata_rma.txt")
> write(eset.mas, file="mydata_mas.txt")
> write.exprs(eset.liwong, file="mydata_liwong.txt")
> write(eset.myfun, file="mydata_myfun.txt")
```

```
expresso(
  afbatch,

  # background correction
  bg.correct = TRUE,
  bgcorrect.method = NULL,
  bgcorrect.param = list(),

  # normalize
  normalize = TRUE,
  normalize.method = NULL,
  normalize.param = list(),

  # pm correction
  pmcorrect.method = NULL,
  pmcorrect.param = list(),

  # expression values
  summary.method = NULL,
  summary.param = list(),
  summary.subset = NULL,

  # misc.
  verbose = TRUE,
  warnings = TRUE,
  widget = FALSE)

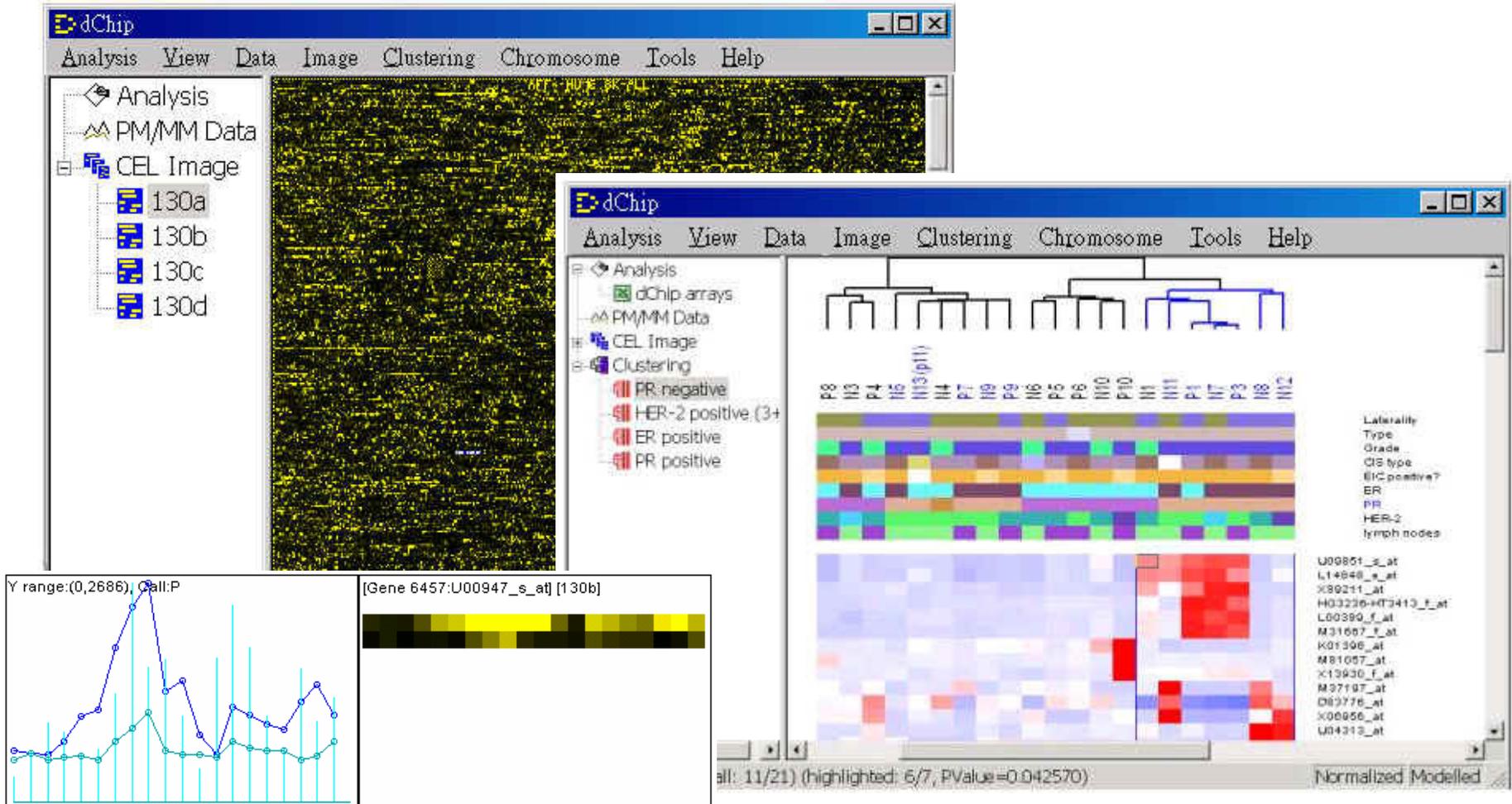
  none,
  mas,
  rma

  constant,
  contrasts,
  invariantset,
  loess, qspline,
  quantiles,
  quantiles.robust

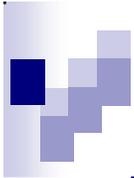
  mas,
  pmonly,
  subtractmm

  avgdiff,
  liwong,
  mas,
  medianpolish,
  playerout
```

DNA-Chip Analyzer (dChip v1.3)



<http://www.biostat.harvard.edu/complab/dchip/>

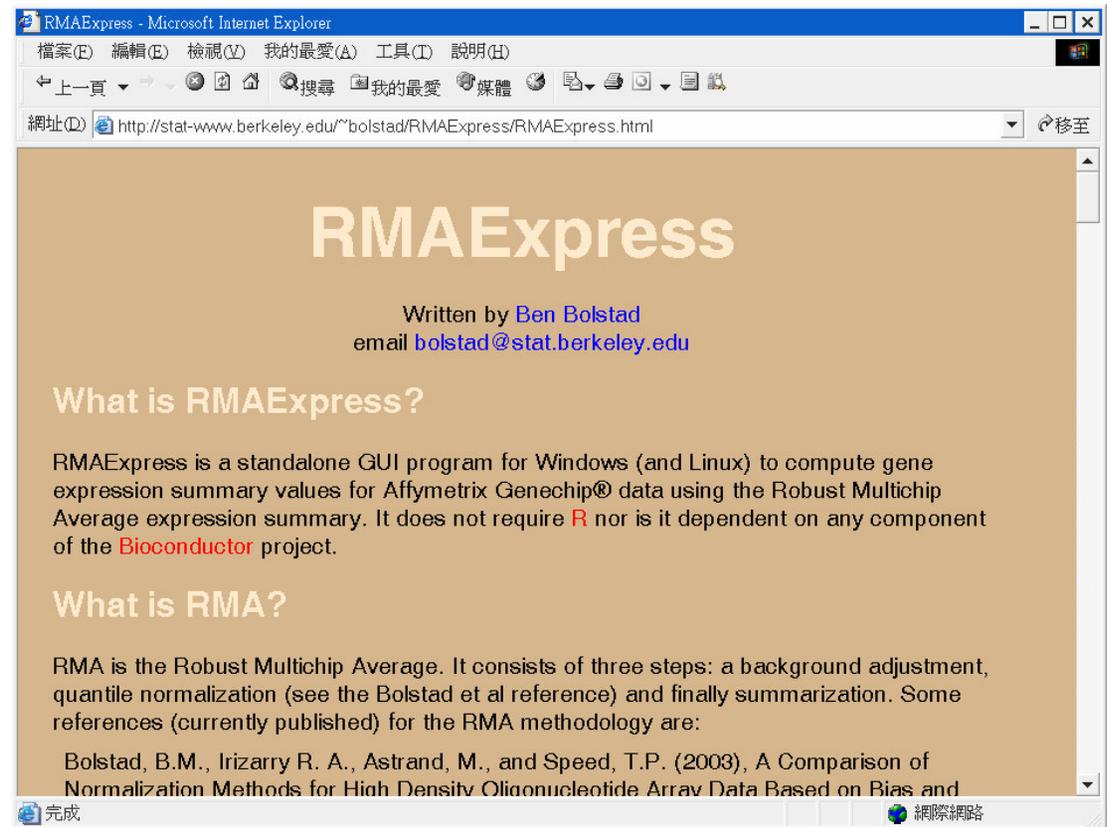
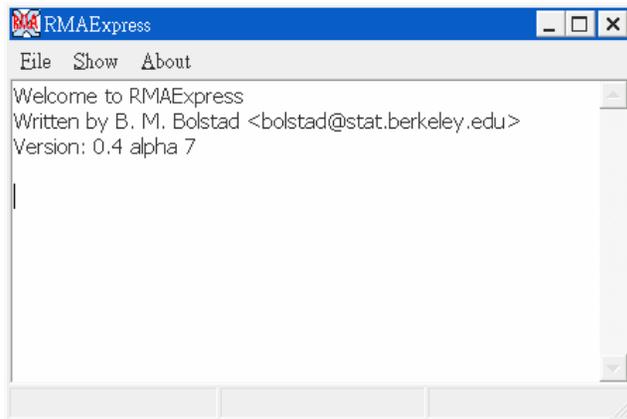


RMAExpress

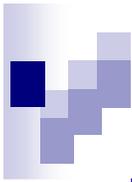


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Ben Bolstad
Biostatistics,
University Of California, Berkeley
<http://stat-www.berkeley.edu/~bolstad/>
Talks Slides



<http://stat-www.berkeley.edu/~bolstad/RMAExpress/RMAExpress.html>



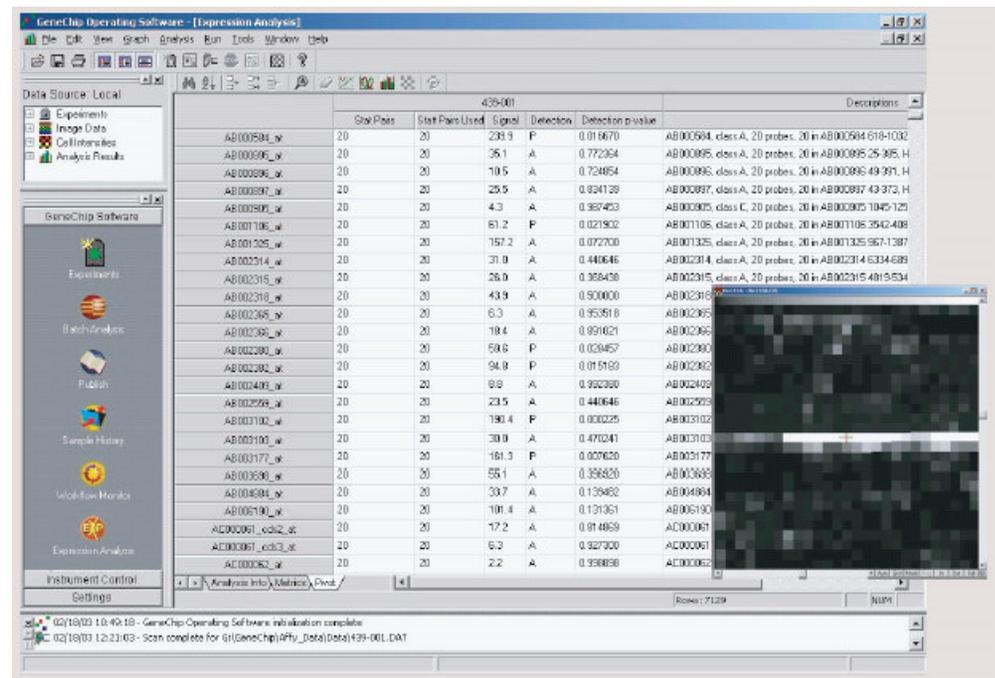
Affymetrix GeneChip Operating Software



<http://www.affymetrix.com>

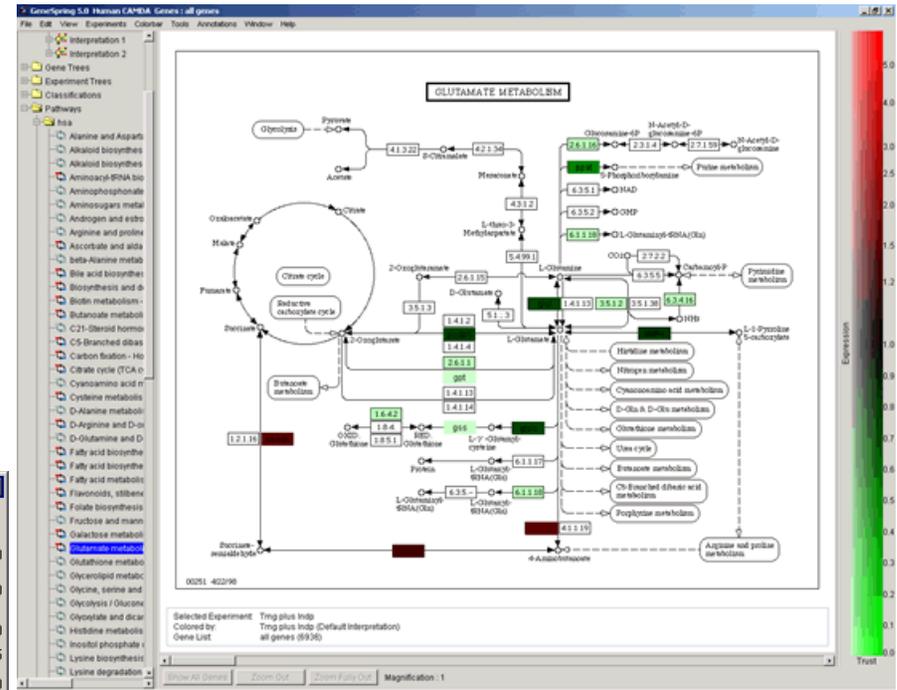
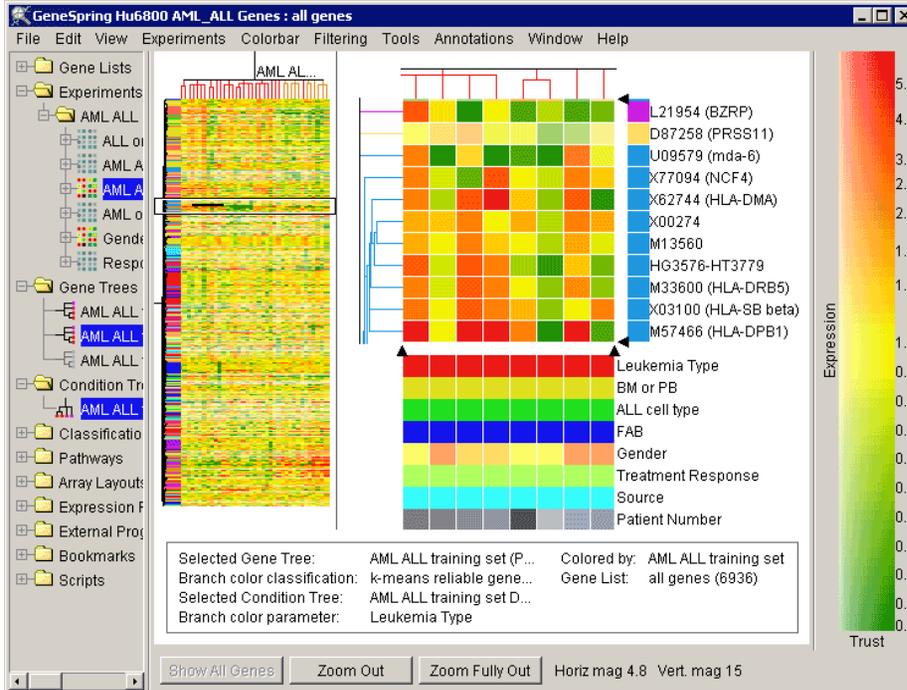
Specifications

Instrument Support	<ul style="list-style-type: none"> Affymetrix GeneChip® Fluidics Station 400 & 450 GeneChip Scanner 3000 GeneArray 2500 Scanner
Affymetrix Software Compatibility	<ul style="list-style-type: none"> Support GeneChip DNA Analysis Software (GDAS) for mapping and resequencing data analysis Support Affymetrix® Data Mining Tool software for statistical and clus analysis
Database Engine	<ul style="list-style-type: none"> Microsoft Data Engine
GCOS Database	<ul style="list-style-type: none"> Process Database Publish Database Gene Information Database
Database Management	<ul style="list-style-type: none"> GCOS Manager GCOS Administrator
Algorithm	<ul style="list-style-type: none"> Affymetrix Statistical Expression Algorithm



GeneSpring GX v7.3

- RMA or GC-RMA probe level analysis
- Advanced Statistical Tools
- Data Clustering
- Visual Filtering
- 3D Data Visualization
- Data Normalization (Sixteen)
- Pathway Views
- Search for Similar Samples
- Support for MIAME Compliance
- Scripting
- MAGE-ML Export



Images from
<http://www.silicongenetics.com>



2004 Articles Citing GeneSpring®

2004 : 2003 : 2002 : 2001 : pre-2001 : Reviews

More than 700 papers

Useful Links and Reference



<http://ihome.cuhk.edu.hk/~b400559/>



<http://www.affymetrix.com>

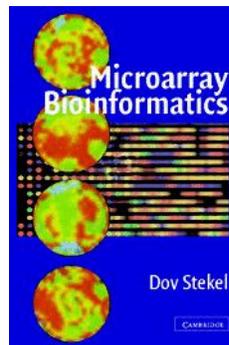


<http://bioinformatics.oupjournals.org>

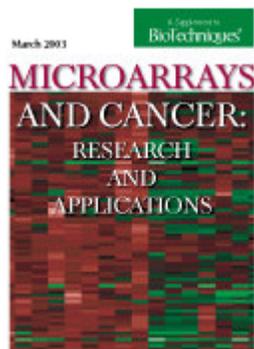


<http://www.nslj-genetics.org/microarray/>

Stekel, D. (2003).
Microarray
bioinformatics,
New York :
Cambridge
University Press.



- Speed Group Microarray Page: Affymetrix data analysis
http://www.stat.berkeley.edu/users/terry/zarray/Affy/affy_index.html
- Statistics and Genomics Short Course, Department of Biostatistics Harvard School of Public Health.
<http://www.biostat.harvard.edu/~rgentlem/Wshop/harvard02.html>
- Statistics for Gene Expression
<http://www.biostat.jhsph.edu/~ririzarr/Teaching/688/>
- Bioconductor Short Courses
<http://www.bioconductor.org/workshop.htm>



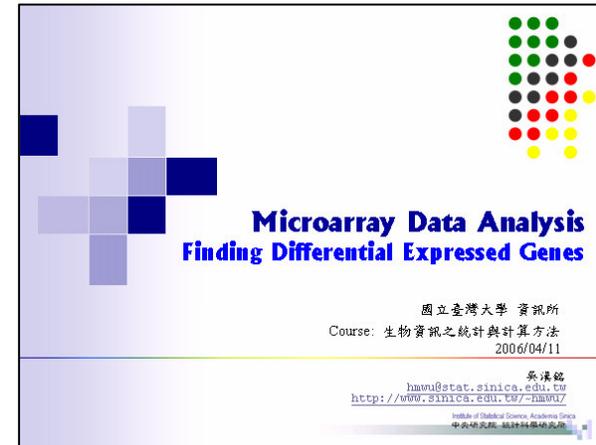
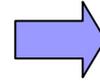
Microarrays and Cancer: Research and Applications
<http://www.biotechniques.com/microarrays/>



Next Class on 2006/4/11

The Normalized Data

	A	B	C	D	HE
1	data.probe	HEAT_15MIN_ROOT	HEAT_30MIN_ROOT	HEAT_1H_ROOT	HE
2	245620_at	0.30779948	-0.005928372	-0.199639348	
3	246102_at	-0.023415964	0.002837064	-0.093222224	
4	246467_at	1.343672347	-0.171424069	-0.373276745	
5	248125_at	-0.25336521	-0.056984896	0.032664987	
6	248564_at	-0.528516312	-0.255649678	0.156424695	
⋮					
18718	AFFX-r2-Ec-bioB-M	0.611156386	-0.317793537	-0.312335996	
18719	AFFX-r2-Ec-bioC-3	0.391053101	-0.058641116	-0.373798991	
18720	AFFX-r2-Ec-bioC-5	0.426674153	-0.021790669	-0.33991678	
18721	AFFX-r2-Ec-bioD-3	0.562698661	-0.125111666	-0.117077629	
18722	AFFX-r2-Ec-bioD-5	0.695590791	-0.021383357	-0.141613023	
18723	AFFX-r2-P1-cre-3	0.526064618	0.007746292	0.088283259	
18724	AFFX-r2-P1-cre-5	0.493449029	0.030815773	0.009662117	



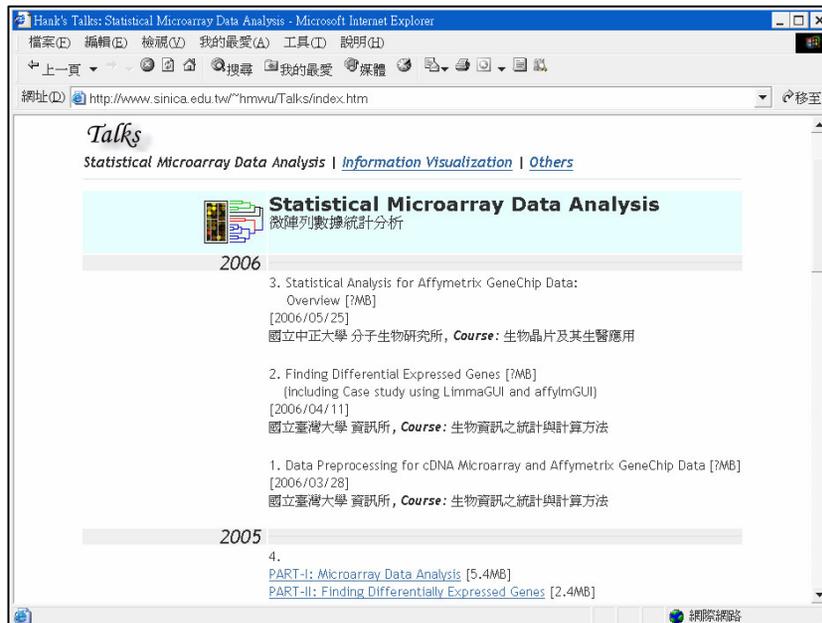
Microarray Data Analysis
Finding Differential Expressed Genes

國立臺灣大學 資訊所
Course: 生物資訊之統計與計算方法
2006/04/11

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Institute of Statistical Science, Academia Sinica
中央研究院 統計科學研究所

- Gene Filtering
- Finding DE Genes
- Case Study



Hank's Talks: Statistical Microarray Data Analysis - Microsoft Internet Explorer

Statistical Microarray Data Analysis | Information Visualization | Others

Statistical Microarray Data Analysis

微陣列數據統計分析

2006

3. Statistical Analysis for Affymetrix GeneChip Data:
Overview [2MB]
[2006/05/25]
國立中正大學 分子生物研究所, Course: 生物晶片及其生醫應用
2. Finding Differentially Expressed Genes [2MB]
(Including Case study using LimmaGUI and affyImGUI)
[2006/04/11]
國立臺灣大學 資訊所, Course: 生物資訊之統計與計算方法
1. Data Preprocessing for cDNA Microarray and Affymetrix GeneChip Data [2MB]
[2006/03/28]
國立臺灣大學 資訊所, Course: 生物資訊之統計與計算方法

2005

4. PART-I: Microarray Data Analysis [5.4MB]
PART-II: Finding Differentially Expressed Genes [2.4MB]

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Institute of Statistical Science, Academia Sinica