

Low-Level Copy Number Analysis

Part 1 - Background

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CEIT Workshop on SNP arrays,
Dec 15-17, 2008, San Sebastian

Acknowledgments

UC Berkeley:

- James Bullard
- Kasper Hansen
- Elizabeth Purdom
- Terry Speed

Lawrence Berkeley National Labs:

- Amrita Ray
- Paul Spellman

John Hopkins, Baltimore:

- Benilton Carvalho
- Rafael Irizarry

WEHI, Melbourne, Australia:

- Mark Robinson
- Ken Simpson

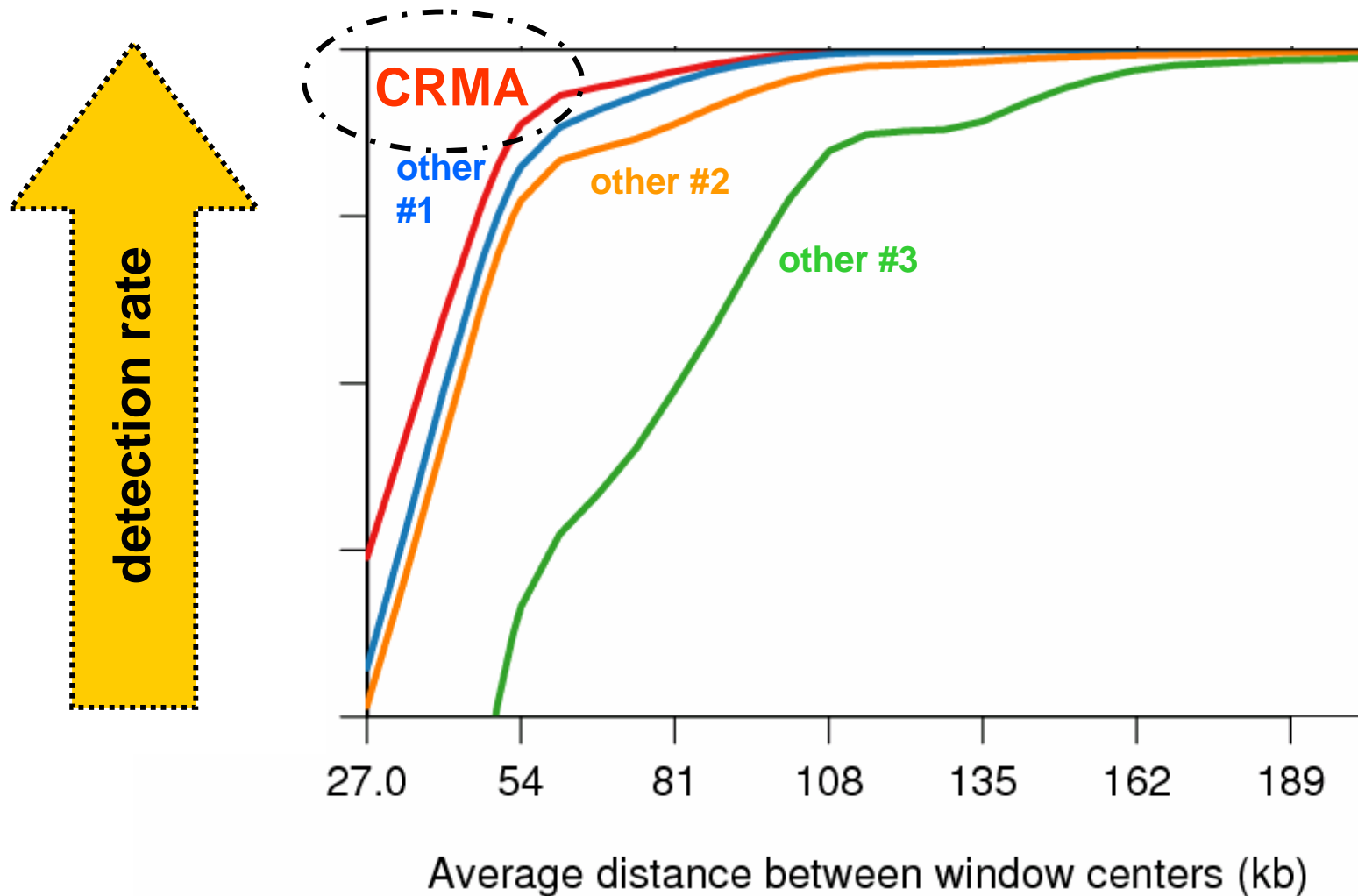
ISREC, Lausanne, Switzerland:

- Pratyaksha “Asa” Wirapati

Affymetrix, California:

- Ben Bolstad
- Simon Cawley
- Steve Chervitz
- Harley Gorrell
- Earl Hubbell
- Luis Jevons
- Chuck Sugnet
- Jim Veitch
- Alan Williams

Detect more and smaller aberrations with less errors



Copy number analysis is about finding "aberrations" in one or several individuals

Chromosome Explorer (© 2006-2008 Henrik Bengtsson)

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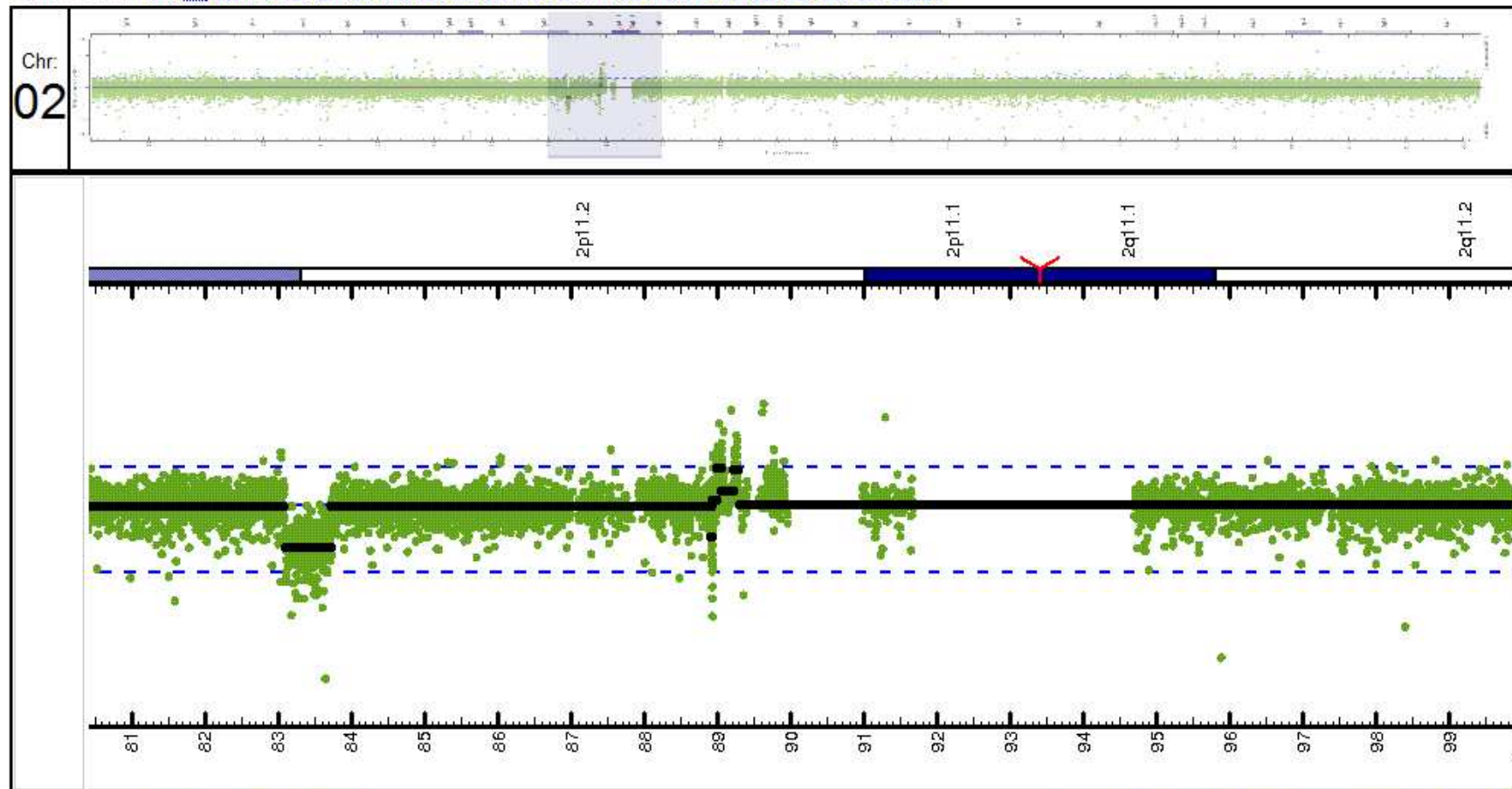
Sample: **NA06985**

Zoom: [\[x1\]](#)[\[x2\]](#)[\[x4\]](#)[\[x8\]](#)[\[x16\]](#)[\[x32\]](#)[\[x64\]](#)[\[x128\]](#)

Sets: [\[cbs\]](#)

Samples: [\[NA06985\]](#)[\[NA06991\]](#)[\[NA06993\]](#)[\[NA06994\]](#)[\[NA07000\]](#)[\[NA07019\]](#) Step: [\[prev\]](#)[\[next\]](#) Play: [\[start\]](#)[\[stop\]](#) ([slower](#)[faster](#))

Chromosome: [\[01\]](#)[\[02\]](#)[\[03\]](#)[\[04\]](#)[\[05\]](#)[\[06\]](#)[\[07\]](#)[\[08\]](#)[\[09\]](#)[\[10\]](#)[\[11\]](#)[\[12\]](#)[\[13\]](#)[\[14\]](#)[\[15\]](#)[\[16\]](#)[\[17\]](#)[\[18\]](#)[\[19\]](#)[\[20\]](#)[\[21\]](#)[\[22\]](#)[\[23\(X\)\]](#)



Identified regions: [GenomeWideSNP_6/cbs/regions.xls](#)

Image URL: [GenomeWideSNP_6/cbs/NA06985_chr02_x0016.png](#)

The HapMap project

- *Large project to identify SNPs in Humans (2003-)*

feature

The International HapMap Project

The International HapMap Consortium*

*Lists of participants and affiliations appear at the end of the paper

The goal of the International HapMap Project is to determine the common patterns of DNA sequence variation in the human genome and to make this information freely available in the public domain. An international consortium is developing a map of these patterns across the genome by determining the genotypes of one million or more sequence variants, their frequencies and the degree of association between them, in DNA samples from populations with ancestry from parts of Africa, Asia and Europe. The HapMap will allow the discovery of sequence variants that affect common disease, will facilitate development of diagnostic tools, and will enhance our ability to choose targets for therapeutic intervention.

The HapMap is a catalog of common genetic variants (SNPs) that occur in human beings. It describes what These variants are, where they occur in our DNA, and How they are distributed among people within populations and among populations in different parts of the world.

URL: <http://www.hapmap.org/>

The HapMap project

*- 270 normal individuals genotyped by different labs
using various technologies*

- 90 CEU individuals (Utah/Europe, 30 trio families)
- 90 YRI individuals (Nigeria; 30 trio families)
- 45 CHB (China; unrelated)
- 45 JPT (Japan; unrelated)

Publicly available:

- High quality data.
- Raw data, e.g. Affymetrix CEL files.
- Genotypes.
- Studied by many groups.

Copy number polymorphism

- People share common CN aberrations (2005-)

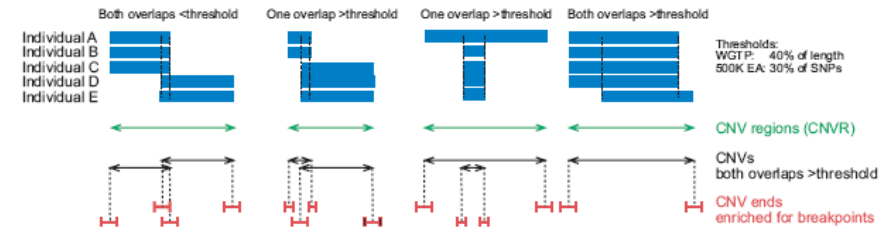
Large-Scale Copy Number Polymorphism in the Human Genome

Jonathan Sebat,¹ B. Lakshmi,¹ Jennifer Troge,¹ Joan A. Jané Young,² Pär Lundin,³ Susanne Månér,³ Hillary I. Megan Walker,² Maoyen Chi,¹ Nicholas Navin,¹ Robert John Healy,¹ James Hicks,¹ Kenny Ye,⁴ Andrew Reiner, T. Conrad Gilliam,⁵ Barbara Trask,² Nick Patterson, Anders Zetterberg,³ Michael Wigler^{1*}

The extent to which large duplications and deletions contribute to human genomic variation and diversity is unknown. Here, we show that large-scale copy number polymorphisms (CNPs) (about 100 kilobases and greater) contribute to genomic variation between normal humans. Representational oligonucleotide microarray analysis of 20 individuals revealed a total of 221 copy number intervals representing 76 unique CNPs. On average, individuals differed by 1.5 CNPs and the average length of a CNP interval was 465 kilobases. We observed copy number variation of 70 different genes within CNP intervals, including genes involved in neurological function, regulation of cell growth, regulatory pathways, and several genes known to be associated with disease.

Many of the genetic differences between humans and other primates are a result of large duplications and deletions (1–3). From these observations, it is reasonable to expect that differences in gene copy number could be a significant source of genetic variation between humans. A few examples of large duplication polymorphisms have

In our previous studies with the use of representational oligonucleotide microarray analysis (4), we detected many genomic deletions in tumor genome comparison to an unrelated normal genome (5), but some of these



nature

Vol 444 | 23 November 2006 | doi:10.1038/nature05329

ARTICLES

Global variation in copy number in the human genome

Richard Redon¹, Shumpei Ishikawa^{2,3}, Karen R. Fitch⁴, Lars Feuk^{5,6}, George H. Perry⁷, T. Daniel Andrews¹, Heike Fiegler¹, Michael H. Shapero⁴, Andrew R. Carson^{5,6}, Wenwei Chen⁴, Eun Kyung Cho⁷, Stephanie Dallaire⁷, Jennifer L. Freeman⁷, Juan R. González⁸, Mónica Gratacòs⁸, Jing Huang⁴, Dimitrios Kalaitzopoulos¹, Daisuke Komura³, Jeffrey R. MacDonald⁹, Christian R. Marshall^{5,6}, Rui Mei⁴, Lyndal Montgomery¹, Kunihiro Nishimura², Kohji Okamura^{5,6}, Fan Shen⁴, Martin J. Somerville⁹, Joelle Tchinda⁷, Armand Valsesia¹, Cara Woodward¹, Fengtang Yang¹, Junjun Zhang³, Tatiana Zerjal¹, Jane Zhang⁴, Lluís Armengol⁸, Donald F. Conrad¹⁰, Xavier Estivill^{8,11}, Chris Tyler-Smith¹, Nigel P. Carter¹, Hiroyuki Aburatani^{12,13}, Charles Lee^{7,13}, Keith W. Jones⁴, Stephen W. Scherer^{5,6} & Matthew E. Hurles¹

Copy number variation (CNV) of DNA sequences is functionally significant but has yet to be fully ascertained. We have constructed a first-generation CNV map of the human genome through the study of 270 individuals from four populations with ancestry in Europe, Africa or Asia (the HapMap collection). DNA from these individuals was screened for CNV using two complementary technologies: single-nucleotide polymorphism (SNP) genotyping arrays, and clone-based comparative genomic hybridization. A total of 1,447 copy number variable regions (CNVRs), which can encompass overlapping or adjacent gains or losses, covering 360 megabases (12% of the genome) were identified in these populations. These CNVRs contained hundreds of genes, disease loci, functional elements and segmental duplications. Notably, the CNVRs encompassed more nucleotide content per genome than SNPs, underscoring the importance of CNV in genetic diversity and evolution. The data obtained delineate linkage disequilibrium patterns for many CNVs, and reveal marked variation in copy number among populations. We also demonstrate the utility of this resource for genetic disease studies.

Genetic variation in the human genome takes many forms, ranging from large, microscopically visible chromosome anomalies to single-nucleotide changes. Recently, multiple studies have discovered an abundance of submicroscopic copy number variation of DNA segments ranging from kilobases (kb) to megabases (Mb) in size^{1–9}. Deletions, insertions, duplications and complex multi-site variants⁹,

at genes at which other types of mutation are strongly associated with specific diseases: CHARGE syndrome²¹ and Parkinson's and Alzheimer's disease^{22,23}. Furthermore, CNVs can influence gene expression indirectly through position effects, predispose to deleterious genetic changes, or provide substrates for chromosomal change in evolution^{9,11,17,24}.

The Cancer Genome Atlas (TCGA) project

- *Large project for genetic mapping of tumors (2007-)*



[Scientific American Magazine](#) - February 18, 2007

Mapping the Cancer Genome

Pinpointing the genes involved in cancer will help chart a new course for human malignancies

By Francis S. Collins and Anna D. Barker

"If we wish to learn more about cancer, we must now concentrate on the cellular level," wrote Paul H. Othman in 1961. In 1986, Paul H. Othman, a pioneer in cancer research, penned those words more than 20 years ago in one of the earliest papers in the Human Genome Project. "We are at a turning point," Dulbecco, a pioneering cancer researcher, wrote in the journal *Science*. Discoveries in preceding years had made clear that much of the damage to the genome stemmed from damage to their genes and alterations in their functioning. "We must discover the genes important in malignancy by a piecemeal approach, or & see

Dulbecco and others in the scientific community grasped that sequencing the human genome itself, would mark just the first step of the quest to fully understand the sequence of nucleotide bases in normal human DNA in hand, scientists would have the sequence of human genes according to their function--which in turn could reveal their roles. Dulbecco's vision has moved from pipe dream to reality. Less than three years after the completion, the National Institutes of Health has officially launched the pilot stage of the catalogue of the genomic changes involved in cancer: The Cancer Genome Atlas.

The main reason to pursue this next ambitious venture in large-scale biology was the impact of cancer on humankind. Every day more than 1,500 Americans die from cancer--about one in four of the population ages, this rate is expected to rise significantly in the years ahead until the identification of new vulnerabilities within cancerous cells and develop novel

Still, however noble the intent, it takes more than a desire to ease human suffering to launch a project of this magnitude. When applied to the 50 most common types of cancer, this effort represents one of more than 10,000 Human Genome Projects in terms of the sheer volume of data generated and therefore be matched with an ambitious but realistic assessment of the emerging strategies for a smarter war against cancer.

doi:10.1038/nature07385

nature

ARTICLES

Comprehensive genomic characterization defines human glioblastoma genes and core pathways

The Cancer Genome Atlas Research Network*

Human cancer cells typically harbour multiple chromosomal aberrations, nucleotide substitutions and epigenetic modifications that drive malignant transformation. The Cancer Genome Atlas (TCGA) pilot project aims to assess the value of large-scale multi-dimensional analysis of these molecular characteristics in human cancer and to provide the data rapidly to the research community. Here we report the interim integrative analysis of DNA copy number, gene expression and DNA methylation aberrations in 206 glioblastomas—the most common type of primary adult brain cancer—and nucleotide sequence aberrations in 91 of the 206 glioblastomas. This analysis provides new insights into the roles of *ERBB2*, *NF1* and *TP53*, uncovers frequent mutations of the phosphatidylinositol-3-OH kinase regulatory subunit gene *PIK3R1*, and provides a network view of the pathways altered in the development of glioblastoma. Furthermore, integration of mutation, DNA methylation and clinical treatment data reveals a link between *MGMT* promoter methylation and a hypermutator phenotype consequent to mismatch repair deficiency in treated glioblastomas, an observation with potential clinical implications. Together, these findings establish the feasibility and power of TCGA, demonstrating that it can rapidly expand knowledge of the molecular basis of cancer.

Cancer is a disease of genome alterations: DNA sequence changes, copy number aberrations, chromosomal rearrangements and modification in DNA methylation together drive the development and progression of human malignancies. With the complete sequencing of the human genome and continuing improvement of high-throughput genomic technologies, it is now feasible to contemplate comprehensive surveys of human cancer genomes. The Cancer Genome Atlas aims to catalogue and discover major cancer-causing genome alterations in large cohorts of human tumours through integrated multi-dimensional analyses.

The first cancer studied by TCGA is glioblastoma (World Health Organization grade IV), the most common primary brain tumour in adults¹. Primary glioblastoma, which comprises more than 90% of biopsied or resected cases, arises *de novo* without antecedent history of low-grade disease, whereas secondary glioblastoma progresses from a pre-existing low-grade glioma. Patients with primary

Results

Data release. As a public resource, all TCGA data are deposited at the Data Coordinating Center (DCC) for public access (<http://cancergenome.nih.gov/>). TCGA data are classified by data type (for example, clinical, mutations, gene expression) and data level to allow structured access to this resource with appropriate patient privacy protection. An overview of the data organization is provided in the Supplementary Methods, and a detailed description is available in the TCGA Data Primer (http://tcga-data.nci.nih.gov/docs/TCGA_Data_Primer.pdf).

Biospecimen collection

Retrospective biospecimen repositories were screened for newly diagnosed glioblastoma based on surgical pathology reports and clinical records (Supplementary Fig. 1). Samples were further selected for inclusion based on histopathological confirmation of glioblastoma

The TCGA project

- *A large number of tissues are studied with many DNA & RNA technologies*

- Tumor types:
 - brain cancer (glioblastoma multiforme, or GBM),
 - lung cancer (squamous cell carcinoma of the lung), and
 - ovarian cancer (serous cystadenocarcinoma of the ovary).
- 234 tumors (of 500) characterized.
- Multiple labs in the US
 - Broad, Harvard, Stanford, LBNL, ...
- High quality data.
- Platforms: Affymetrix, Illumina, Agilent, ...
- Gene-, exon-, microRNA- expression, methylation, SNP & CN, sequencing...
- Raw and summarized data immediately available (publicly), e.g. Affymetrix CEL files.

Combining copy numbers across platforms & labs

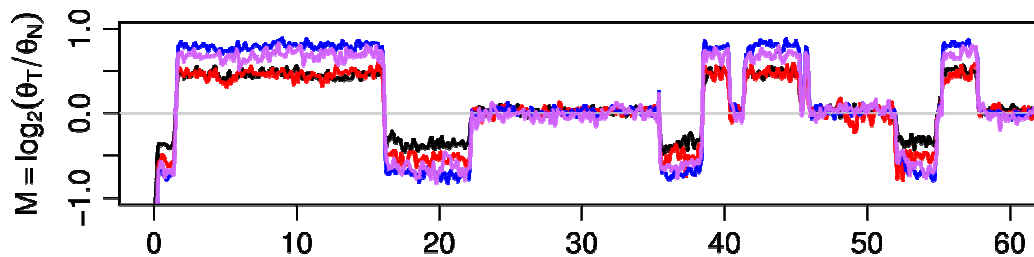
Henrik Bengtsson (UC Berkeley), Amrita Ray (LBNL), Paul Spellman (LBNL), Terry Speed (UC Berkeley)

BACKGROUND:

Whole-genome copy-number (CN) studies are rapidly expanding, and with this expansion comes a **demand for increased precision and resolution** of CN estimates. Several recent studies have obtained **CN estimates from more than one platform** on the same samples, and it is natural to want to **combine** the different estimates in order to meet this demand.

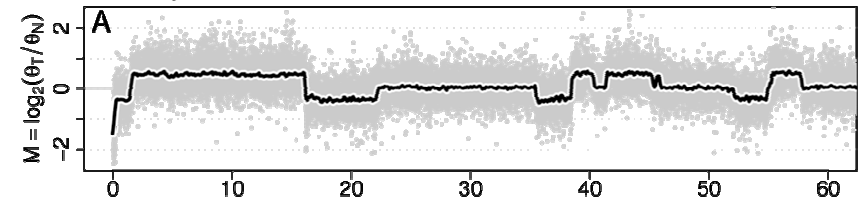
PROBLEM:

CN estimates from **different platforms show different degrees of attenuation** of the true CN changes. Differences can also be observed in CN estimates from the same platform run in different labs, or in the same lab, with different analytical methods. This is the reason why it is **not straightforward matter to combine CN estimates from different sources** (platforms, labs, analysis methods, etc).

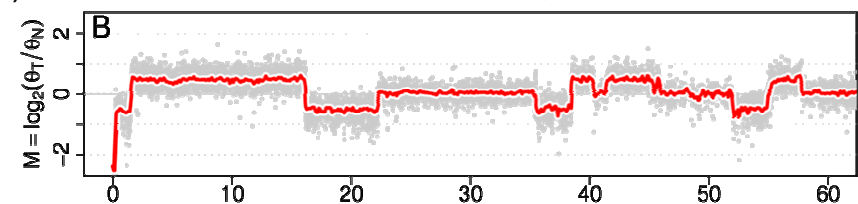


The smoothed raw CNs from the four sources have similar CN profiles but different mean levels.

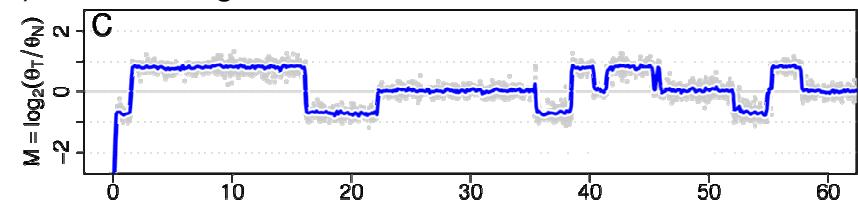
(A) Broad, Affymetrix GWS6, n=1800K, 1.59kb/locus, 25-mers



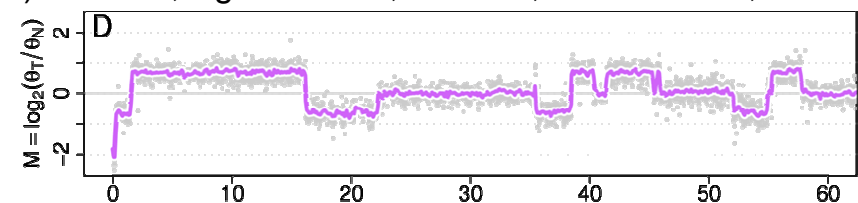
(B) Stanford, Illumina 550K, n=550K, 5.53kb/locus, 50-mers



(C) MSKCC, Agilent 244K, n=236K, 12.7kb/locus, 60-mers



(D) Harvard, Agilent 244K, n=236K, 12.7kb/locus, 60-mers



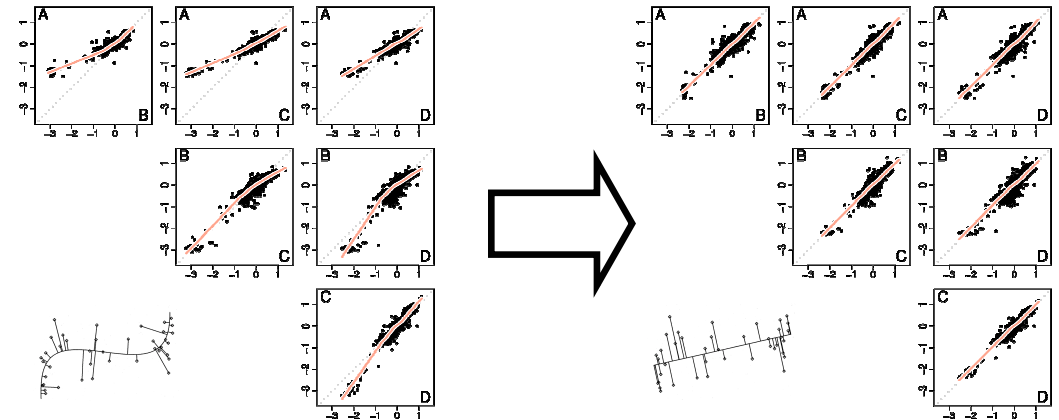
Tumor/normal CNs by four TCGA centers (“sources”) in a 60Mb region on Chr3 in sample TCGA-02-104. (The combined set would consist of 2,822K loci with 0.95kb/locus.)

METHOD:

We have developed a single-sample multi-source normalization that **brings full-resolution CN estimates to the same scale** across sources.

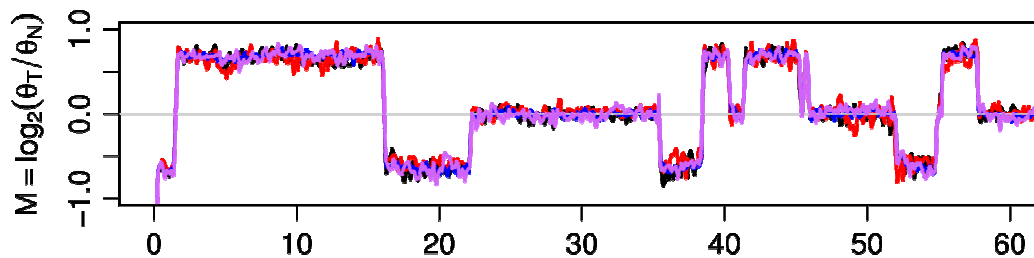
Kernel estimators and principal component curves are used to estimate the **non-linear relationships** between the sources. Full-resolution data is then normalized such that these **relationships become linear**.

The normalized estimates are such that for any underlying CN level, **the mean level of the CN estimates is the same regardless of source**. CNs with consistent mean levels are **better suited for being combined across sources**, e.g. existing segmentation methods may be used to identify aberrant regions.

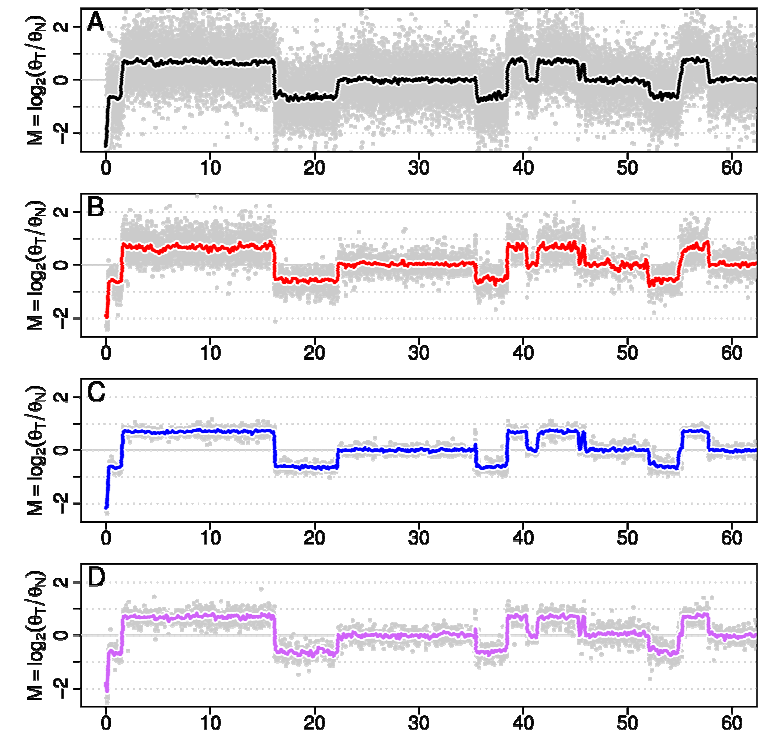


*Before normalization:
Non-linearity between pairs*

*After normalization:
Linearity between pairs*



The smoothed normalized CNs from the four sources have similar CN profiles and same mean levels.

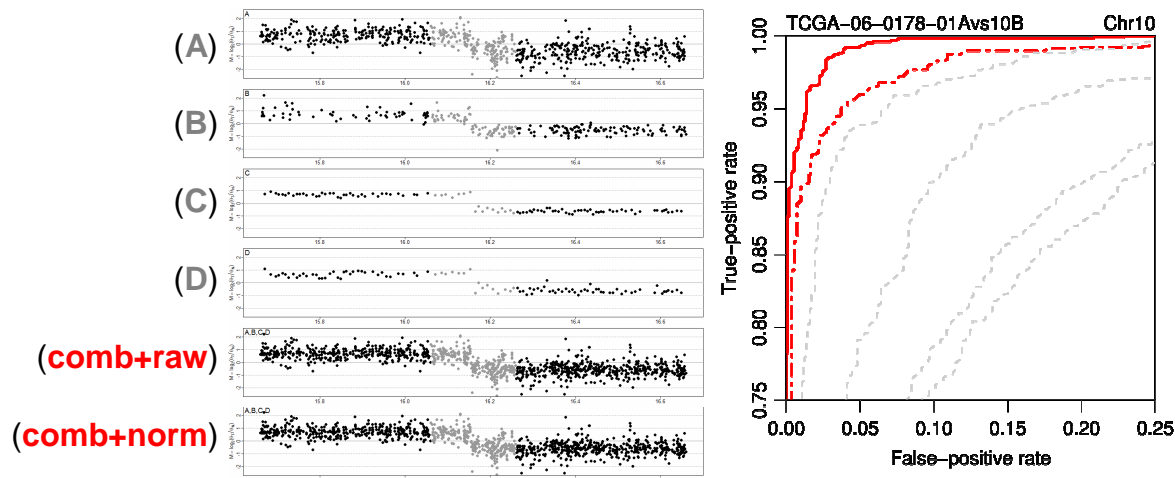


Normalized full-resolution CNs for the four sources.

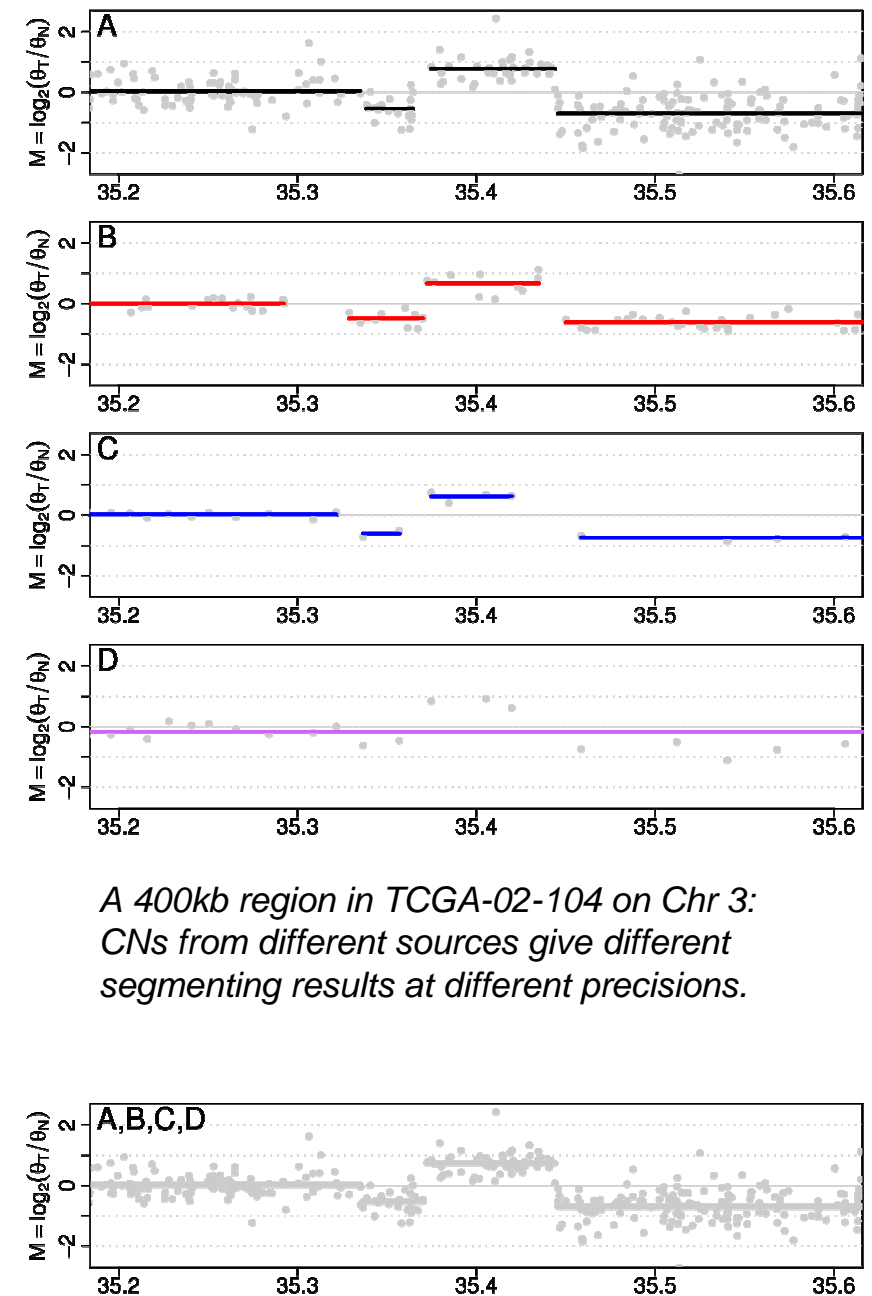
RESULTS:

We use microarray-based CN estimates from **The Cancer Genome Atlas (TCGA)** project to illustrate the method. We show that **after normalization the mean levels of randomly selected CN aberrations are the same across platforms**, and that the normalized and combined data better separate two CN states at a given resolution.

We conclude that it is possible to **combine CNs** from multiple sources such that the **resolution becomes effectively larger**, and when multiple platforms are combined, they also **enhance the genome coverage** by complementing each other in different regions.



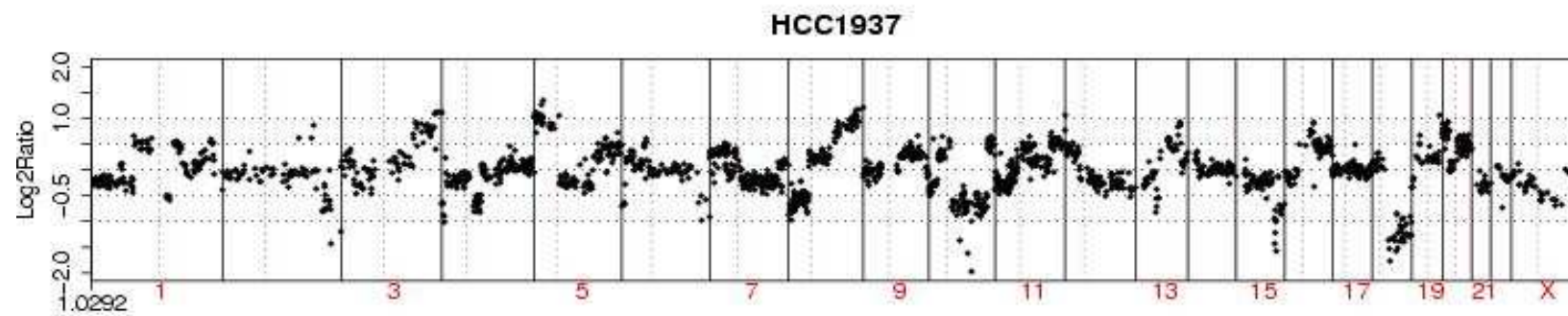
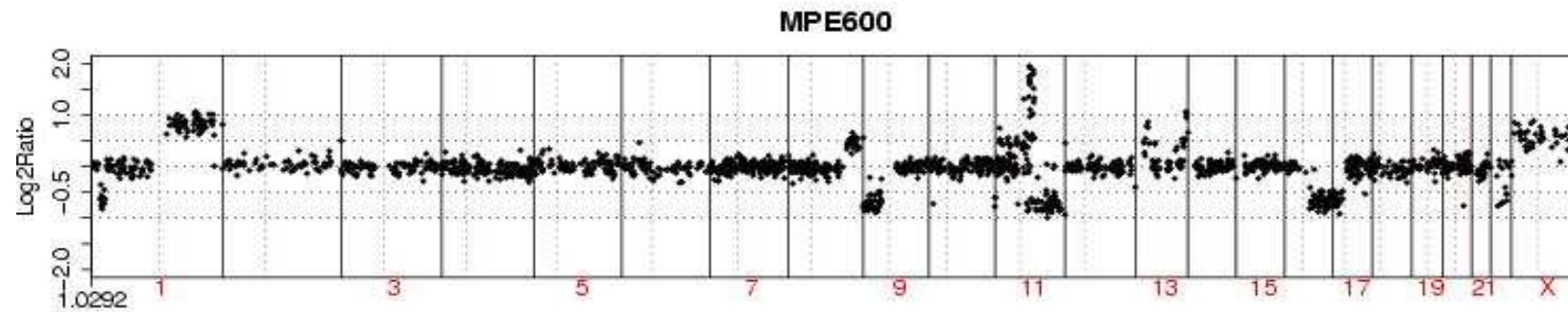
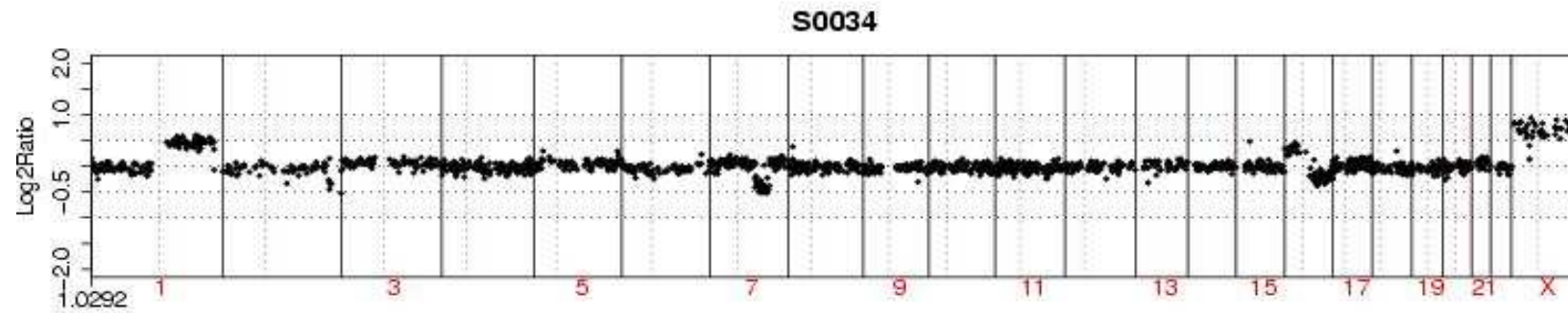
At any given resolution (amount of smoothing), with combined normalized CNs (**solid red**) one can separate two CN states **better** than with combined raw CNs (**dot-dashed red**), and with each of the individuals sources (**gray dotted**).



A 400kb region in TCGA-02-104 on Chr 3:
CNs from different sources give different
segmenting results at different precisions.

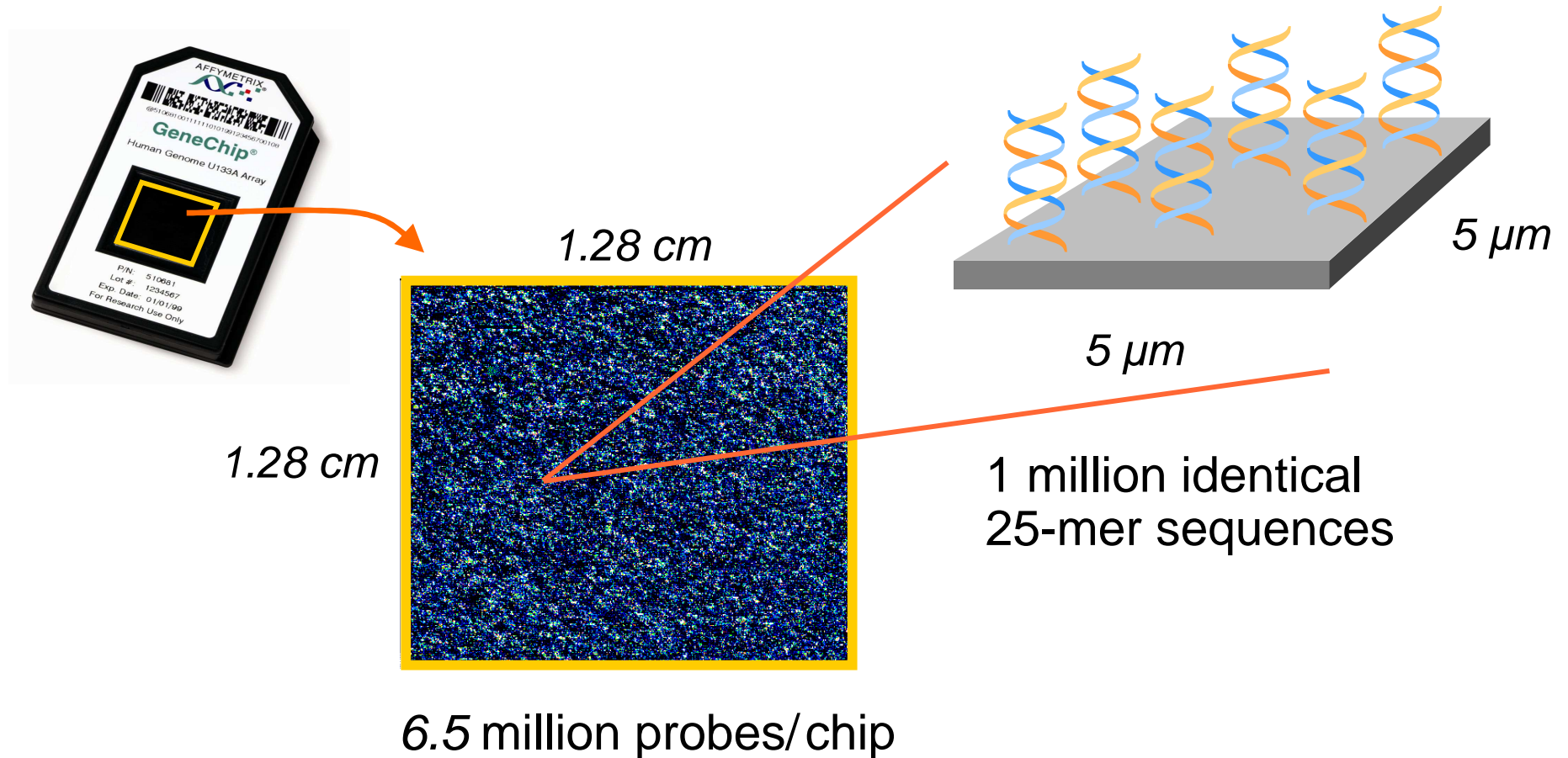
With combined normalized CNs, there is more
power to detect change points (CPs) and their
locations are more precise.

Examples of genomic profiles



The Affymetrix platform

The Affymetrix GeneChip is a synthesized high-density (single-array) microarray



Copy-number probes are used to quantify the amount of DNA at known loci

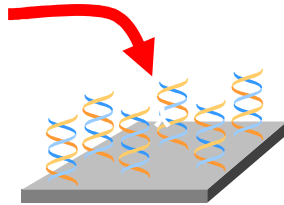
CN locus:

...CGTAGCCATCGGTAAGTACTCAATGATAG...

PM:

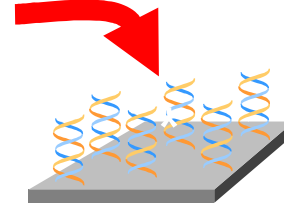
ATCGGTAGCCATTCATGAGTTACTA

CN=1



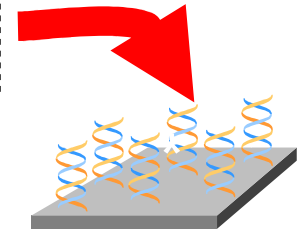
PM = c

CN=2



PM = 2c

CN=3



PM = 3c

Single Nucleotide Polymorphism (SNP)

Definition:

A sequence variation such that two chromosomes may differ by a single nucleotide (A, T, C, or G).

Allele A:

. . . CGTAGCCATCGGTA / GTACTCAATGATAG . . .

Allele B:

A

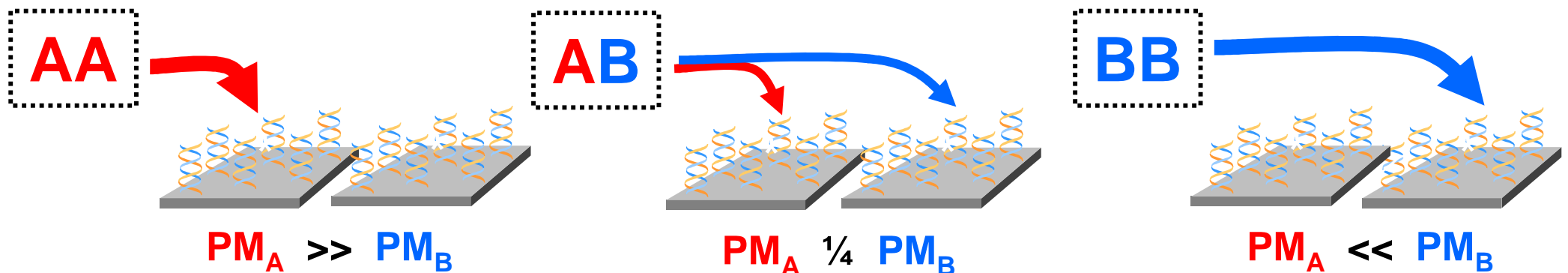
G

A person is either **AA**, **AB**, or **BB** at this SNP.

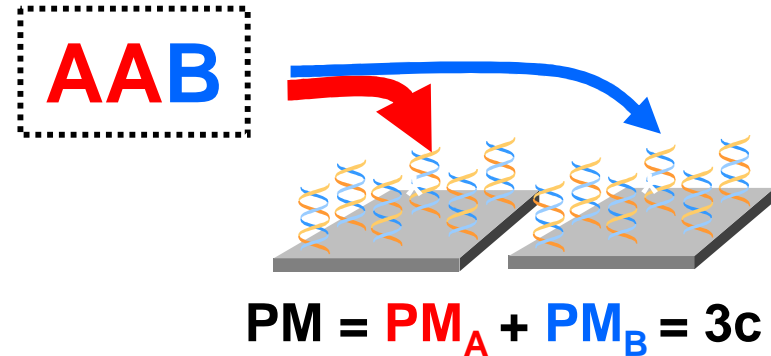
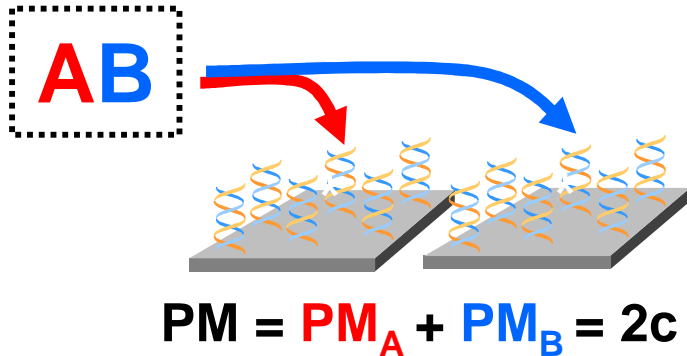
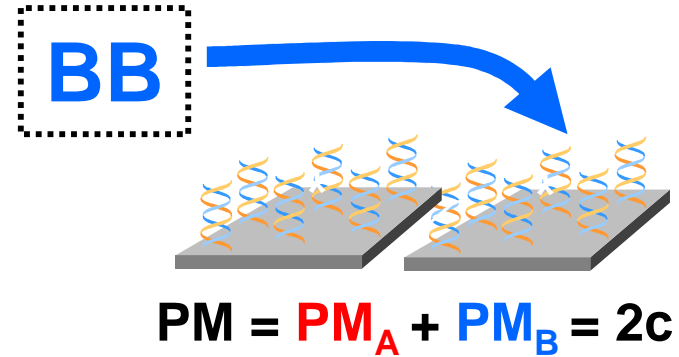
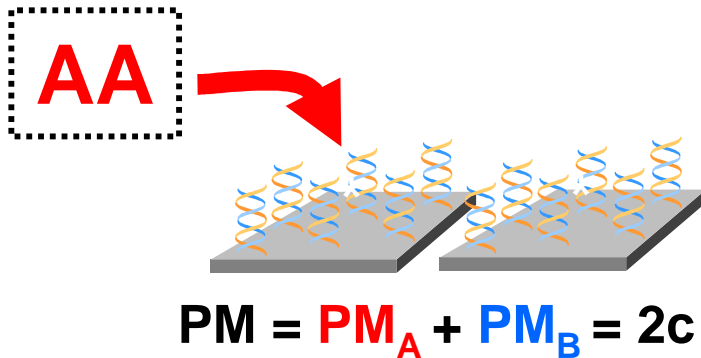
Probes for SNPs

PM_A: ATCGGTAGCCAT**T**CATGAGTTACTA
Allele A: . . . *CGTAGCCATCGGT**A**GTACTCAATGATAG* . . .
Allele B: . . . *CGTAGCCATCGGT**G**GTACTCAATGATAG* . . .
PM_B: ATCGGTAGCCAT**C**CATGAGTTACTA

(Also MMs, but not in the newer chips, so we will not use these!)



SNP probes can also be used to estimate total copy numbers



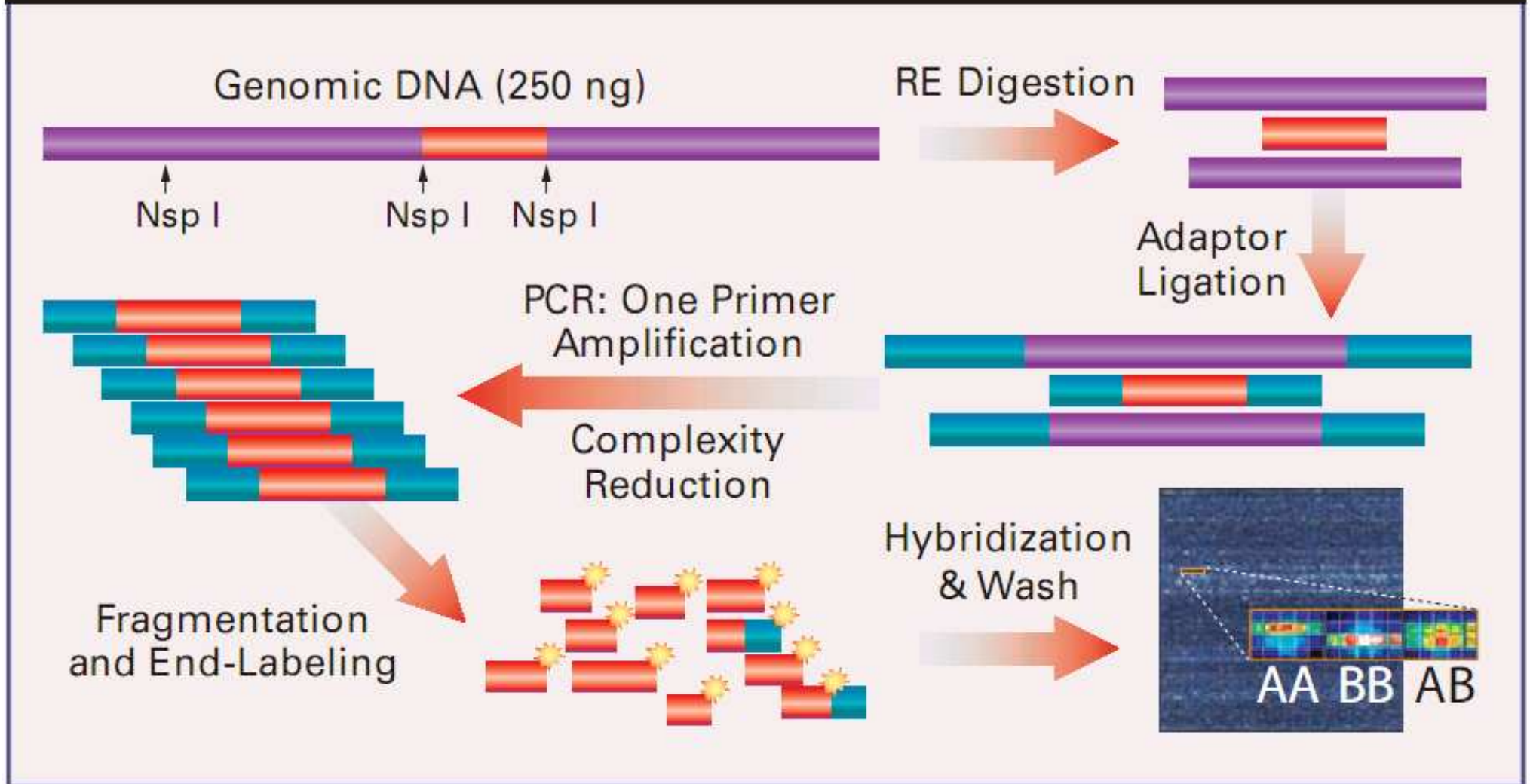
The Affymetrix assay

- *takes 4-5 working days to complete*

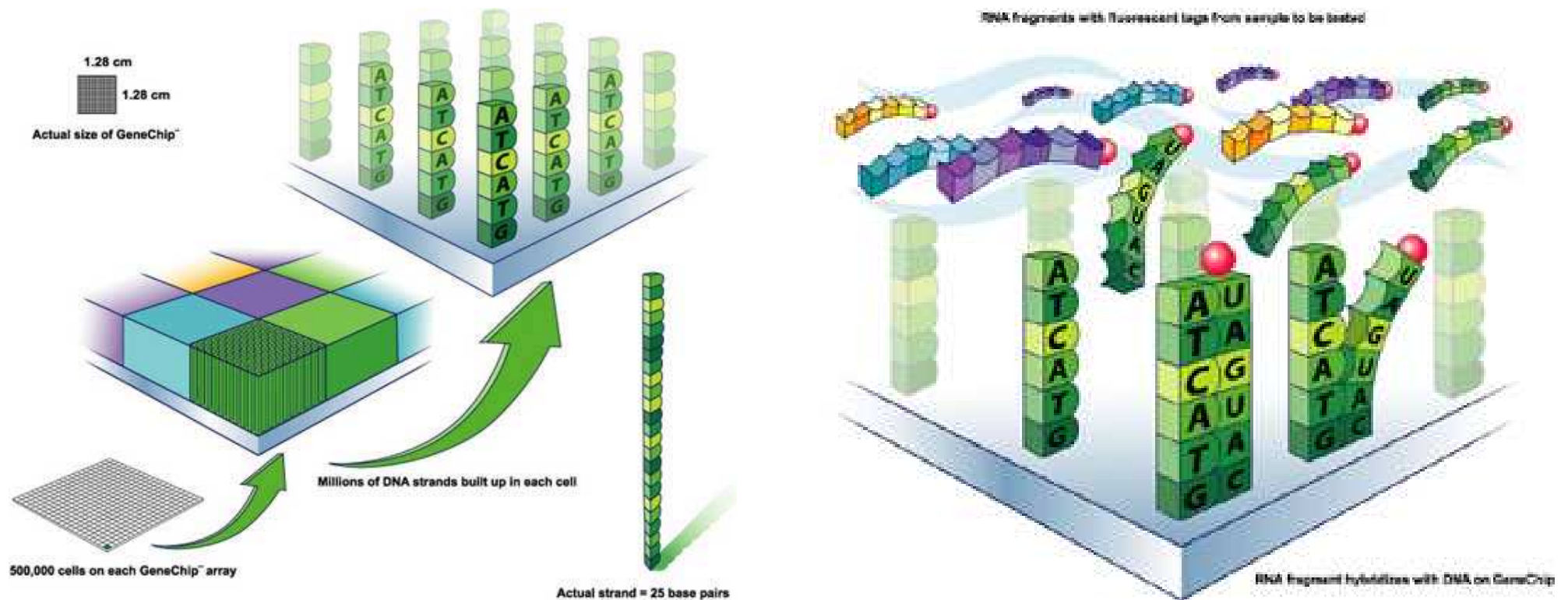
1. Start with target **gDNA** (genomic DNA) or **mRNA**.
2. Obtain **labeled single-stranded** target DNA fragments for hybridization to the probes on the chip.
3. After hybridization, washing, and scanning we get a **digital image**.
4. Image summarized across pixels to **probe-level intensities** before we begin. This is our "raw data".

Restriction enzymes digest the DNA, which is then amplified and hybridized

Figure 1: GeneChip® Mapping Assay Overview.



Target DNA find their way to complementary probes by massive parallel hybridization



Scanning

Example array: 1600x1600 cells; 65536 intensity levels (16 bits).

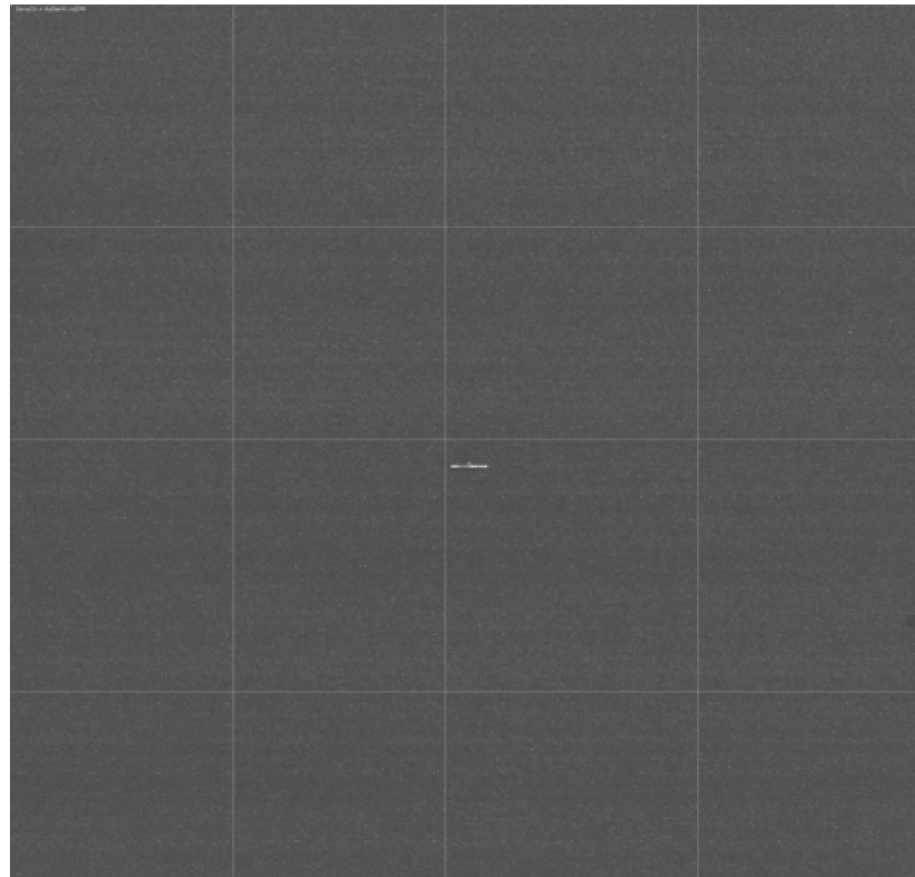


Image Analysis

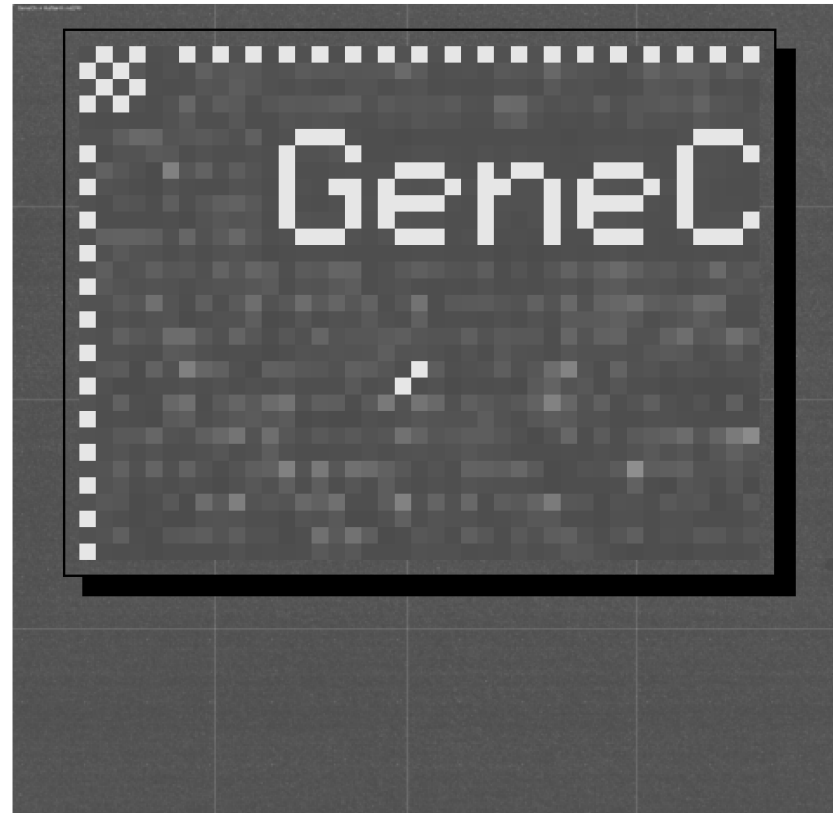
Example array:

Dimensions: 1600x1600 cells

Each cell: 3x3 pixels

Dynamic range: 65536 (16-bits) intensity levels

Cell summaries: (mean pixel, stddev pixel, #pixels)



**Preparation
+ Hybridization
+ Scanning**



DAT File(s)
[Image, pixel intensities]

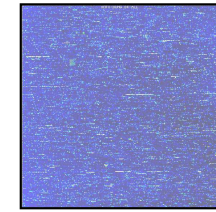


Image analysis



workable raw data

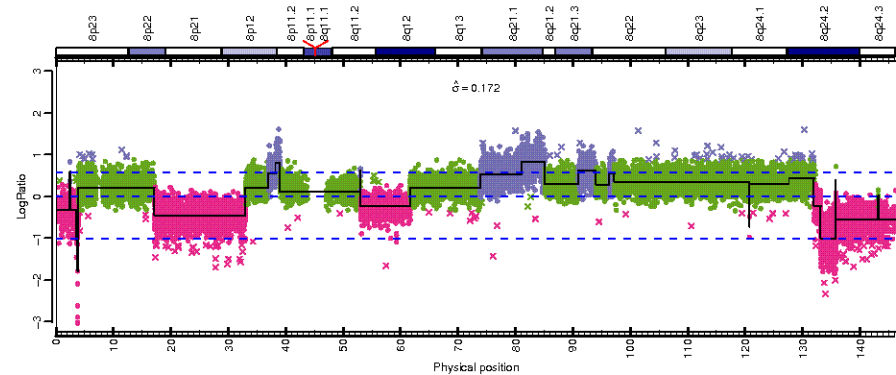
CEL File(s)
[Probe Cell Intensity]

+

CDF
[Chip Description File]

Low-level analysis

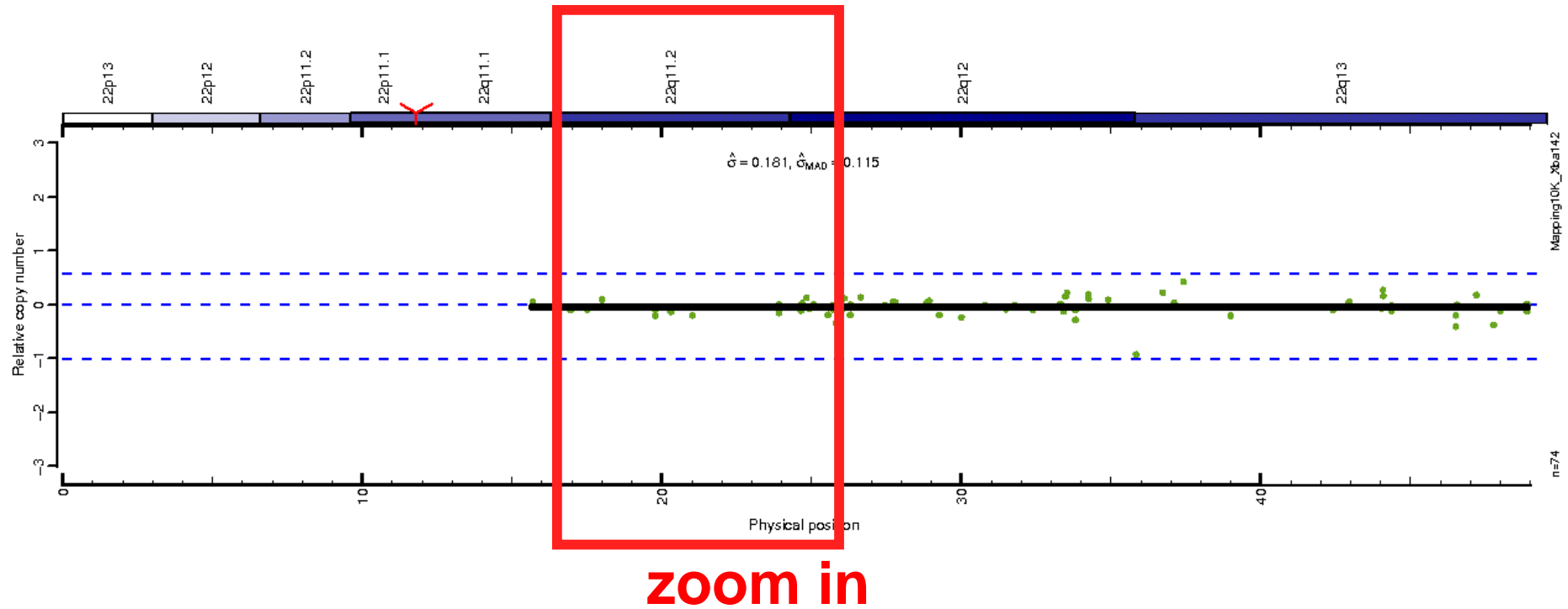
Segmentation



A brief history of Affymetrix SNP & CN arrays

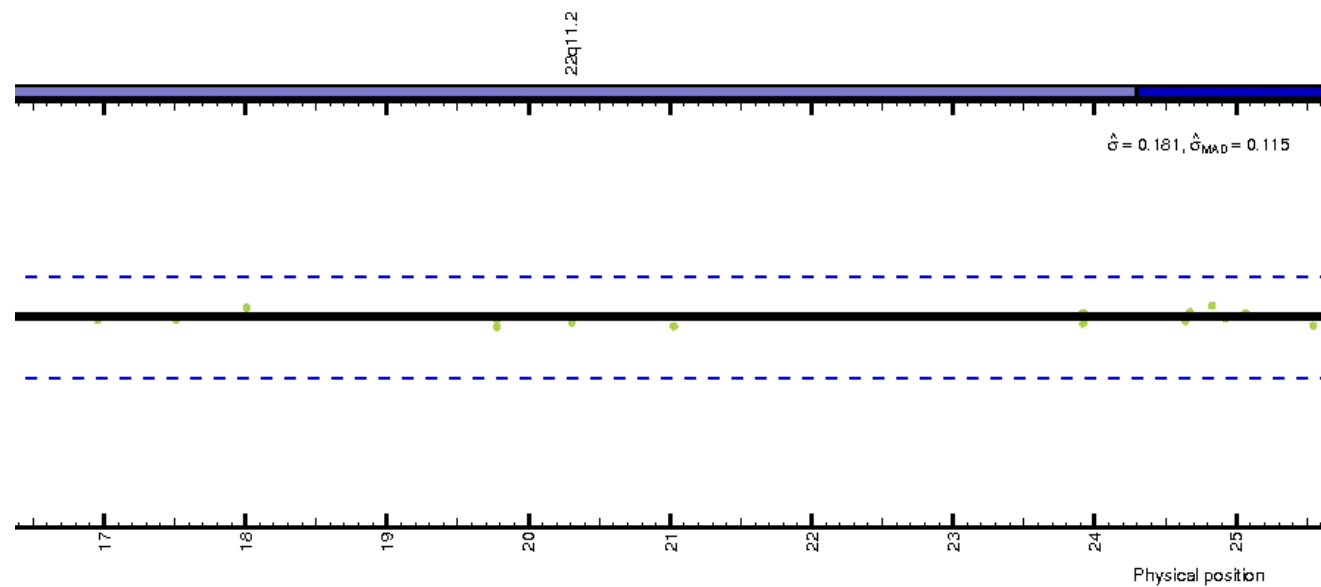
How did we get here?

Data from 2003 on Chr22 (on of the smaller chromosomes)



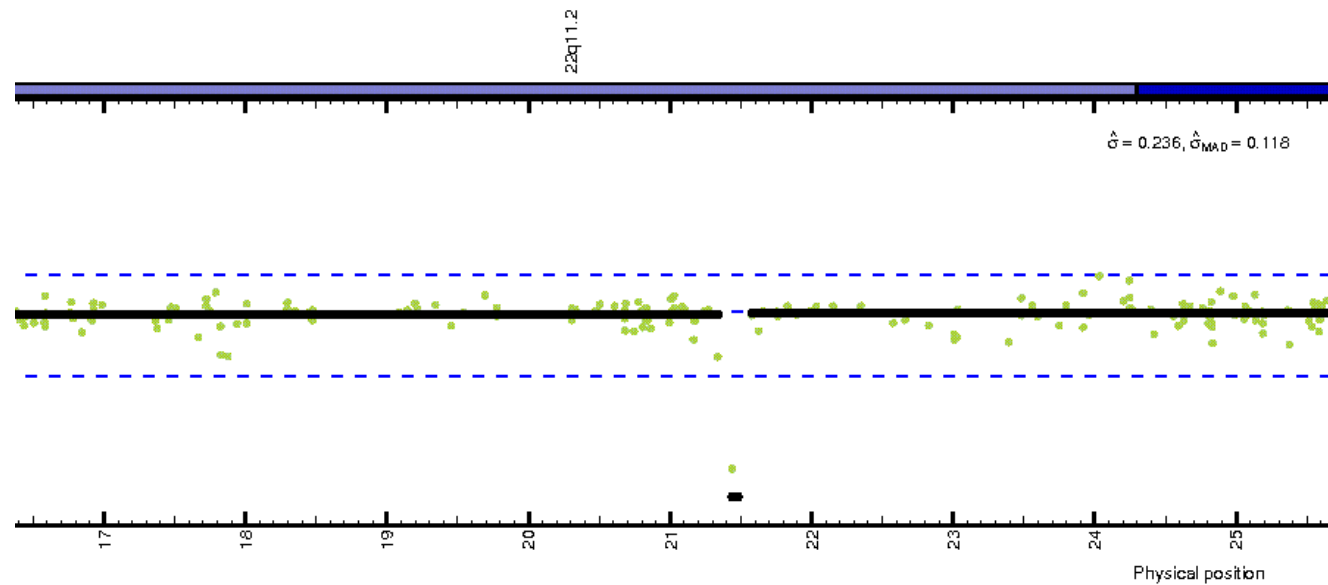
2003: 10,000 loci

x1



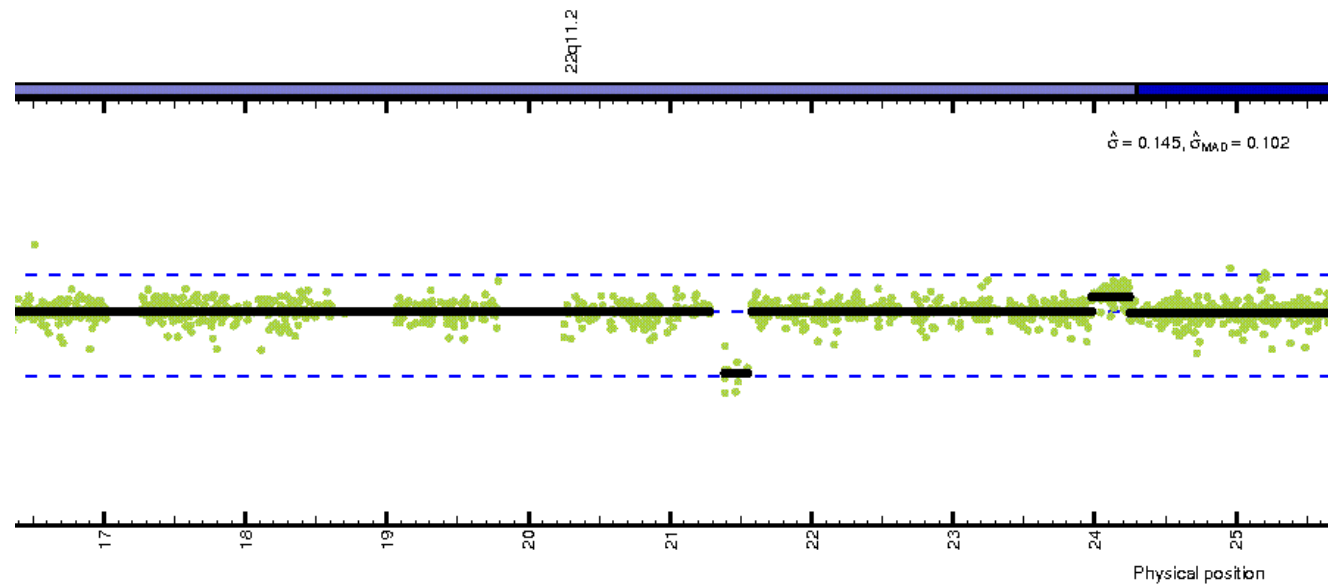
2004: 100,000 loci

x10



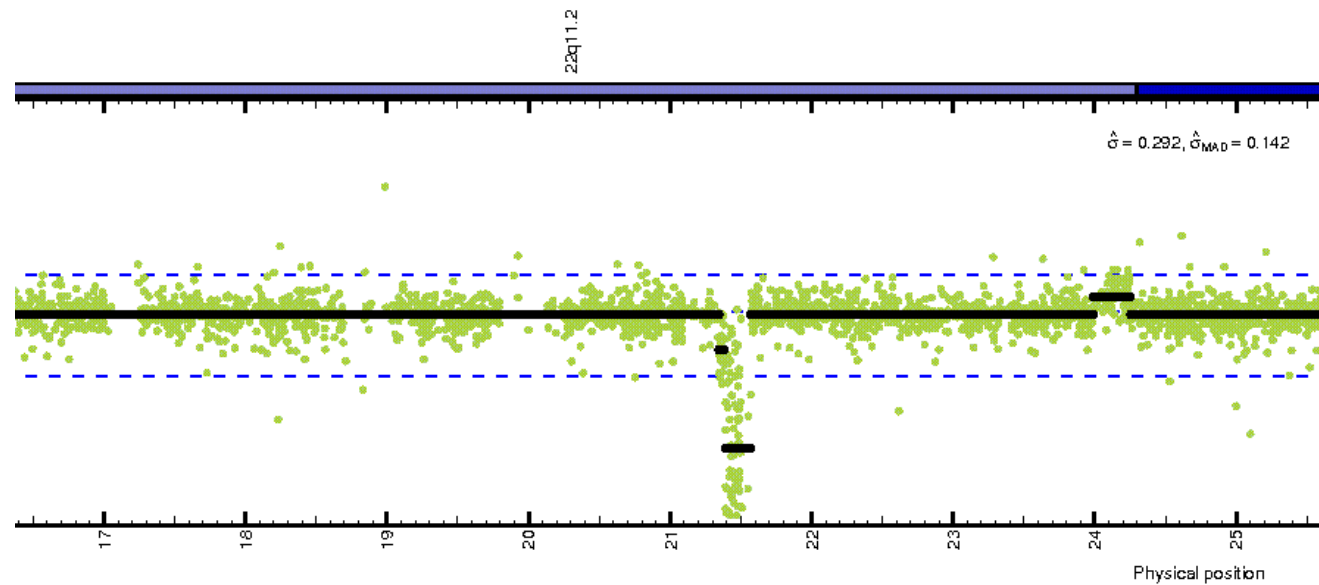
2005: 500,000 loci

x50



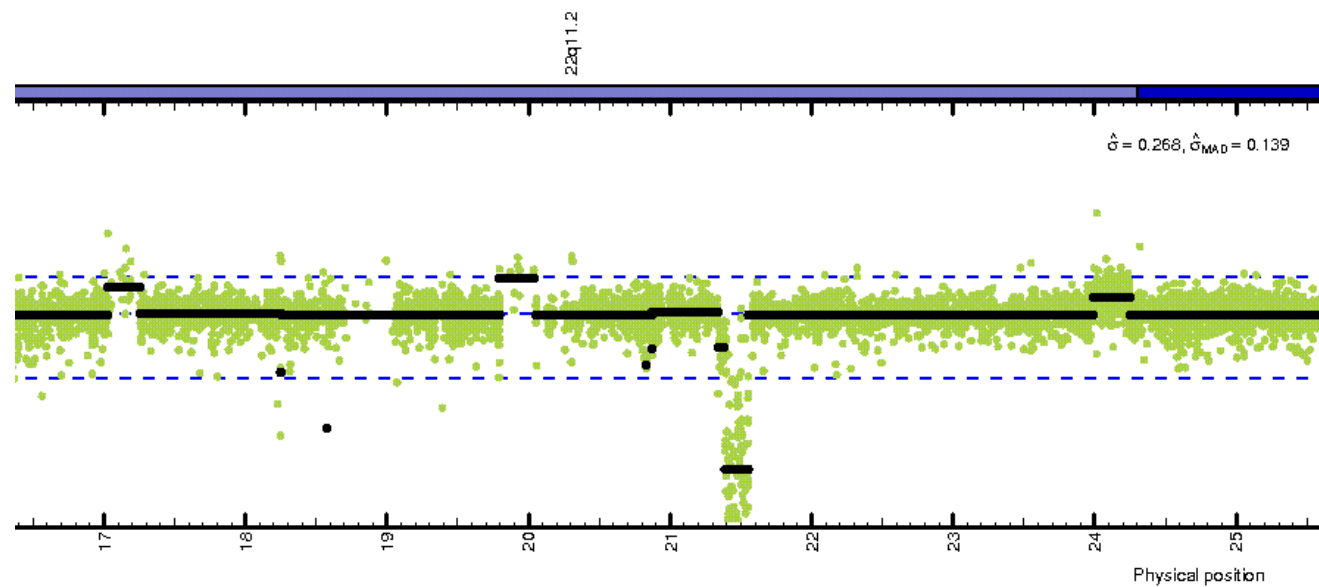
2006: 900,000 loci

x90



2007: 1,800,000 loci

x180



Genome-Wide Human SNP Array 6.0

- *state-of-the-art array*

- **> 906,600 SNPs:**

- Unbiased selection of 482,000 SNPs:
historical SNPs from the SNP Array 5.0 (== 500K)
- Selection of additional 424,000 SNPs:
 - Tag SNPs
 - SNPs from chromosomes X and Y
 - Mitochondrial SNPs
 - Recent SNPs added to the dbSNP database
 - SNPs in recombination hotspots

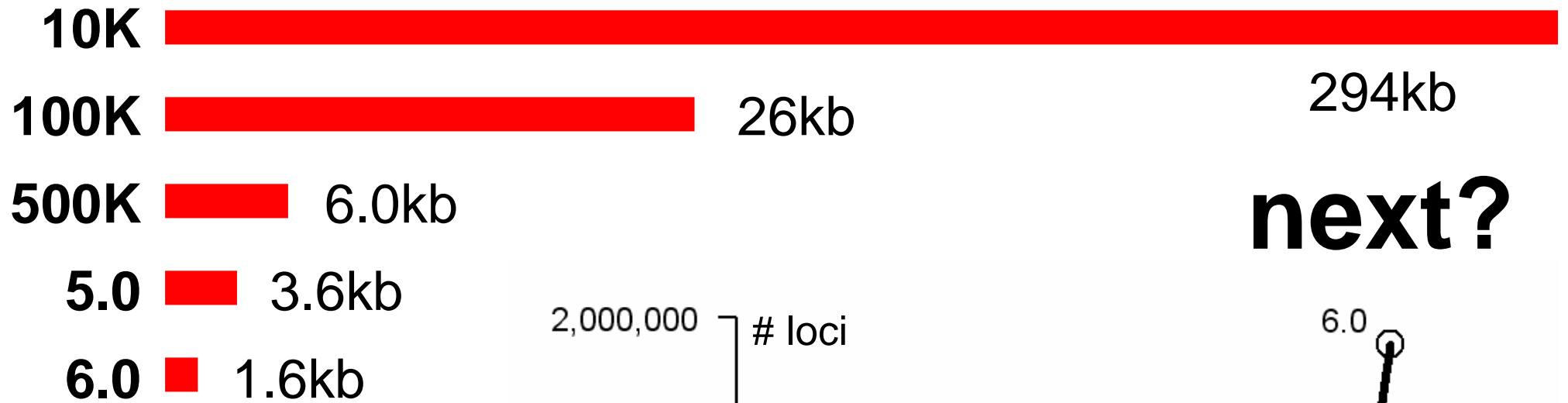
- **> 946,000 copy-number probes:**

- 202,000 probes targeting 5,677 CNV regions from the Toronto Database of Genomic Variants. Regions resolve into 3,182 distinct, non-overlapping segments; on average 61 probe sets per region
- 744,000 probes, evenly spaced along the genome

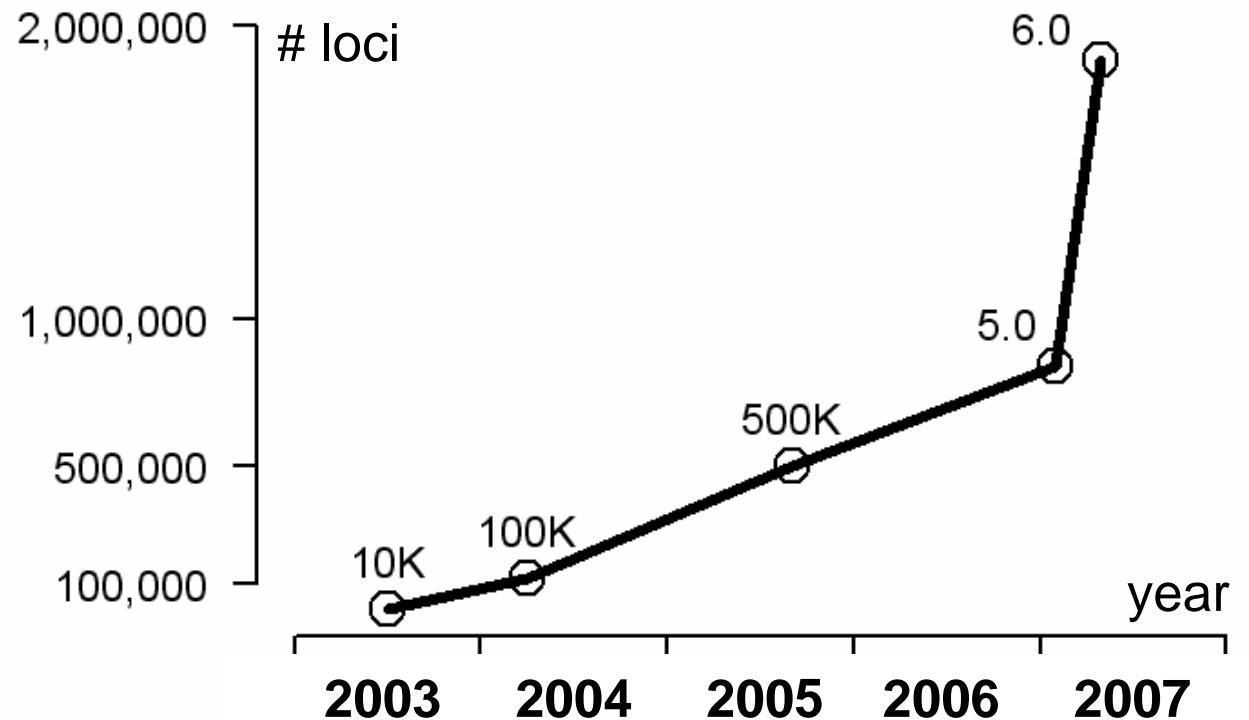
Rapid increase in density

Distance between loci:

4x further out...



next?



Affymetrix & Illumina are competing

- *we get more bang for the buck (cup)*

| | 10K | 100K | 500K | 5.0 | 6.0 |
|--|-----------------|-----------------|------------------|------------------|------------------|
| Released | July 2003 | April 2004 | Sept 2005 | Feb 2007 | May 2007 |
| # SNPs | 10,204 | 116,204 | 500,568 | 500,568 | 934,946 |
| # CNPs | - | - | - | 340,742 | 946,371 |
| # loci | 10,204 | 116,204 | 500,568 | 841,310 | 1,878,317 |
| Distance | 294kb | 25.8kb | 6.0kb | 3.6kb | 1.6kb |
| Price / chip set | 65 USD | 400 USD | 300 USD | 175 USD | 300 USD |
| # loci / cup of espresso (\$1.35) | 116 loci | 215 loci | 1236 loci | 3561 loci | 4638 loci |

Price source: Affymetrix Pricing Information [<http://store.affymetrix.com/>] and Berkeley Coffee Shops, Dec 2008.

Affymetrix are moving away from MM probes
- *therefore we don't utilize them*

Target DNA:

...CGTAGCCATCGGTAAGTACTCAATGATAG...

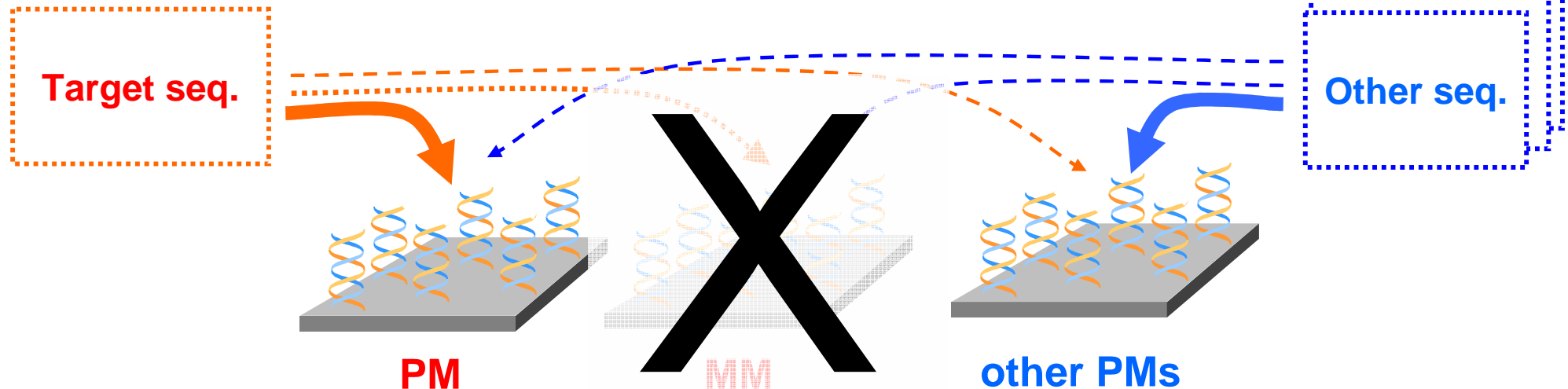
Perfect match (PM):

|||||
ATCGGTAGCCATTGAGTTACTA

Mis-match (MM):

ATCGGTAGCCATACATGAGTTACTA

25 nucleotides



Low-Level Copy Number Analysis

Part 2 – Simple preprocessing

Henrik Bengtsson

Post doc, Department of Statistics,
University of California, Berkeley, USA

CEIT Workshop on SNP arrays,
Dec 15-17, 2008, San Sebastian

Recap: Copy-number probes

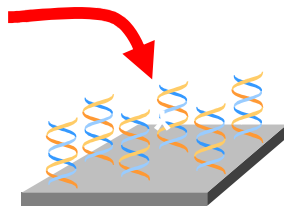
CN locus:

...CGTAGCCATCGGTAAGTACTCAATGATAG...

PM:

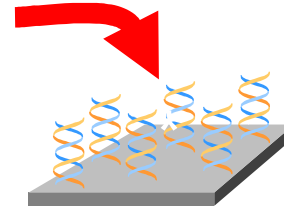
ATCGGTAGCCATTCATGAGTTACTA

CN=1



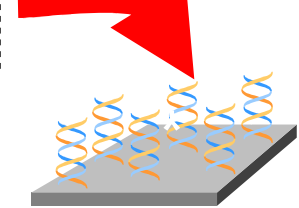
PM = c

CN=2



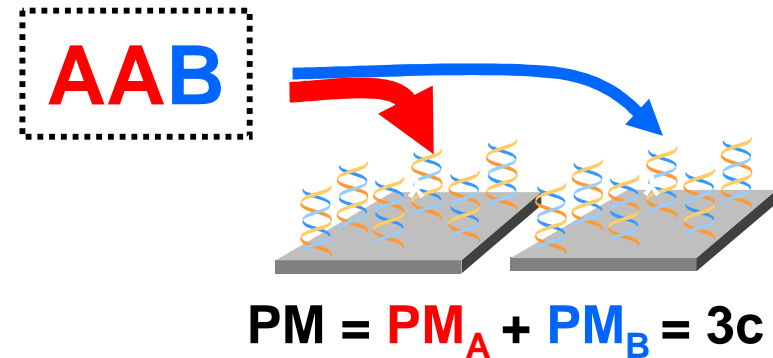
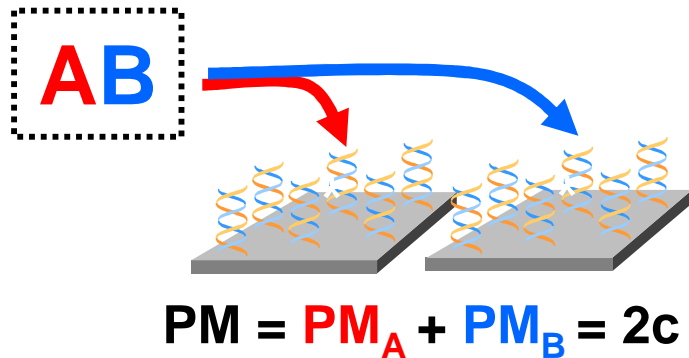
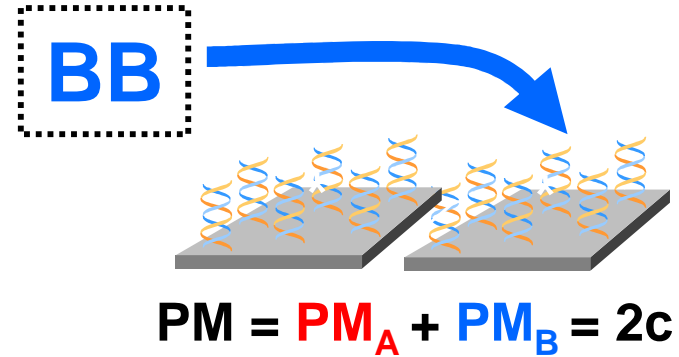
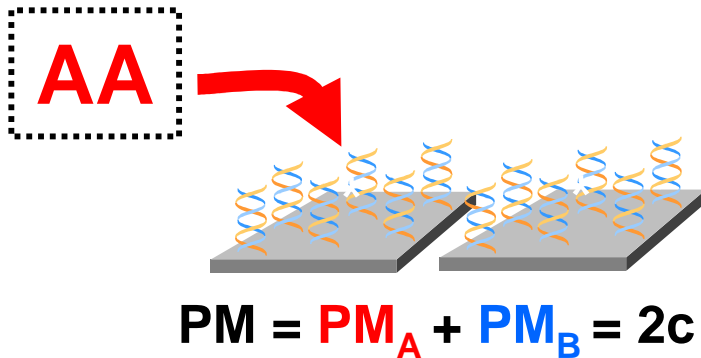
PM = 2c

CN=3



PM = 3c

Recap: Adding SNP probes gives total CN signal



Notation

- *here and in our papers*

Indices:

Arrays/samples: $i = 1, 2, \dots, I$

Loci/SNPs/CN units: $j = 1, 2, \dots, J$

Replicated probes for SNP: $k = 1, 2, \dots, K$

Probe signals:

CN locus: $y_{ij} = PM_{ij}$ (single-probe units)

SNP allele pair k : $(y_{ijkA}, y_{ijkB}) = (PM_{ijkA}, PM_{ijkB})$

Summarized signals (“chip effects”):

CN locus: θ_{ij}

SNP: $(\theta_{ijA}, \theta_{ijB})$

A simple way to obtain CN estimates

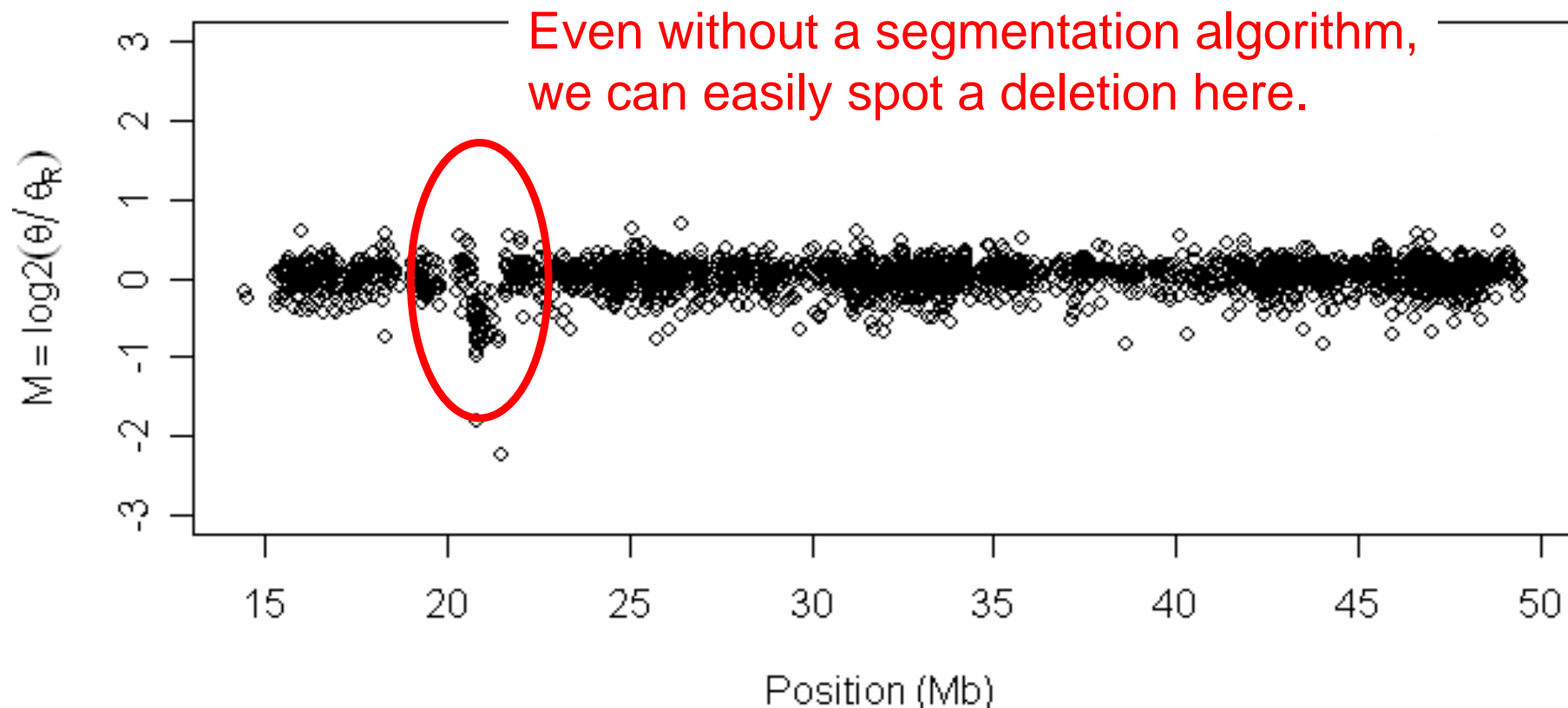
- Calculate non-polymorphic SNP summaries:
 - For each array $i=1,\dots,I$ and SNP $j=1,\dots,J$:
 - Probe allele pairs: (PM_{ijkA}, PM_{ijkB}) ; $k=1,\dots,K$
 - For both alleles, average across probes:
 $\theta_{ijA} = \text{median}_k \{PM_{ijkA}\}$, $\theta_{ijB} = \text{median}_k \{PM_{ijkB}\}$
 - Sum both alleles: $\theta_{ij} = \theta_{ijA} + \theta_{ijB}$
- Calculate reference θ_{Rj} across all arrays:
 - For each SNP $j=1,\dots,J$:
 - $\theta_{Rj} = \text{median}_i \{\theta_{ij}\}$
- Calculate CN log-ratios:
 - For each array $i=1,\dots,I$ and SNP $j=1,\dots,J$:
 - $M_{ij} = \log_2 (\theta_{ij} / \theta_{Rj})$

The software tools make this easy for you
- *using aroma.affymetrix package*

```
cs <- AffymetrixCelSet$byName("GSE8605",  
                               chipType="Mapping10K_Xba142");  
  
plm <- AvgCnPlm(cs, combineAlleles=TRUE);  
fit(plm);  
ces <- getChipEffectSet(plm);  
  
theta <- extractTheta(ces);  
thetaR <- rowMedians(theta);  
M <- log2(theta / thetaR);
```

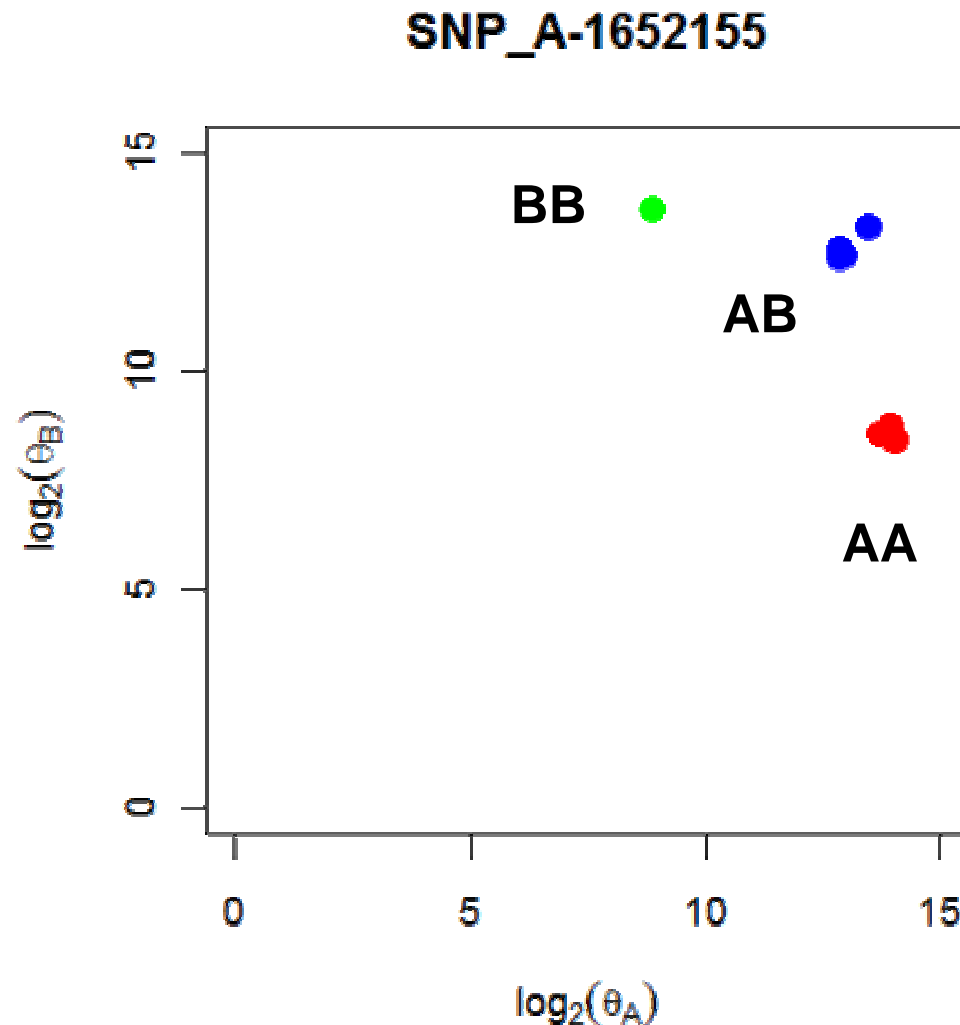
Copy number regions are found by lining up estimates along the chromosome

Example: Log-ratios for one sample on Chromosome 22.



If we don't add up the alleles, we get allele-specific estimates from which we can get genotypes

Example: $(\theta_{ijA}, \theta_{ijB})$ for one SNP across all samples

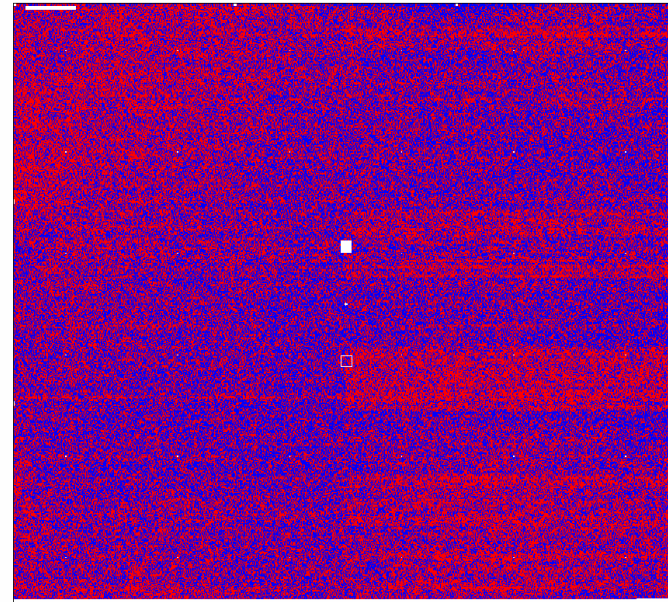
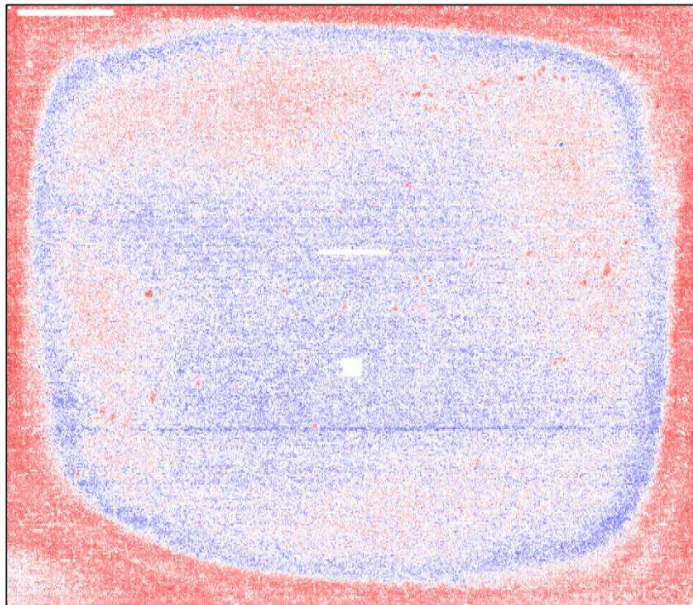
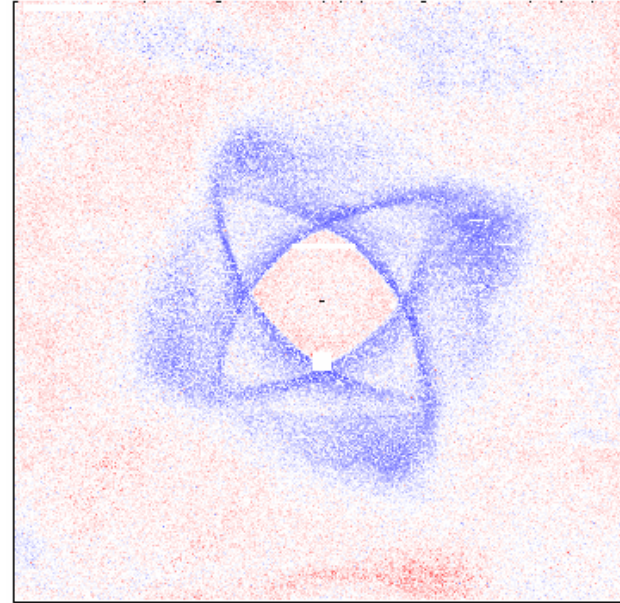
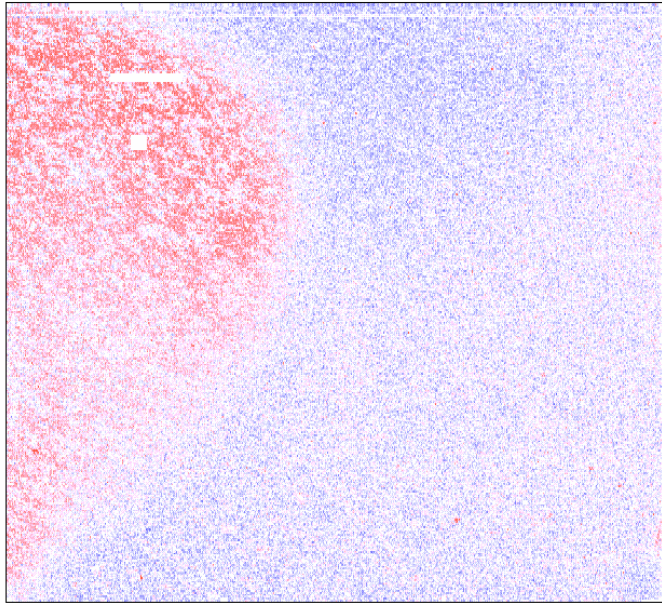


There are a lot of artifacts in microarray data
- *can we do better?*

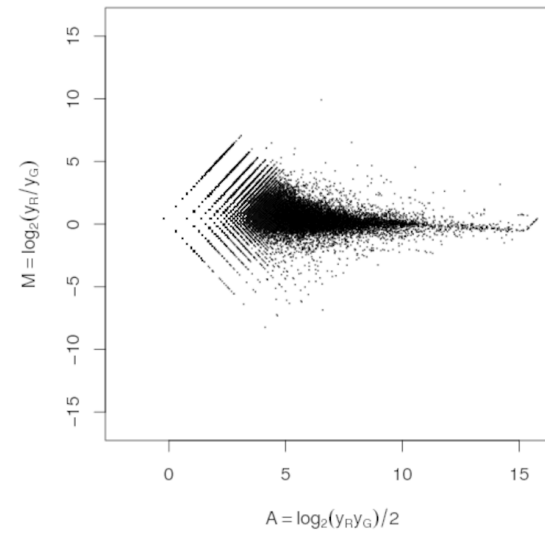
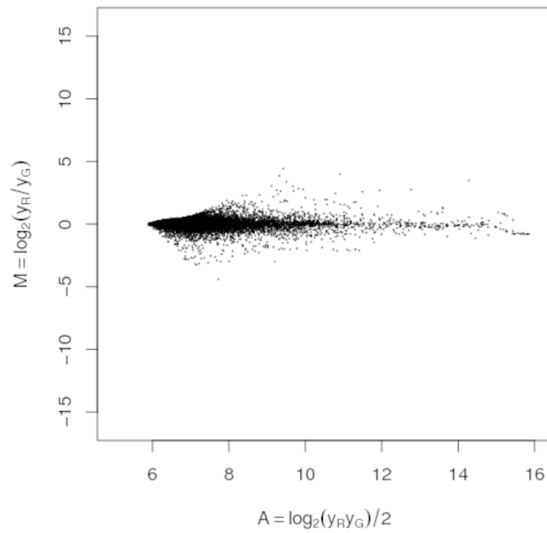
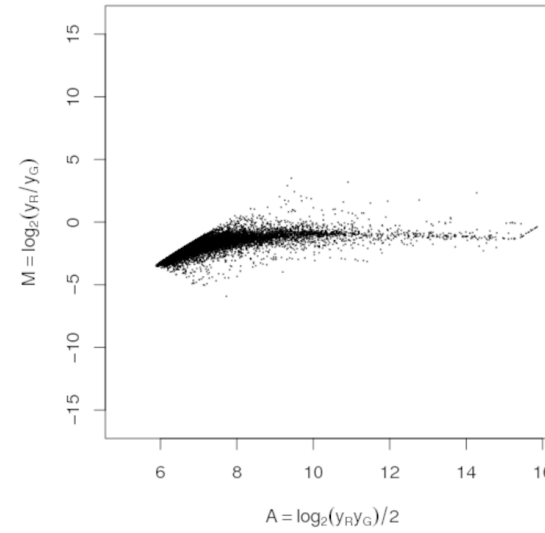
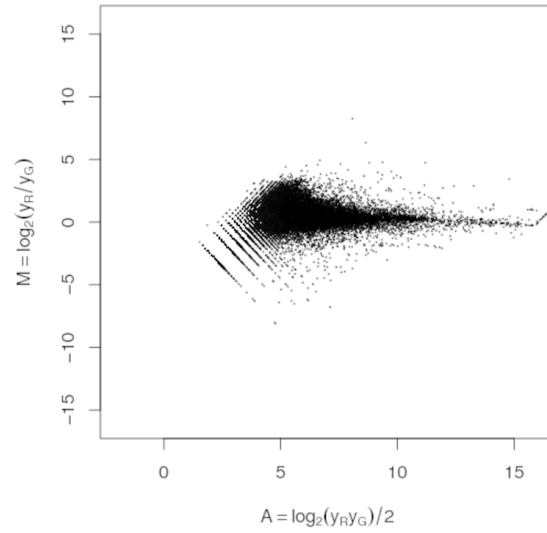
Systematic variation can be added due to:

- Spatial artifacts
- Intensity dependent effects
- Probe-sequence dependent effects
- GC-content effects
- PCR effects
- Lab & people effects
- Non-calibrated scanners
- ...?

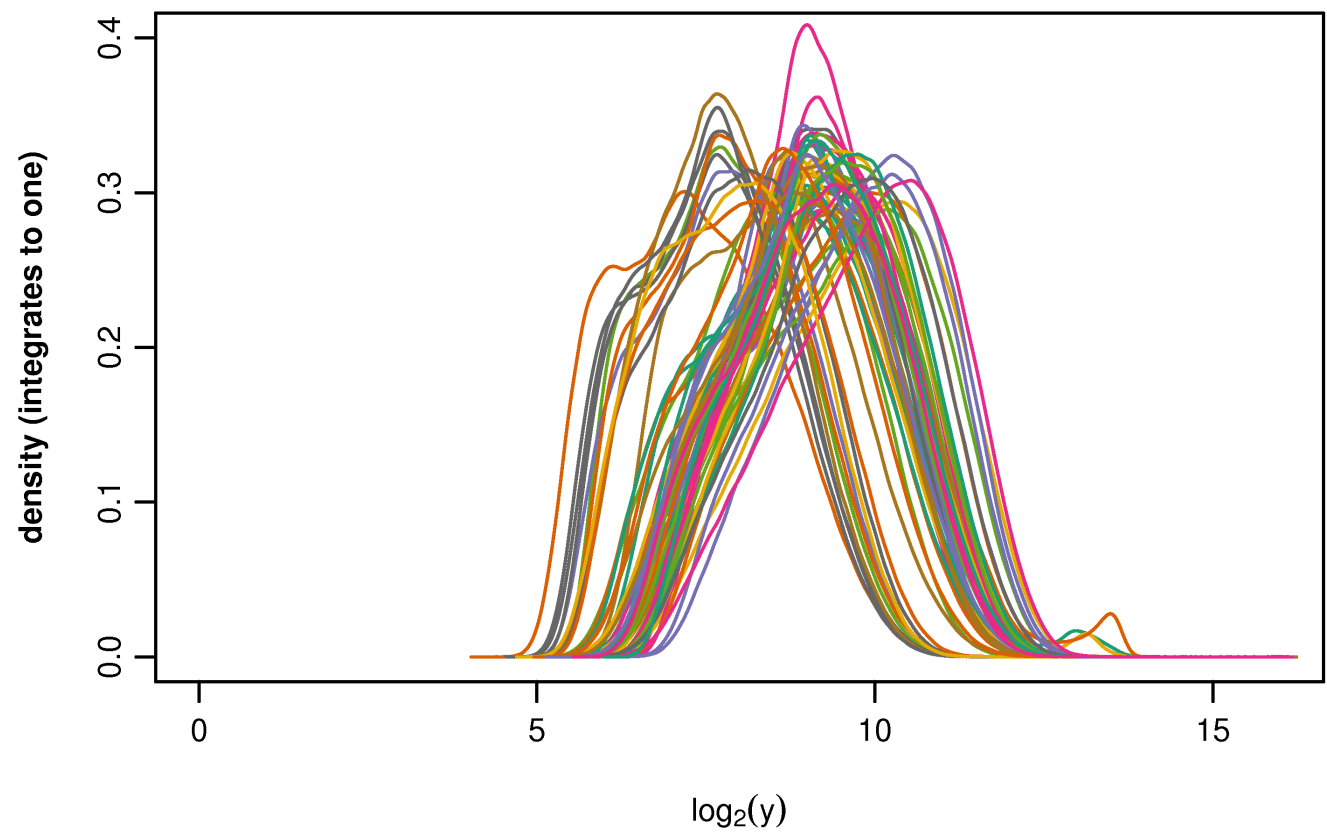
Spatial artifacts (“extreme”)



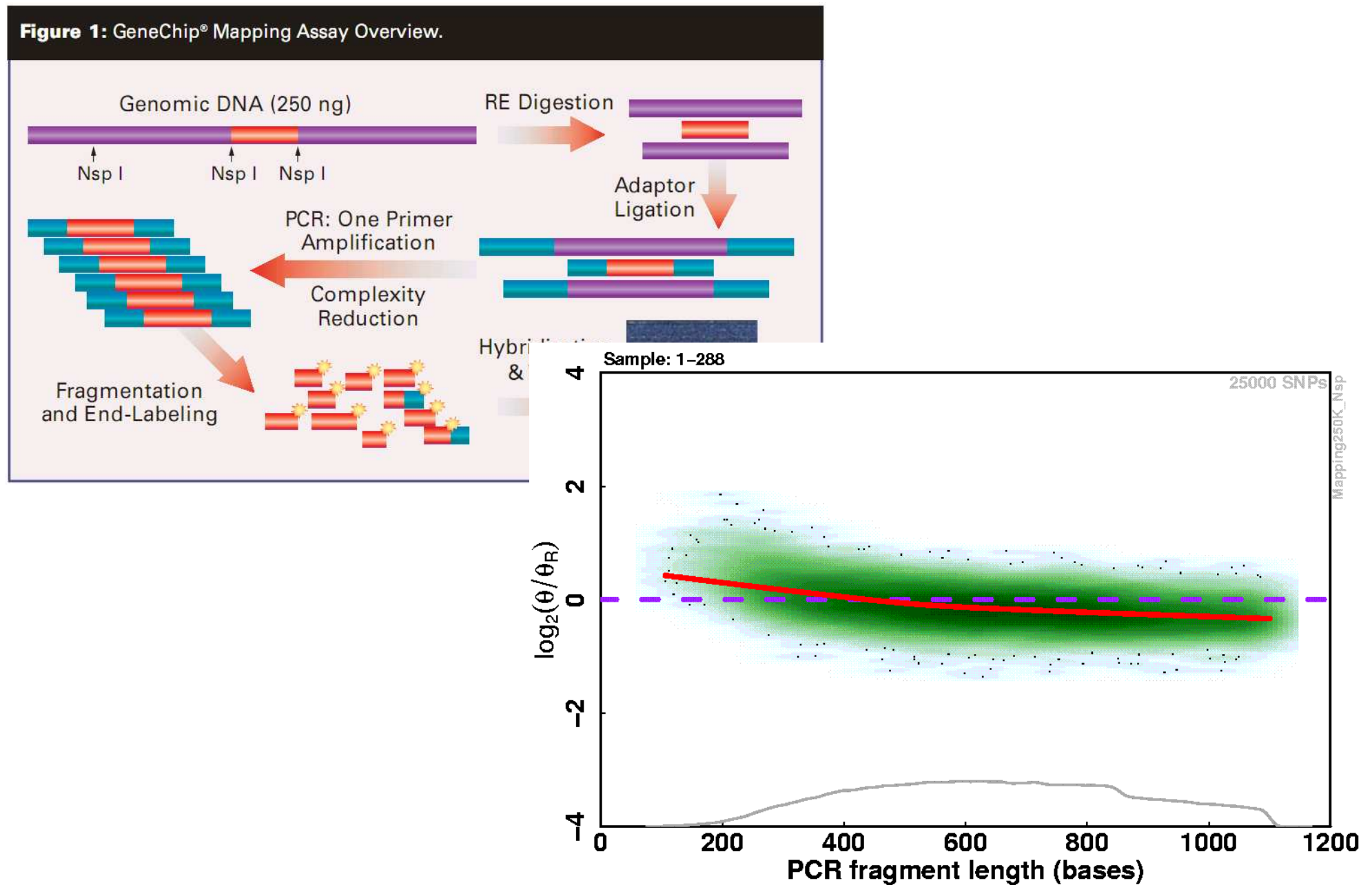
Intensity dependent artifacts/variation



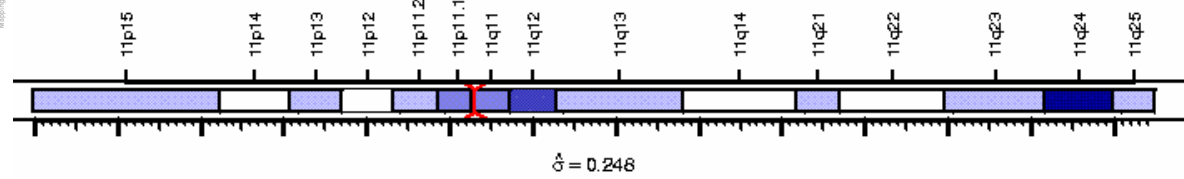
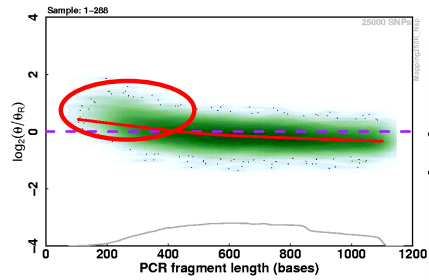
Lab and people effects/variation



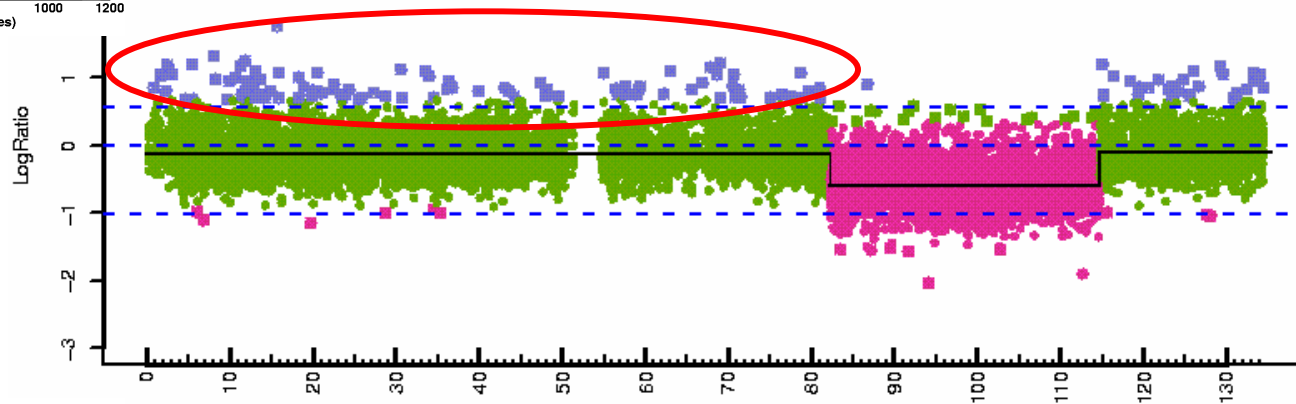
PCR fragment length effects/variation



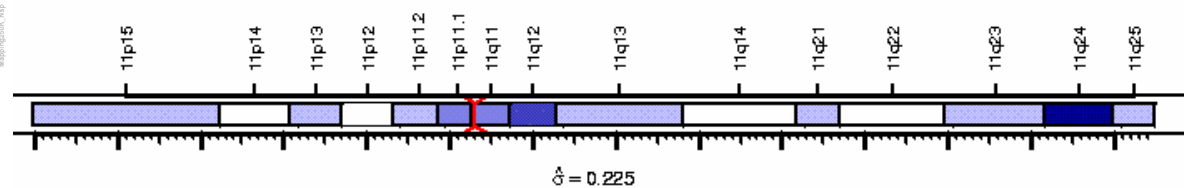
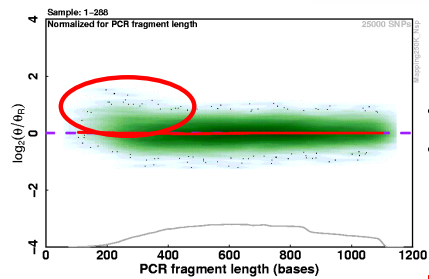
32.5Mb deletion on chr 11



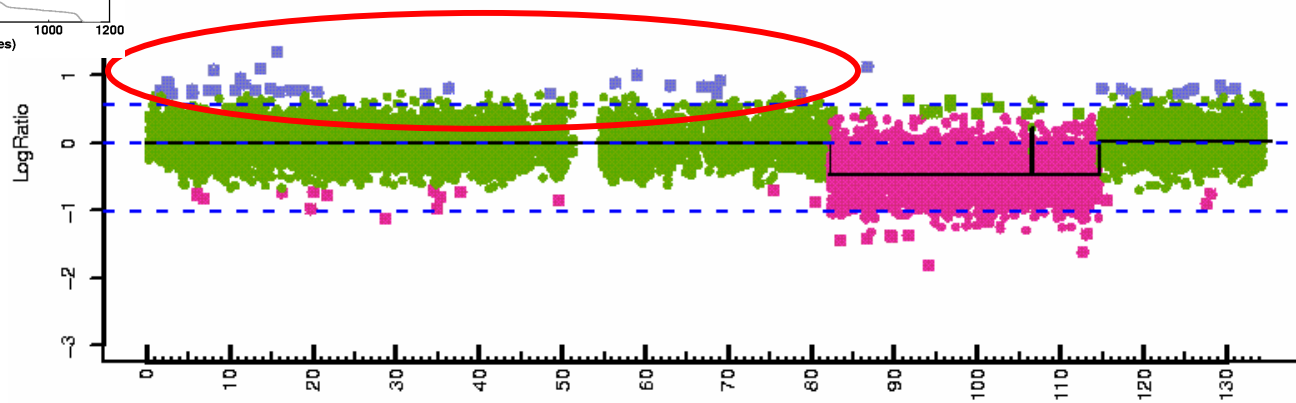
Before



$$\sigma = 0.246$$

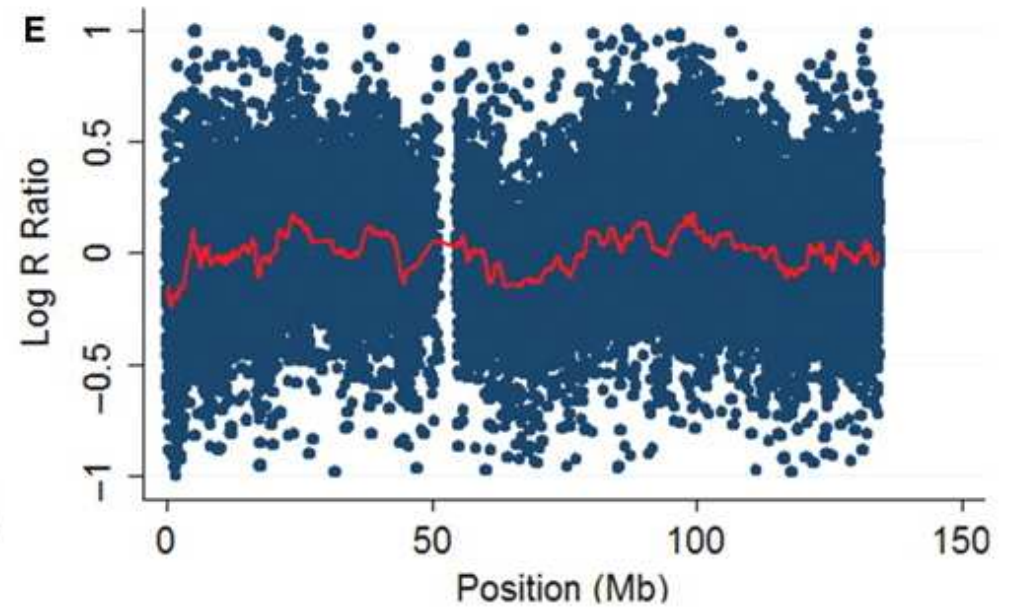
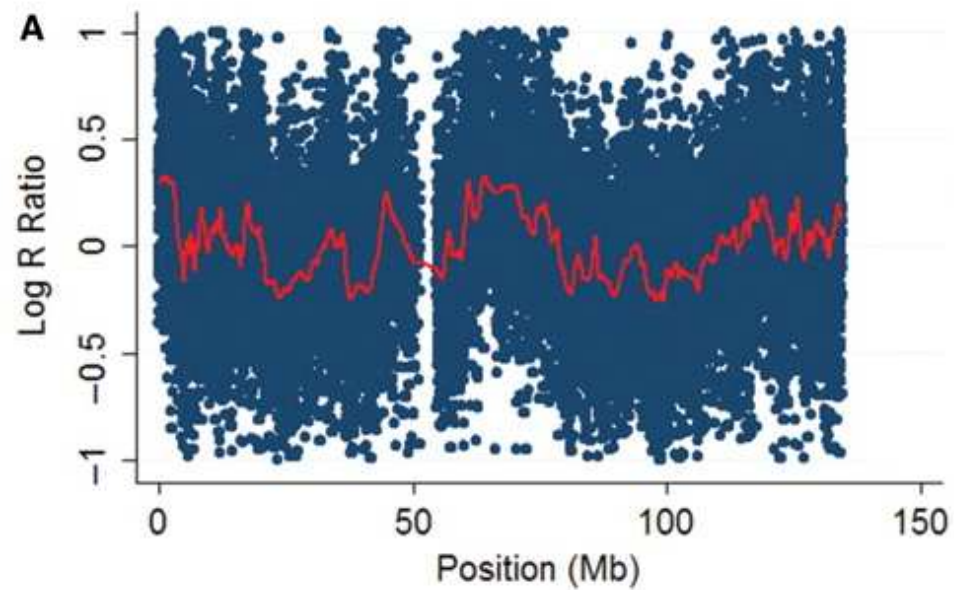


After



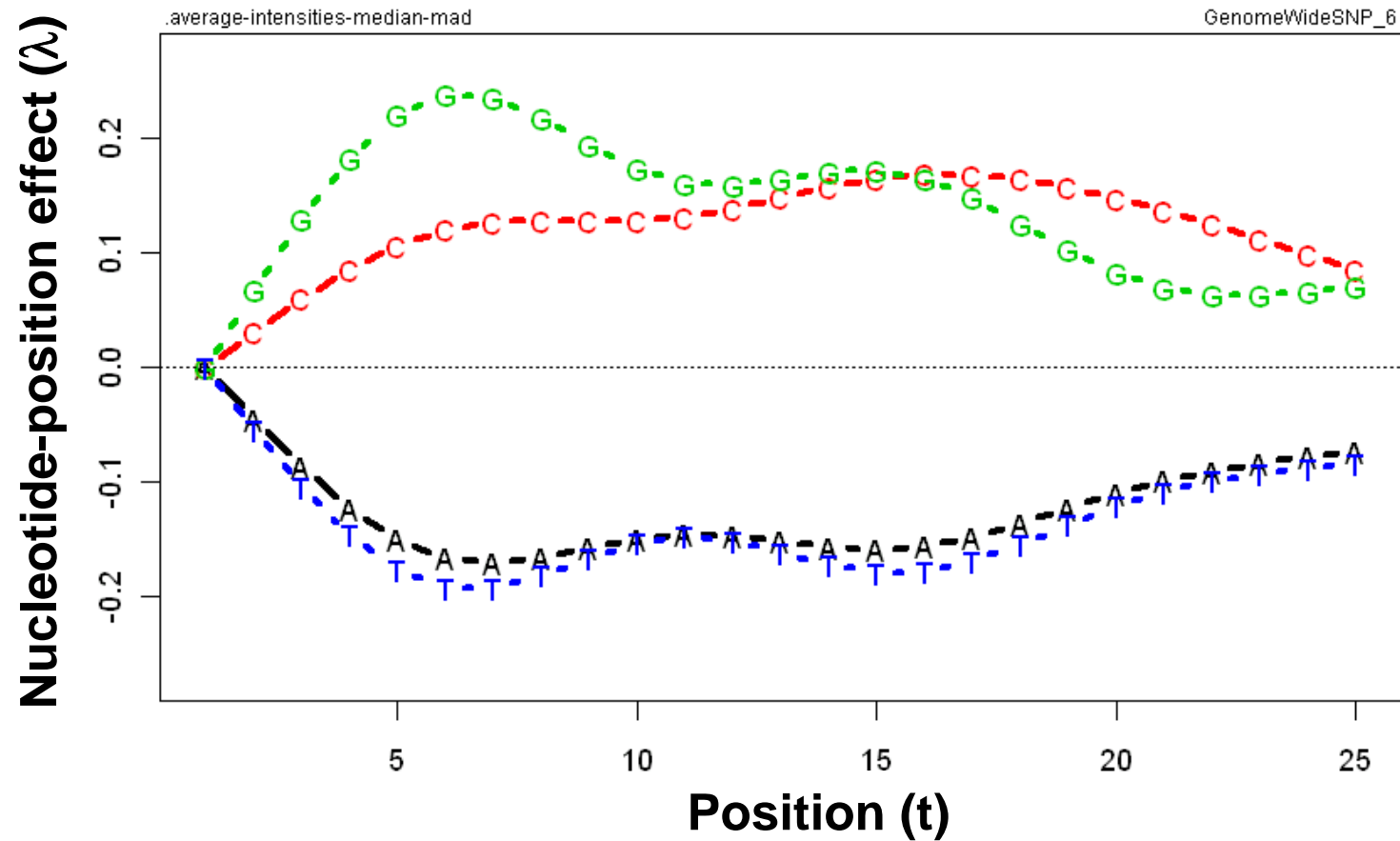
$$\sigma = 0.225$$

“Wave” patterns along genome



Probe-sequence effects/variation

- probes respond differently



Low-Level Copy Number Analysis

Part 3 – aroma.affymetrix

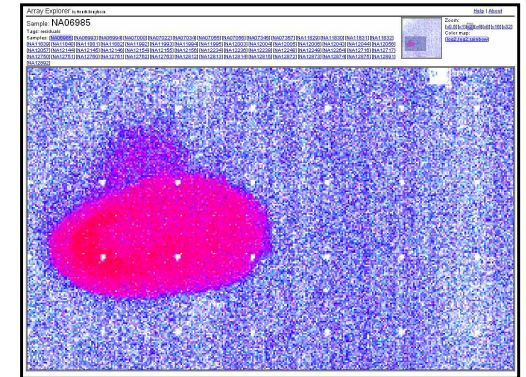
Henrik Bengtsson

Post doc, Department of Statistics,
University of California, Berkeley, USA

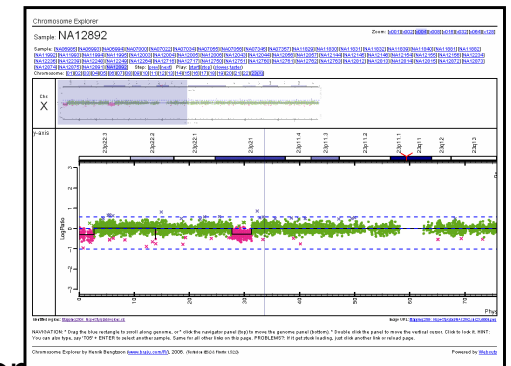
CEIT Workshop on SNP arrays,
Dec 15-17, 2008, San Sebastian

aroma.affymetrix processes unlimited number of arrays

- Processes **unlimited number of arrays**:
 - Bounded memory algorithms.
 - Works toward file system.
 - Persistent memory: robust & picks up where last stopped.
- Memory requirements: **1.0-2.0GB RAM**.
 - Example: RMA on 4500 HG-U133A arrays uses ~500MB of RAM.
 - Example: CRMA on 300 SNP6.0 arrays uses ~1.5GB of RAM.
 - Example: FIRMA on 200 HuEx-1.0 arrays uses ~1.5GB of RAM.
- **Cross platform**: Linux/Unix, Windows, OSX.
- Supports **most Affymetrix chip types**:
 - All chip types with a CDF (and some more).
 - Custom CDFs.



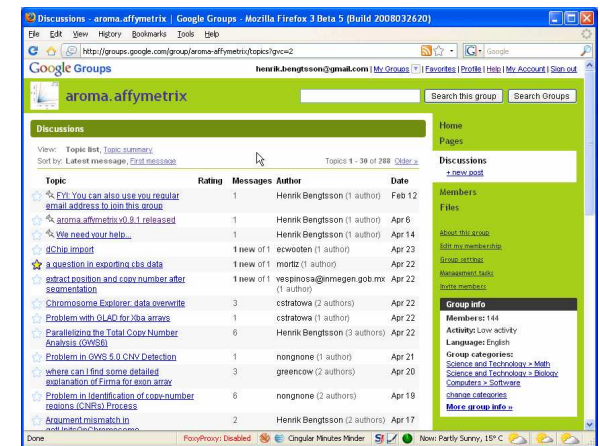
aroma.affymetrix "implements" several existing methods



- **Calibration and normalization:**
 - Background correction methods: RMA, gcRMA, ...
 - Allelic cross-talk calibration, quantile normalization, spatial normalization, probe-sequence normalization, ...
 - PCR fragment-length normalization, GC-content normalization.
- **Probe-level summarization:**
 - multiplicative (dChip), affine, and log-additive (RMA) models. Easy to add new.
- **Quality assessment:**
 - RLE (*Relative Log Expressions*), NUSE (Normalized Unscaled Standard Error)
 - Spatial plots: probe signals, PLM residuals, chip effects, CDF annotations, ...
- **Paired & non-paired **copy-number analysis**:**
 - All SNP & CN platforms. Multiple chip types.
 - CRMA (our methods for estimating raw CNs).
 - Allele-specific and/or total CN estimates
 - Genotyping via CRLMM
 - Segmentation method: CBS & GLAD. Easy to add more.
- **Miscellaneous:**
 - **Alternative splicing (exon arrays):** Finding Isoforms using RMA (FIRMA)
 - **Tiling-array analysis:** MAT processing
 - **Resequencing arrays**
 - **Gene expression arrays** (of course)

aroma.affymetrix is an open-source solution

- Community:
 - **250+ users** worldwide (approx 10 installation per day)
 - Active mailing list (Google Groups; 150+ message per month)
 - **Collaborative documentation** and vignettes (Google Groups).
- Development:
 - **~3 years** since start:
 - Jan 2006-Oct 2006: Phase I: **Identifying API** (1-3 person project).
 - Oct 2006-Feb 2007: Phase II: **Maturing API** and testing (10-15 users & developers).
 - Feb 2007-Aug 2007: Phase III: **Extended real-world testing** (30-50 users & developers).
 - Aug 2007-Fall 2008: Phase IV: **Public release** and heaps of CPU mileage (more "wild" use cases).
 - Fall 2008-... Phase V: Third party extensions are coming in. More chip types supported.
 - 3-5 active developers. One main maintainer / code coordinator.
 - Some external code snippet contributors.
 - Lots of **validation code** - catches existing and future bugs.
 - 1,000+ pages code / Rd pages.
- Standards:
 - **Standard file formats**, e.g. reads/writes CEL (via **affxparser**/Fusion SDK).
 - Imports and exports to: APT, GTC, CNAG, CNAT, dChip, Bioconductor etc.
 - **Strict directory structures** and relative pathnames
=> portable scripts, robustness, more automated validations, easier to troubleshoot, simplified support.
 - Utilizes **existing packages**, e.g. preprocessCore, gcRMA, DNACopy...



Walk-through example

Complete aroma.affymetrix script for copy-number analysis of 270 SNP6.0 samples

```
cdf <- AffymetrixCdfFile$byChipType("GenomeWideSNP_6")
csR <- AffymetrixCelSet$byName("HapMap270", cdf=cdf)

acc <- AllelicCrosstalkCalibration(csR)
csC <- process(acc)

bpn <- BasePositionNormalization(csC)
csN <- process(bpn)

plm <- AvgCnPlm(csN, combineAlleles=TRUE)
fit(plm)

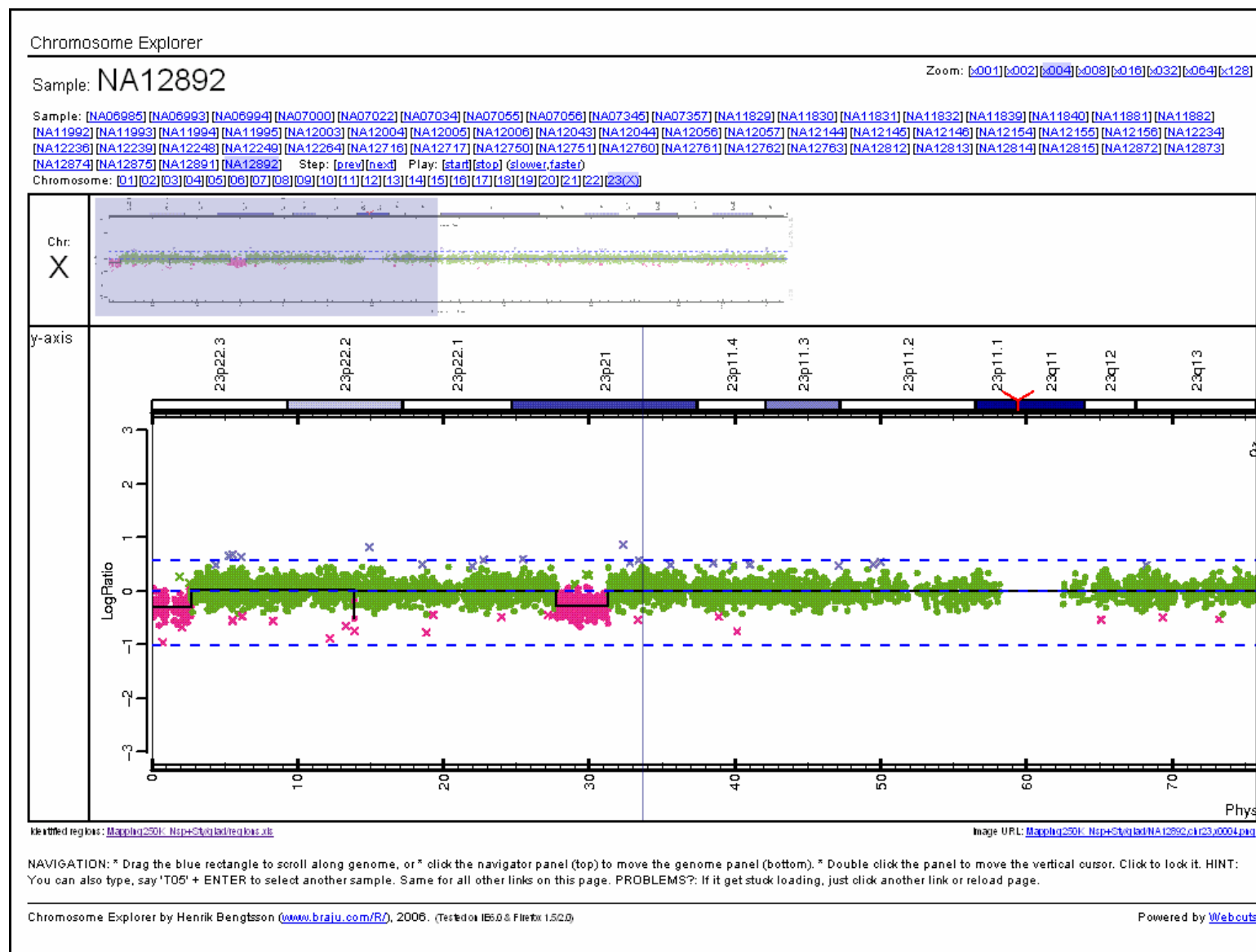
ces <- getChipEffectSet(plm)
fln <- FragmentLengthNormalization(ces)
cesN <- process(fln)

seg <- CbsModel(cesN)

ce <- ChromosomeExplorer(seg)
process(ce)
```

Offline & online dynamic HTML reports

Example: ChromosomeExplorer



Setup is as simple as placing the files in
a strict & standardized directory structure

```
annotationData/  
  chipTypes/  
    GenomeWideSNP_6/  
      GenomeWideSNP_6.CDF  
      GenomeWideSNP_6.UGP  
      GenomeWideSNP_6.UFL  
  
rawData/  
  HapMap270,CEU/  
    GenomeWideSNP_6/  
      *.CEL
```

No (absolute) pathnames are used
- maximizes portability

```
annotationData/  
  chipTypes/  
    GenomeWideSNP_6/  
      GenomeWideSNP_6.CDF  GenomeWideSNP_6.UGP  ...  
  
cdf <- AffymetrixCdfFile$byChipType("GenomeWideSNP_6")  
print(cdf)
```

```
AffymetrixCdfFile:  
Path: annotationData/chipTypes/GenomeWideSNP_6  
Filename: GenomeWideSNP_6.cdf  
Filesize: 470.44MB  
File format: v4 (binary; XDA)  
Chip type: GenomeWideSNP_6  
Dimension: 2572x2680  
Number of cells: 6892960  
Number of units: 1881415  
...
```

The file system is the memory

- data is loaded only when needed

```
cdf <- AffymetrixCdfFile$byChipType("GenomeWideSNP_6")  
csR <- AffymetrixCelSet$byName("HapMap270", cdf=cdf)
```

AffymetrixCelSet:

Name: HapMap270

Tags: CEU

Path: rawData/HapMap270,CEU/GenomeWideSNP_6

Chip type: GenomeWideSNP_6

Number of arrays: 270

Names: NA06985, NA06991, ..., NA07019

Total file size: 17.7GB

RAM: 0.01MB

Normalized data is stored as CEL files

- import to any software

```
acc <- AllelicCrosstalkCalibration(csR)
csC <- process(acc)
print(csC)
AffymetrixCelSet:
Name: HapMap270
Tags: CEU,ACC,ra,-XY
Path: probeData/HapMap270,CEU,ACC,ra,-XY/GenomeWideSNP_6
Chip type: GenomeWideSNP_6
Number of arrays: 270
Names: NA06985, NA06991, ..., NA07019
Total file size: 17.7GB
RAM: 0.01MB

files <- getPathnames(csC)
print(files[1])
[1] "probeData/HapMap270,CEU,ACC,ra,-XY/
      GenomeWideSNP_6/NA06985.CEL"
```

Data sets (directories) are marked
with unique tags

```
qn <- QuantileNormalization(csC)
csN <- process(qn)
print(csN)
```

AffymetrixCelSet:

Name: HapMap270

Tags: CEU,ACC,ra,-XY,ACC,QN

Path: probeData/HapMap270,CEU,ACC,ra,-XY,QN/GenomeWideSNP_6

Chip type: GenomeWideSNP_6

Number of arrays: 270

Names: NA06985, NA06991, ..., NA07019

Total file size: 17.7GB

RAM: 0.01MB