# Population structure II PCA

Anders Albrechtsen

# The idea in general

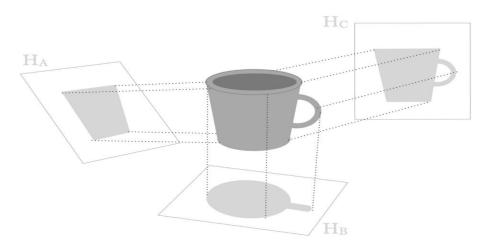
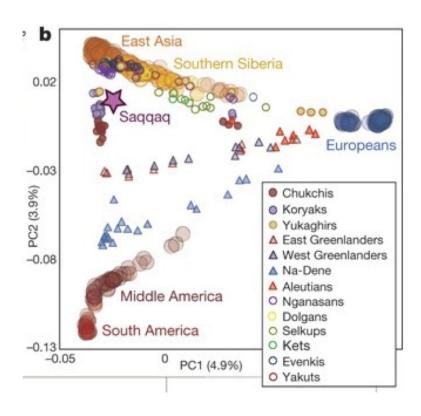
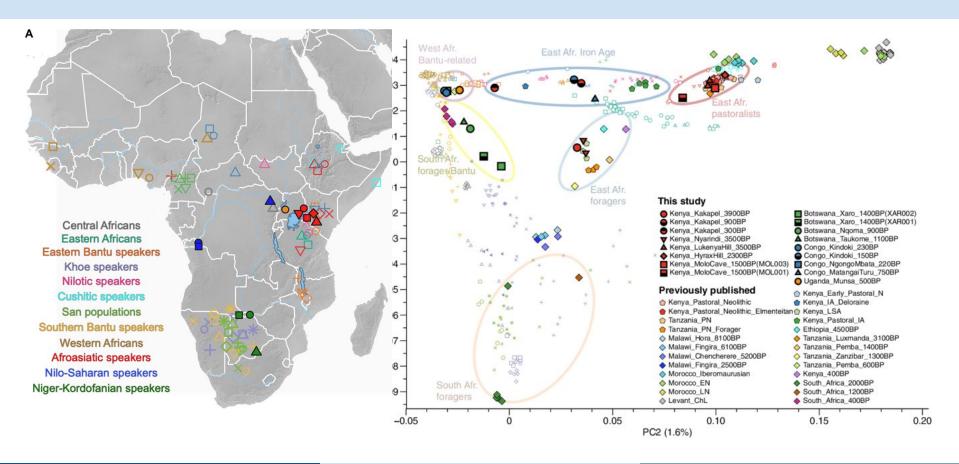


Figure 1.6: Three projections of a mug-shaped cloud points

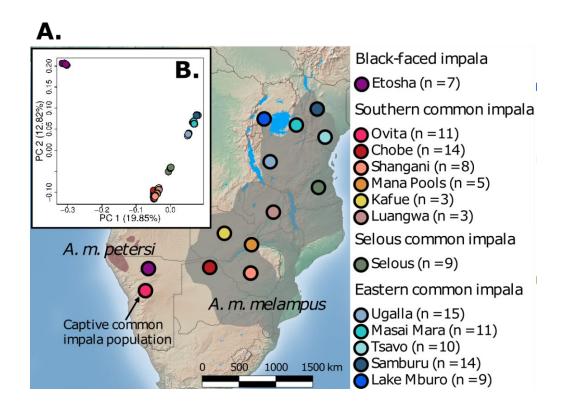
It matters which of the three we pick, right?
We want it to reflect the genetic relationship between all pairs

### PCA for population structure



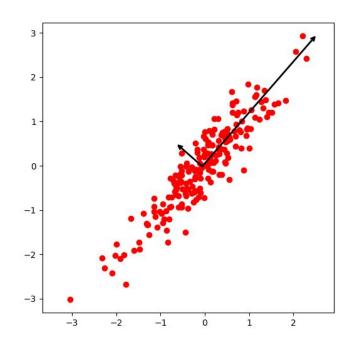


### Impala



### Principal component analysis (PCA)

- Dimensionality reduction
- Axis of variation
- Principal components
- Models more *Continuous\** population structure than
   ADMIXTURE

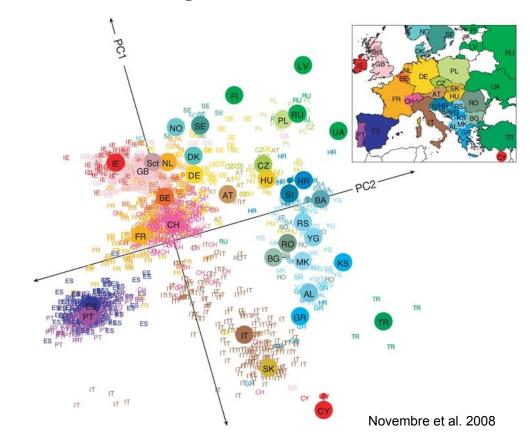


### \*not really true

### Principal component analysis (PCA)

#### Genetic data

- m > 1 million
- Captures genetic structure



### Today you will learn

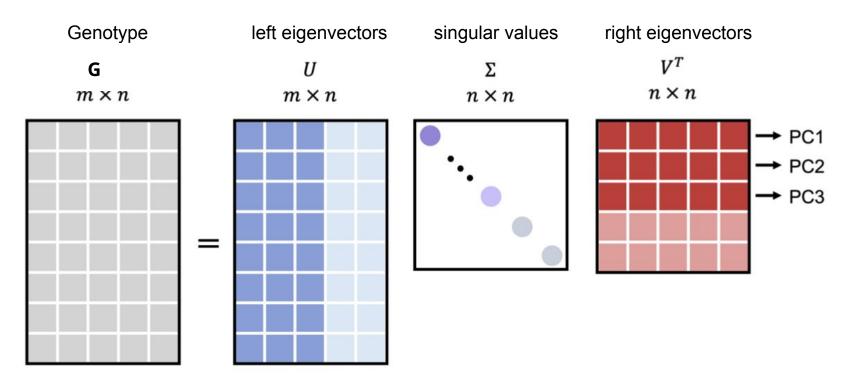
- The underlying "model" of PCA and MDS
  - What these two methods are trying to achieve
- The relationship between admixture proportions and PCA
- How PCA predict genotypes
- Issues with missingness
  - For call genotypes and for low depth sequencing
- How to deal with missingness
- How PCA can be used for selection scan (teaser)

# Genotype data

Ind1	Ind2	Ind3	Ind4	Ind5
AG	AG	AG	AA	AA
TT	TA	AA	AT	AA
AA	AC	AC	СС	AC
GG	GG	GC	СС	СС
TT	ТС	ТС	СС	СС
AA	AA	AC	AC	AC
TT	TT	TC	ТС	СС
	AG TT AA GG TT AA	AG AG TT TA AA AC GG GG TT TC AA AA	AG AG AG  TT TA AA  AA AC AC  GG GG GC  TT TC TC  AA AA AC	AG AG AG AA  TT TA AA AT  AA AC AC CC  GG GG GC CC  TT TC TC CC  AA AA AC AC

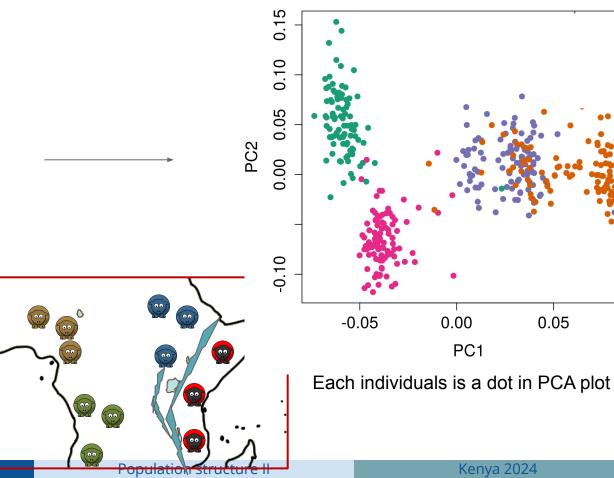
SNPs

lŋd	Ind 2	lŋd	Iŋd	lŋd
1	1	1	0	0
0	1	2	1	2
2	1	1	0	1
0	0	1	2	2
2	1	1	0	0
0	0	1	1	1
2	2	1	1	0



**G** is a genotype matrix, n is the number of samples, m is the number of SNPs

lηd	Ind 2	Ind	lŋd	Ind
1	1	1	0	0
0	1	2	1	2
2	1	1	0	1
0	0	1	2	2
2	1	1	0	0
0	0	1	1	1
2	2	1	1	0





### Multi-dimensional scaling (MDS)

Goal: Project the data into a low dimensional space that preserves distances

- Choose a distance
- Choose a dimension (K)

lηd	Ind 2	Ind 3	lŋd	Ind
1	1	1	0	0
0	1	2	1	2
2	1	1	0	1
0	0	1	2	2
2	1	1	0	0
0	0	1	1	1
2	2	1	1	0

Pairwise distance

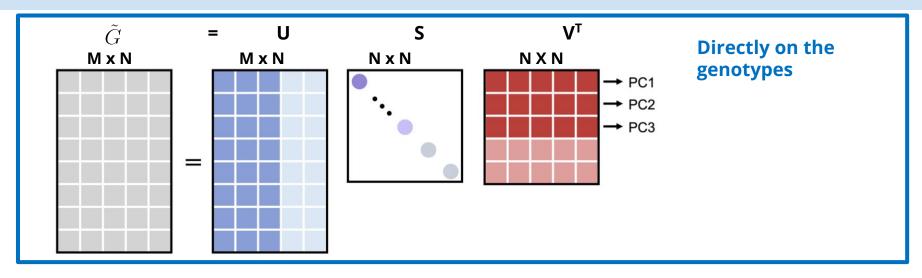
#### Manhattan distance

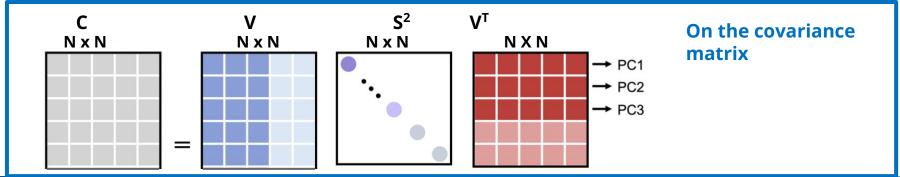
	lŋd	Ind 2	Ind	lŋd	Ind
lηd	0	3	7	10	11
Ind 2	3	0	4	7	8
Ind	7	4	0	5	4
Iŋd	10	7	5	0	6
Ind 5	11	8	4	3	0

Project into 1 dimension

	Ind1	Ind2	Ind3	Ind4	Ind5
Dim 1	6.1	3.08	-0.62	-3.7	-4.85

### Two ways to do PCA





Anders Albrechtsen

Population structure II

Kenya 2024

# Principal component analysis

Goal: Project the data into a low dimensional space that explains the largest amount of variance

Choose a dimension (K)

lŋd	Ind 2	lŋd	lŋd	Ind 5
1	1	1	0	0
0	1	2	1	2
2	1	1	0	1
0	0	1	2	2
2	1	1	0	0
0	0	1	1	1
2	2	1	1	0

Calculate Covariance

#### Project into 1 dimension

	Ind1	Ind2	Ind3	Ind4	Ind5
Dim 1	0.65	0.36	-0.08	-0.4	-0.53

#### Covariance matrix

	Ind1	Ind2	Ind3	Ind4	Ind5
Ind1	12.6	5.6	-2.0	-7.0	-9.1
Ind2	5.6	4.7	-0.8	-3.7	-5.8
Ind3	-2.0	-0.8	2.3	-0.8	1.3
Ind4	-7.0	-3.7	-0.8	6.7	4.7
Ind5	-9.1	-5.8	1.3	4.7	8.9

### Genotype covariance matrix

M number of sites

G genotype

 $G_i$  genotype for individual i

 $G_{ij}$  genotype for individual i site j

 $f_i$  frequency for site j

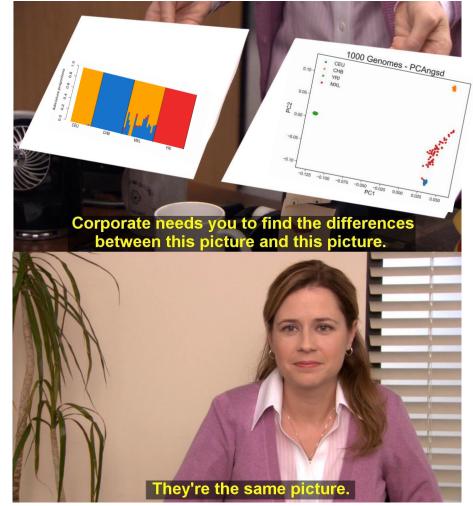
$$ilde{G}_{ij} = rac{G_{ij} - 2f_j}{\sqrt{2f_j(1-f_j)}}$$

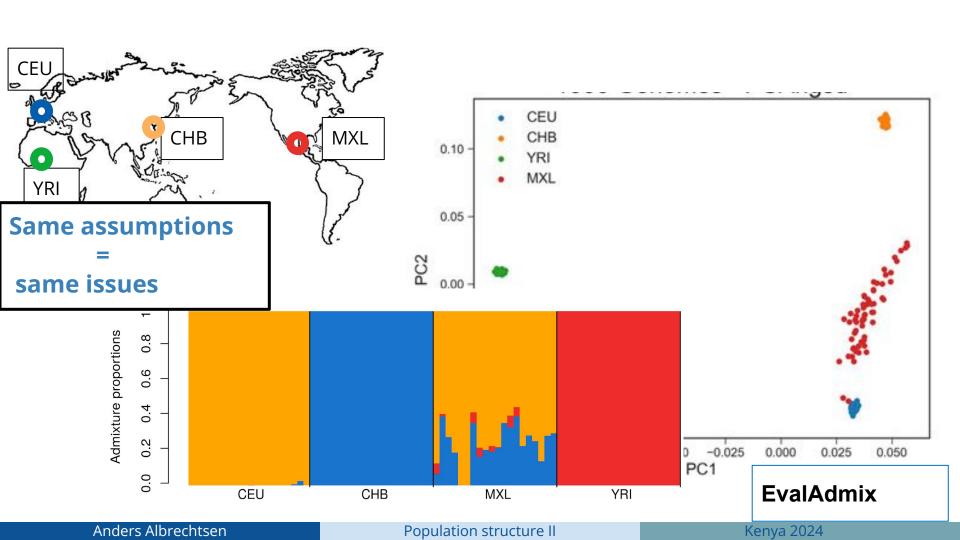
$$var(G_{ij}) = 2f_j(1-f_j)$$

After normalization all SNPs have the same mean and variance

$$cov( ilde{G}_i, ilde{G}_l)=rac{1}{M}\sum_{j=1}^{M}rac{(G_{ij}-2f_j)(G_{lj}-2f_j)}{2f_i(1-f_i)}=rac{1}{M} ilde{G} ilde{G}^T$$

Connection between Admixture analysis and PCA

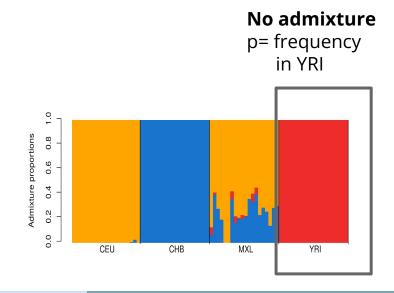




### Individual allele frequencies

- ullet Population allele frequency:  $\mathbb{E}[g]=2p$
- Individual allele frequency:  $\mathbb{E}[g_i] = 2\pi_i = 2p$

$$p(g) = \begin{cases} p^2 & g = 0\\ 2p(1-p) & g = 1\\ (1-p)^2 & g = 2 \end{cases}$$



# Individual allele frequencies

$$\mathbb{E}[g_i] = 2$$

$$p(g_i) =$$

• Individual allele frequencies  $\mathbb{E}[g_i] = 2$ 

$$\pi_{ij} = \sum_{k=1}^K f_{jk} q_{ik}$$

K = #populations

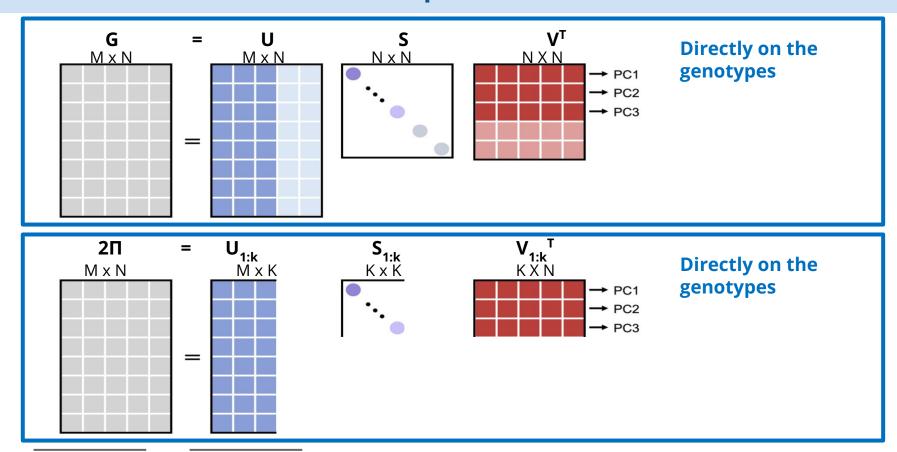
i = individual i

$$j = site j$$

$$\Pi = QF$$



### Individual allele frequencies from PCA



### Individual allele frequencies

• Allele frequency:

$$\mathbb{E}[g] = 2p$$

Admixture proportions
0.0 0.2 0.4 0.6 0.8 1.0
1.0 0.2 0.4 0.6 0.8 1.0

- Low-rank approximation
  - Admixture

 $rac{1}{2}\mathbb{E}[\mathbf{G}]pprox\mathbf{\Pi}=\mathbf{QF}$ 

PCATruncatedSVD

$$\frac{1}{2}\mathbb{E}[\mathbf{G}] \approx \mathbf{\Pi} = \mathbf{U}_{[1:k]}\mathbf{S}_{[1:k]}\mathbf{V}_{[1:k]}^T$$
1000 Genomes - PCAngsd

### Admixture and PCA from Π

### Π is the matrix of individual frequencies

#### ADMIXTURE → PCA

$$cov( ilde{G}_i, ilde{G}_l)$$

$$pprox rac{1}{M} \sum_{j=1}^{M} rac{(\Pi_{ij} - f_j)(\Pi_{lj} - f_j)}{f_j(1 - f_j)} \ pprox rac{1}{M} ilde{G} ilde{G}^T$$

$$pprox rac{1}{M} { ilde G} { ilde G}^T$$

#### PCA → ADMIXTURE

$$argmin_{Q,F}\|\Pi-QF\|$$

Solved with NMF

### Time for exercises

Run the admixture notebook