Multivariate analysis of genetic data — an introduction —

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Genetic data analysis using R, University of Leuven
28-10-2014

Outline

Multivariate analysis in a nutshell

Applications to genetic data

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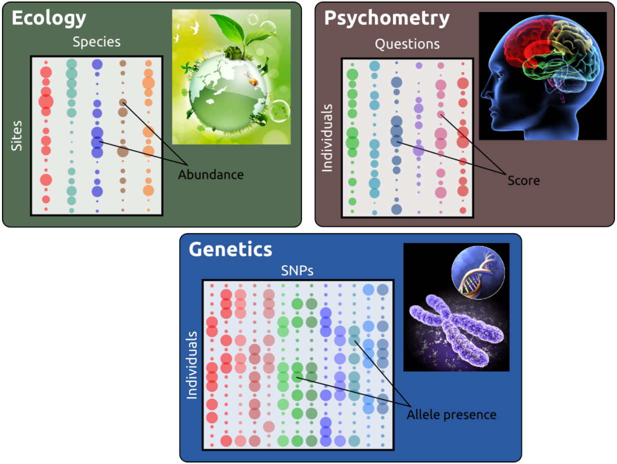
Applications to genetic data

Multivariate data: some examples



Association between individuals? Correlations between variables?

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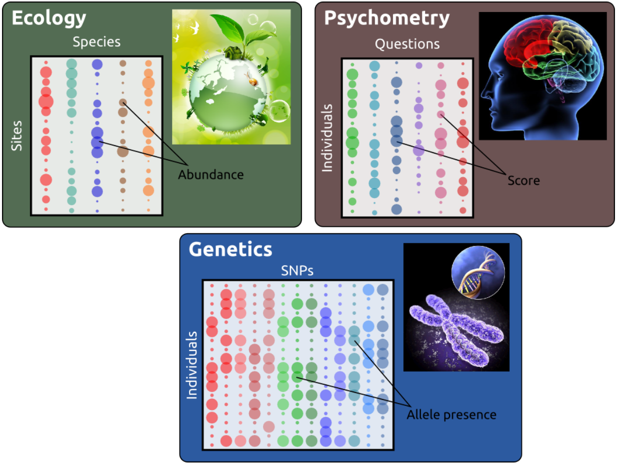

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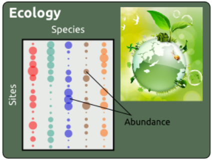
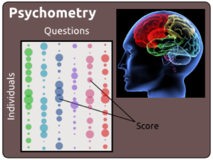
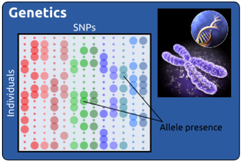
Multivariate analysis to summarize diversity







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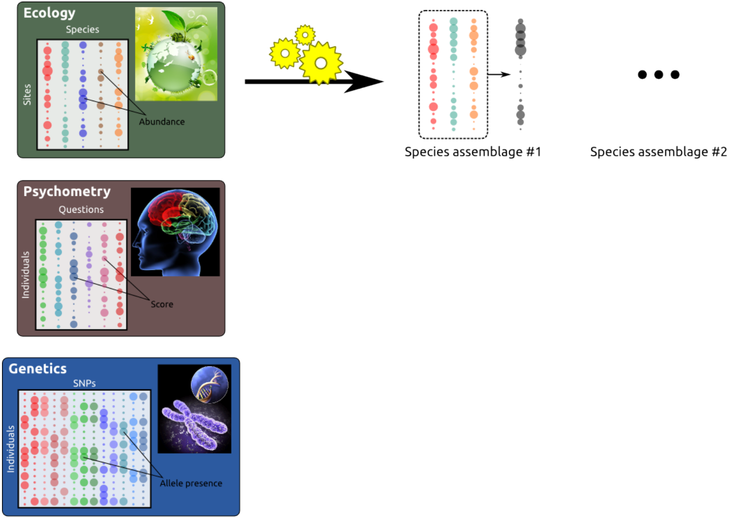

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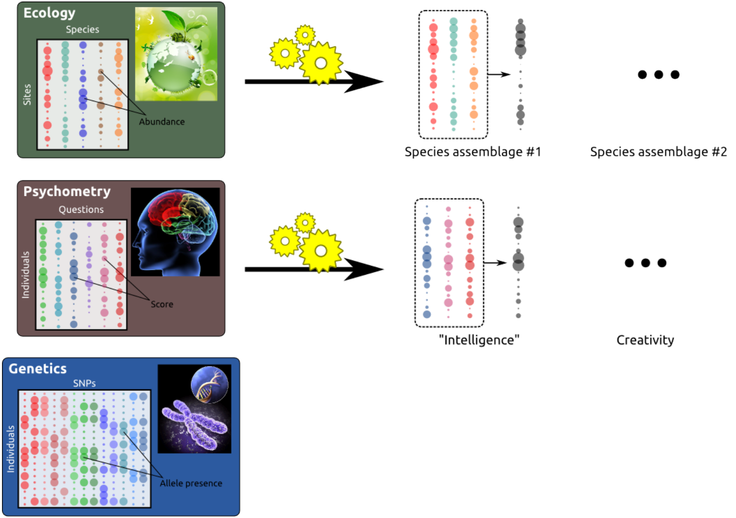

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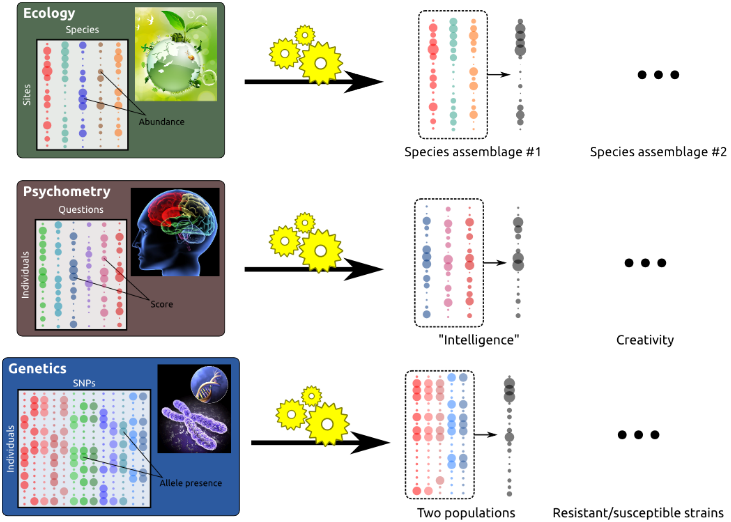

Multivariate analysis: an overview

Multivariate analysis, a.k.a:

- "*dimension reduction techniques*"
- "*ordinations in reduced space*"
- "*factorial methods*"

Purposes:

- summarize diversity amongst observations
- summarize correlations between variables

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Differences lie in input data:

- quantitative/binary variables: *Principal Component Analysis* (PCA)
- 2 categorical variables: *Correspondance Analysis* (CA)
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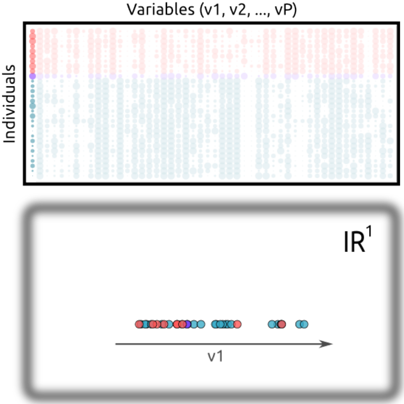
1 dimension, 2 dimensions, P dimensions



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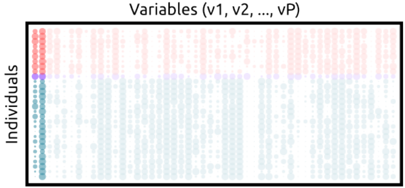

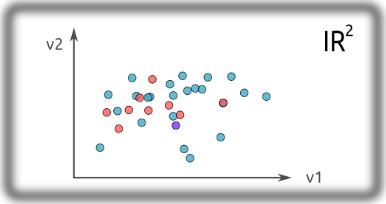

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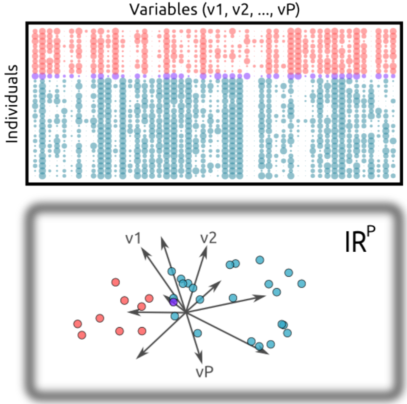

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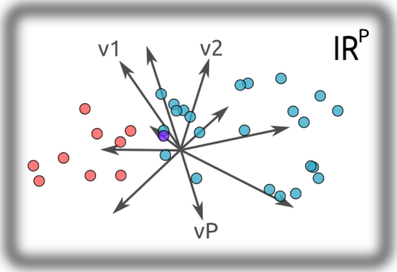
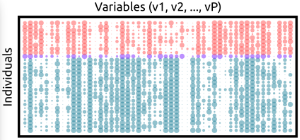
Reducing P dimensions into 1





- $\mathbf{X} \in \mathbb{R}^{N \times P}$; $\mathbf{X} = [\mathbf{x}_1 | \dots | \mathbf{x}_P]$: data matrix
- $\mathbf{u} \in \mathbb{R}^P$; $\mathbf{u} = [u_1, \dots, u_P]$: **principal axis** $(\|\mathbf{u}\|^2 = \sum_{j=1}^P u_j^2 = 1)$
- $\mathbf{v} \in \mathbb{R}^N$; $\mathbf{v} = \mathbf{X}\mathbf{u} = \sum_{j=1}^P u_j \mathbf{x}_j$: **principal component**

$\rightarrow$ find $\mathbf{u}$ so that $\frac{1}{N}\|\mathbf{v}\|^2 = \text{var}(\mathbf{v})$ is maximum.

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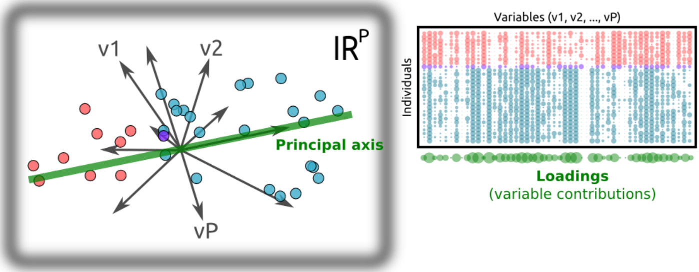

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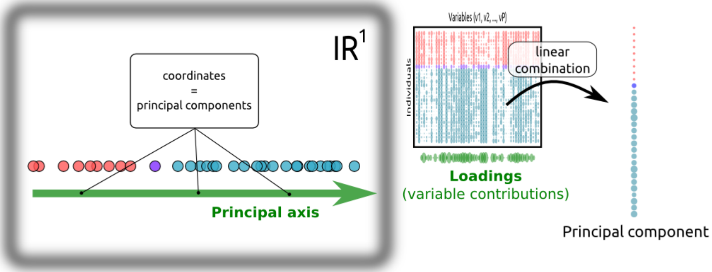

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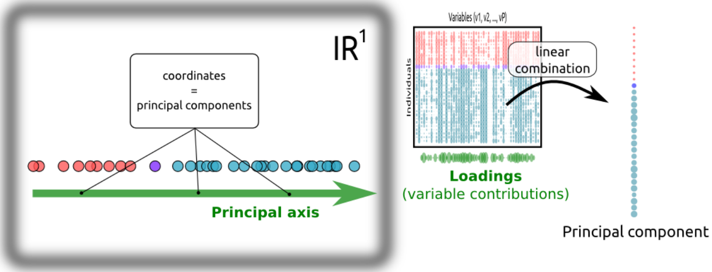

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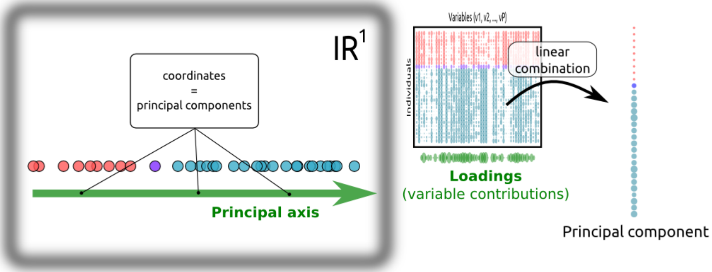
Keeping more than one principal component



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- $\mathbf{u}_2$ and $\mathbf{v}_2$: **2nd principal axis and component**

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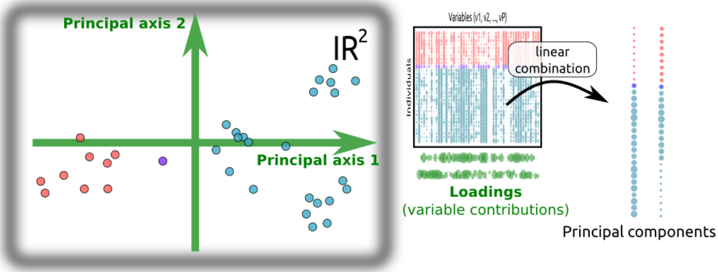

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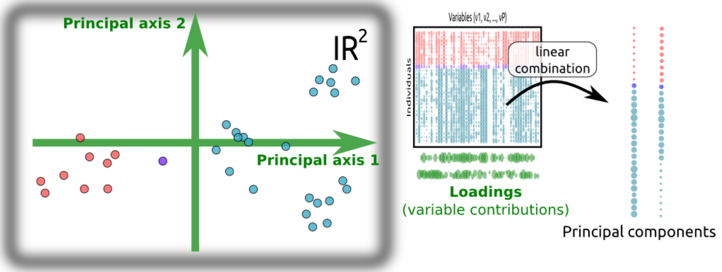

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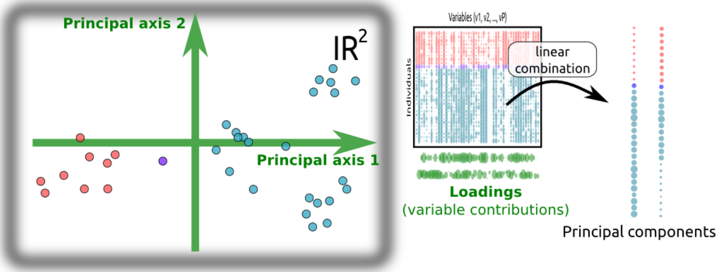

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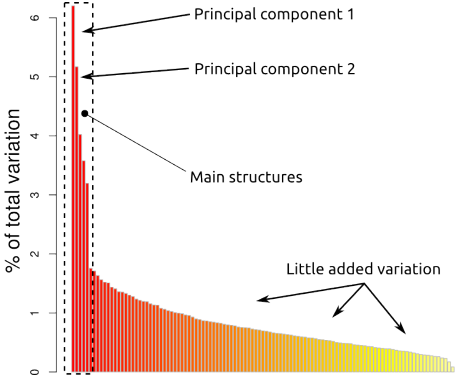
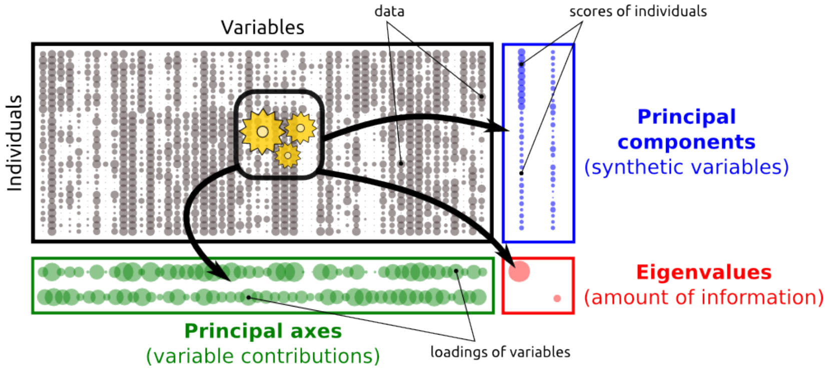
How many principal components to retain?

Choice based on "**screeplot**": barplot of eigenvalues



Retain only "significant" structures... but not trivial ones.

Outputs of multivariate analyses: an overview



Main outputs:

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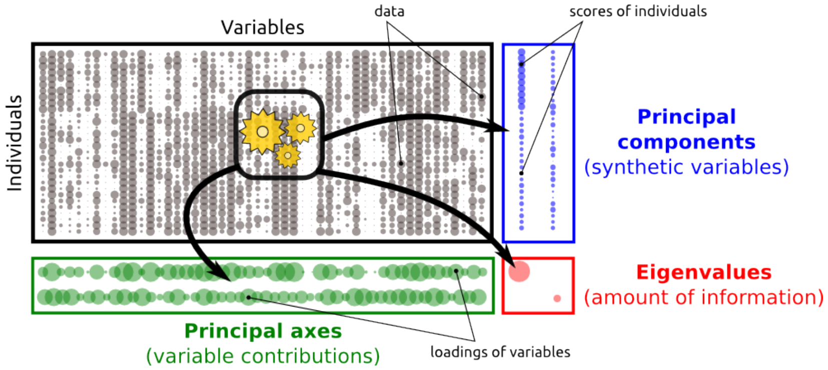

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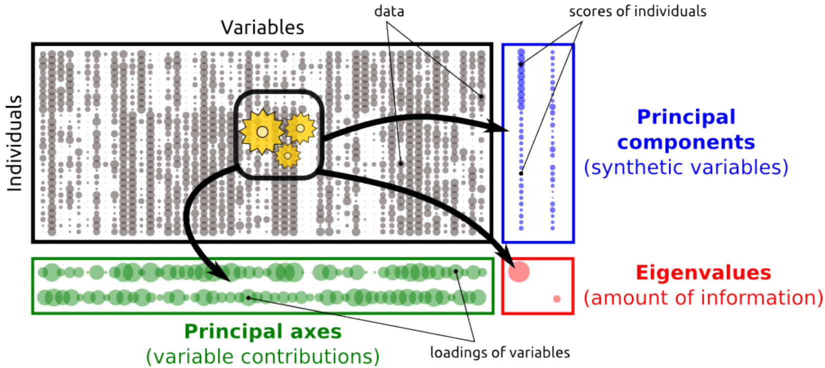

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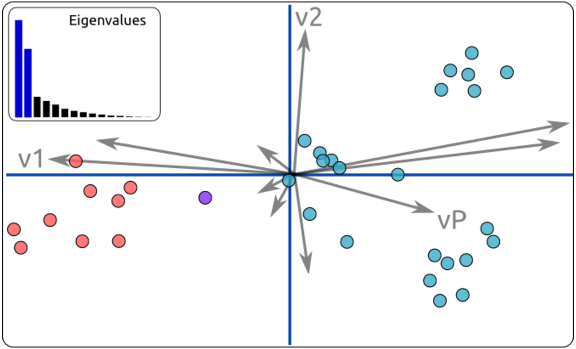
Usual summary of an analysis: the biplot



Biplot: principal components (points) + loadings (arrows)

- groups of individuals
- discriminating variables (longest arrows)
- magnitude of the structures

Multivariate analysis in a nutshell

- **variety of methods** for different types of variables
- **principal components** (PCs) summarize diversity
- **variable loadings** identify discriminating variables
- other uses of PCs: **maps** (spatial structures), **models** (response variables or predictors), ...

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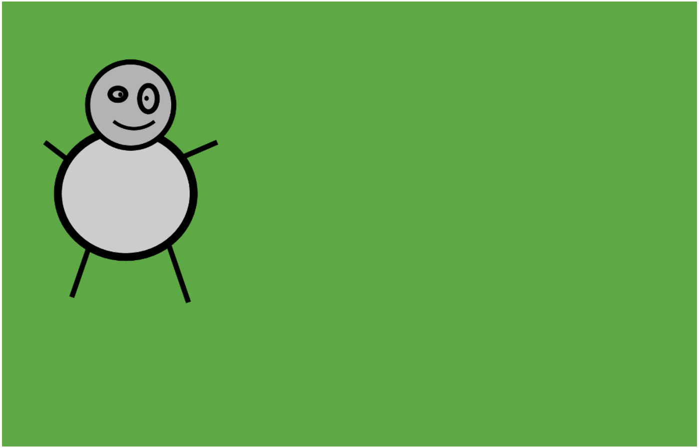
Applications to genetic data

From DNA sequences to patterns of biological diversity



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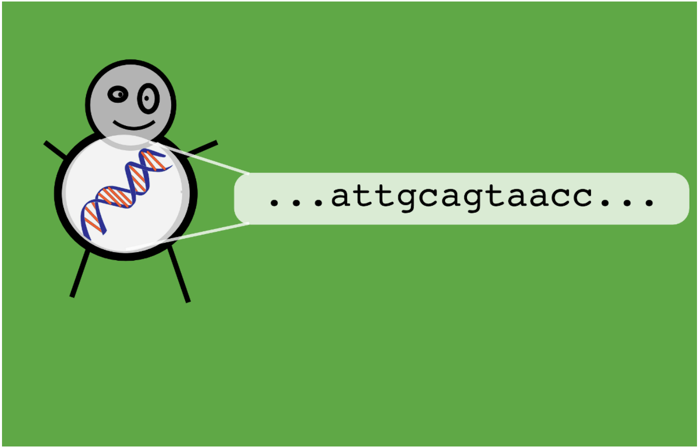

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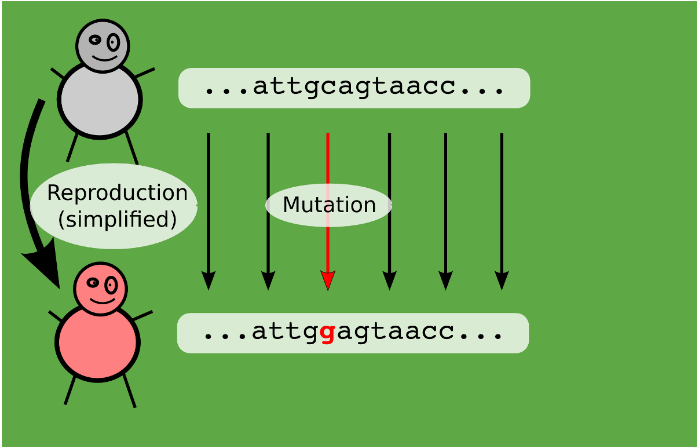

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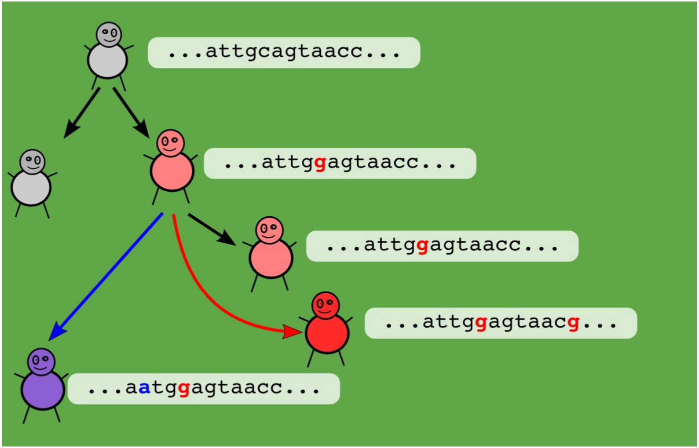

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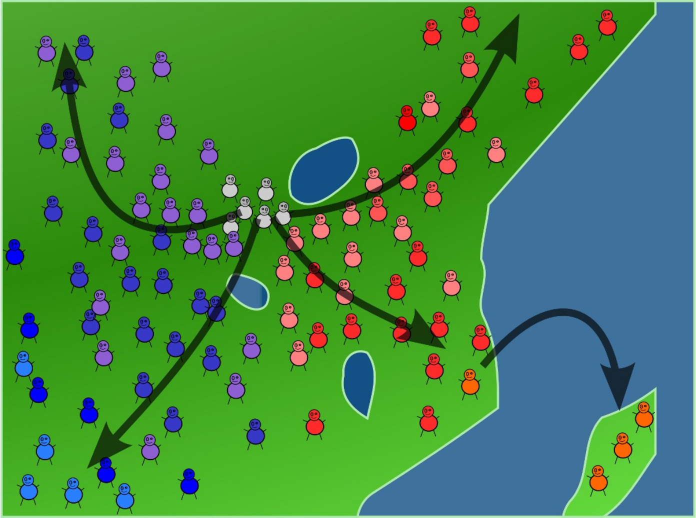

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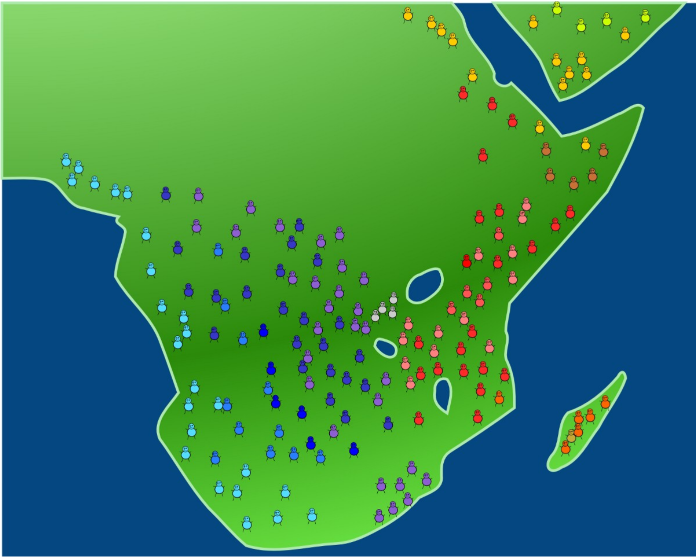

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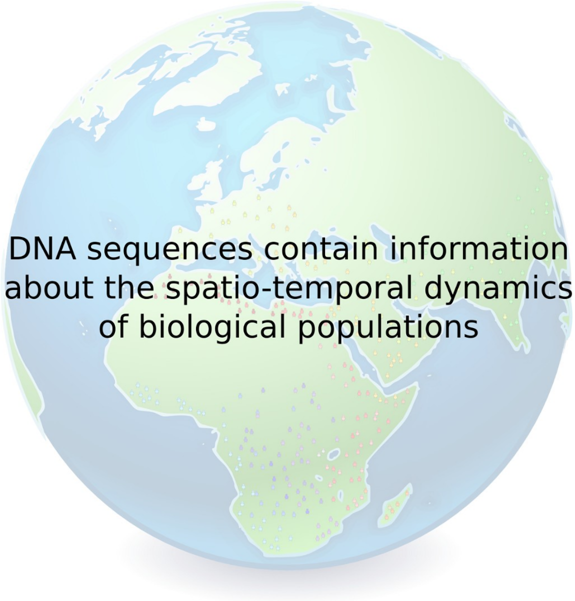
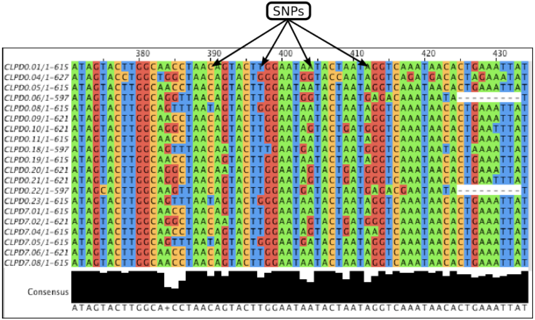


DNA sequences contain information
about the spatio-temporal dynamics
of biological populations

DNA sequences: a rich source of information



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- up to millions of single nucleotide polymorphism (SNPs)

$\Rightarrow$ **Multivariate analysis use to summarize genetic diversity.**

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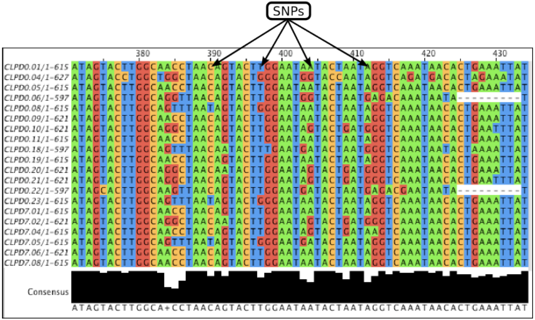

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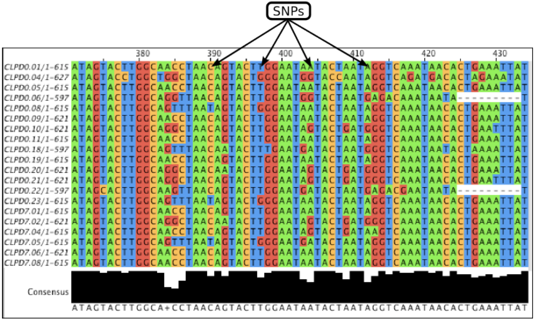

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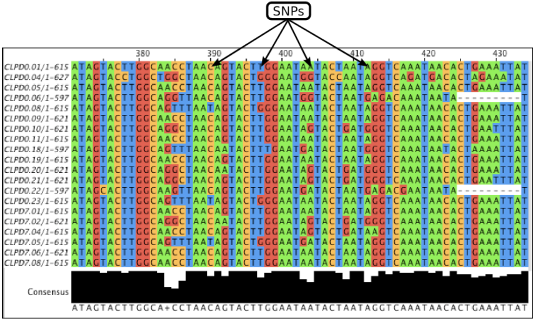

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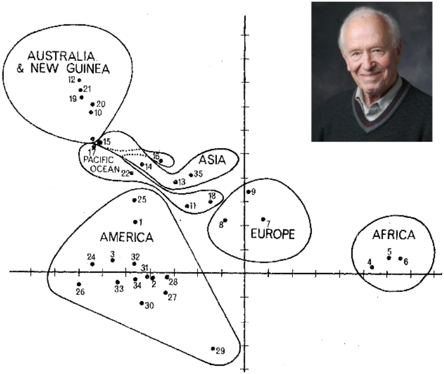
First application of multivariate analysis in genetics

PCA of genetic data, native human populations (Cavalli-Sforza 1966, *Proc B*)



First 2 principal components separate populations into continents.

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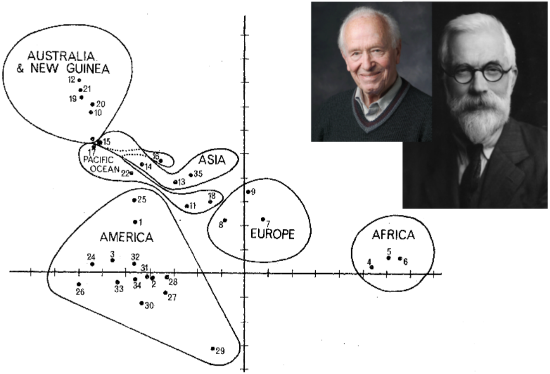

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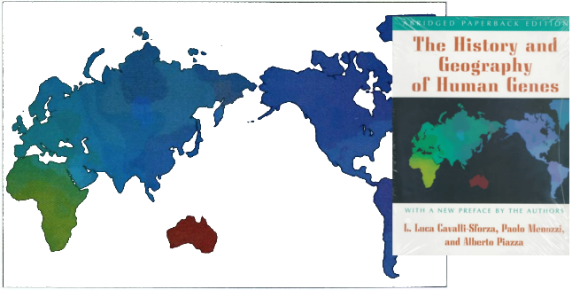
Applications: some examples

PCA of genetic data + colored maps of principal components

(Cavalli-Sforza et al. 1993, *Science*)



Signatures of Human expansion out-of-Africa.

Since then...

Multivariate methods used in genetics

- Principal Component Analysis (PCA)
- Principal Coordinates Analysis (PCoA) / Metric Multidimensional Scaling (MDS)
- Correspondance Analysis (CA)
- Discriminant Analysis (DA)
- Canonical Correlation Analysis (CCA)
- ...

Since then...

Applications

- reveal spatial structures (historical spread)
- explore genetic diversity
- identify cryptic species
- discover genotype-phenotype association
- ...
- review in Jombart et al. 2009, *Heredity* **102**: 330-341

In practice

Multivariate analysis of genetic data using R

Usual pipeline

1. read data in (*adegenet*)
2. convert data into numeric values (*adegenet*)
3. replace missing values (*adegenet*)
4. use "classical" methods (*ade4*/*adegenet*)
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5. graphics and interpretation (*ade4*/*adegenet*)

Recoding data numerically

- Presence/absence (e.g. RFLP, AFLP) and SNPs: binary coding
- Multiallelic data (e.g. microsatellites) are recoded as frequencies

Example using microsatellites:

Raw data:

	locus1	locus2
1	80/80	30/30
2	50/55	30/30
3	80/50	29/30
4	50/50	30/30
5	50/50	29/29

Recoded data:

	locus1.50	locus1.55	locus1.80	locus2.29	locus2.30
1	0.0	0.0	1.0	0.0	1.0
2	0.5	0.5	0.0	0.0	1.0
3	0.5	0.0	0.5	0.5	0.5
4	1.0	0.0	0.0	0.0	1.0
5	1.0	0.0	0.0	1.0	0.0

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3	0.5	0.0	0.5	0.5	0.5
4	1.0	0.0	0.0	0.0	1.0
5	1.0	0.0	0.0	1.0	0.0

Time to get your hands dirty!

The pdf of the practical is online:

`http://adegenet.r-forge.r-project.org/`

or

Google → adegenet → documents → "Workshop Leuven, October 2014"