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Estimating copy number polymorphisms from genotyping arrays

Stephen Cristiano Johns Hopkins University



November 5, 2013

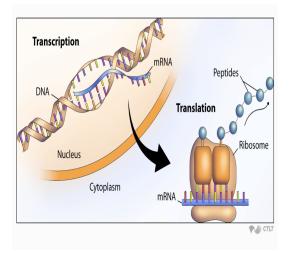
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COPY NUMBER VARIATION

A loss or gain of chromosomal DNA copy number spanning hundreds to thousands of basepairs, or even entire chromosomes (aneuploidy)

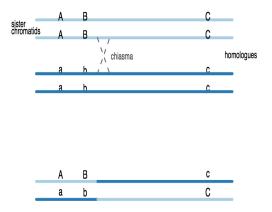
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COPY NUMBER VARIATION

- Structural variation that often arises from abnormal recombination events.
- Defined as 1 kilobase or larger.
- Gain and loss of copy number indicated increase risk to common diseases such as schizophrenia and driving processes of clonal selection in tumors
- ► Preferentially occur in repetitive regions of the genome.
- Accounts for as much as 12% of the human genome.
- Can arise from germ line or somatic mutations. Our work is focused on germline.

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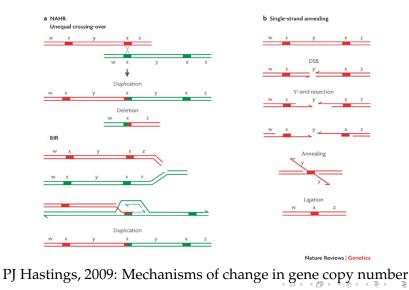
NORMAL RECOMBINATION DURING MEIOSIS



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CHANGE BY HOMOLOGOUS RECOMBINATION



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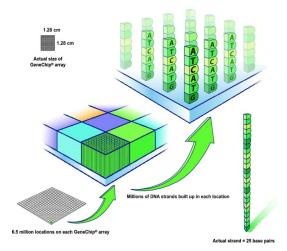
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Note

High throughput genotyping arrays can only detect low-copy repeats (0, 1, 2, 3, or 4+ copies) because of saturation of the intensities.

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AFFYMETRIX PLATFORM



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AFFYMETRIX PLATFORM

- Quickly scan for presence of particular genes in a biological sample.
- Each gene represented by a unique set of probe pairs (roughly 12-12 probe pairs per probe set)
- Each spot on array represents a single probe millions of copies.
- Probes fixed to array.
- ► A tissue sample is prepared so its mRNA has fluorescent tags.
- mRNA samples hybridize to probes.

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OTHER PLATFORMS

- Other genotyping arrays (Illumina etc).
- Comparative genomic hybridization (CGH).
- Next generation sequencing: still very challenging for surveying copy number.

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CNV ESTIMATION

There are multiple modes of CNV estimation:

- ► By sample.
- ► By locus.
- ► Hybrid approach.

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GOAL

Can we improve copy number estimates at copy number polymorphic regions?

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Software

- ► Birdsuite (Korn, 2008).
- ► CNVtools (Barnes, 2008).
- ▶ cnvCall (Cardin, 2011).
- ► CNPbayes (Cristiano, 2013).

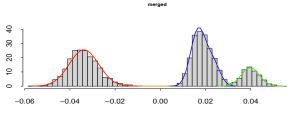
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- Cardin (2011)
 - "Bayesian hierarchical mixture modeling to assign copy number from a targeted CNV array"
 - ► For robustness, uses a mixture of t-distributions.
 - Introduces a hierarchical structure over the mean and variance across samples from different data collections.
 - Uses merging algorithm to combine neighboring components with significant overlap.
 - ► Implemented in R package cnvCall.

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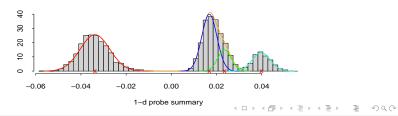
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CNVCALL



1-d probe summary





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CNVCALL

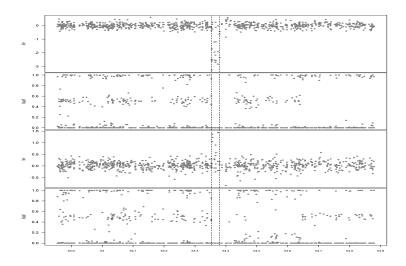
- Our model is most similar to CNV call.
- However, they assume copy number polymorphic regions are known.
- CNP regions will differ between populations of different ancestries, etc.
- We define CNP regions on the basis of Hidden Markov Model calls.

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Data

- 8,598 participants of European ancestry who participated in the Atherosclerosis Risk in Communities (ARIC) Study
- Genomic data: log R ratios and B allele frequencies measured from Affymetrix 6.0 arrays

LOW LEVEL SUMMARIES FOR 2 SAMPLES



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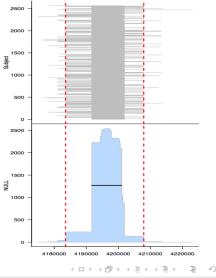
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Method				

- A 6 state hidden Markov model was fit genome-wide to each subject.
 - Approximately 500 regions were identified for which deletions or duplications are common in greater than 1% of subjects.
 - GenomicRanges used to find copy number polymorphic loci from the HMM calls.
 - A Bayesian finite Gaussian mixture model fit to the average log R ratios improves copy number estimates.

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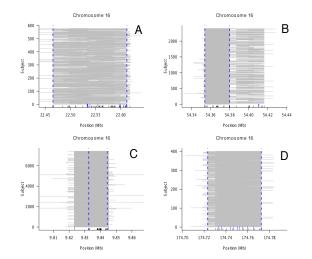
DEFINING REGIONS

- HMM gives non-perfectly overlapping sample specific regions.
- GenomicRanges used to to find copy number polymorphic loci from HMM calls.
- Regions can be complex.
- There may be large gaps in coverage of genotyping arrays.



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DEFINING REGIONS

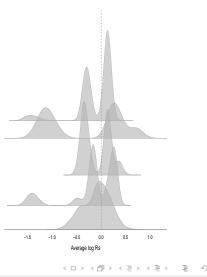


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EMPIRICAL ESTIMATES

- Mean and variances differ between loci .
- Expected value for diploid component is 0.
- When many deletions or duplications present, the diploid mean is biased away from 0.





MIXTURE MODEL

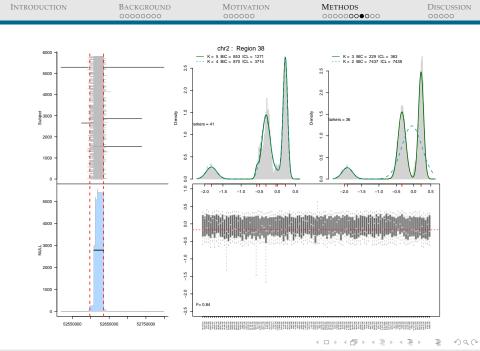
- The average log R ratios follow a mixture of Gaussian distributions.
- ► A finite dimensional Gaussian mixture model assumes data y = (y₁,..., y_n) ∈ Rⁿ are a sample from a from a probability density function of the form

$$f(\mathbf{y}|K,\theta,\sigma^2,p) = \sum_{k=1}^{K} p_k \phi_k(\mathbf{y}|\theta_k,\sigma_k^2)$$

Where K represents the number of components, $\phi(\cdot | \theta, \sigma^2)$ is a Gaussian distribution with mean θ and variance σ^2 and $\sum_{k=1}^{K} p_k = 1$.

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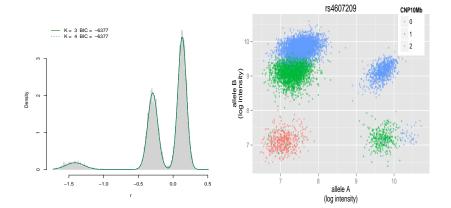
- Sample from a constrained full conditional on the θ's ensure identifiability and help convergence.
- ► Run chains of 5000 with a burn-in of 1000 for the 415 regions for each of K = 1...5 and choose constraints to ensure the means have a separation of 0.2.
- ► The Bayesian Information Criterion (BIC) was used to assess which of the five models arising from the choices of *K* best fit the data.



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Log-transformed intensities for the A and B allele for a SNP inside one locus on chromosome 4.



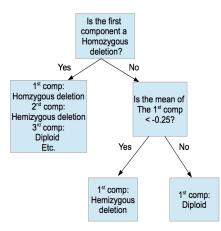
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ASSIGNMENT

- Need a way to infer what copy number state each component is.
- Average log R ratios are biased in CNPs, so we can't assume the component closest to 0 is diploid.
- Many CNPs do not contain SNPs, so information about heterozygosity is often not available.
- On the log-scale, distance between homozygous deletions and hemizygous deletions is large, and homozygous deletions have a large variance relative to the other components.
- ► Homozygous deletions are easy to detect.

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AD HOC APPROACH



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DISCUSSION

- ► We do not necessarily need to use the maximum a priori estimates to infer copy number.
- Our model has the advantage that we can assign a probability to each copy number assignment.
- This uncertainty in copy number estimates can be propagated to association models.

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COMPLICATIONS

- ► BIC often overestimates the number of components.
- When skew is present in one of the components, a model with an additional component to capture the skew will be preferred.
- A mixture model of skewed normal distributions may be more robust.



SKEW-NORMAL DISTRIBUTION

► A finite dimensional skew-normal mixture model assumes data y = (y₁,..., y_n) ∈ Rⁿ are a sample from a from a probability density function of the form

$$f(\mathbf{y}|K,\theta,\sigma^2,\alpha,p) = \sum_{k=1}^{K} p_k f_{SN_k}(\mathbf{y}|\theta_k,\sigma_k^2,\alpha_k)$$

Where α a skewness parameter.

 Full conditionals are available for the proper parameter transformations and Gibbs sampling is still feasible. (Frühwirth-Schnatter, 2010)

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Software

- R package CNPbayes available on github.
- MCMC methods implemented using Rcpp for rapid computations.
- Currently being prepared for submission to Bioconductor.

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WHAT NEXT

- Develop regression model for associating copy number classification with disease phenotype.
- Batch effects may be present. Consider adding a hierarchical structure to the parameters.
- Compare with other methods.

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THANKS

- ► Rob Scharpf
- ► Gary Rosner
- Leonardo and Jean-Philippe