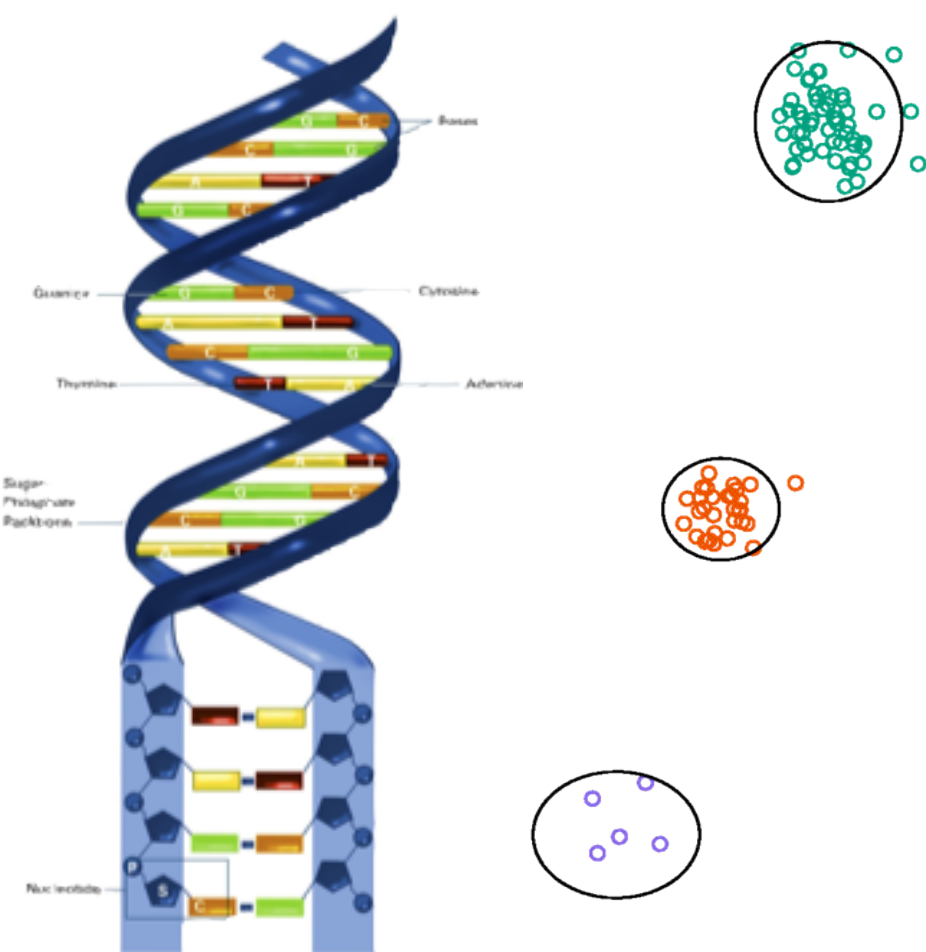




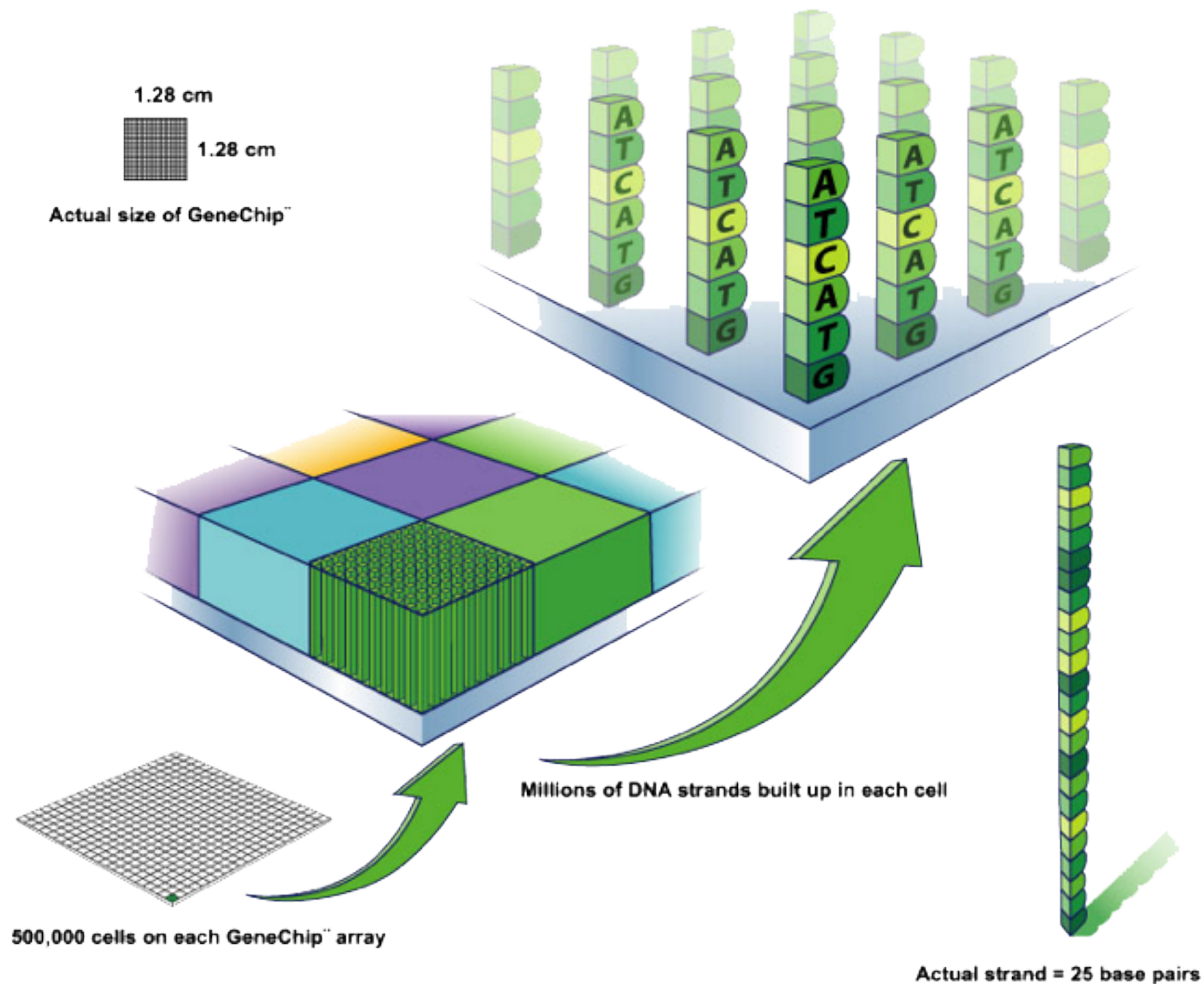
UNIVERSITY OF  
CAMBRIDGE



# SNP Analysis

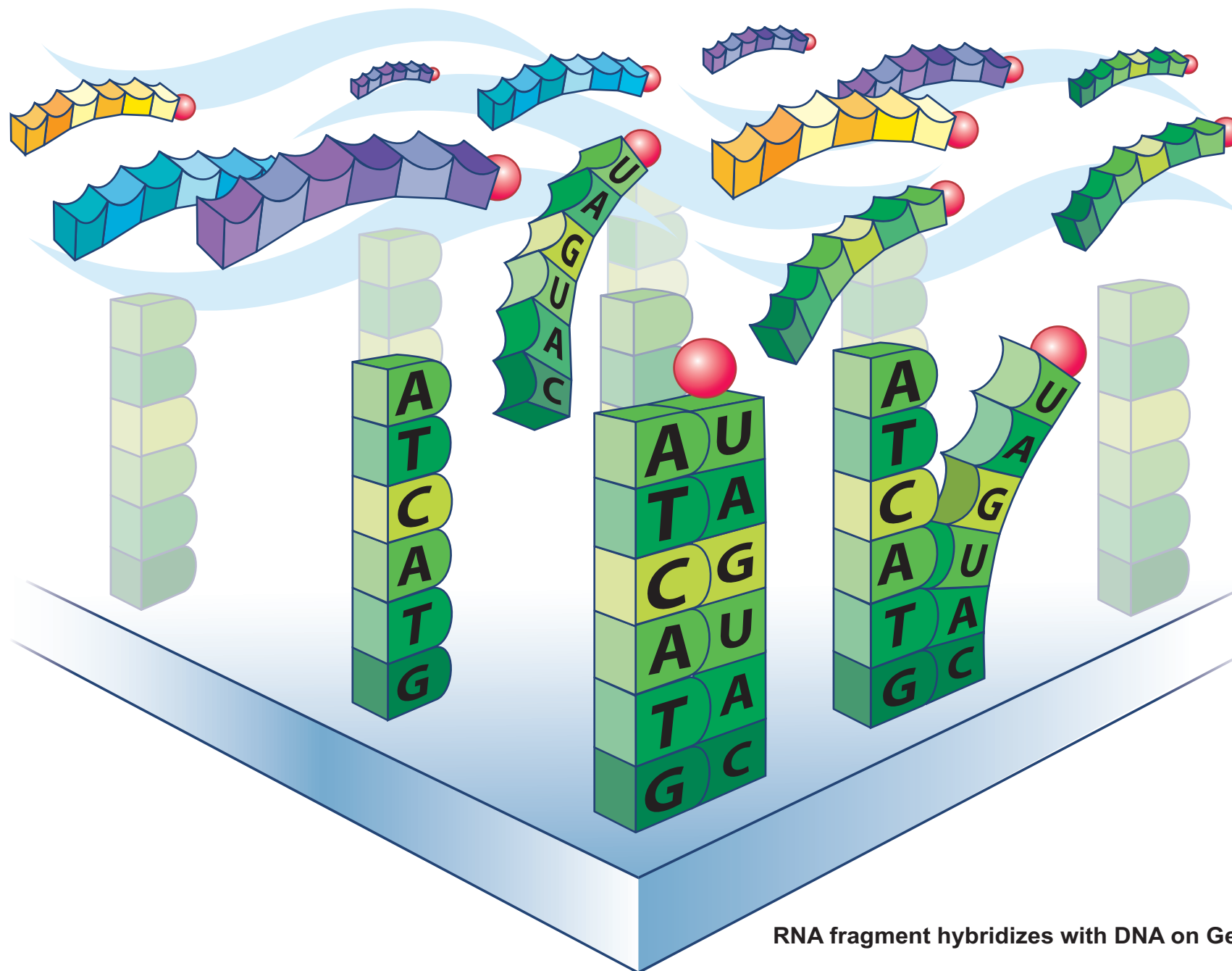
*Benilton S Carvalho*

# Array Design



# Hybridization

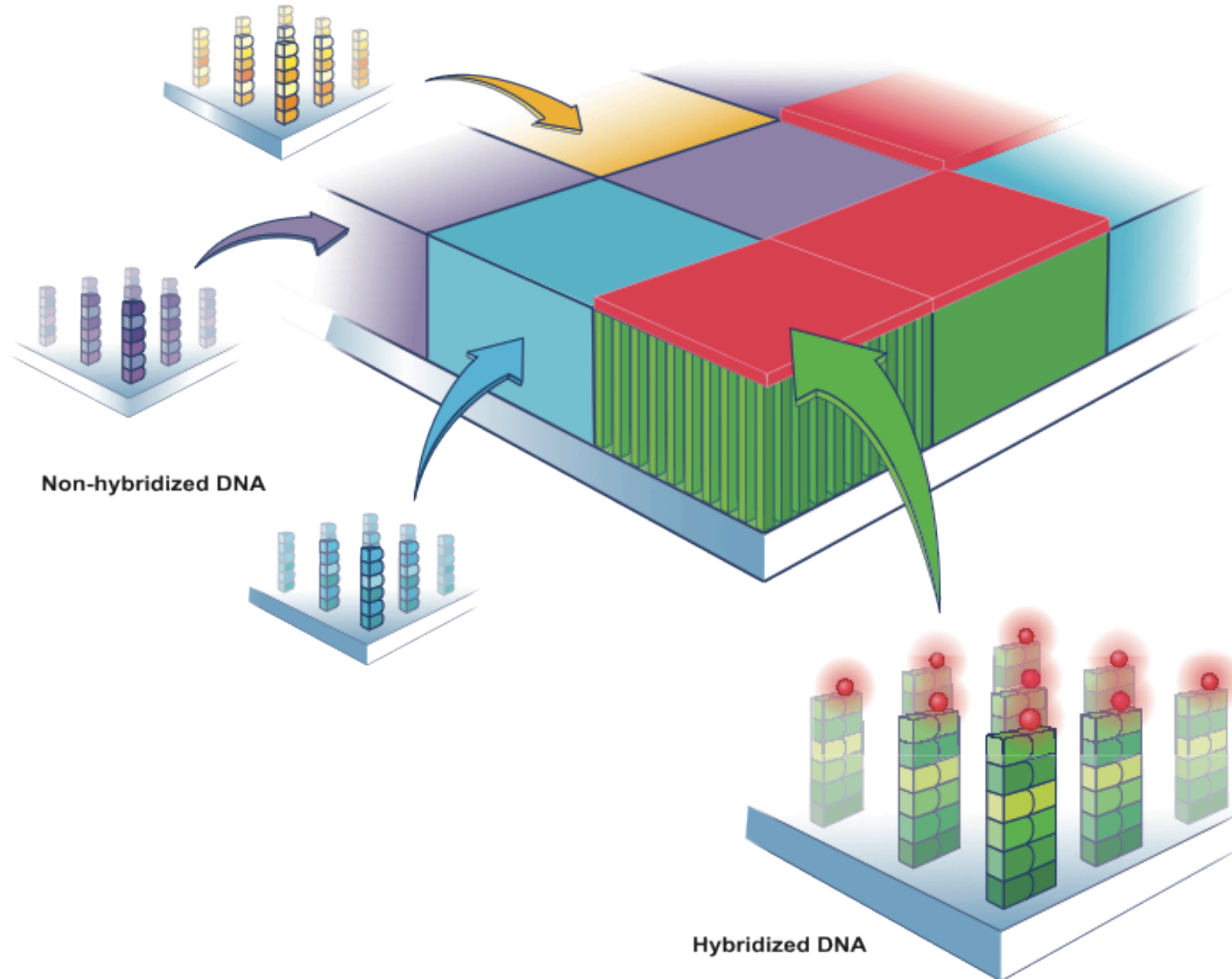
RNA fragments with fluorescent tags from sample to be tested



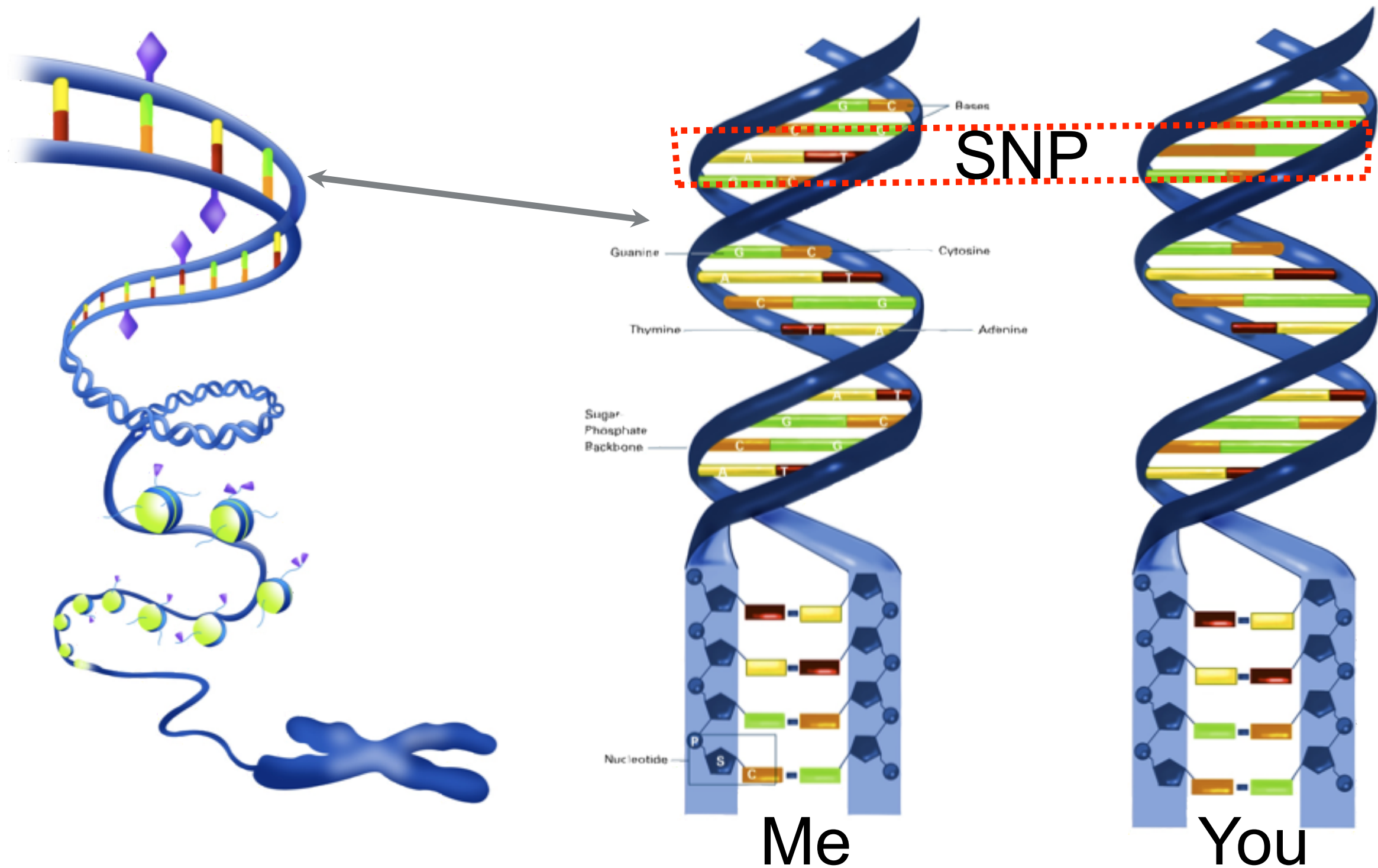
RNA fragment hybridizes with DNA on GeneChip® array

# Scanning

Shining a laser light at GeneChip® array causes tagged DNA fragments that hybridized to glow



# What is a SNP?



# SNP's

- DNA sequence variations;
- Prevalence  $> 1\%$ ;
- Responsible for  $\sim 90\%$  of all genetic variation;
- In average, at every 100-300 bp;



# SNP's and Disease Associations

- Yasuda *et. al.* show that each allele C in rs2237892 increases the odds of type 2 diabetes by 1.40 times compared to TT;
- Ferreira *et. al.* show that each T in rs4948418 increases the odds of bipolar disease by 1.45 times compared to CC;
- Nature Genetics, Aug 17, 2008.

Genotype accurately at  
high-density using  
oligonucleotide  
microarrays!



# Part I

## Creating the genotyping algorithm

- Carvalho et al. Exploration, normalization, and genotype calls of high-density oligonucleotide SNP array data. Biostatistics (2007) vol. 8 (2) pp. 485-99
- Lin et al. Validation and extension of an empirical Bayes method for SNP calling on Affymetrix microarrays. Genome Biol (2008) vol. 9 (4) pp. R63

# SNP Chip

- Genomic unit of interest: SNP;
- Intensities are observed for a list of SNP's on both alleles (A and B) often on two directions (sense and antisense);

$$\begin{aligned} M &= \log \frac{\theta_A}{\theta_B} \\ &= \log \theta_A - \log \theta_B \\ S &= \frac{\log \theta_A + \log \theta_B}{2} \end{aligned}$$

# Naïve Genotyping with Log-Ratio

$$M = \log \theta_A - \log \theta_B$$

$$M > K \rightarrow AA$$

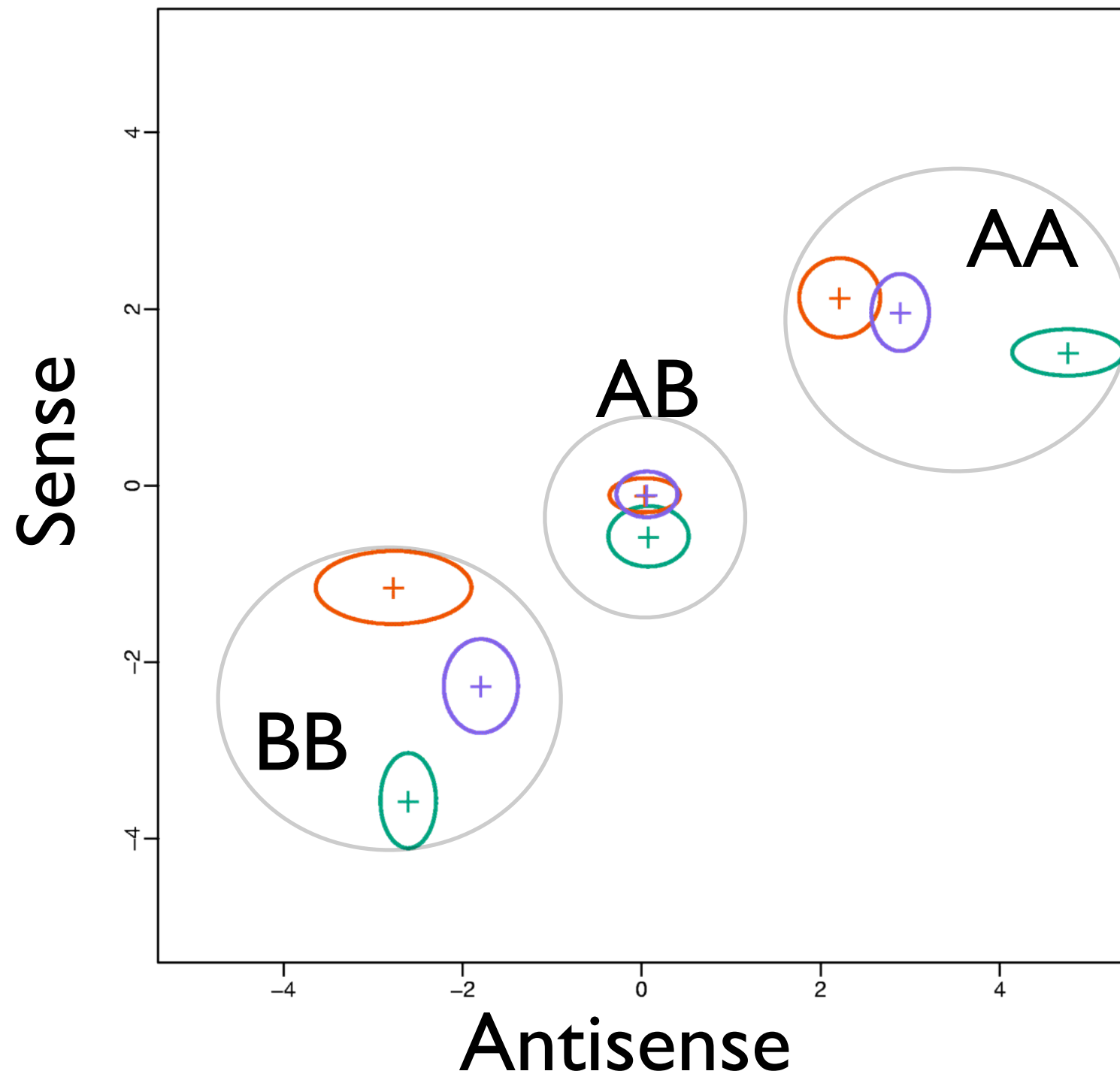
$$-K \leq M \leq K \rightarrow AB$$

$$M < -K \rightarrow BB$$

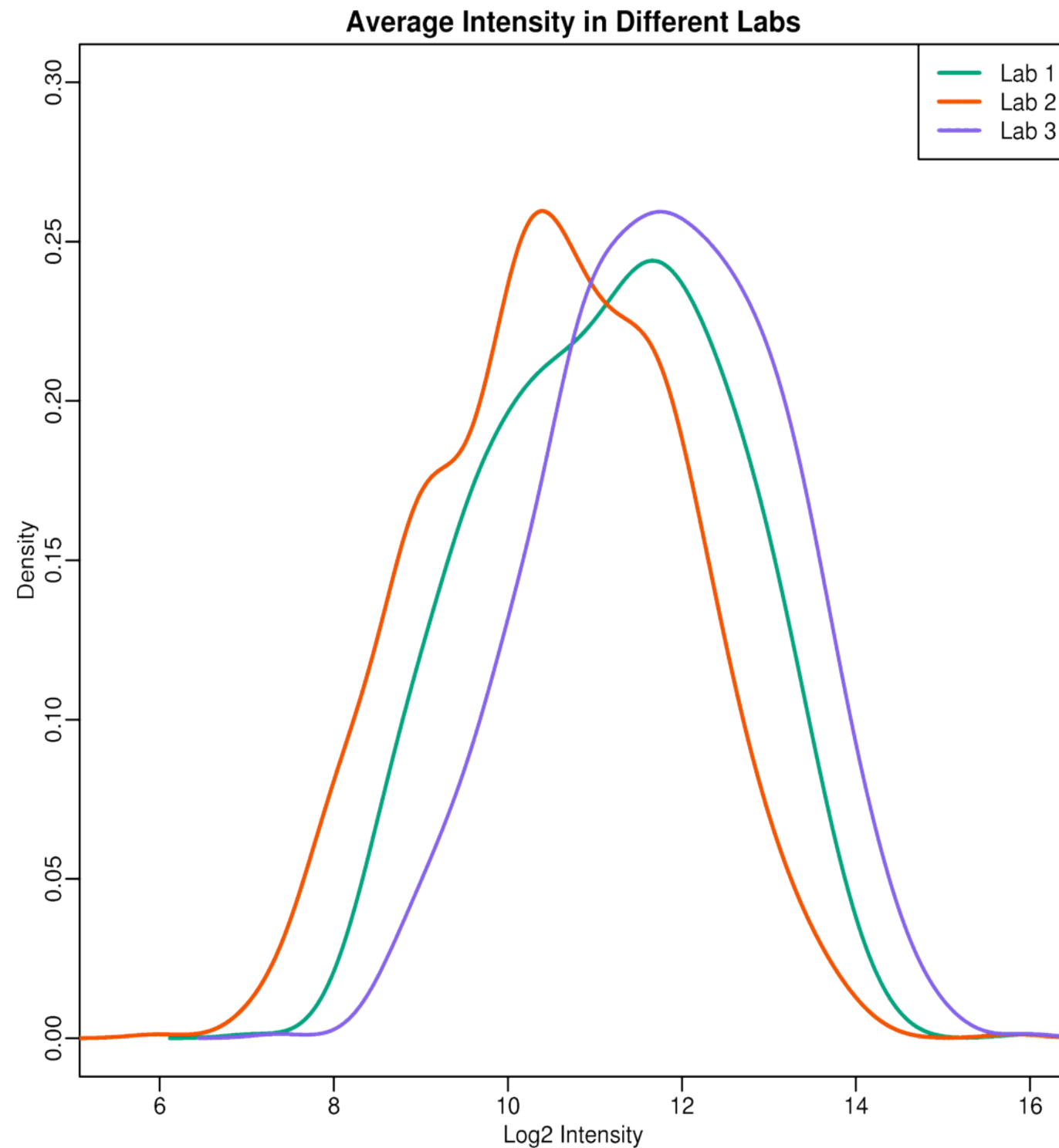
# HapMap Dataset

- 270 subjects (1000+ on Phase 3);
- Different ethnicities (eg. CEU, CHB, JPT, YRI);
- Gold-standard genotypes publicly available;
- Samples available in different SNP platforms;

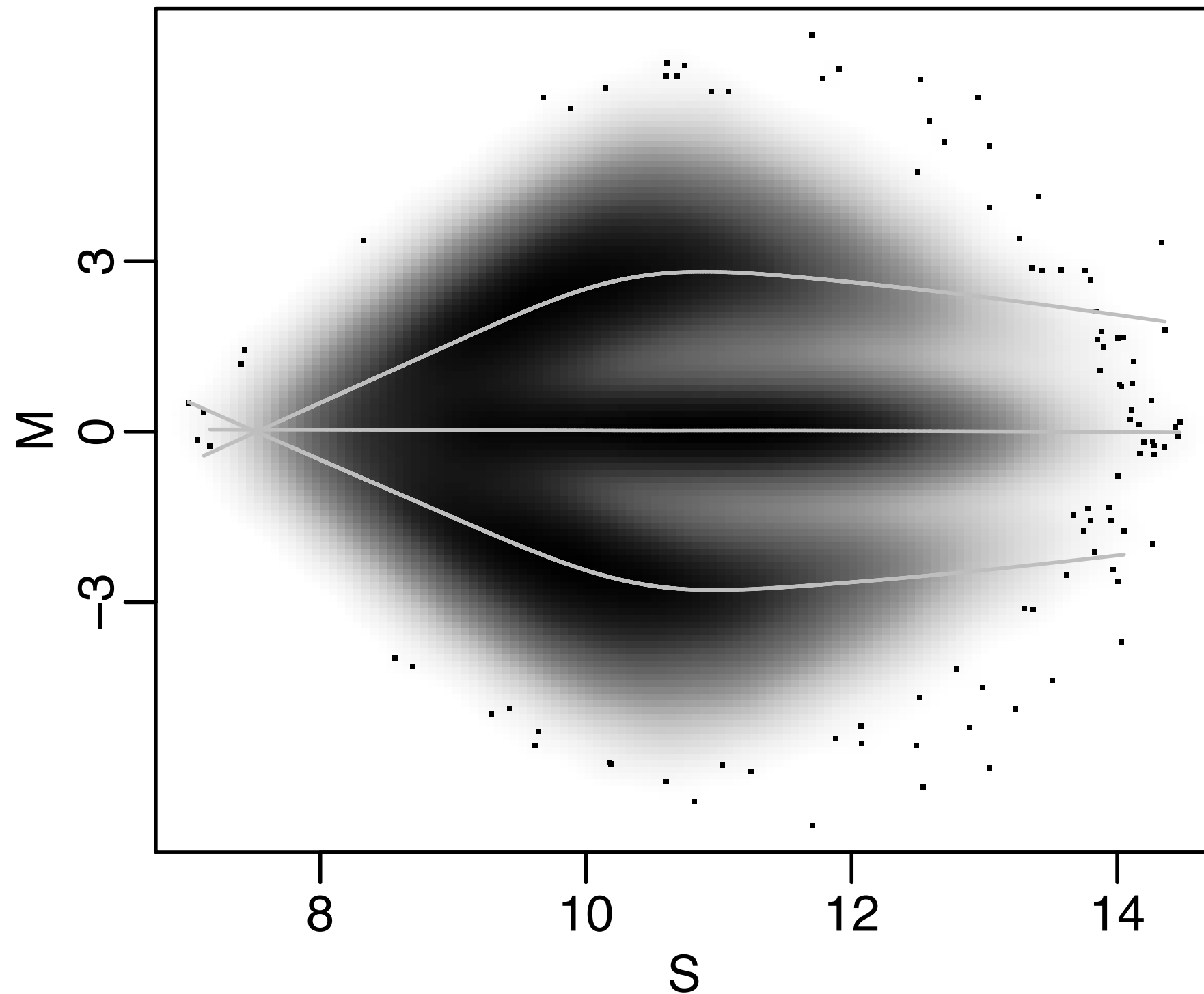
# Learning from HapMap



# Different Distributions



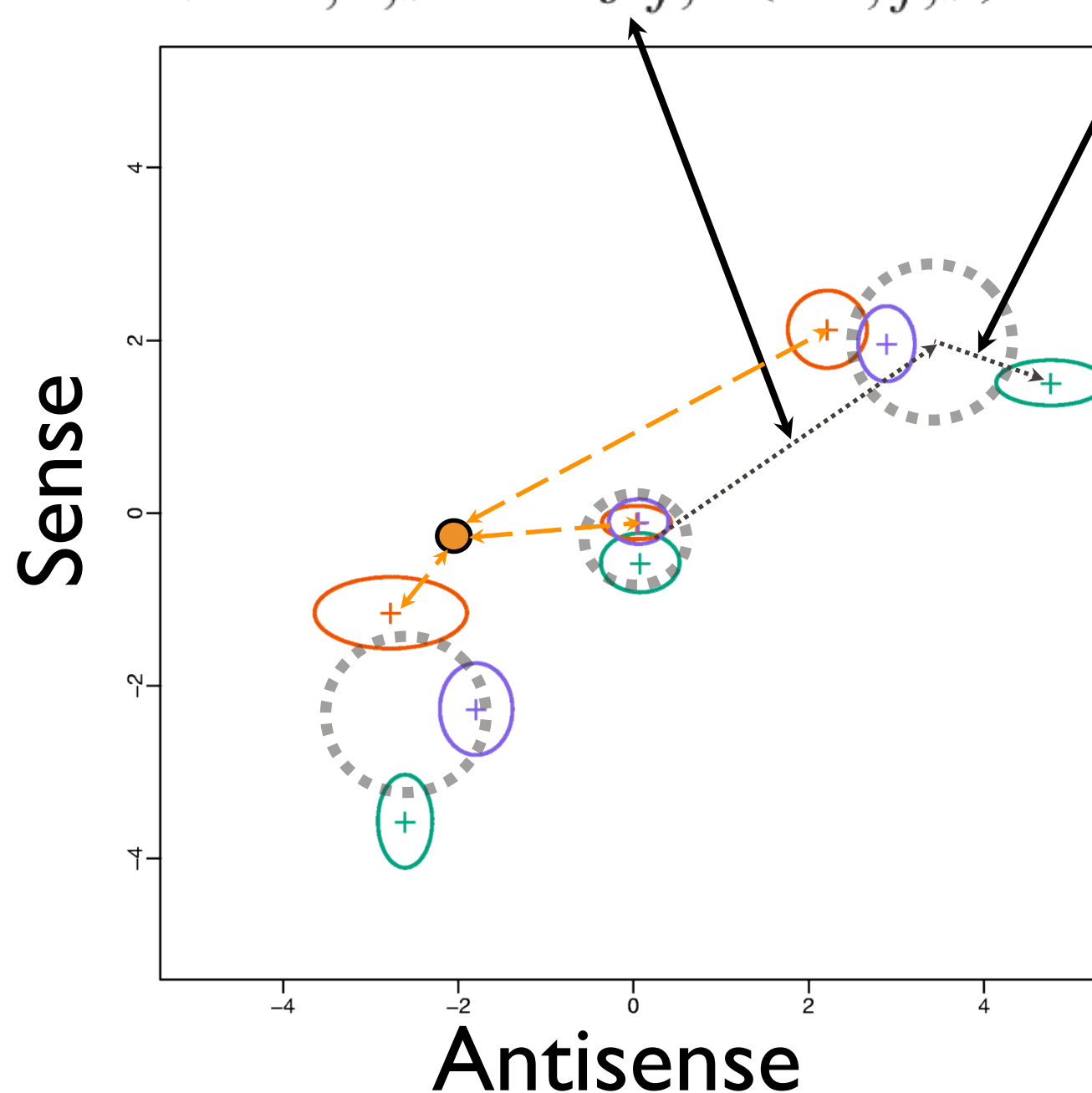
# Log-ratio and Strength



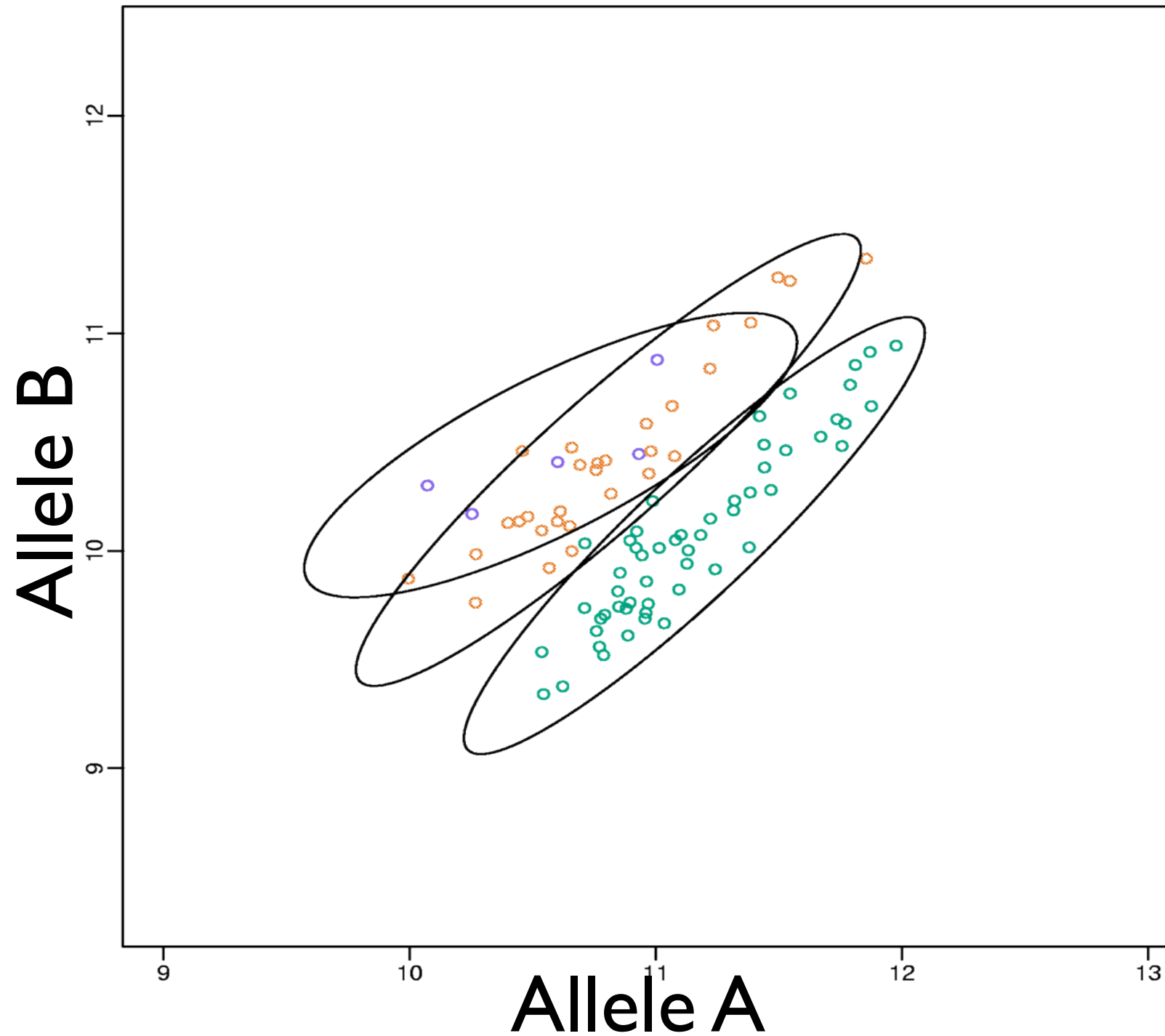


# Model Used by CRLMM

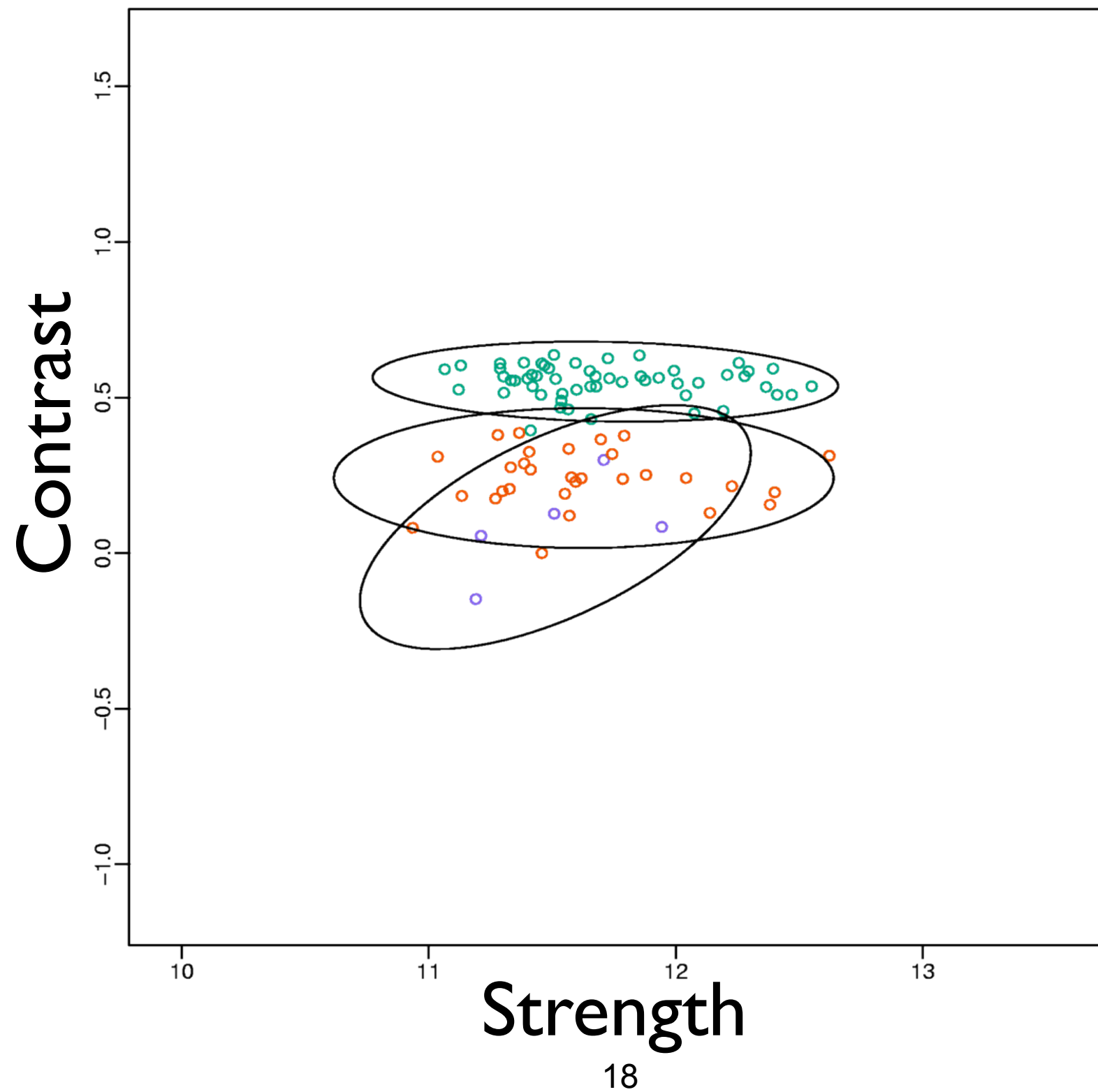
$$[M_{i,j,s} | Z_{i,j} = k, m_{i,k,s}] = f_{j,k}(\mathbf{X}_{i,j,s}) + m_{i,k,s} + \epsilon_{i,j,k,s}$$



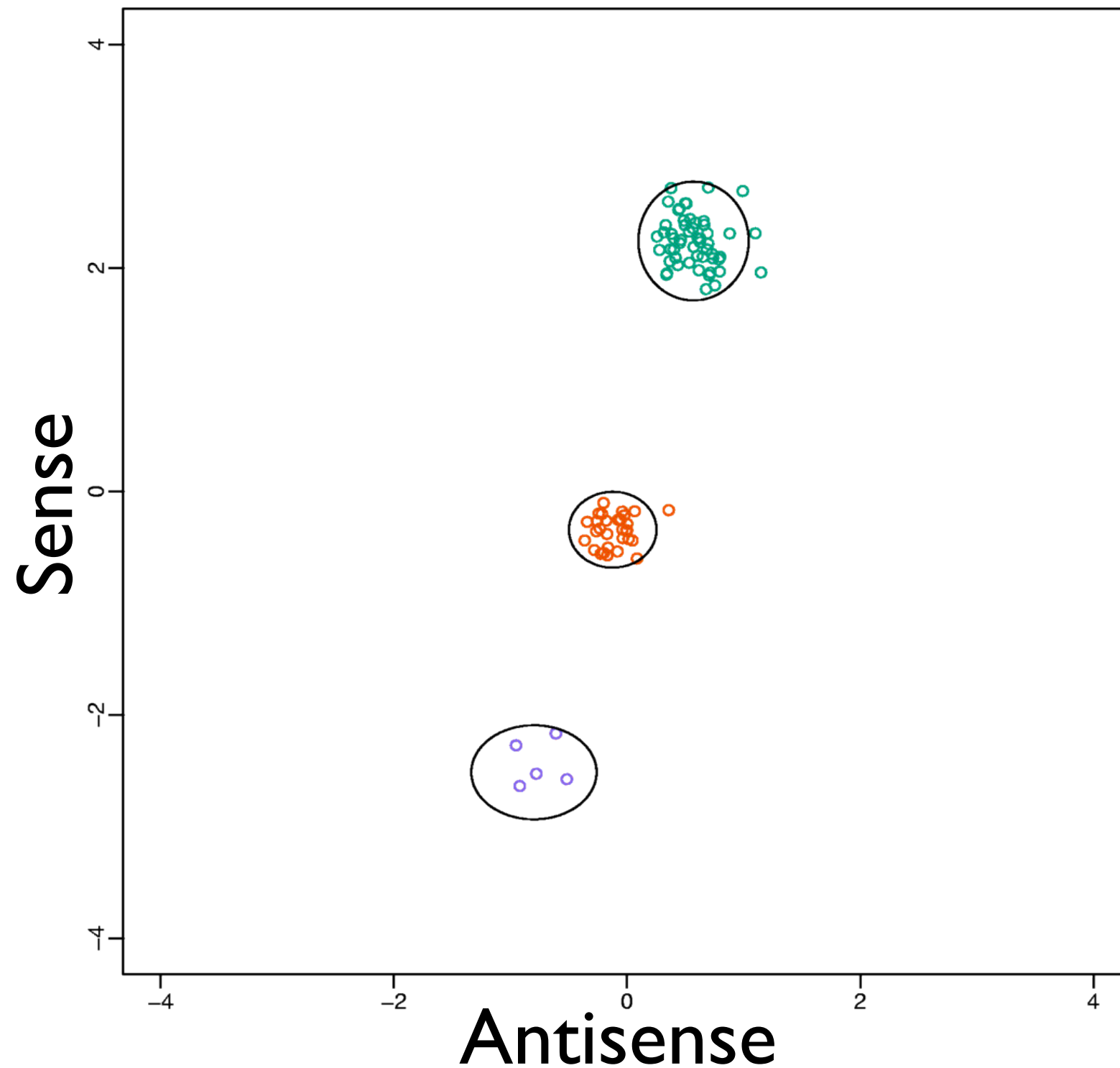
# RLMM and Strand Discrimination



# BRLMM and Strand Discrimination



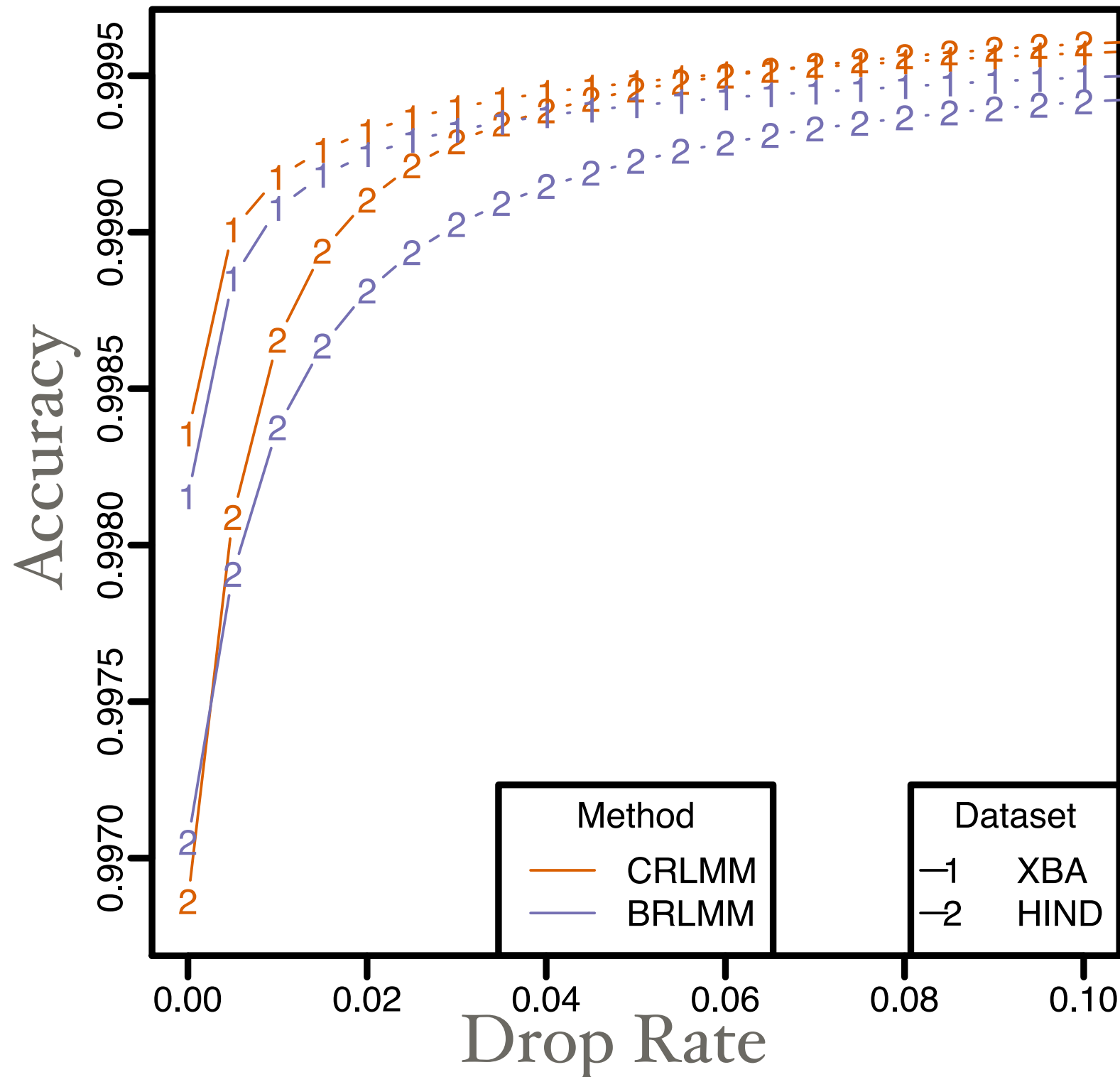
# CRLMM and Strand Discrimination



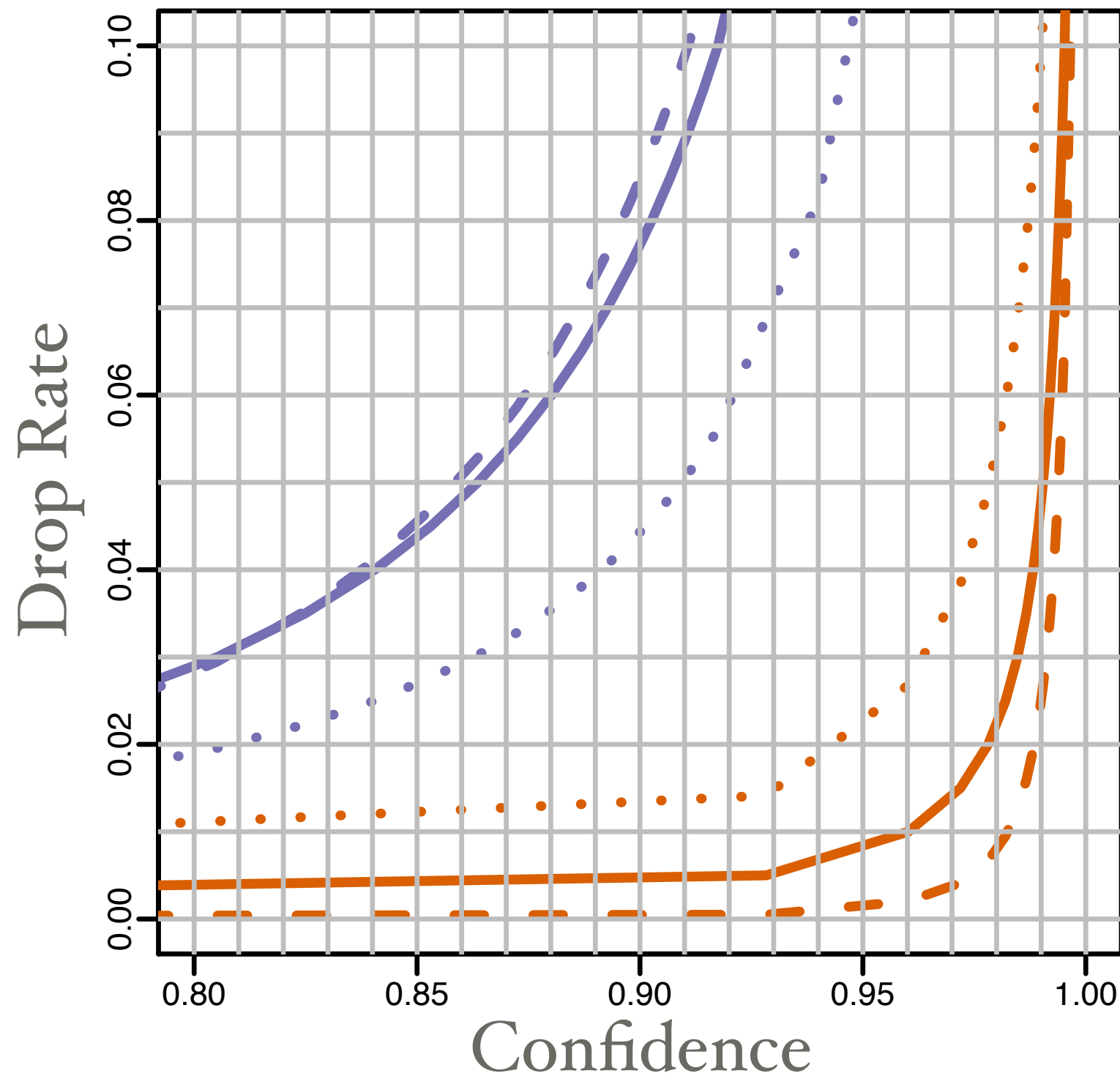
# Assessment of a Genotyping Algorithm

- Accuracy - algorithm's calls compared to the gold-standard calls;
- Observed drop-rate when filtering;
- Confidence scores not associated to genotypes;

# Accuracy vs. Drop Rate

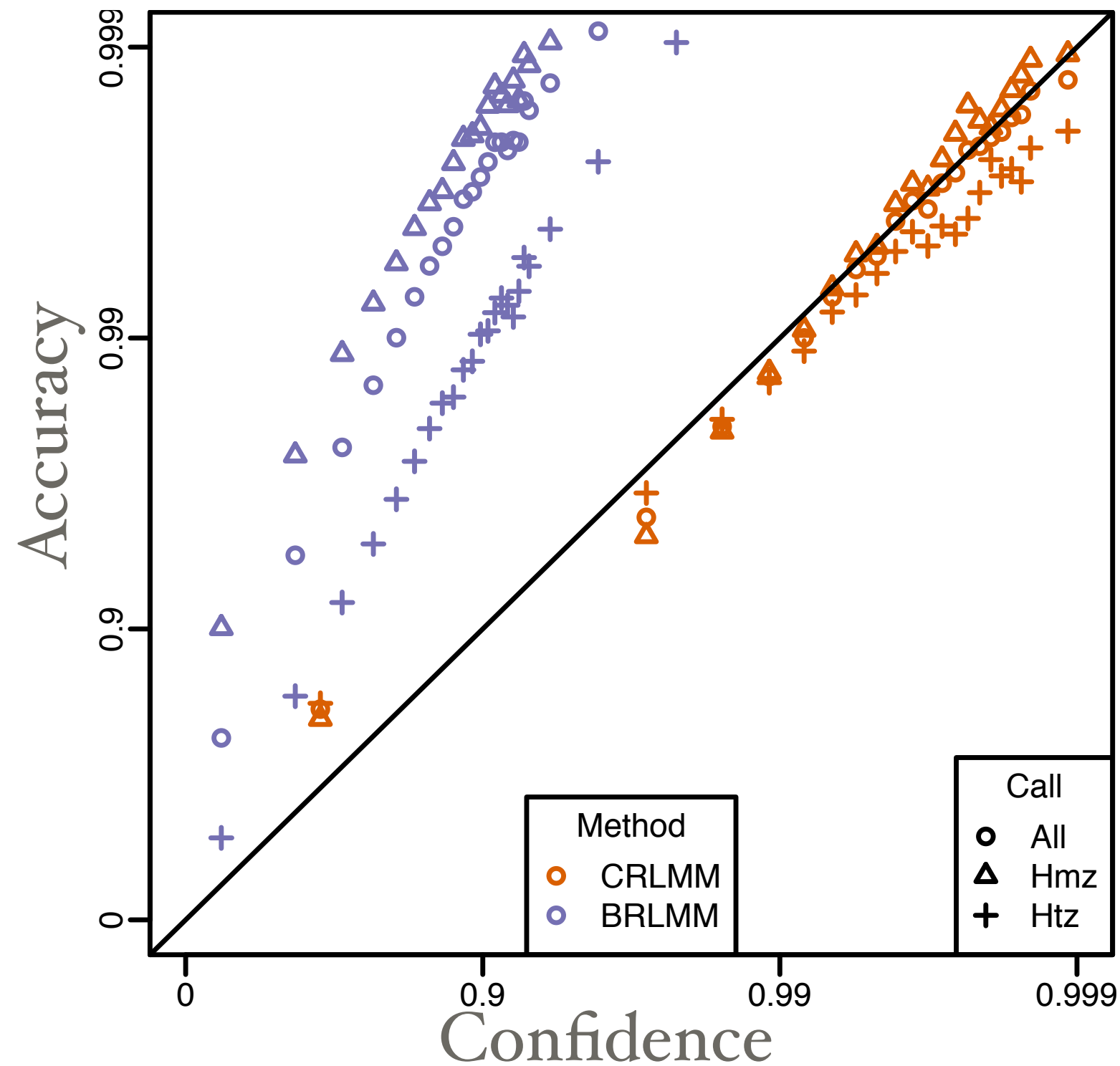


# Drop Rate vs. Confidence





# Accuracy vs. Confidence



# Summary

- CRLMM is a genotyping algorithm for the Affymetrix platform (50K, 250K, 500K and 1M);
- Outperforms standard tools:
  - HapMap: 50K, 250K, 1M;
  - Repetition: 250K, 1M;
- Freely available via BioConductor.

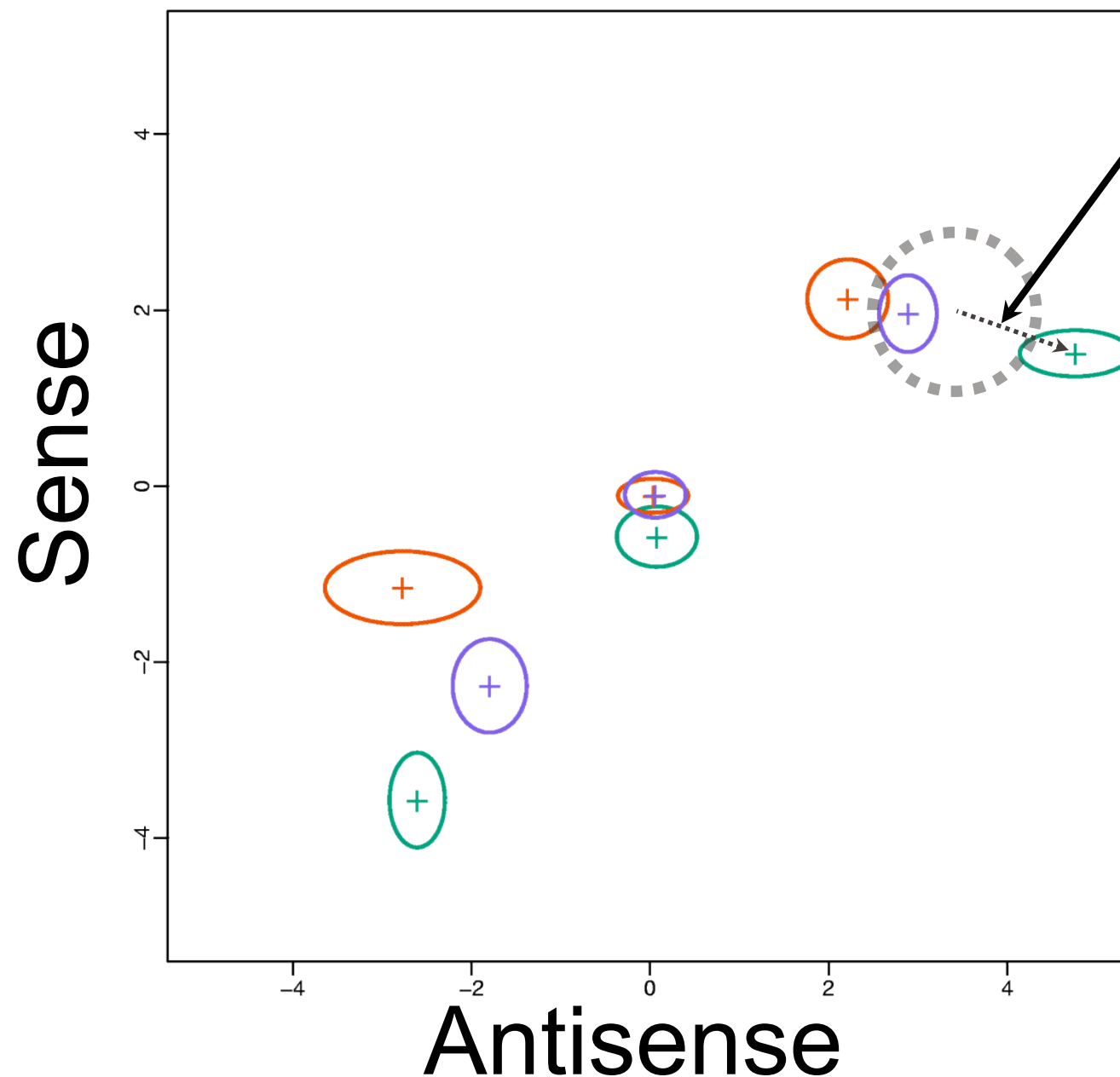
# Part II

## Improving the genotyping algorithm

Carvalho et al. Quantifying uncertainty in genotype calls. Bioinformatics (2010) vol. 26 (2) pp. 242-9

# Model Used by CRLMM

$$[M_{i,j,s} | Z_{i,j} = k, m_{i,k,s}] = f_{j,k}(\mathbf{X}_{i,j,s}) + \textcircled{m_{i,k,s}} + \epsilon_{i,j,k,s}$$

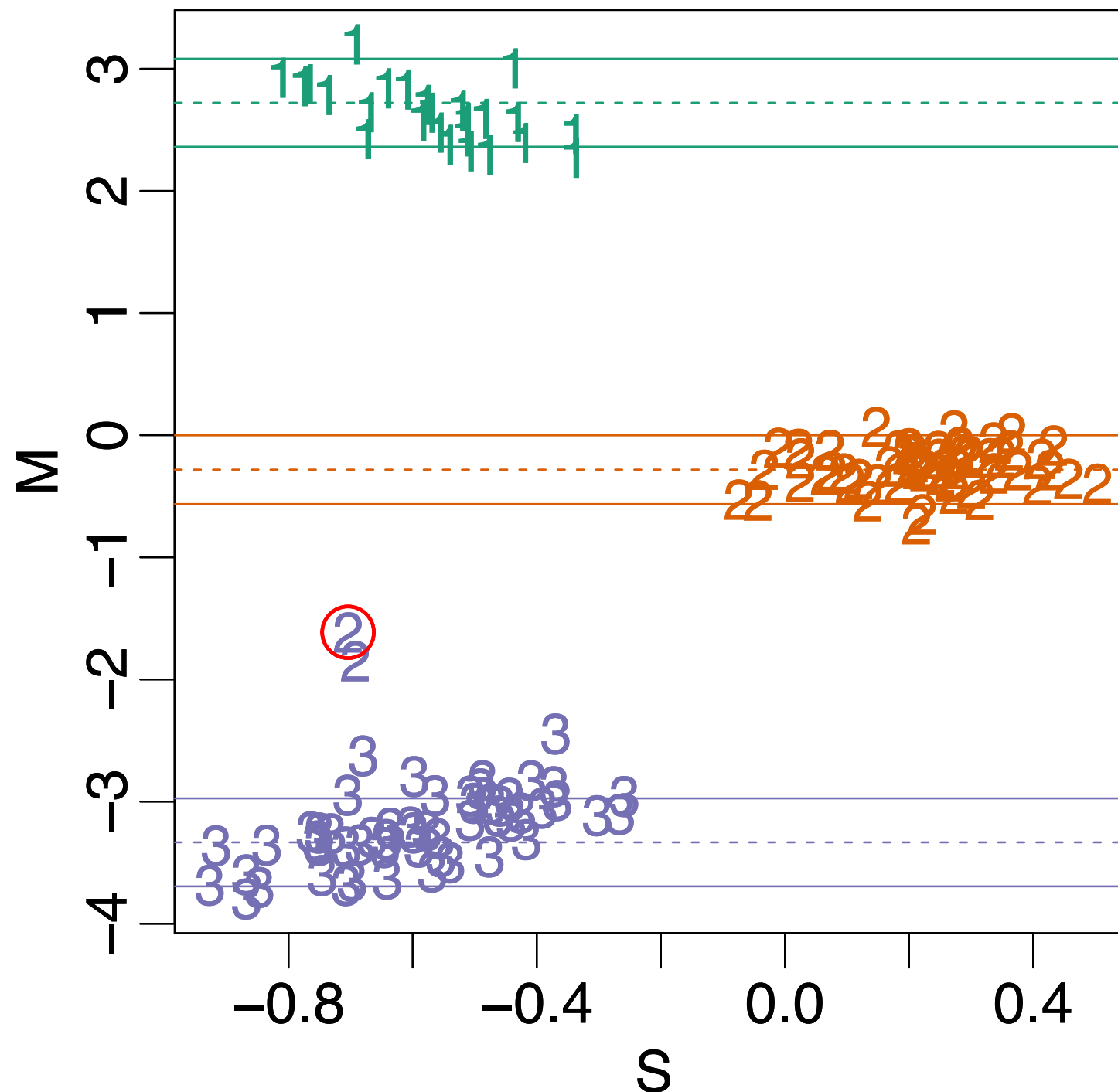


# CRLMM Model

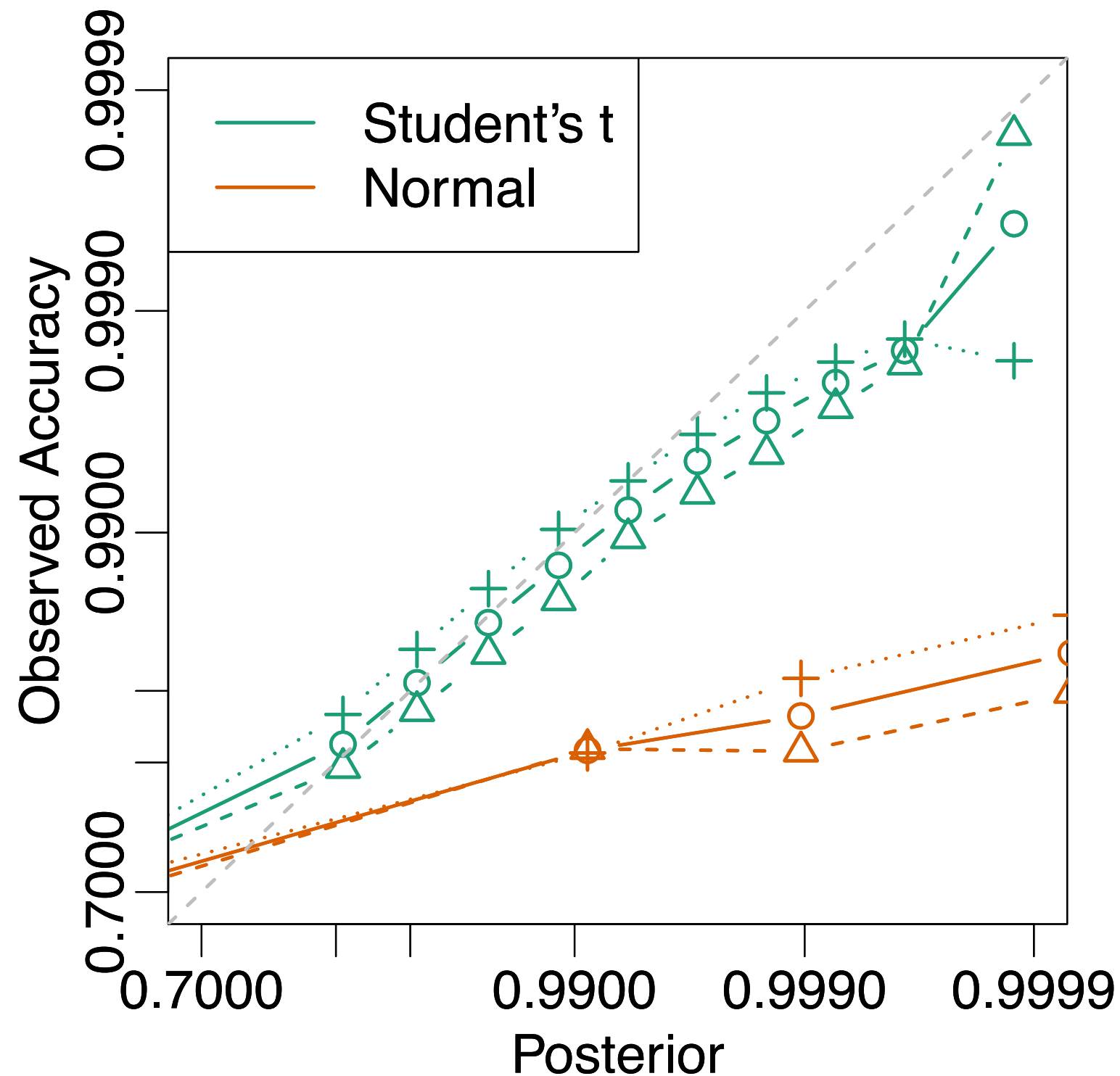
$$[M_{i,j,s} | Z_{i,j} = k, m_{i,k,s}] = f_{j,k}(\mathbf{X}_{i,j,s}) + m_{i,k,s} + \epsilon_{i,j,k,s}$$

- The location parameters for SNP's were estimated from the HapMap dataset;
- Assumes the SNP-specific shift is a fixed effect;
- SNP's with few observations on HapMap should have their confidences penalized somehow, and they don't;
- Error follows a Normal distribution;

# Observed Improvements



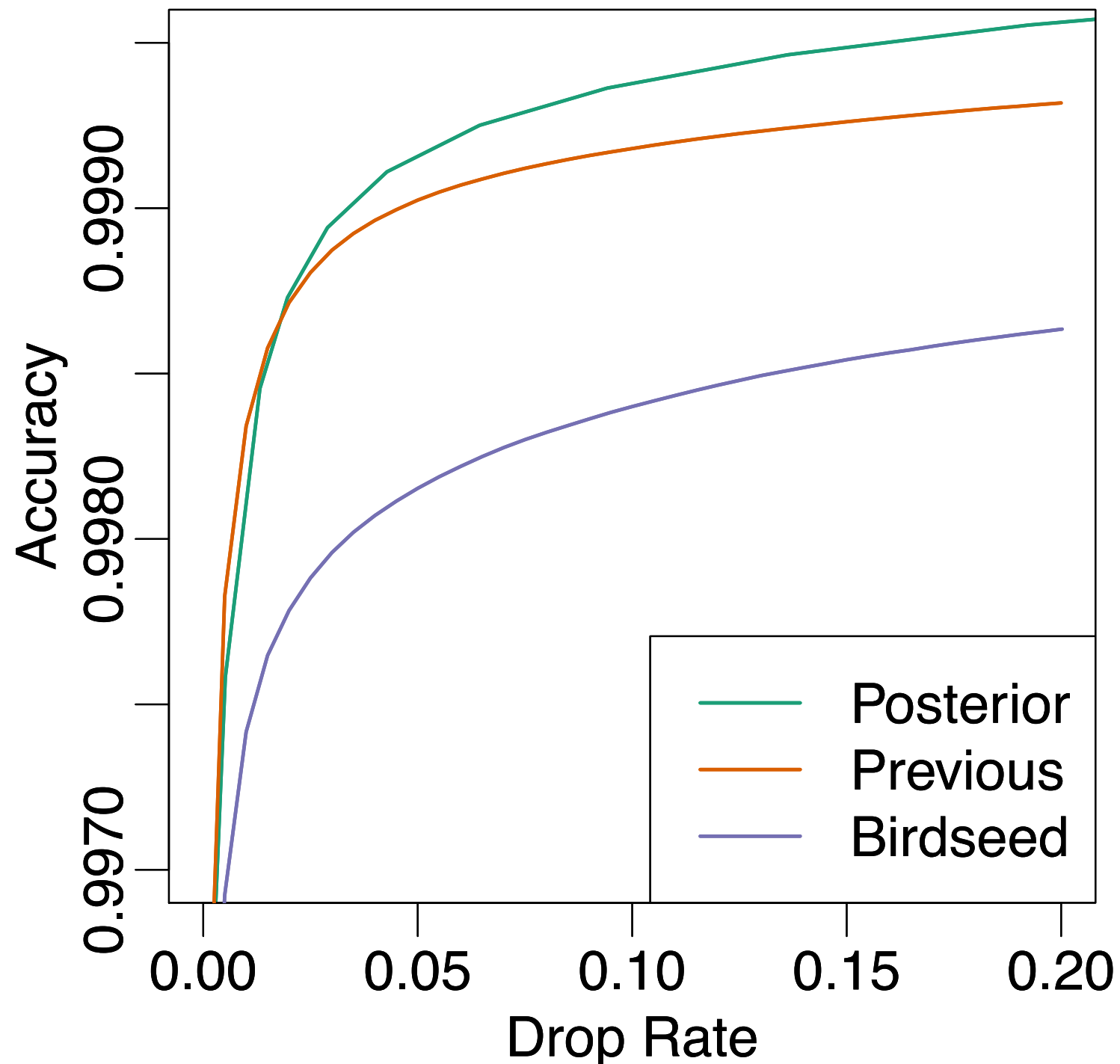
# Observed Improvements





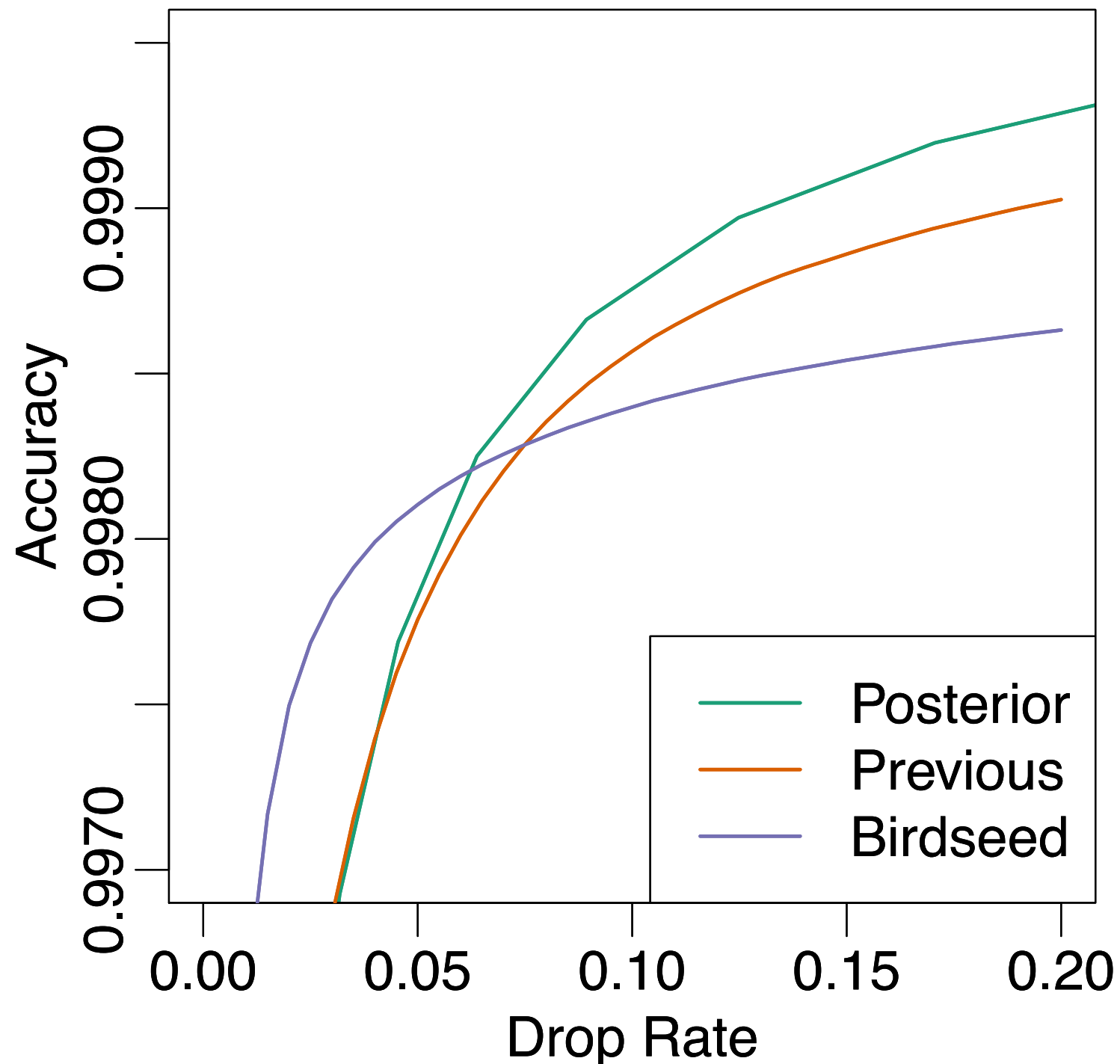
# Observed Improvements

**Dataset A – Batch QC = 0.0337**



# Observed Improvements

**Dataset B – Batch QC = 0.0745**



# Summary

- New approach evaluated in different datasets;
- All samples are part of HapMap;
- Experiments performed in 7 laboratories;
- Posterior probabilities outperformed CRLMM;
- Sample size in training set was adequately accounted for;
- Also available for Illumina chips;