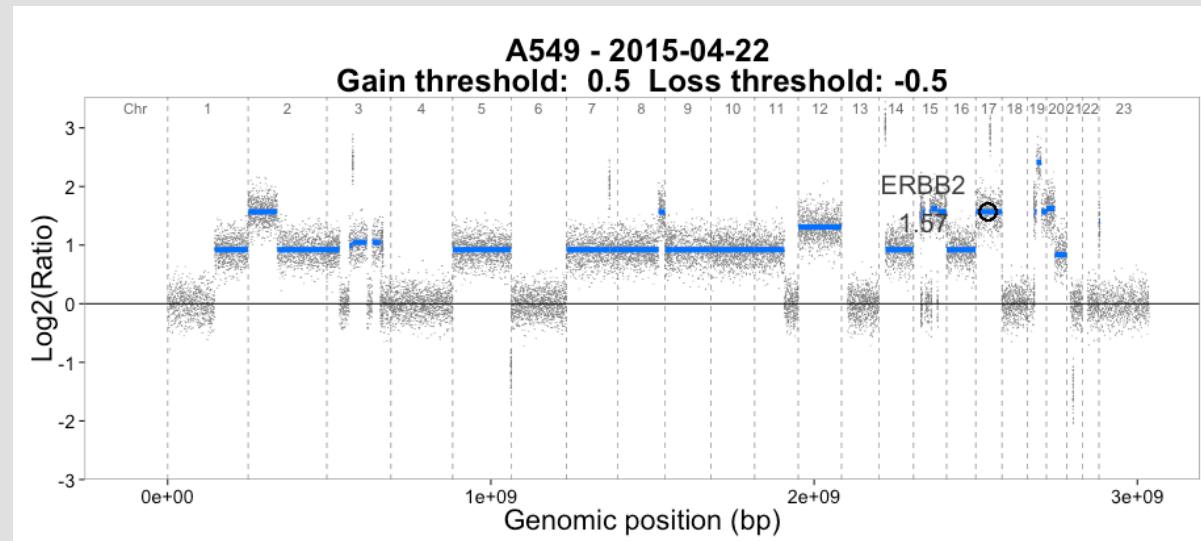


Array-based Genomic Profiles



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In this module

- Cancer & genome, a very brief overview
- Array-based CGH Technologies
- Genomic Profile analysis
- “Do it yourself!”

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« [...] malignant tumours might be the consequence of a certain abnormal chromosome constitution » Theodor Boveri (1862-1915)



« the evidence shows clearly that the characters of wild animals and plants, as well as those of domesticated races, are inherited both in the wild and in domesticated forms according to the Mendel's Law » Thomas H Morgan (1866-1945)



*The one gene-one enzyme paradigm.
Genetic Control of Biochemical Reactions in Neurospora. Beadle & Tatum, PNAS 1941*

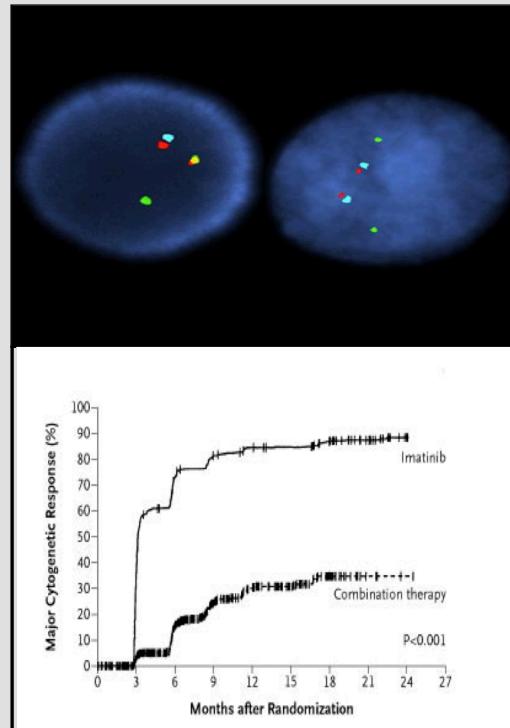


*The effect of mutated Hras on cell lines (fibroblast NCI/3T3)
Mechanism of activation of a human oncogene. Tabin C et al. Nature 1982*

Early 2000s' Relations between molecular alterations and treatment efficacy

BCR-Abl and imatinib

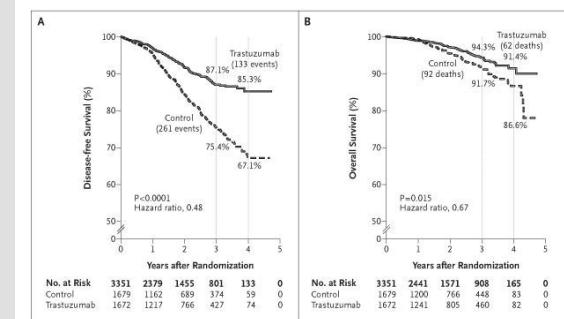
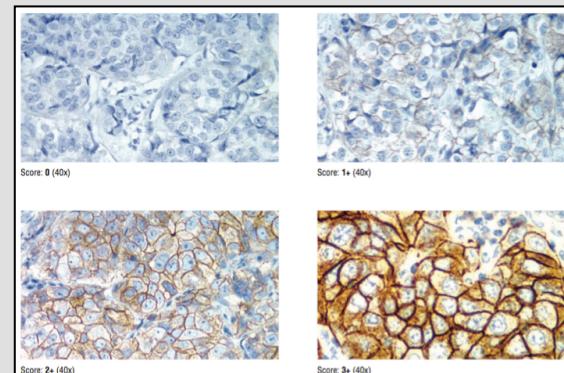
BCR-Abl FISH



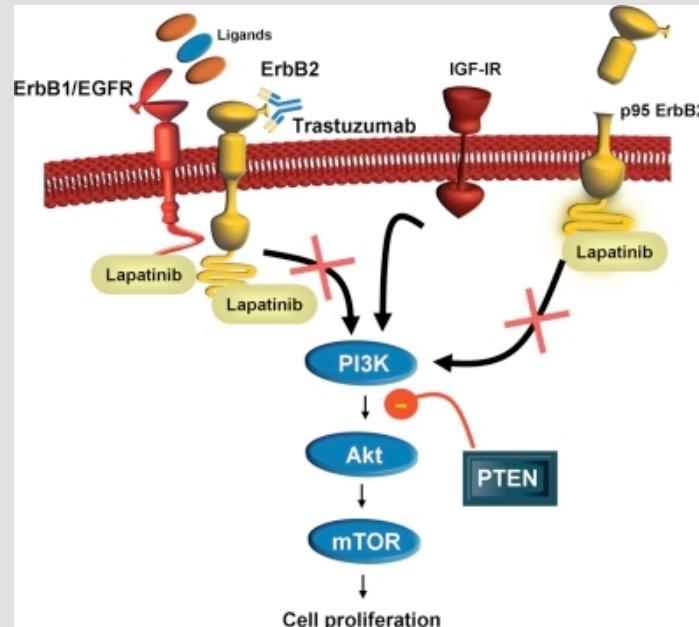
O'Brien et al. N Engl J Med. 2003

ERBB2 and trastuzumab

Her2/neu IHC

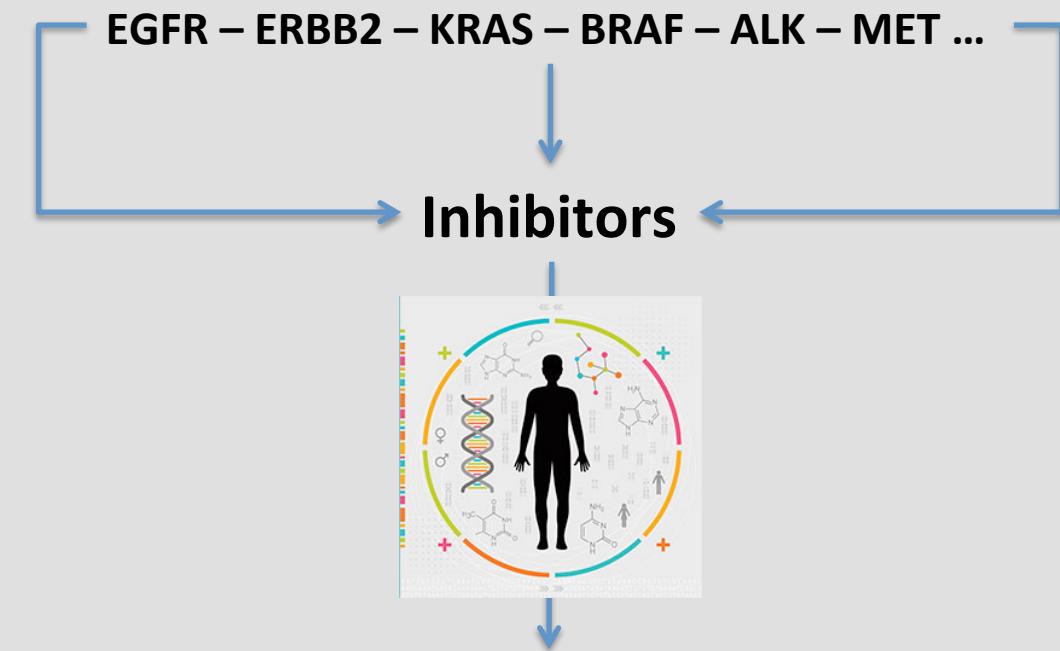


Romond et al. N Engl J Med 2005

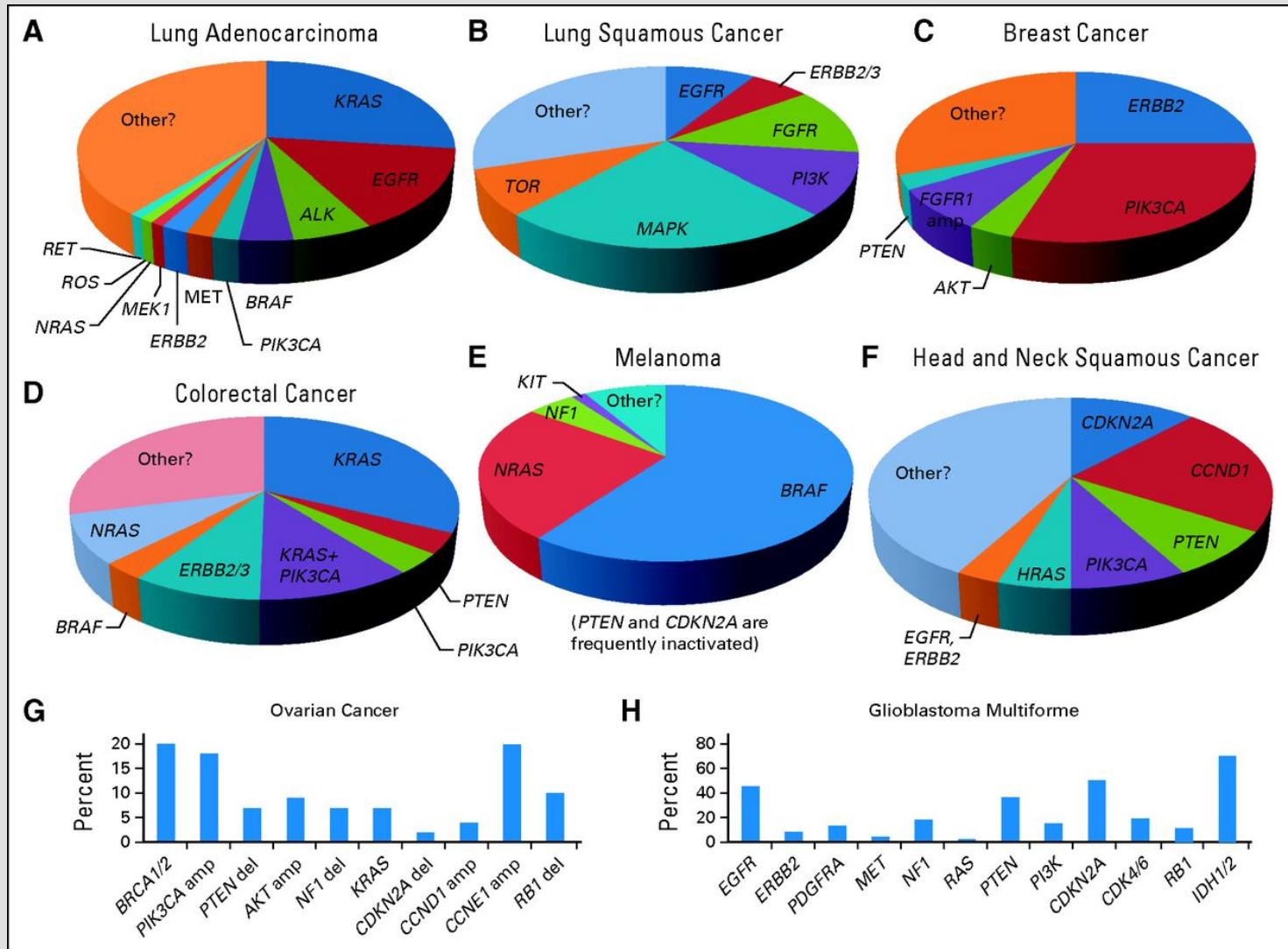


From Vogel et al. Jpn J Clin Oncol. 2010

Matching alterations to targeted therapies

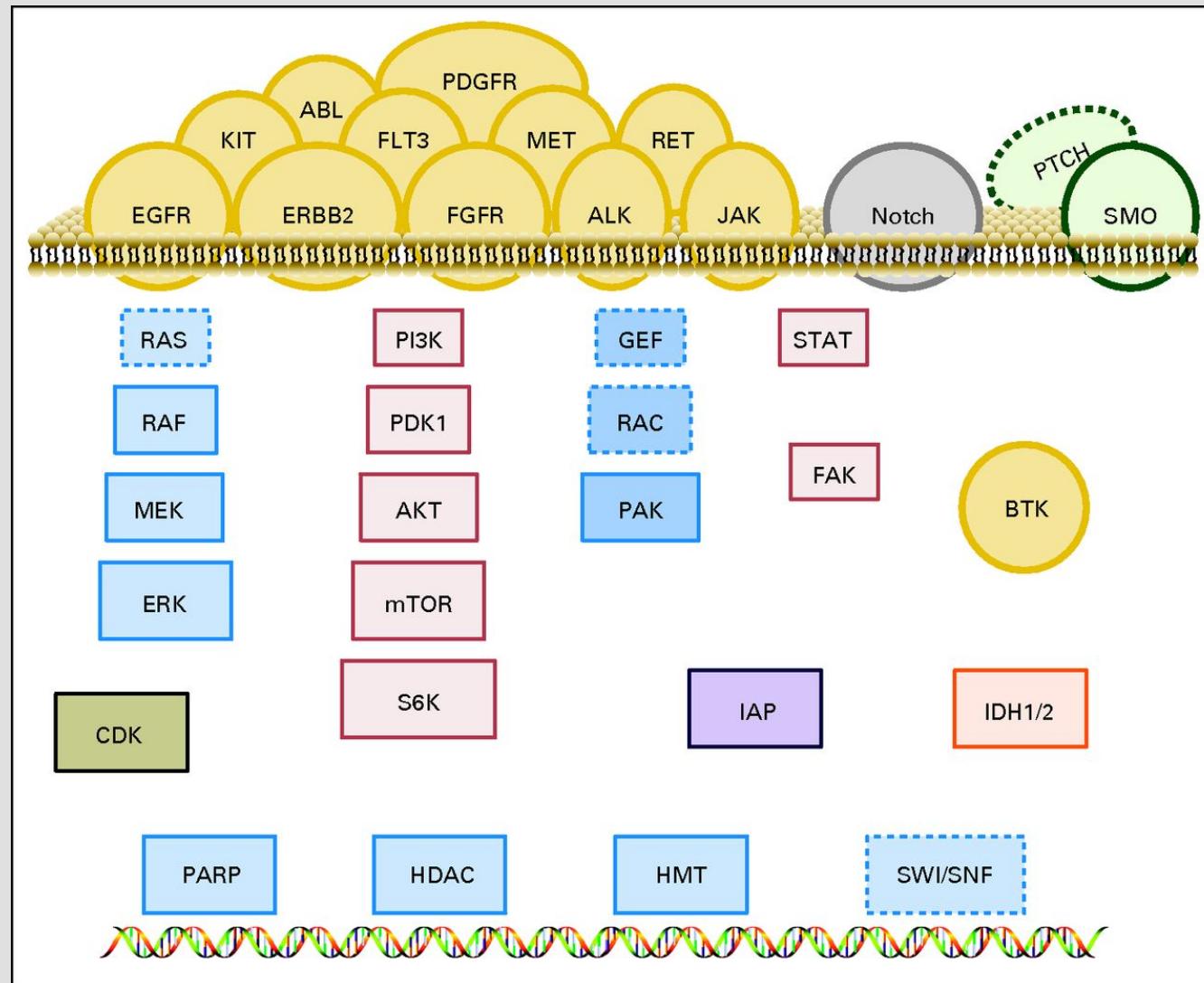


Genomic alterations affecting actionable signaling pathways in common solid tumors.



Levi A. Garraway JCO 2013;31:1806-1814

Spectrum of targeted anticancer agents in clinical development.



Levi A. Garraway JCO 2013;31:1806-1814

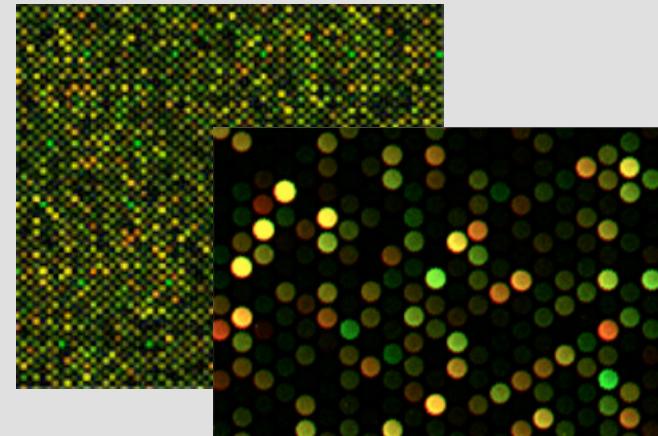
- Cancer & genome, a very brief overview
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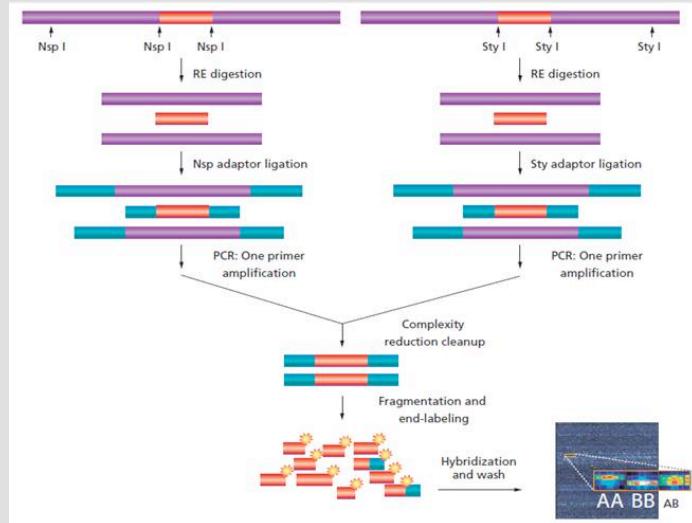
Agilent dual-color hybridization

Competitive hybridization between two DNAs

Sample Vs. Reference



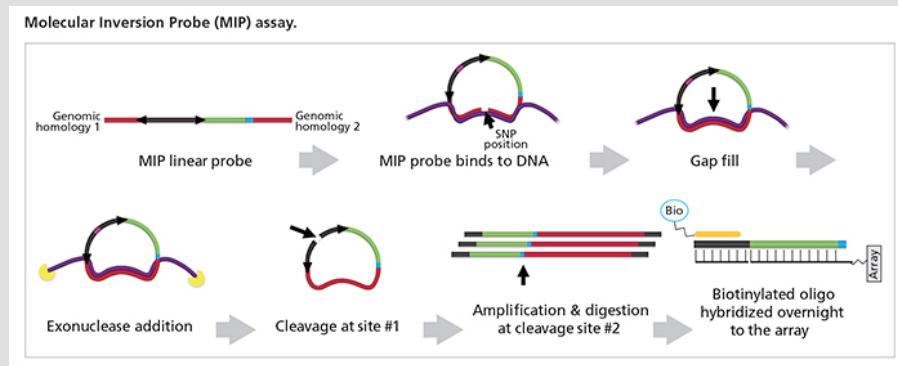
$$\log_2 \left(\frac{\text{sample}}{\text{reference}} \right) = LRR \begin{cases} > & \text{gain} \\ = & \text{neutral} \\ < & \text{loss} \end{cases}$$



Affymetrix technologies

SNP5 → SNP6 → cytoScanHD (~2.7e6 probes)

- Single-color hybridization
- CN + SNP probes
- ‘virtual’ reference (hapmap270)
- Average spacing: 880bp (range: 384 – 1737)

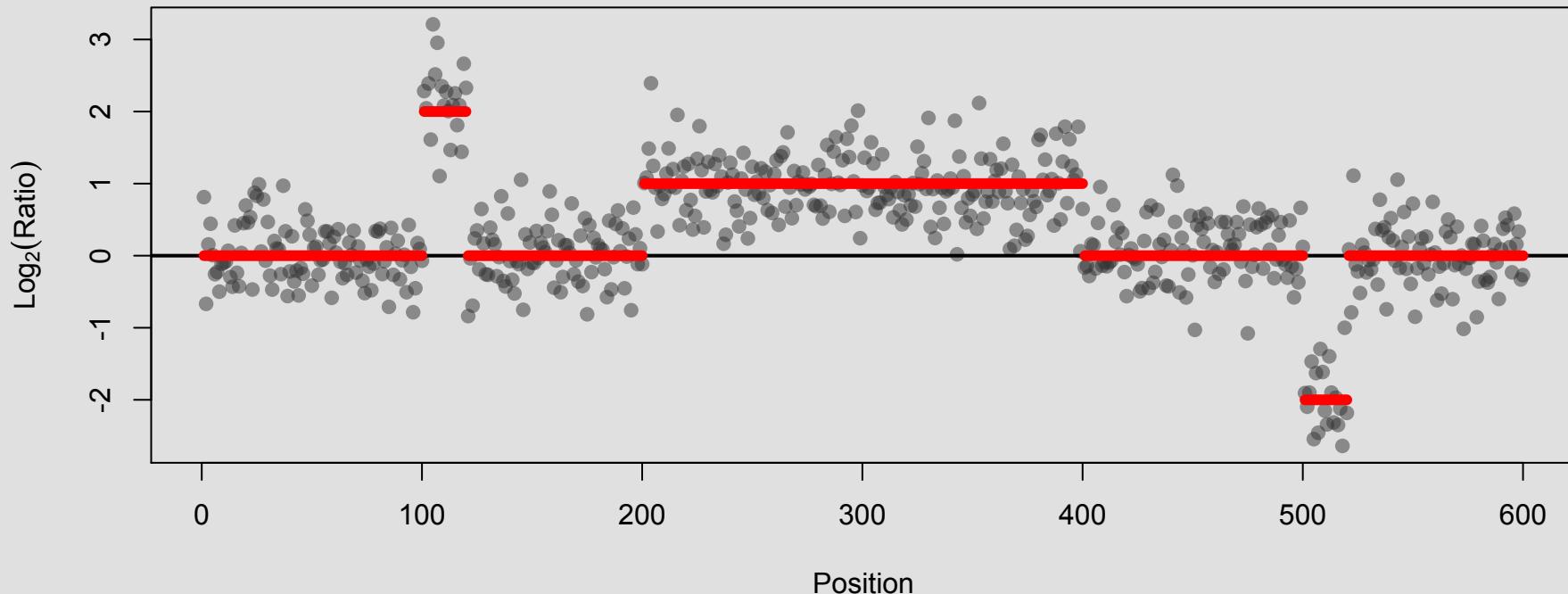


OncoScan, dedicated to FFPE samples
~230K probes exclusively SNP, new technology
- Average spacing: 2.8Kb

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The main idea:

- taking into account the physical relation between markers (probes).
- Summarizing the signal over all the related points.



Issues:

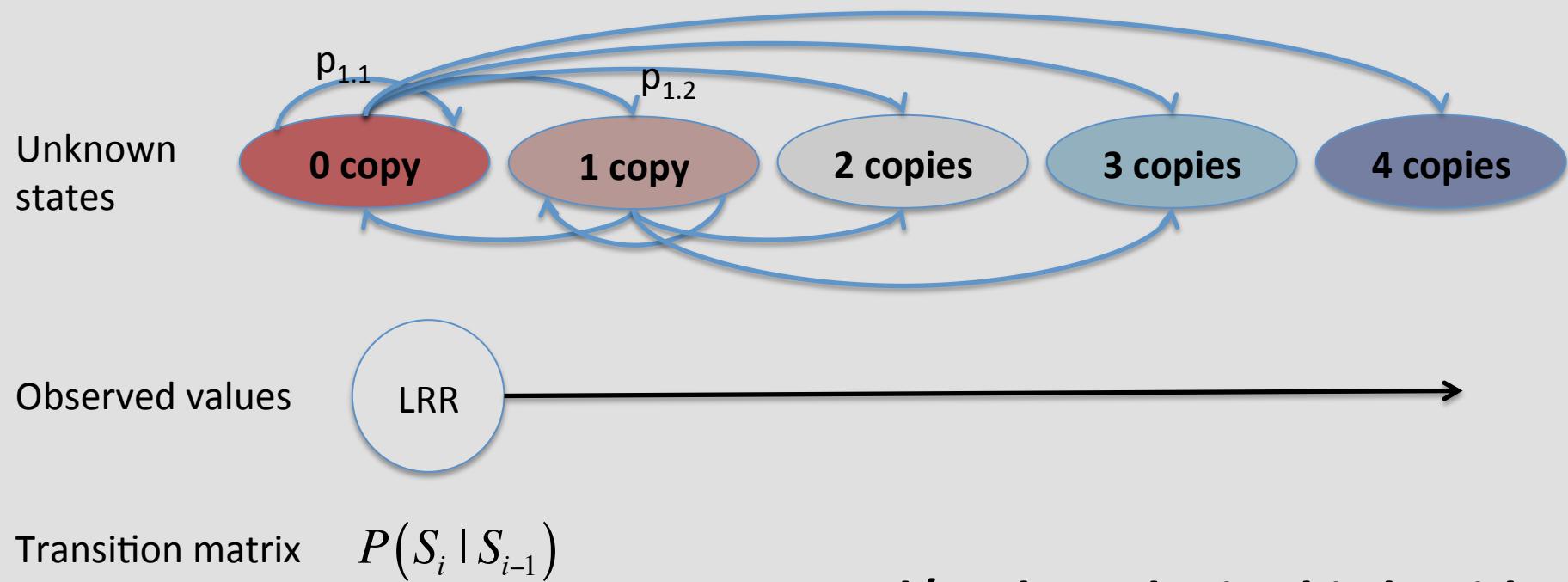
- **How to segment efficiently ?**  **A matter of algorithm**

- **How to estimate gains & losses ?**  **A matter of neutral 2-copies line ... ?**

Segmentation algorithms

The Hidden Markov Model (HMM)

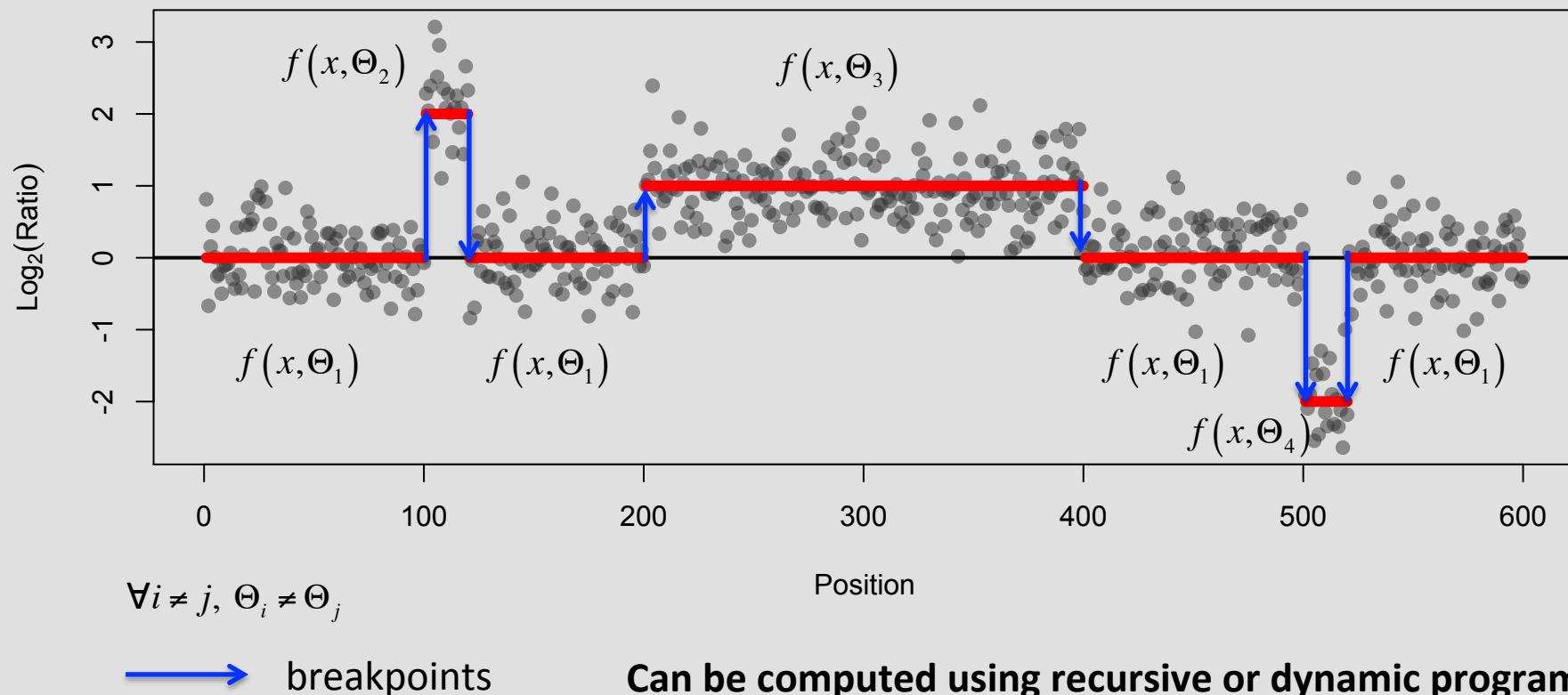
Rational: contiguous states might be somehow linked due to their contiguous positions



Segmentation algorithms

The circular binary segmentation (CBS)

Rational: there exist a sequence of k breakpoints t_1, \dots, t_k such that the LRR mean (and possibly the variance) is the same between two changes, and different from one to another.



Several solutions in R (do not reinvent the wheel...)

BioHMM: a heterogeneous hidden Markov model for segmenting array CGH data.
Marioni et al. Bioinformatics 2006

A faster circular binary segmentation algorithm for the analysis of array CGH data.
Venkatraman E S and Olshen Adam B. Bioinformatics 2007

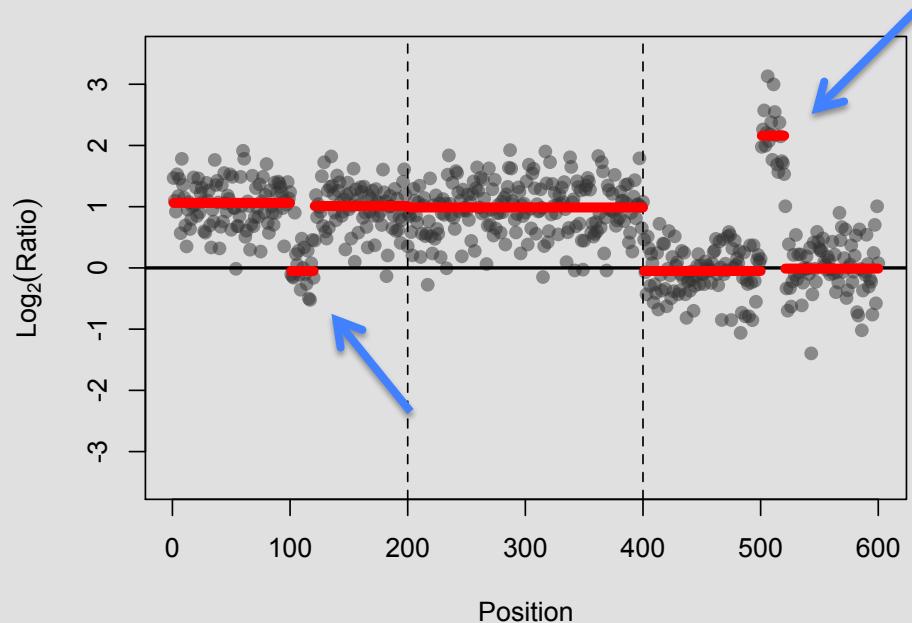
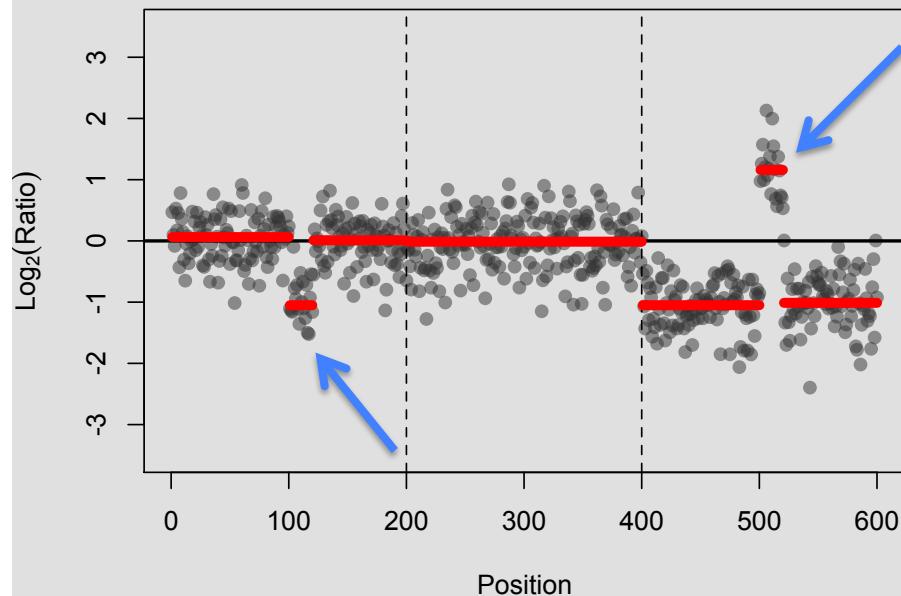
Method comparisons:

A comparison study: applying segmentation to array CGH data for downstream analyses.
Willenbrock H and Fridlyand J, Bioinformatics 2005.

Comparative analysis of algorithms for identifying amplifications and deletions in array CGH data
Lai et al. Bioinformatics 2005

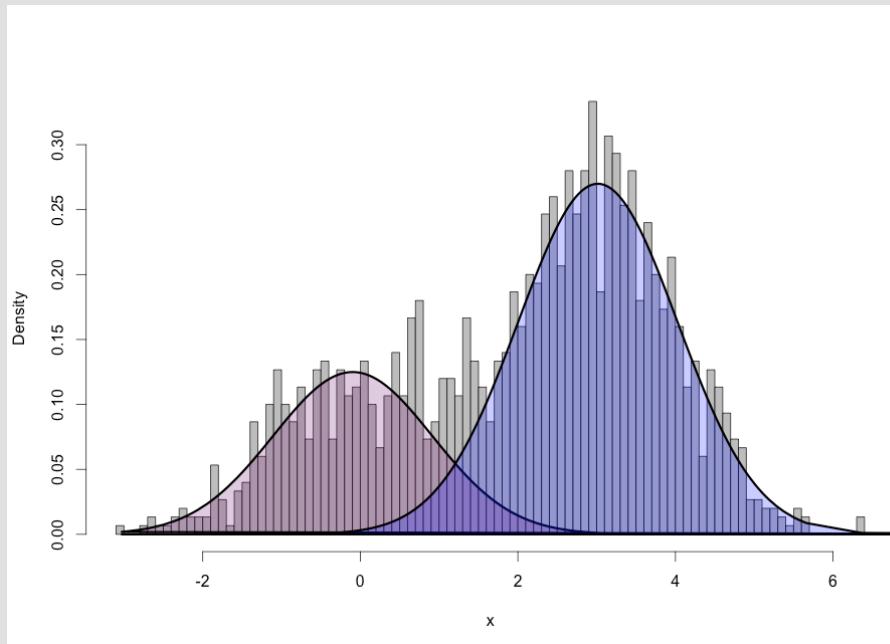
The centralization problem

Depending on the centralization choice, alterations can be different, and so the decision.



Which one is correct ?

Centralizing using the Expectation-Maximization (EM) algorithm



$$g(x, \Theta) = \sum_{k=1}^K \pi_k f_k(x, \theta_k)$$

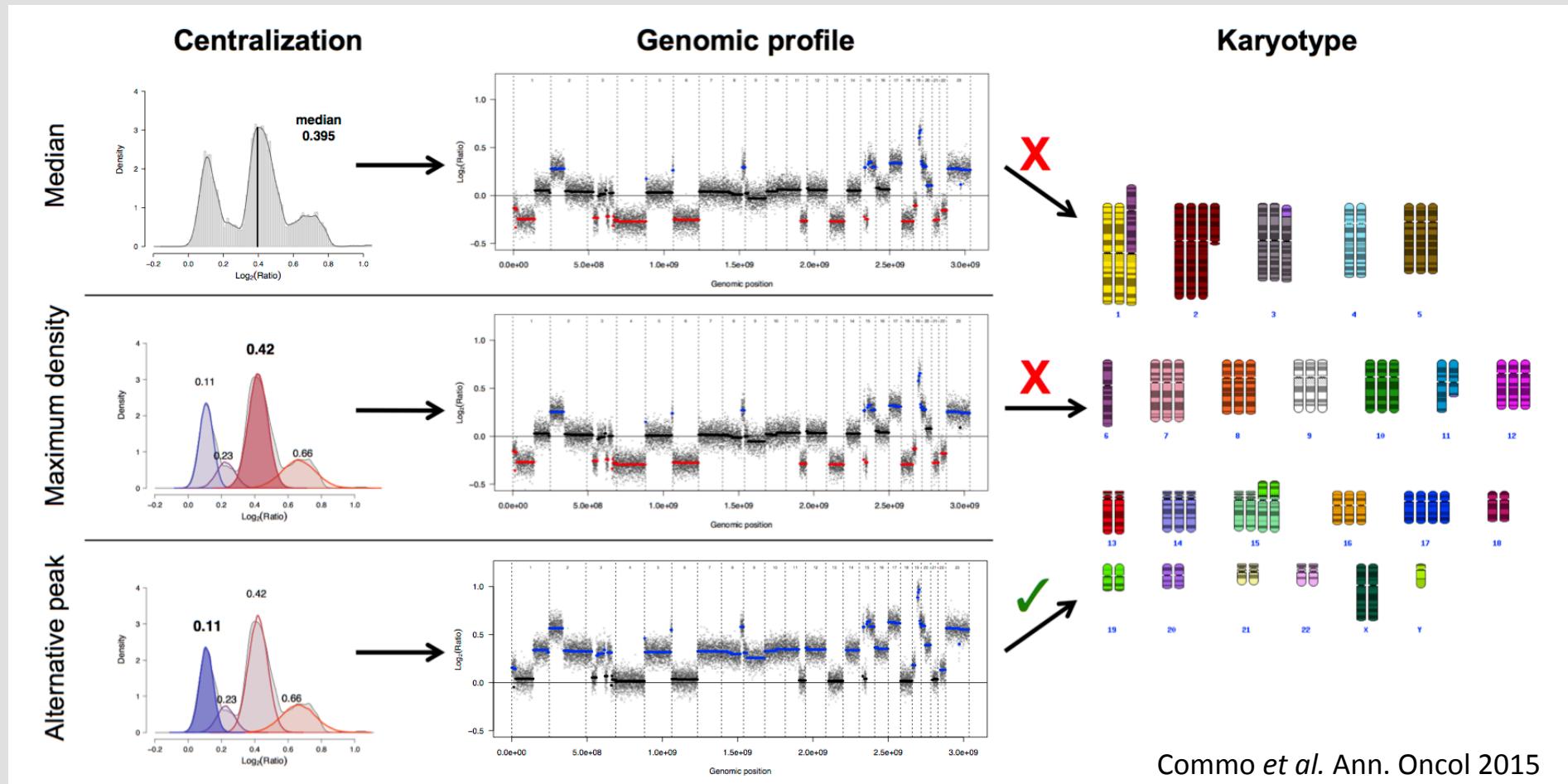
Where K is the number of classes,
 π_k the proportion of class k ,
 θ_k the set of parameters for the density f_k

Do not reinvent the wheel (again...), the R package *mclust* does the job for you.

This approach was suggested in Chen *et al.* (Bioinformatics, 2008), where they choose the highest density peak, with a .95 tolerance, for centralizing the LRRs.

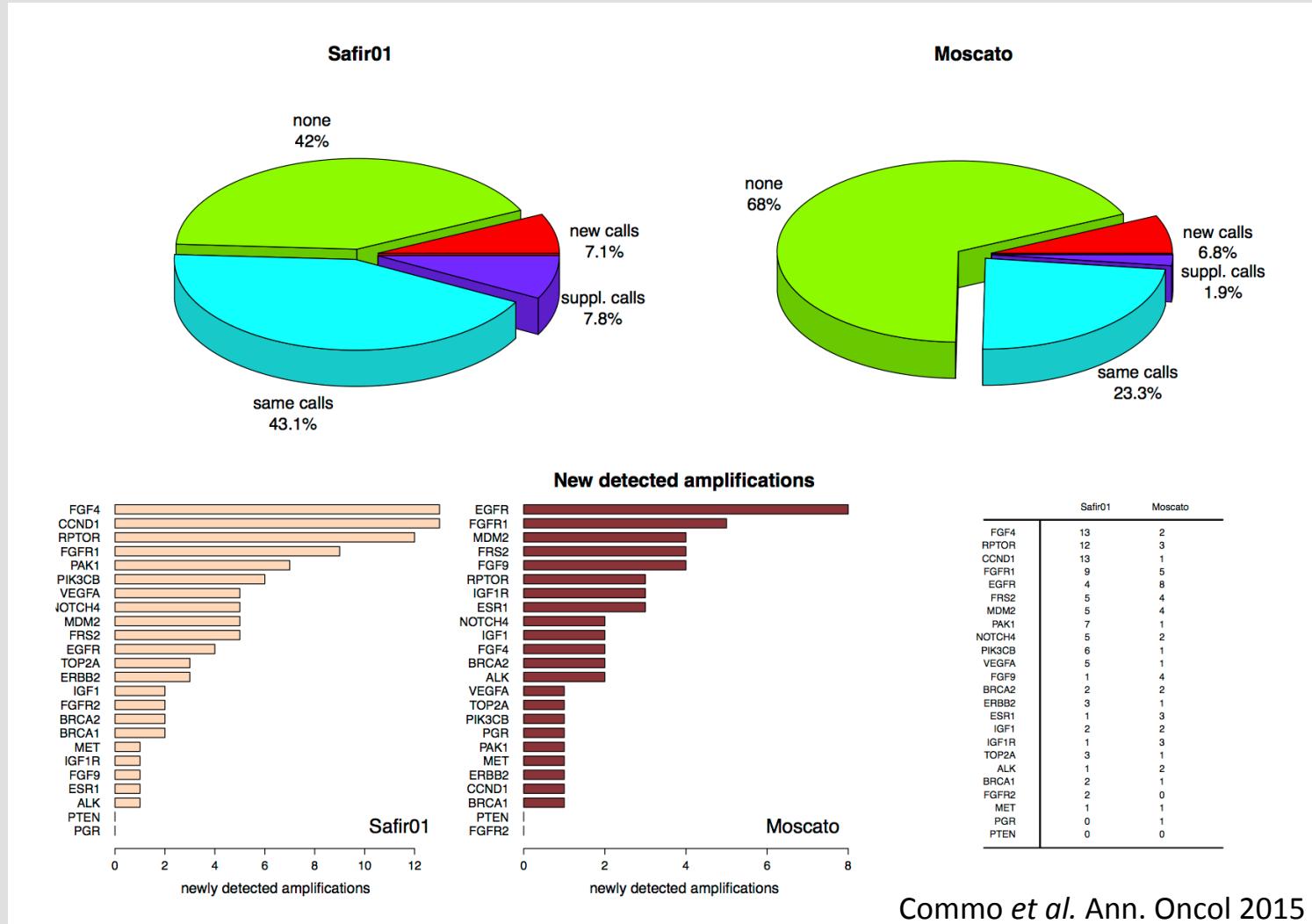
Real cases: the NCI-60 cell lines, aCGH profiles compared to skygrams

"NCI and NCBI's SKY/M-FISH and CGH Database (2001), <http://www.ncbi.nlm.nih.gov/sky/skyweb.cgi>"



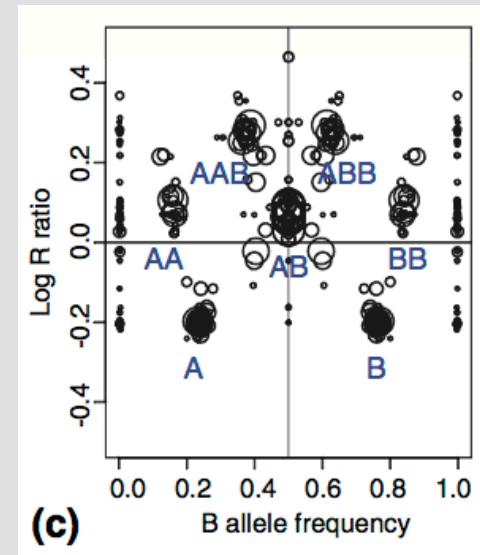
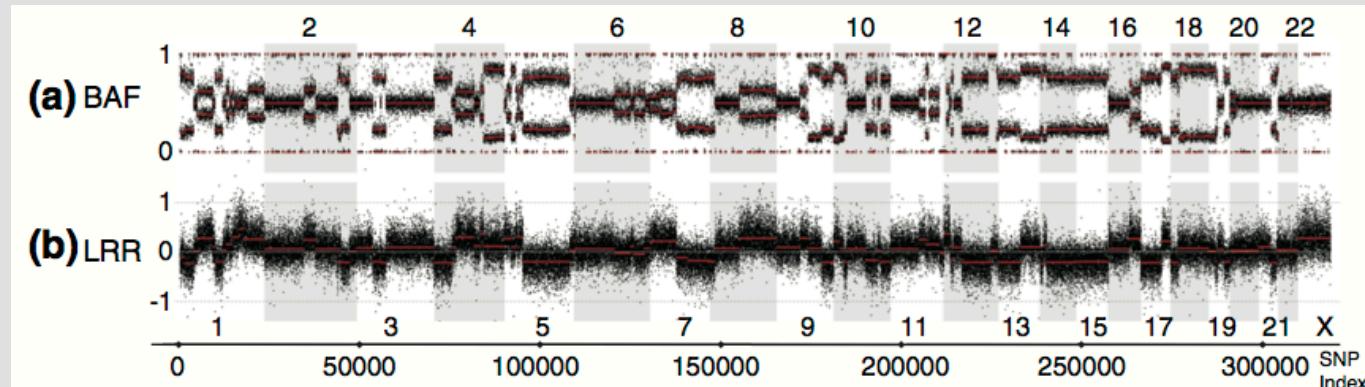
Commo *et al.* Ann. Oncol 2015

Impact on decisions for a therapeutic orientation



Alternatives

Genome Alteration Print (GAP)



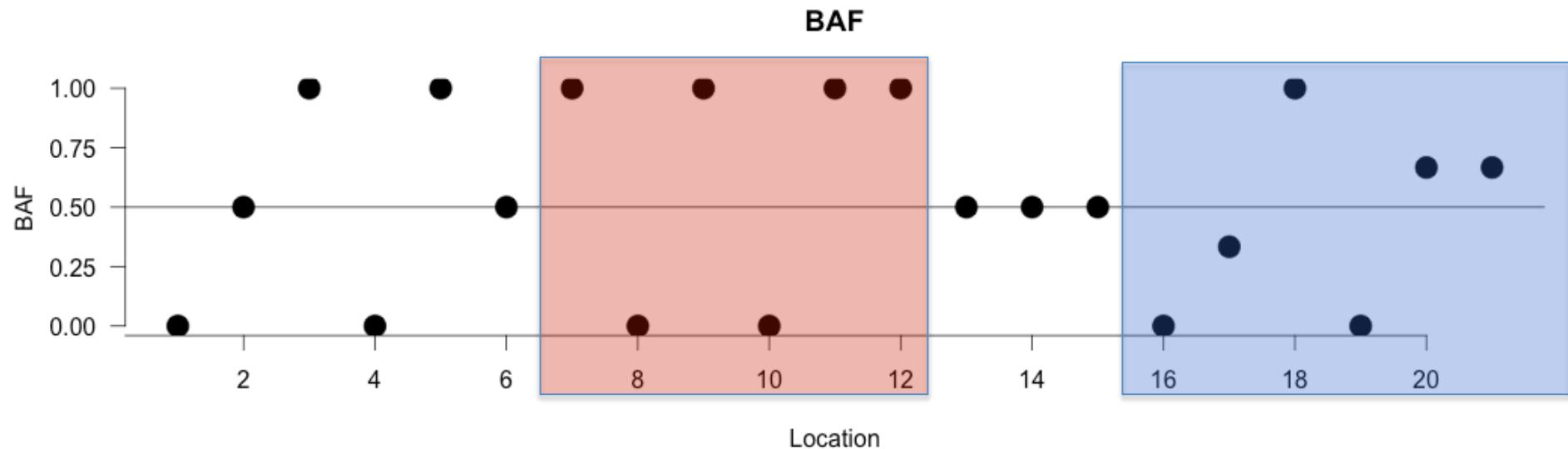
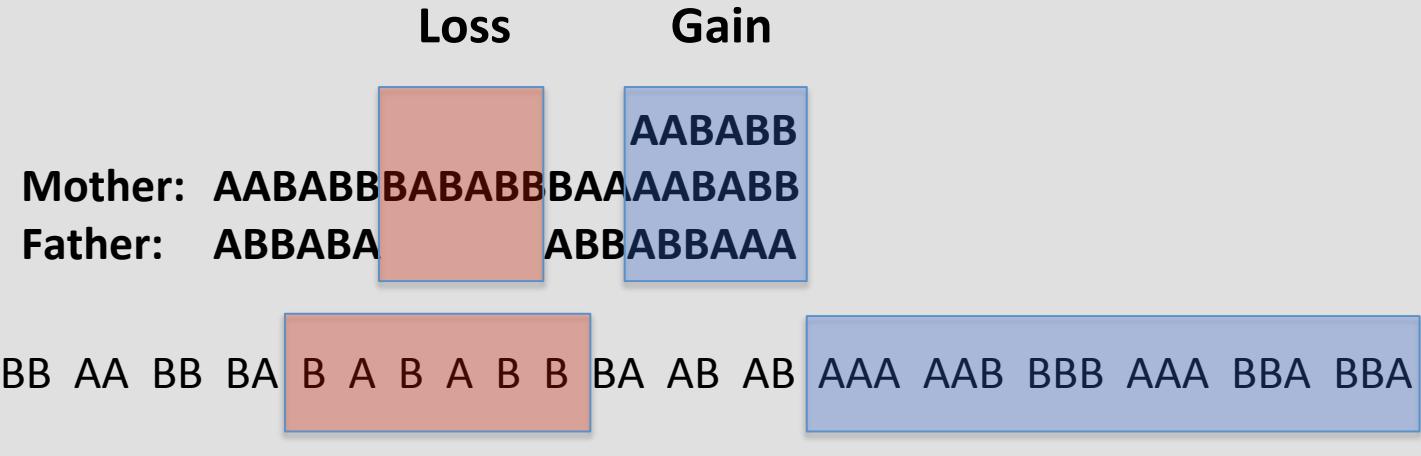
The whole-genome single-nucleotide polymorphism (SNP) array profile and genome alteration print (GAP). The whole-genome profile of genomic rearrangements in the BLC_B1_T45 sample measured by 300K Illumina SNP-array and corresponding GAP. (a) Allelic imbalances are represented by B-allele frequency (BAF). (b) Copy-number variation profile is represented by log R ratio (LRR), centered at zero. (c) The GAP of the sample is a combined sideview projection of segmented LRR and BAF. Each region of the genome is represented by two symmetric circles in the case of allelic imbalance and by one circle centered at $BAF = 0.5$ in the case of a balanced genotype. Attribution of copy numbers and genotypes corresponds to a near-diploid model of rearrangements.

Popova et al. Genome Biology 2009 10:R128 doi:10.1186/gb-2009-10-11-r128

Other methods: Absolute, ASCAT, SOMATICS, PICNIC

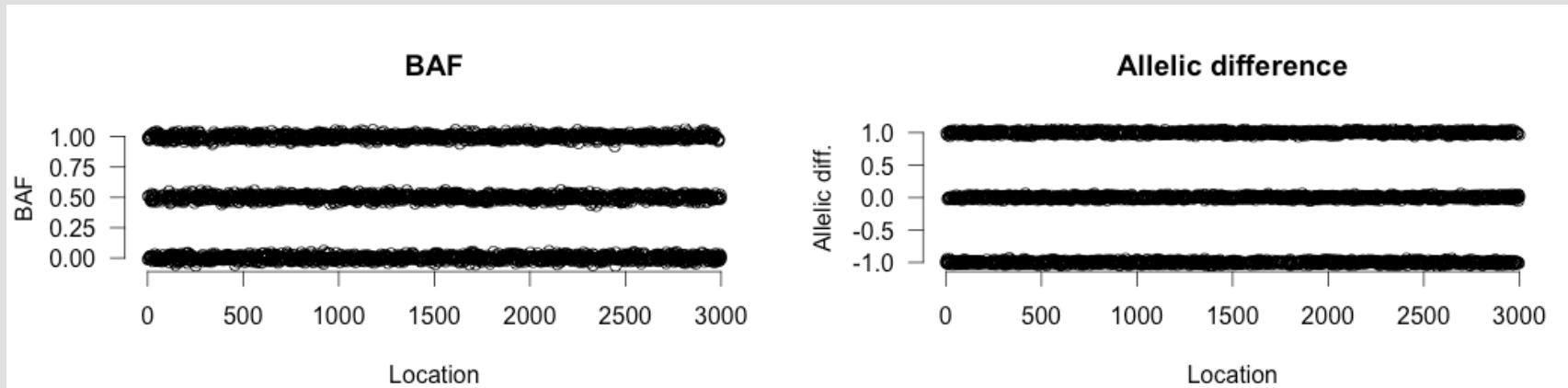
Interpreting loss of heterozygosity (LOH)

$$BAF = \frac{B}{A + B}$$

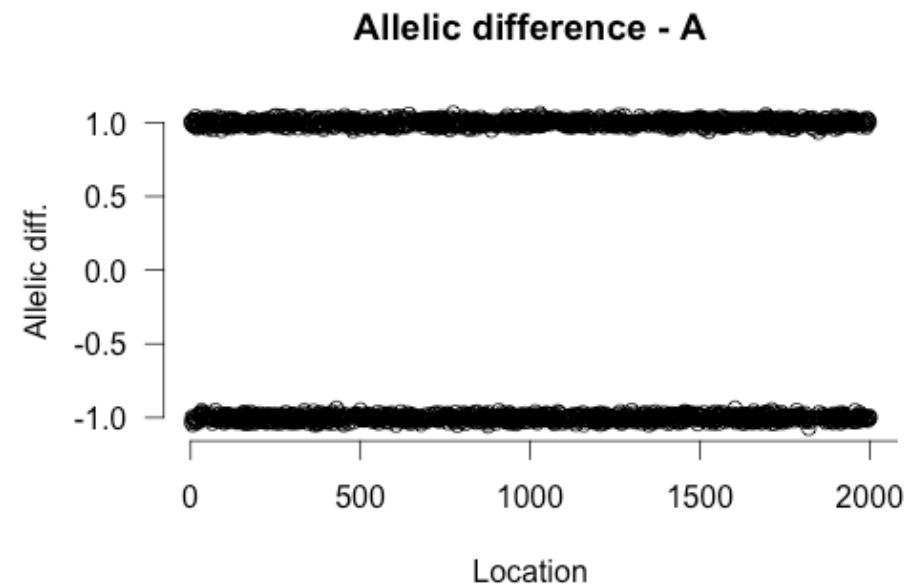
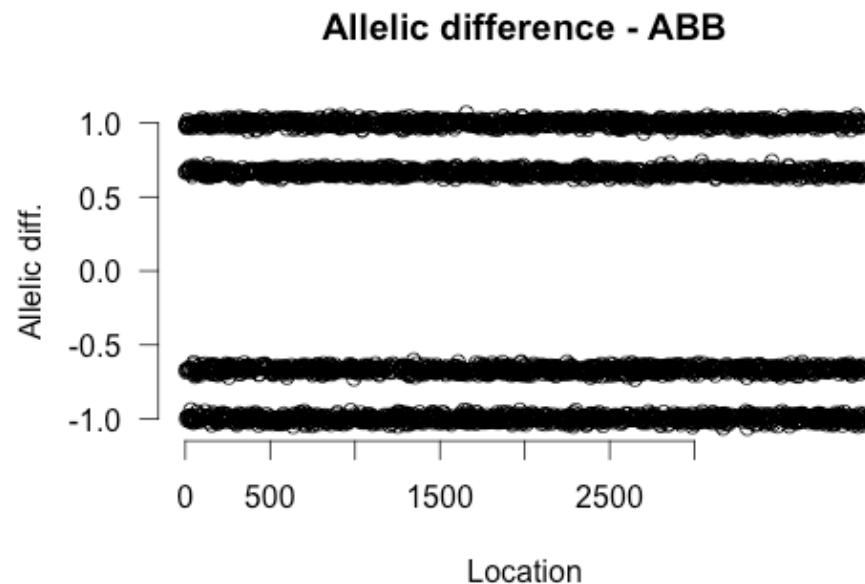


$$BAF = \frac{B}{A + B} ; \text{ Allelic.Difference} = \frac{A - B}{A + B}$$

snp	1	2	3	4	5	6	7	8	9	10
Genotype A	a	b	a	b	b	a	a	b	b	a
Genotype B	a	b	b	b	a	a	a	a	b	b
BAF = B/(A+B)	0	1	0.5	1	0	0	0	0	1	0.5
Allelic diff = (A-B)/(A+B)	1	-1	0	-1	0	1	1	0	-1	0

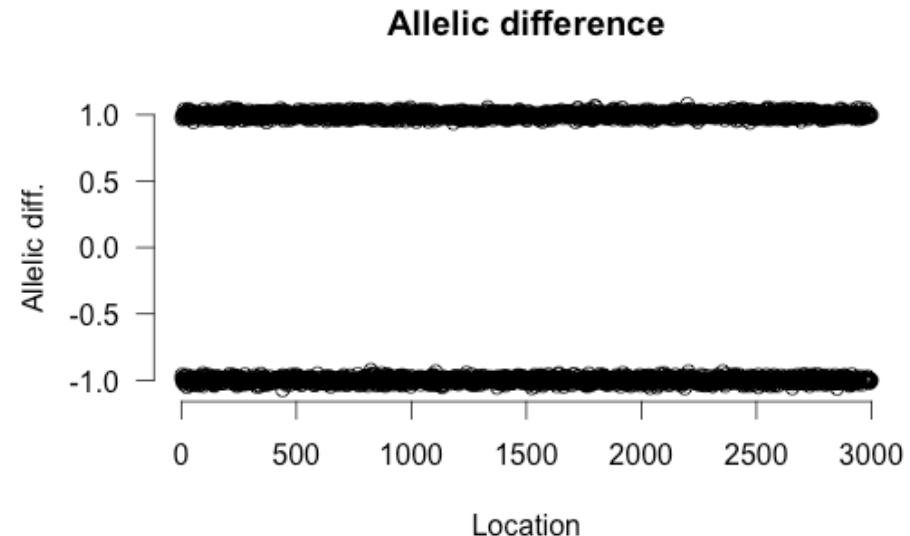
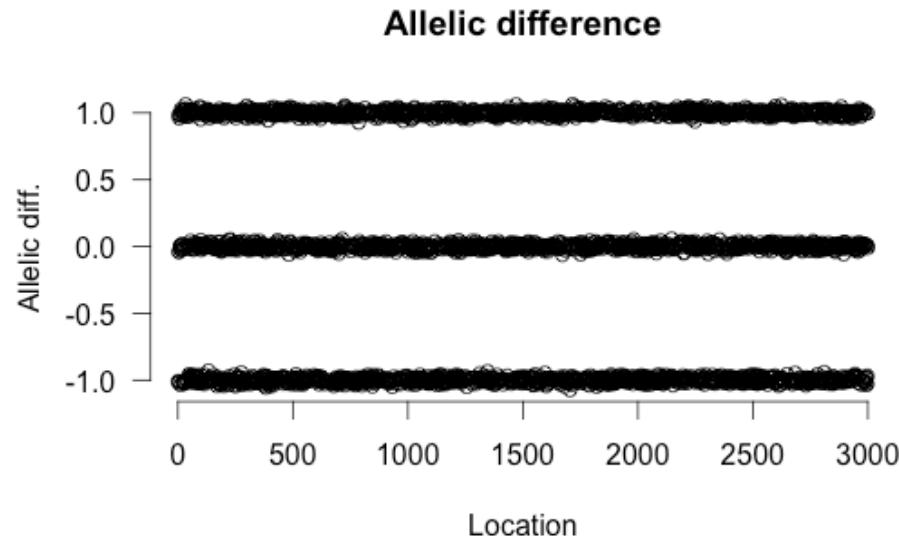


Probe location	1	2	3	4	5	6	7	8	9	10
Genotype A	a	b	a	b	b	a	a	b	b	a
Genotype B	a	b	b	b	a	a	a	a	b	b
Genotype B	a	b	b	b	a	a	a	a	b	b
Allelic diff = (A-B)/(A+B)	1	-1	-2/3	-1	2/3	1	1	2/3	-1	-2/3



The problem is...

Since signals are adjusted such that $AA = 1$ and $BB = -1$, and so 0 is AB ...

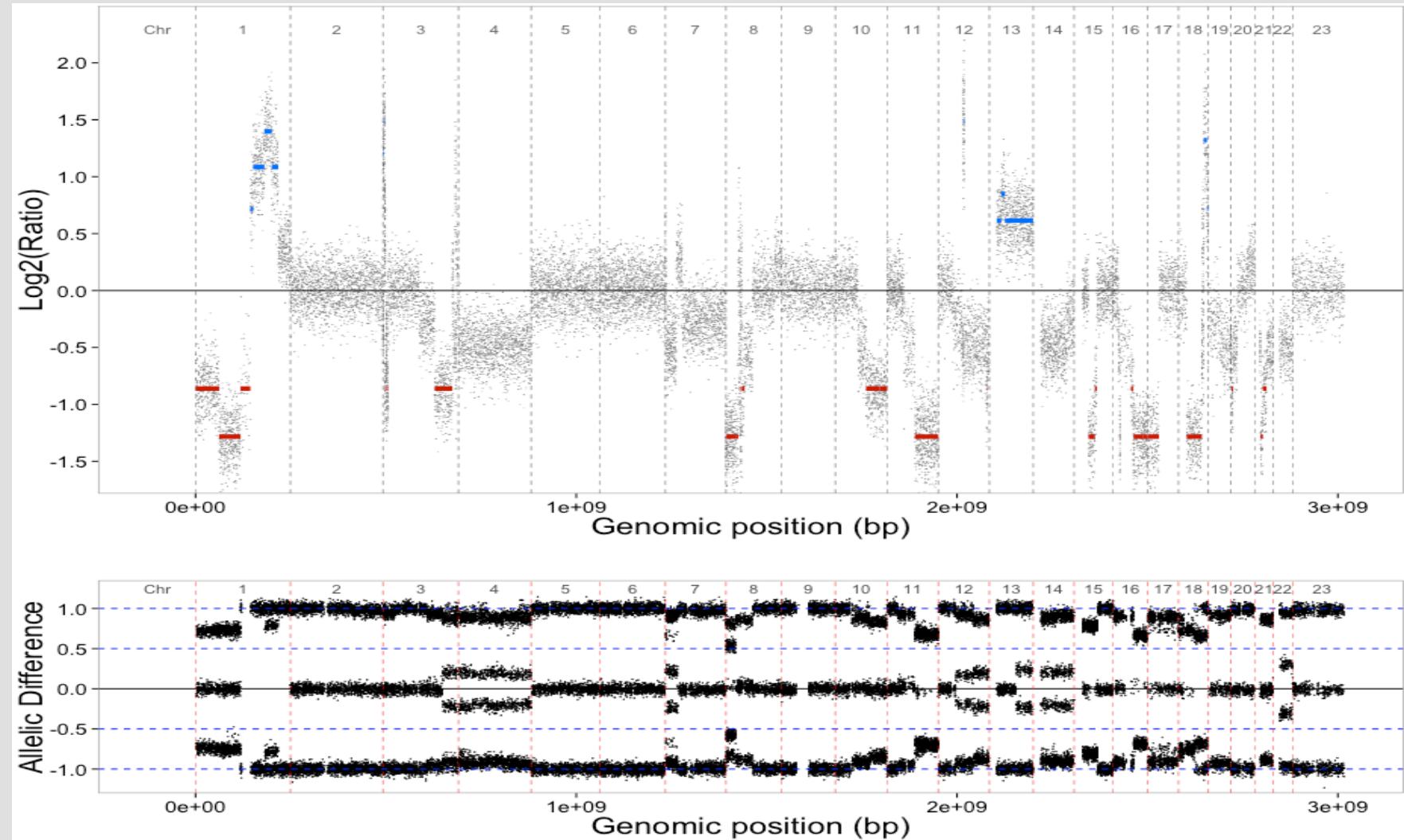


Can be any balanced genotype: AB or AABB

Can be any genotype A or AA or AAA

In case of mosaicism, things can be even more complicated...

A real case...



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```
#####
# Using DNAcopy
#####

> require(DNAcopy)
> op <- par(no.readonly = TRUE)

# Loading supp. data
> path <- "/Users/fredcommo/Documents/myProjects/IFSBM/data"
> load(file.path(path, "hg19.rda"))
> load(file.path(path, "geneDB.rda"))

# Reading file
> filePath <- file.path(path, "Affy_cytoScan.cyhd.CN5.CNCHP_short.txt.gz")
> foo <- readLines(filePath, n=750)
> idx <- grep("ProbeSet", foo)
> cnSet <- read.delim(filePath, skip=idx-1, stringsAsFactors=FALSE)
> dim(cnSet)
> head(cnSet)
```

	ProbeSetName	Chromosome	Position	CNState	Log2Ratio	SmoothSignal	LOH	Allele.Difference
1	C-7SARK	1	849467	2	0.059410	1.859233	0	NA
2	C-6HYCN	1	874571	2	-0.209187	1.855083	0	NA
3	C-7SEBI	1	874841	2	-0.391675	1.852993	0	NA
4	S-3WRNV	1	882803	-1	0.000000	2.000000	0	-0.47663
5	C-7SBEJ	1	884724	2	-0.058026	1.854296	0	NA
6	C-5YZUW	1	884761	2	0.128548	1.850769	0	NA

```
# Filtering SNP probes
> cnSet <- cnSet[grep("^S", cnSet$ProbeSet),]
> dim(cnSet)
> head(cnSet)

  ProbeSetName Chromosome Position CNState Log2Ratio SmoothSignal LOH Allele.Difference
4      S-3WRNV          1    882803     -1  0.000000   2.000000  0       -0.476630
9      S-4GXBG          1    888659      2 -0.296734   1.856312  0        0.604524
23     S-4LYTY          1    918573      2  0.440532   1.888353  0        0.258405
24     S-4HQZX          1    920733      2  0.092134   1.891228  0        1.078725
46     S-4KCPC          1   1039857      2 -0.184646   1.958233  0       -0.706869
47     S-3UOZS          1   1041366      2 -0.071947   1.960523  0       -0.014035
```

```
# Checking Chr names
> table(cnSet$Chromosome)

 1   10   11   12   13   14   15   16   17   18   19   2   20   21   22   3
14913  9329 10249  8950  7328  7017  6624  5488  4664  5467  2904 16500  4255  2667  2280 13735
      4      5      6      7      8      9      X
12947 12383 13733 12208 10245  8060  5748

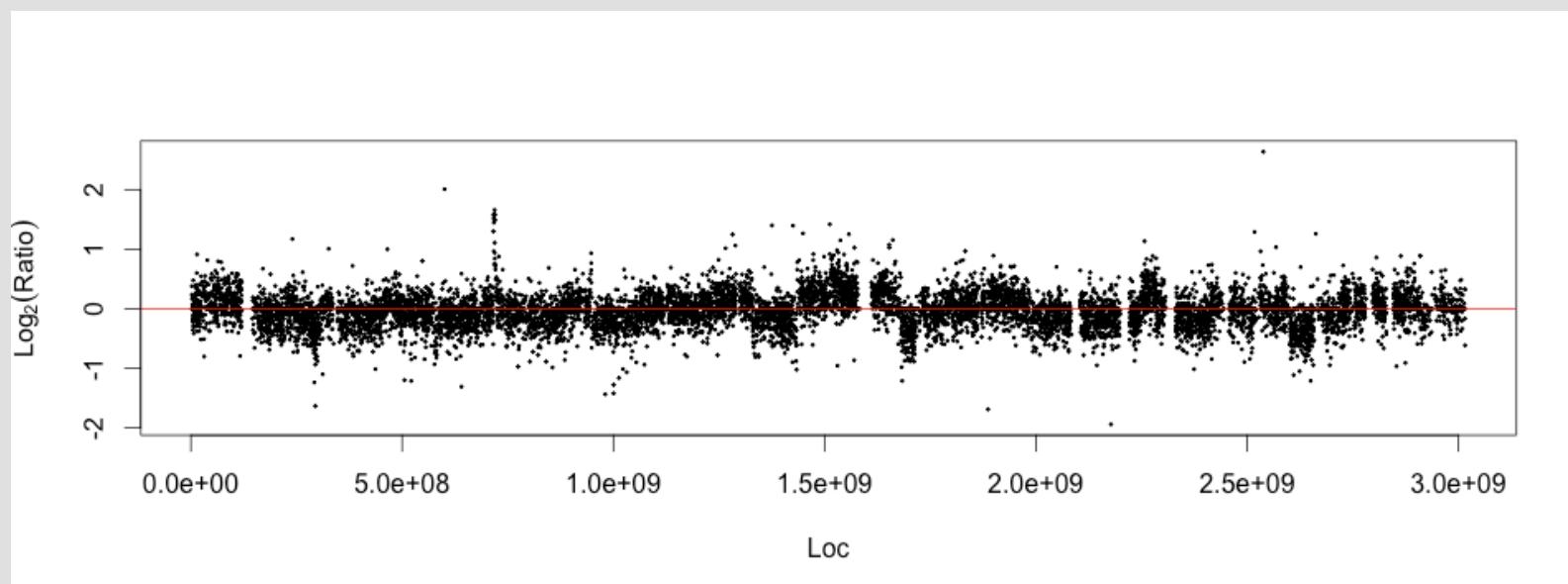
> cnSet$Chromosome[cnSet$Chromosome=="X"] <- 23
> cnSet$Chromosome <- as.numeric(cnSet$Chromosome)
> table(cnSet$Chromosome)

 1   2   3   4   5   6   7   8   9   10   11   12   13   14   15   16
14913 16500 13735 12947 12383 13733 12208 10245  8060  9329 10249  8950  7328  7017  6624  5488
    17   18   19   20   21   22   23
    4664  5467  2904  4255  2667  2280  5748

> cnSet <- cnSet[order(cnSet$Chromosome, cnSet$Position),]
```

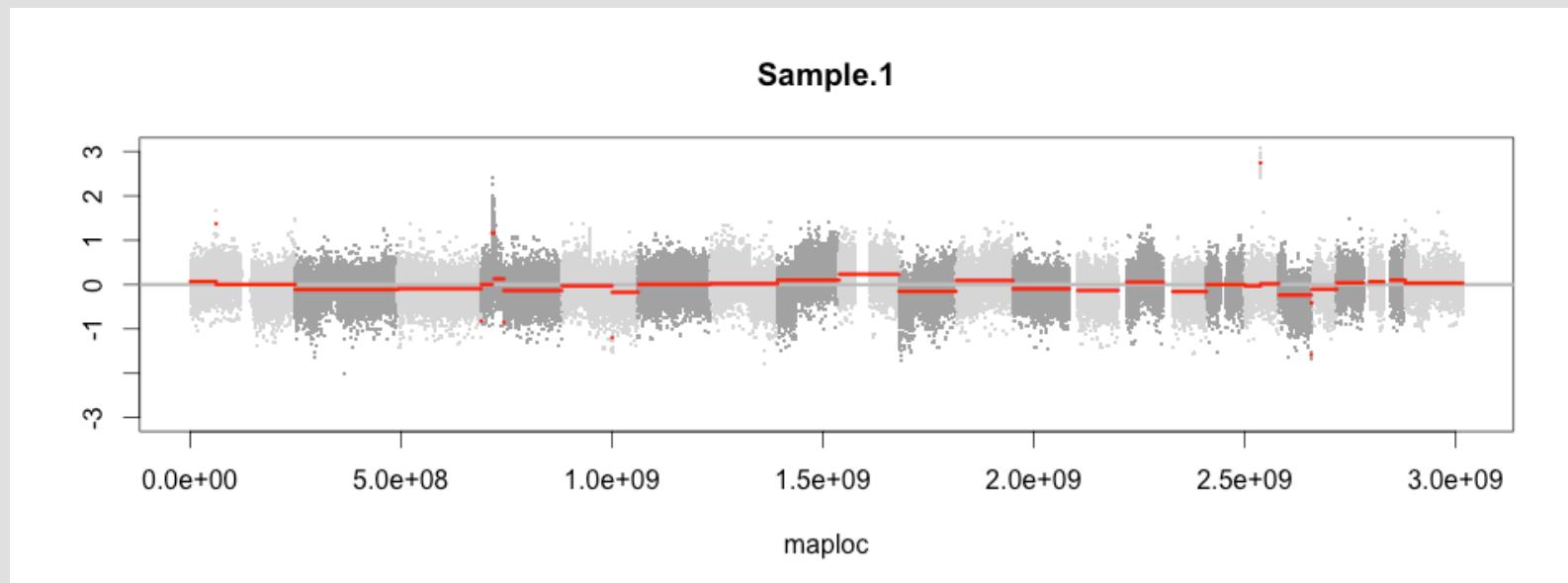
```
# Calculating genomic positions
> locs <- lapply(1:24, function(chr) {
  l <- cnSet$Position[cnSet$Chromosome==chr]
  return(l + hg19$cumlen[chr])
})
> locs <- do.call(c, locs)
> s <- sample(1:nrow(cnSet), 1e4)

# A quick preview
> plot(locs[s], cnSet$Log2Ratio[s], cex=.2, xlab="Loc", ylab=expression(Log[2]
(Ratio)))
> abline(h = 0, col="red")
```



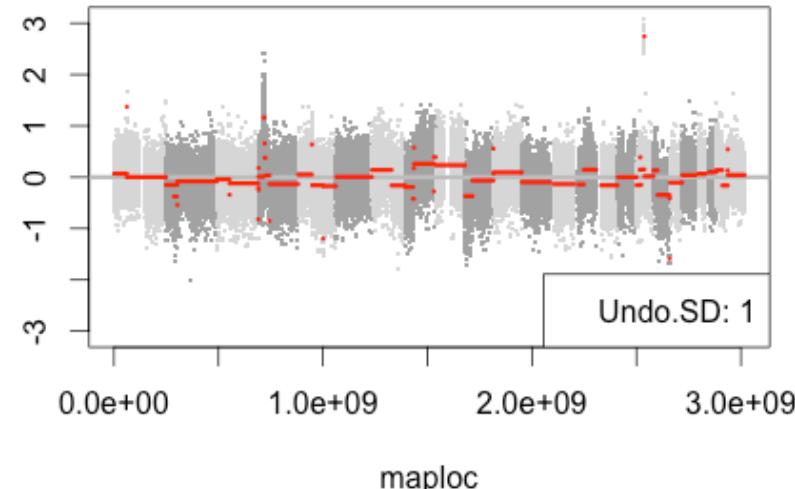
```
# Segmenting using DNAcopy and the default params
  # Constructing a DNAcopy object
> LR <- cnSet$Log2Ratio
> Chr <- cnSet$Chromosome
> ptcols <- c("grey65", "grey85")
> cnaObj <- CNA(LR, Chr, locs, presorted = TRUE)
> cnaObj <- smooth.CNA(cnaObj)
> segObj <- segment(cnaObj, undo.splits = "sdundo")

  # Plotting
> ptcols <- c("grey65", "grey85")
> plot(segObj, xmaploc=TRUE, pt.cols=ptcols)
```

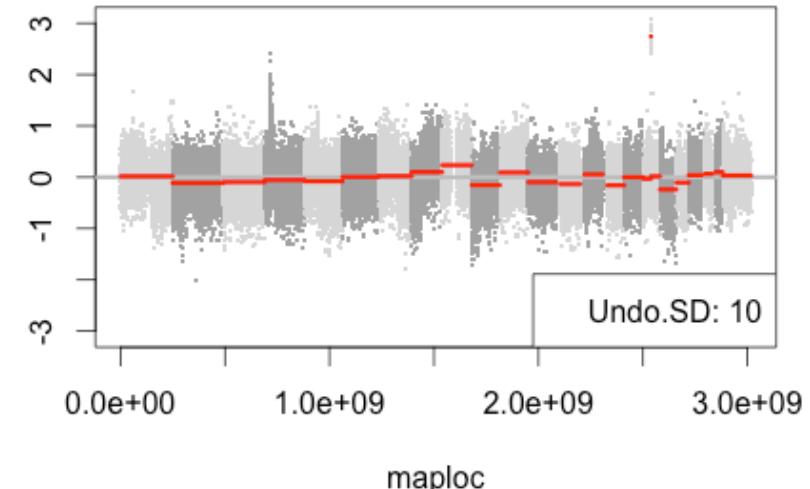


```
# The Undo.SD effect
> par(mfrow=c(1, 2))
> for(s in c(1, 10)){
  segObj <- segment(cnaObj, undo.splits = "sdundo", undo.SD = s)
  plot(segObj, xmaploc=TRUE, pt.cols=ptcols)
  legend("bottomright", legend=sprintf("Undo.SD: %s", s))
}
> par(op)
```

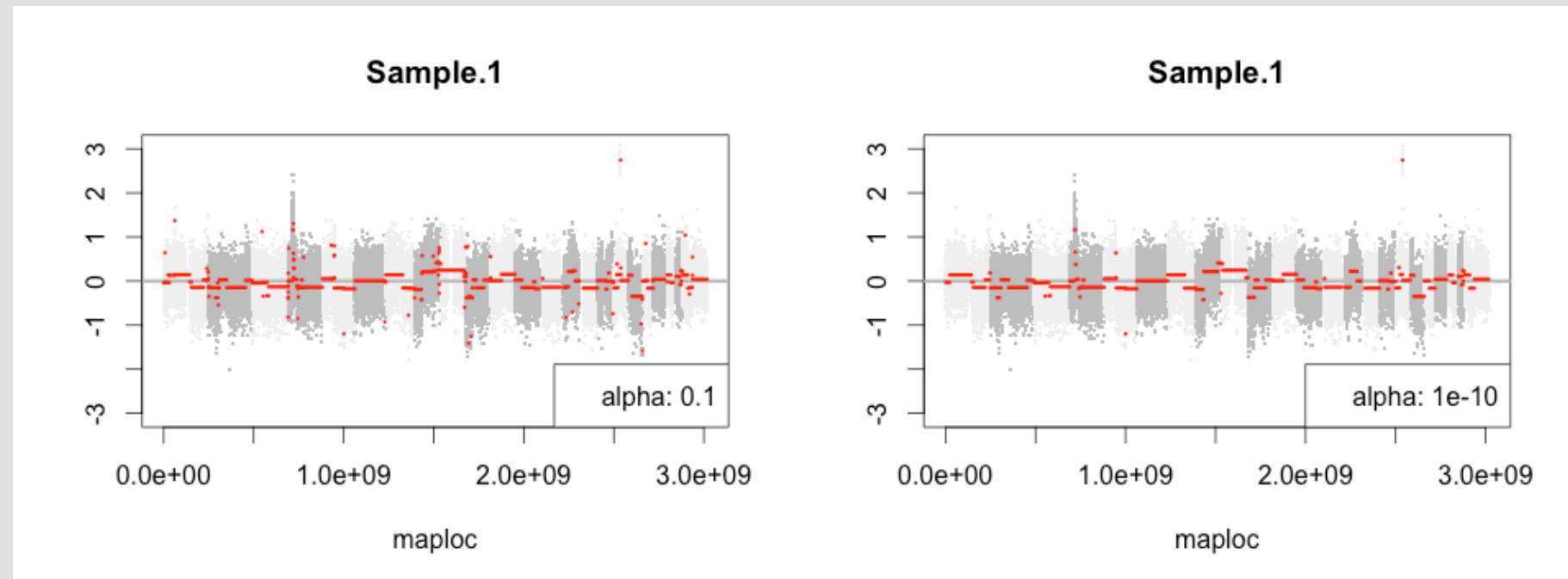
Sample.1



Sample.1



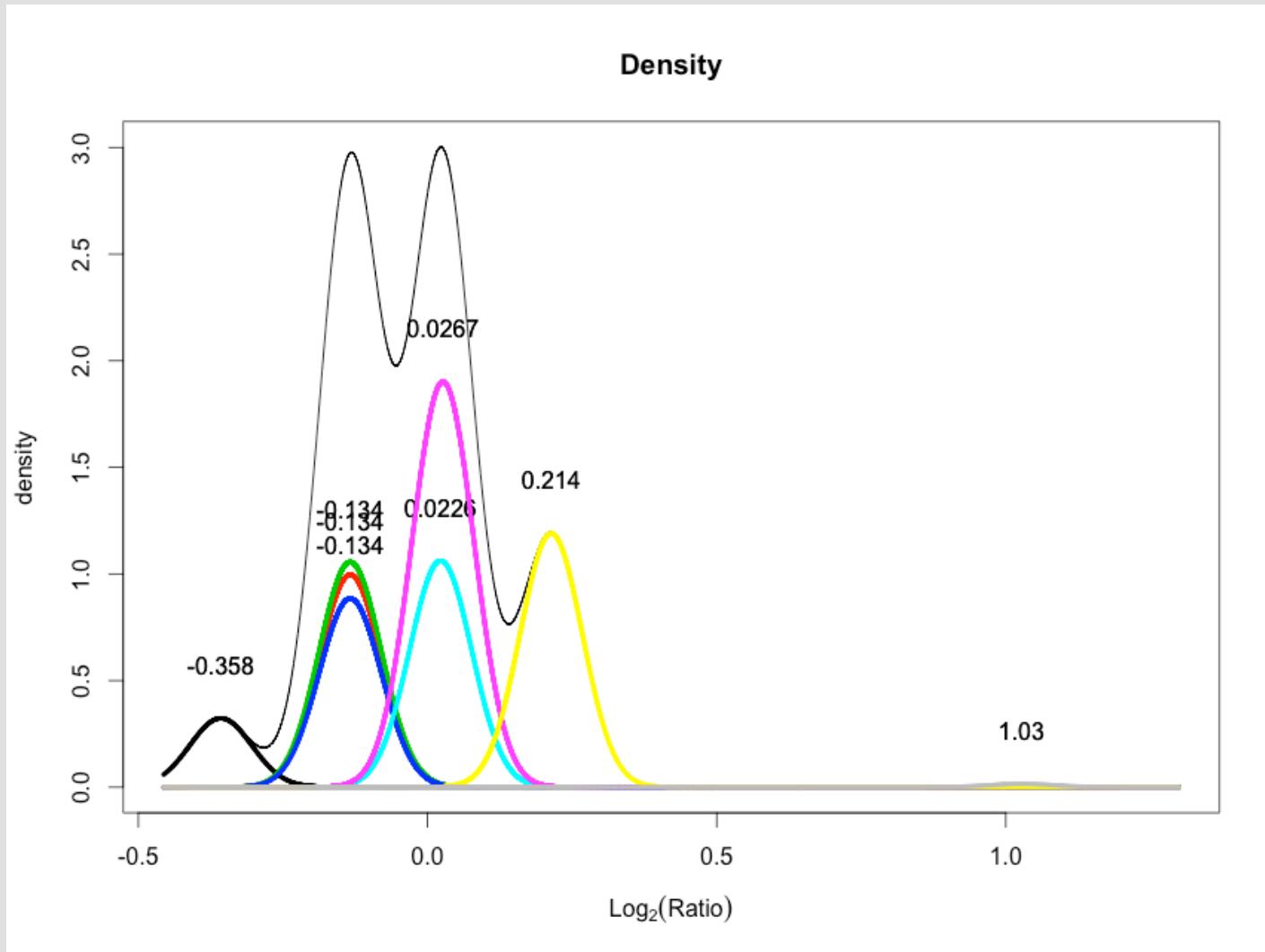
```
# The alpha tolerance effect
> par(mfrow=c(1, 2))
> for(a in c(1e-1, 1e-10)){
  segObj <- segment(cnaObj, undo.splits = "sdundo", undo.SD = .5, alpha = a)
  plot(segObj, xmaploc=TRUE, pt.cols=c("grey75", "grey95"))
  legend("bottomright", legend=sprintf("alpha: %s", a))
}
> par(op)
```



```
# Centering the profile
> require(mclust)
> rLR <- runmed(LR, k=101)
> rLR <- sort(rLR)
> idx <- seq(1, length(rLR), len=25e3)
> model <- Mclust(rLR[idx])
> means <- model$parameters$mean
> props <- model$parameters$pro
> s2 <- model$parameters$variance$sigmasq
> if(length(s2)==1) s2 <- rep(s2, length(means))

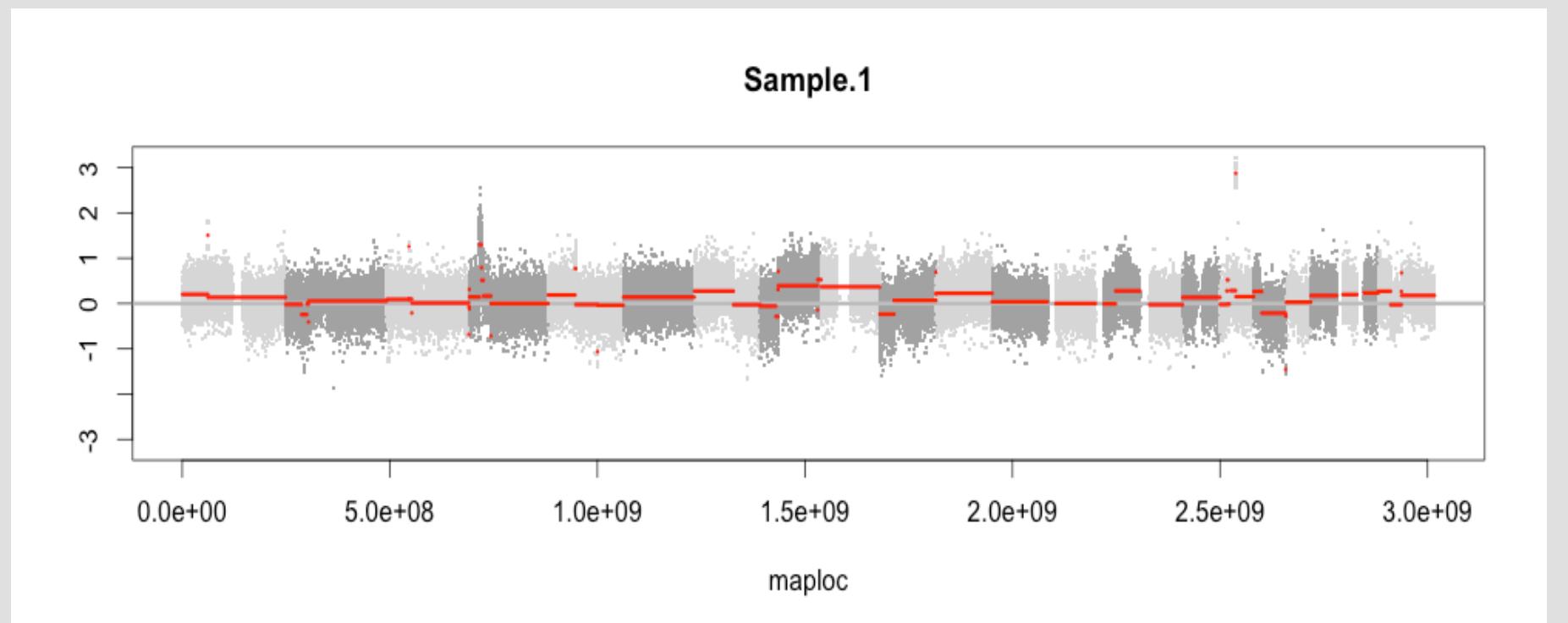
> plot(model, what="density", xlab=expression(Log[2](Ratio)))
> for(ii in 1:length(means)){
  m <- means[ii]; s <- sqrt(s2[ii]); p <- props[ii]
  d <- dnorm(rLR, m, s)*p
  lines(rLR, d, col=ii, lwd=4)
  text(m, max(d)+.25, labels=format(m, digits=3))
}
```

Expectation-Maximization modeling



```
# Final profile
> choice <- -0.134
> LR <- LR - choice

> cnaObj <- CNA(LR, Chr, locs, presorted = TRUE)
> cnaObj <- smooth.CNA(cnaObj)
> segObj <- segment(cnaObj, undo.splits = "sdundo", undo.SD = 1, alpha = 1e-2)
> plot(segObj, xmaploc=TRUE, pt.cols=ptcols)
```



```
# Getting the gene list within a specific segment
> st <- segObj$output
> chr <- 17
> sgt <- st[st$chrom==chr,]
> subdb <- geneDB[geneDB$chr==chr,]
> s <- sgt$loc.start[6]
> e <- sgt$loc.end[6]

> idx <- which(s <= subdb$genomStart & subdb$genomEnd<=e)
> subdb[idx, c("symbol", "fullName")]

  symbol                               fullName
4560  CDK12                         cyclin-dependent kinase 12
8489  ERBB2 v-erb-b2 avian erythroblastic leukemia viral oncogene homolog 2
9428  FBXL20                        F-box and leucine-rich repeat protein 20
11279  GRB7                          growth factor receptor-bound protein 7
13682  IKZF3                         IKAROS family zinc finger 3 (Aiolos)
15386  TCAP                           titin-cap
16967  MED1                           mediator complex subunit 1
17252  MIEN1                         migration and invasion enhancer 1
18670  MIR4728                       microRNA 4728
20625  NEUROD2                       neuronal differentiation 2
23462  PNMT                           phenylethanolamine N-methyltransferase
23572  PGAP3                          post-GPI attachment to proteins 3
24598  PPP1R1B                        protein phosphatase 1, regulatory (inhibitor) subunit 1B
35517  STARD3                        STAR-related lipid transfer (START) domain containing 3
```

Any question ?