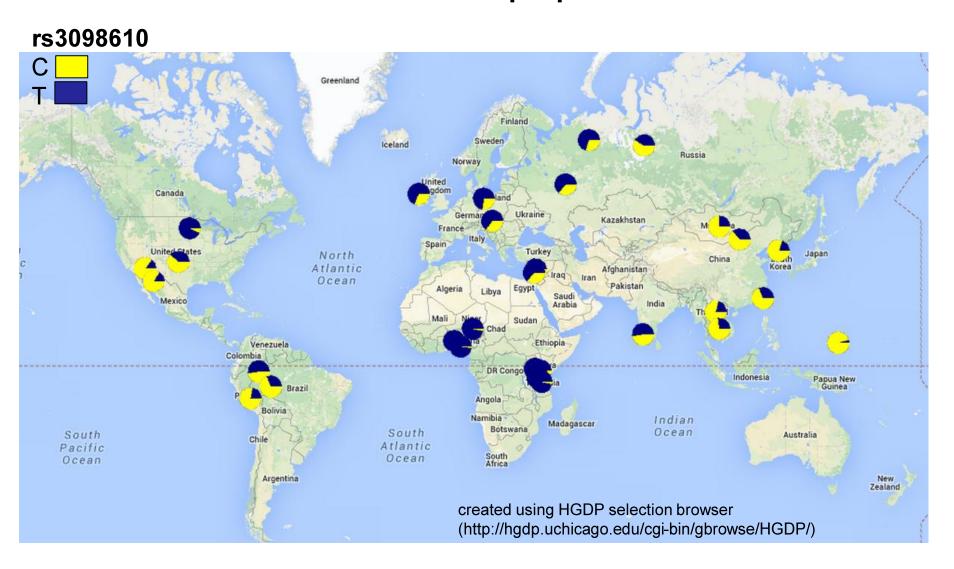
Fast individual ancestry inference from DNA sequence data leveraging allele frequencies from multiple populations*

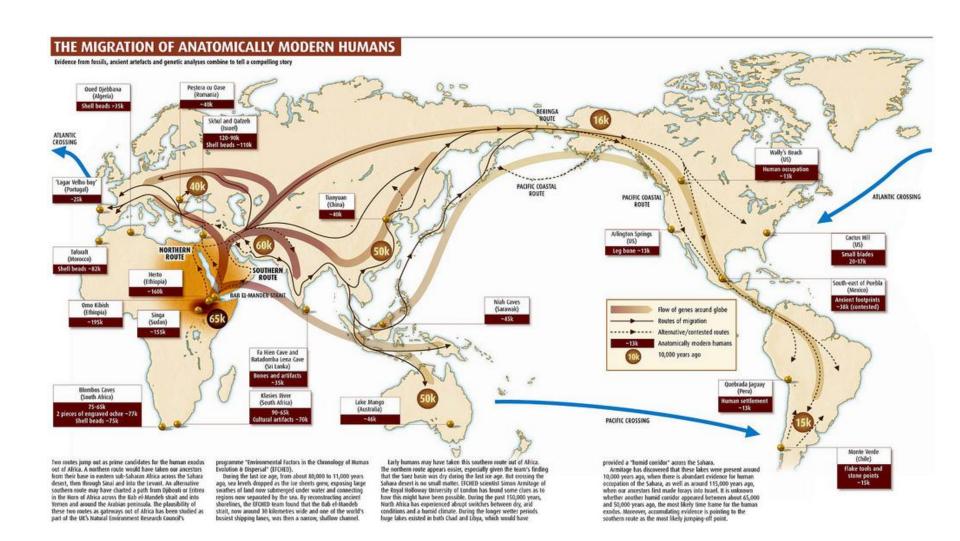
Vikas Bansal, Ph.D.

Department of Pediatrics

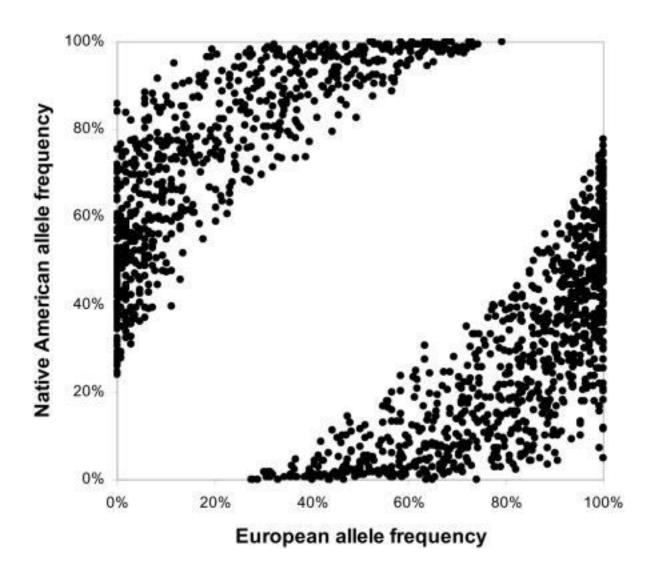
UC San Diego

Allele frequencies at polymorphic sites differ across human populations





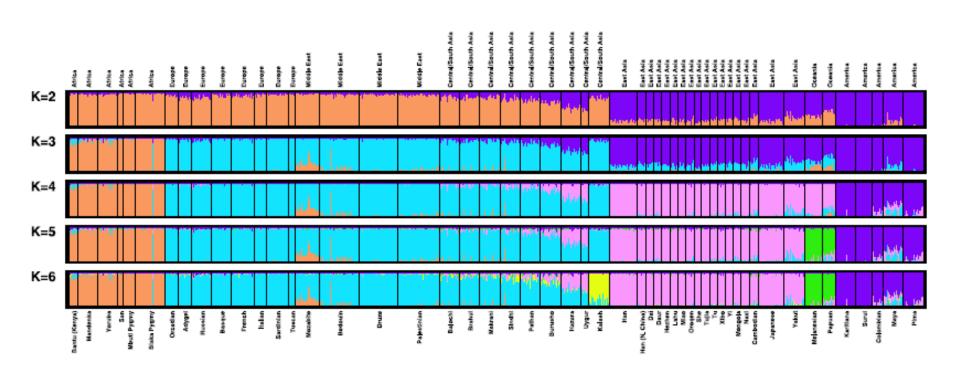
from the New Scientist



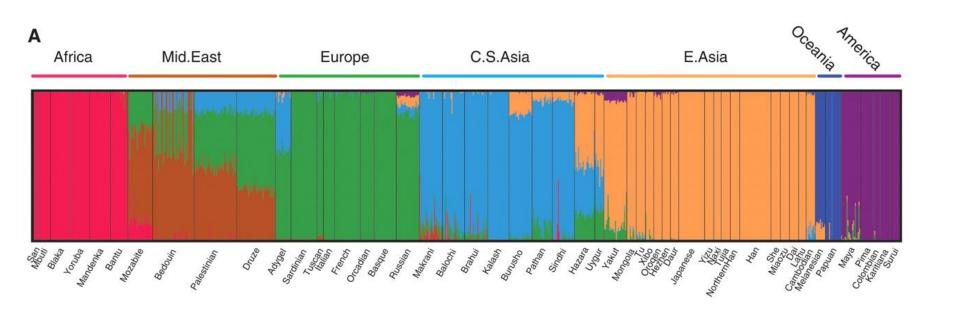
European and Native American allele frequencies for the 1,649AIMs (Figure 4 from Price et al., AJHG 2007)

Differences in allele frequencies can be used to reconstruct human population structure using genetic data from a number of polymorphic loci

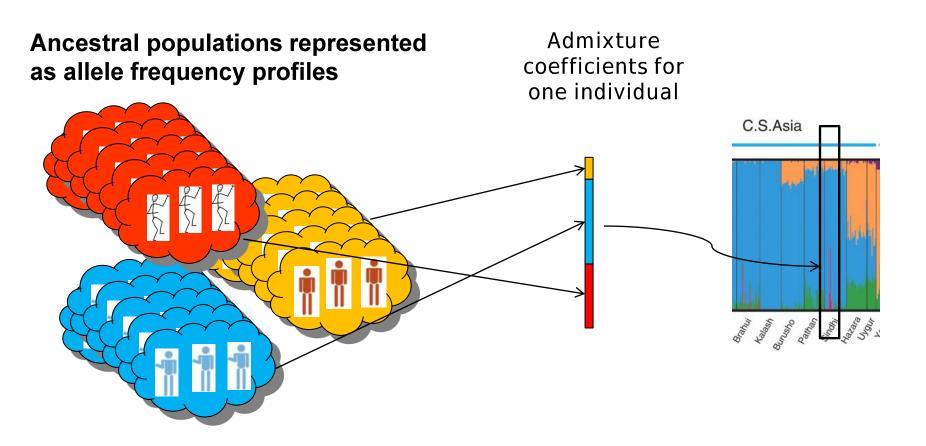
Rosenberg et al. 2002: genotyped 1052 individuals from 52 populations at 377 microsatellites



Fine-scale genetic structure of human populations using 650,000 markers



The admixture model

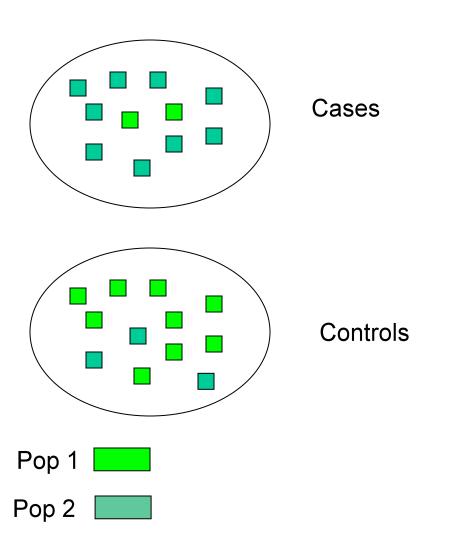


- Allele frequencies for each cluster derived using genotypes of individuals that have non-zero admixture coefficient for that cluster
- Each individual's admixture estimated using allele frequencies

Methods for reconstructing population structure

- STRUCTURE (Pritchard et al. 2000): Bayesian MCMC method for simultaneous inference of allele frequencies for 'K' populations and admixture coefficients for each individual
 - very popular and useful tool
 - Not scalable to genome-wide datasets
- ADMIXTURE (Alexander et al. 2009): Maximum likelihood approach to population structure that used fast optimization algorithms for efficiency

Important to control for population stratification in disease association studies



- Cases and controls are sampled from two populations in different proportions
- Loci that differ in allele frequency between the two ancestral populations will show association with the phenotype

Motivation for our work

- Previous methods designed for unsupervised population structure analysis but not for individual ancestry determination
 - Analysis of one new individual requires genotype data for individuals with known ancestry and analysis of all individuals
 - Cannot handle sequence data where genotypes are not known with confidence, e.g. low coverage sequence data
- Efficient method designed for ancestry estimation for a single individual
 - Utilizes allele frequency from known populations
 - Works with genotype and sequence data (BAM, VCF files)

Admixture likelihood model

INPUT:

- Allele frequencies at 'n' SNPs for K populations
- Genotypes or genotype likelihoods for an individual
- **OUTPUT**: $A = [a_1, a_2, a_K]$ of admixture proportions such that the sum of admixture proportions = 1

$$L(A) = \sum_{i=1}^{n} \ln(Pr(G_i = g_i|A))$$

Admixture likelihood model (contd..)

$$L(A) = \sum_{i=1}^{n} \ln(Pr(G_i = g_i|A))$$

$$Pr(G_i = 0|A) = (1 - f_i)^2$$

$$Pr(G_i = 1|A) = 2f_i(1 - f_i)$$

$$Pr(G_i = 2|A) = f_i^2$$

$$f_i = \sum_{j=1}^k q_{ij} a_j$$

 Non-linear optimization problem with K variables with constraints on the admixture coefficients

Optimization using the BFGS method

- Broyden-Fletcher-Goldfarb-Shanno algorithm is a quasi-Newton method for unconstrained non-linear optimization
- Uses first derivatives and approximation of Hessian matrix

Features

- Good performance even for 1000's of variables
- BFGS-B variant handles box constraints on variables
- Several open-source implementations are available
- Constraint on sum can be addressed by replacing a_j with $\frac{a_j}{\sum_k a_k}$
- First derivates can be easily calculated as:

$$\frac{\partial L(A)}{\partial a_j} = \sum_{i=1}^n \left[\frac{g_i q_{ij}}{f_i} - \frac{g_i}{S(a)} + \frac{(2 - g_i)(1 - q_{ij})}{S(a) - f_i} - \frac{2 - g_i}{S(a)} \right]$$

Parsimonious estimation of admixture coefficients

- BFGS optimization finds maximum likelihood estimate of admixture coefficients
- Useful to determine if a non-zero admixture coefficient is statistically significant
 - Previous methods estimate confidence intervals using bootstrap
- Backward elimination method for variable selection to obtain parsimonious vector of admixture coefficients
 - Find population 'j' for which setting a_j to 0 reduces the likelihood value the least
 - 2. Fix a_i = 0 and iterate until possible

Analysis of Mozabite individuals from HGDP

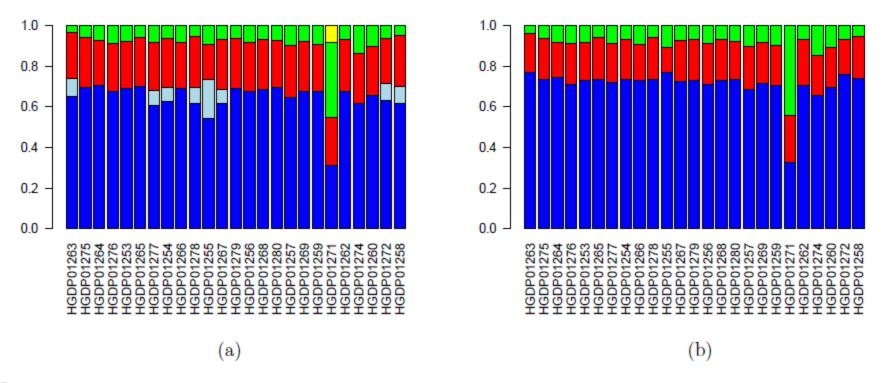


Figure 1: Admixture proportions for 25 Mozabite individuals estimated using the HapMap reference populations and using two methods: iAdmix (a) and ADMIXTURE(b). The population labels are as follows: TSI (blue), CEU (light blue), MKK (red), YRI (green) and LWK (yellow).

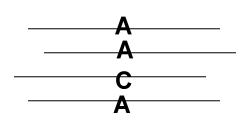
Implementation and running time

- Fortran implementation of L-BFGS-B algorithm (Zhu et al. 1997) was converted to C
- Computational complexity is linear in number of SNPs and number of reference populations
- Number of iterations for convergence (delta < 0.0001) was typically 20-30
- Our method was 10-15 times faster than ADMIXTURE (run in supervised mode) on simulated and real datasets

Estimating ancestry from sequence reads

Likelihood model for sequence reads

- Uncertainty in genotype calls derived from sequence reads
- Genotype likelihoods Pr(reads | genotype) capture uncertainty



$$e = 0.01$$

$$Pr(\mathbf{R_i} \mid g = AA) = 0.0097$$

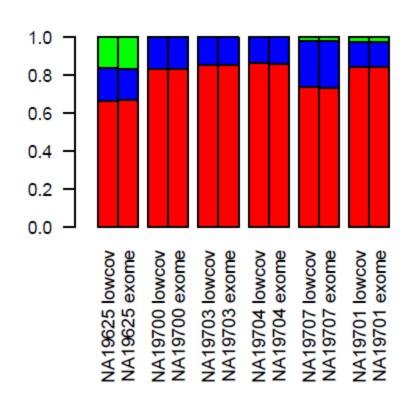
$$Pr(\mathbf{R_i} \mid g = AC) = 0.0625$$

$$Pr(\mathbf{R_i} \mid g = CC) = 0.99 \times 10-6$$

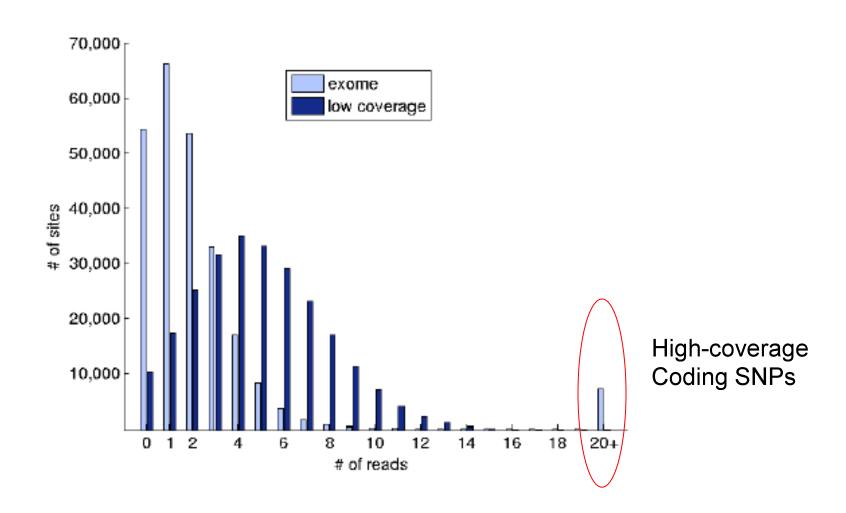
$$L(A) = \sum_{i=1}^{n} \ln \left[\sum_{g=0}^{2} Pr(\mathcal{R}_i | G_i = g) Pr(G_i = g | A) \right]$$

Analysis of 1000 Genomes data

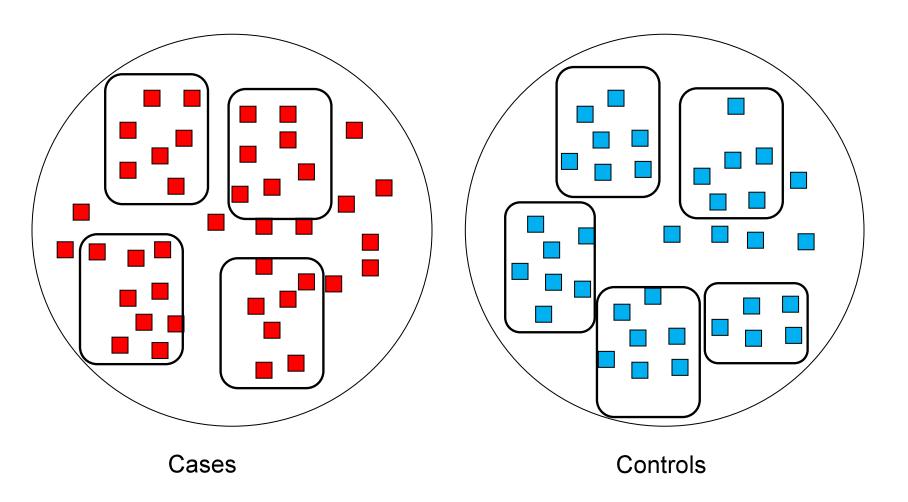
- Analyzed sequence reads for 6 individuals from the ASW (African-Americans in USA) population
- BAM files for low-coverage whole genome sequencing and exomesequencing available
- genotype likelihoods calculated for 249,075 SNPs that overlap the HapMap allele frequency data



Distribution of read-depth for HapMap3 sites

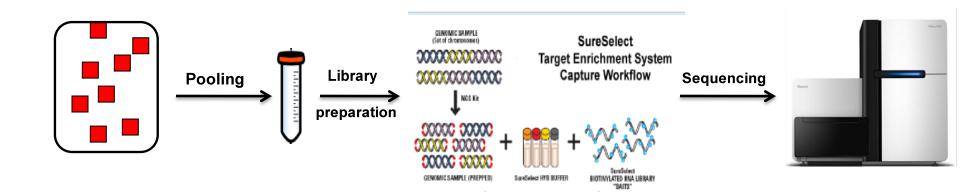


Estimating ancestry of 'artificial' DNA pools



 DNA from multiple individuals (20-30) pooled to form a single sample before sequencing

Cost-effective association studies using DNA pooling



- 2000 individuals -> 100 pools of size 20
- Targeted sequencing of coding sequence of 200-250 genes can be done for \$60,000
- Individual sequencing would cost ~ \$300,000

Ancestry estimation from pools: simulated data

- Extended genotype likelihood calculation for 'pooled' genotypes
- Evaluated ability to detect admixture in a single pool using 1000 Genomes data

Table 2: Admixture coefficients for four pools constructed from 1000 Genomes data using allele frequencies from 8 HapMap reference populations.

Pool composition	Admixture coefficients							
	CEU	TSI	$_{\mathrm{CHB}}$	CHD	$_{ m JPT}$	YRI	LWK	MKK
20 GBR	0.683	0.317	0	0	0	0	0	0
19 GBR, 1 CHS	0.6423	0.3042	0	0.0535	0	0	0	0
19 GBR, 1 LWK	0.6528	0.3125	0	0	0	0	0.0347	0
18 GBR, 1 LWK, 1 CHS	0.6064	0.3052	0	0.0562	0	0	0.0323	0

Summary

- Fast method for estimation of admixture coefficients from genotype or sequence data using allele frequencies
 - 10-15 times faster than previous methods
 - Ancestry can be analyzed using even targeted sequence data
 - Valuable tool for sequencing based studies
- Admixture likelihood model ignores linkage disequilibrium (LD) between markers
 - Haplotype-based likelihood model using haplotype frequencies and dynamic programming
 - BFGS algorithm can be used for optimization
- BFGS algorithm is a fast method for constrained high-dimensional non-linear optimization
 - Useful for many problems, e.g. genome scaffolding, logistic regression for low-coverage sequence data, variant calling