

Modelling complex population structure using F -statistics and Principal Component Analysis

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Abstract

Human genetic diversity is shaped by our complex history. Population genetic tools to understand this variation can broadly be classified into data-driven methods such as Principal Component Analysis (PCA), and model-based approaches such as F -statistics. Here, I show that these two perspectives are closely related, and I derive explicit connections between the two approaches. I show that F -statistics have a simple geometrical interpretation in the context of PCA, and that orthogonal projections are the key concept to establish this link. I illustrate my results on two examples, one of local, and one of global human diversity. In both examples, I find that population structure is sparse, and only a few components contribute to most statistics. Based on these results, I develop novel visualizations that allow for investigating specific hypotheses, checking the assumptions of more sophisticated models. My results extend F -statistics to non-discrete populations, moving towards more complete and less biased descriptions of human genetic variation.

1 Introduction

As in most species, the genetic diversity of human populations has been influenced by our history and environment over the last several hundred thousand years (e.g Cavalli-Sforza et al., 1994, ?, Reich, 2018, ?). In turn, an important goal of population genetics is to use observed patterns of variation to investigate and reconstruct the demographic and evolutionary history of our species (Schraiber and Akey, 2015, ?).

The complicated genetic structure observed in present-day human populations (The 1000 Genomes Project Consortium, 2015, ?) is caused by the interplay of demographic and evolutionary processes with both discrete and continuous components (Pritchard et al., 2000, Rosenberg et al., 2002, Serre and Pääbo, 2004, Rosenberg et al., 2005, Bradburd et al., 2018, Reich, 2018, Peter et al., 2020). In particular, populations are expected to slowly differentiate if they are isolated from each other (Wahlund, 1928, Cavalli-Sforza and Piazza, 1975). In humans, this may be caused because continental-scale geographic distances limit migration, causing a pattern known as isolation-by-distance (SLATKIN, 1985). However, these patterns are usually not uniform, but shaped by geography, particularly barriers to migration such as mountain ranges, oceans or deserts (Cavalli-Sforza et al., 1994, ?, Rosenberg et al., 2005, Bradburd et al., 2013, Peter et al., 2020). In addition, major historical population movements such as the out-of-Africa, Austronesian or Bantu expansions lead to more gradual patterns of genetic diversity over space (Cavalli-Sforza et al., 1994, Ramachandran et al., 2005, Novembre et al., 2008, Stoneking, 2016, Racimo et al., 2020). Local migration between neighboring populations will reduce differentiation, and long-distance migrations (Alves et al., 2016), and secondary contact between diverged populations, such as Neandertals and modern humans (Green et al., 2010) may lead to locally increased diversity (?).

40 Particularly for large and heterogeneous data sets, disentangling all these processes is challenging,
41 and we cannot expect to devise a single model catching both broad strokes and minute details of
42 human history. A commonly used analysis paradigm is thus to integrate tools based on different sets
43 of assumptions. each emphasizing particular aspects of the data.

44 A typical analysis starts with data-driven, exploratory methods that summarize data making
45 minimal assumptions (e.g. Schraiber and Akey, 2015). Examples are population trees (Cavalli-
46 Sforza and Edwards, 1967, Felsenstein, 1973, Cavalli-Sforza and Piazza, 1975), Principal Component
47 Analysis (PCA, Cavalli-Sforza et al., 1994, Patterson et al., 2006)) structure-like models (Pritchard
48 et al., 2000, Alexander et al., 2009) or multidimensional scaling (MDS ?)). However, these methods
49 are not designed to answer specific research questions, and are limited in their ability to estimate
50 biologically meaningful parameters. For this purpose, methods based on explicit demographic models
51 are often used that aim to fit a specified or estimated model of divergence, migration and genetic
52 drift to the data (Gutenkunst et al., 2009, Excoffier et al., 2013, Kamm et al., 2015). The drawback
53 of these methods is that, to make inference mathematically feasible, we need to introduce strong
54 modeling assumptions such as that populations are discrete, randomly mating, or at equilibrium.
55 While in most cases these assumptions are violated to some extent and cannot be verified, we hope
56 that the resulting model fits provide sufficiently accurate answers to specific research questions.

57 **F-statistics** However, when the number of populations exceeds a few dozen, even codifying rea-
58 sonable population models can be prohibitively difficult. One approach is to pick a small set of
59 “representative” samples, and restrict modeling to this subset (e.g. Gravel et al., 2011, Harney et al.,
60 2021). However, this has the drawback that a large proportion of the available data remains unused.
61 An increasingly popular alternative approach, particularly in the analysis of human ancient DNA, is
62 therefore to build up complex models from smaller building blocks based on the relationship between
63 two, three or four populations.

64 The framework is based on a set of parameters called F -statistics *sensu* Patterson (Reich et al.,
65 2009, Patterson et al., 2012, Peter, 2016). Formal definition will be given in the Theory section; but
66 an informal motivation starts with the null model that populations are related as a tree, in which
67 each F -statistic measures the length of a particular set of branches. (Figure 2; Semple and Steel,
68 2003, Peter, 2016).

69 In most applications, F -statistics are estimated from data, and then used as tests of treeness. In
70 particular, under the assumption of a tree, F_3 is restricted to be non-negative, and many F_4 -statistics
71 will be zero (Semple and Steel, 2003, Patterson et al., 2012), and data that violates these constraints
72 is incompatible with a tree-like relationship between populations. The canonical alternative model is
73 an admixture graph (or phylogenetic network) (Patterson et al., 2012, Huson et al., 2010), which is
74 a tree which allows for additional edges reflecting gene flow (Figure 3A). However, admixture graphs
75 are not the only plausible alternative model, and expected F -statistics can be calculated for a wide
76 range of population genetic demographic models (Peter, 2016).

77 **F-statistics and PCA** The practical issue addressed in this study is how F -statistics can be
78 reconciled with PCA, one of the most widely used data-driven modeling techniques. One way PCA
79 can be motivated is as generating a low-dimensional representation of the data, with each dimension
80 (called principal component, PC) retaining a maximum of the variance present in the data. To
81 understand population structure, the use of PCA has been pioneered by Cavalli-Sforza et al. (1964),
82 who used allele-frequency data at a population level to visualize genetic diversity (Cavalli-Sforza et al.,
83 1994). Currently, PCA is most commonly performed on individual-level genotype data (e.g. Patterson
84 et al., 2006, Novembre et al., 2008), making use of the hundreds of thousands of loci available in
85 most genome-scale data sets. The PCA-decomposition has been studied for a number of explicit
86 population genetic models including trees (Cavalli-Sforza and Piazza, 1975), spatially continuous
87 structure (Novembre and Stephens, 2008), the coalescent (McVean, 2009) and discrete population

models (?). Here, in order to link PCA to F -statistics, I interpret both of them geometrically in *allele frequency space*, i.e. as functions of a high-dimensional Euclidean space. For F -statistics, this interpretation was recently developed by Oteo-Garcia and Oteo (2021), and for PCA it follows naturally from the interpretation of approximating a high-dimensional space with a low-dimensional one.

In the next section, I will formally derive the connection between F -statistics and PCA, and show how F -statistics can be interpreted geometrically, with a particular emphasis on two-dimensional PCA plots. In the Results section, I will then discuss how some of the most common applications of F -statistics manifest themselves on a PCA, and illustrate them on two example data sets, before ending with a discussion.

2 Theory

In this section, I will introduce the mathematics and notations for F -statistics and PCA. A comprehensive treatise on PCA is given by e.g. Jolliffe (2013), a useful primer on the mathematics is Pachter (2014), and a helpful guide to interpretation is Cavalli-Sforza et al. (1994). Readers unfamiliar with F -statistics may find Patterson et al. (2012), Peter (2016) or Oteo-Garcia and Oteo (2021) helpful.

2.1 Formal Definition of F -statistics

Let us assume we have a set of populations for which we have SNP allele frequency data from S loci. Let x_{il} denote the frequency at the l -th SNP in the i -th population; and let $X_i = (x_{i1}, x_{i2}, \dots, x_{iS})$ be a vector collecting all allele frequencies for population i . As X_i will be the only data summary considered here for population i , I make no distinction between the population and the allele frequency vector used to represent it.

The three F -statistics are defined as

$$F_2(X_1, X_2) = \frac{1}{S} \sum_{l=1}^S (x_{1l} - x_{2l})^2 \quad (1a)$$

$$F_3(X_1; X_2, X_3) = \frac{1}{S} \sum_{l=1}^S (x_{1l} - x_{2l})(x_{1l} - x_{3l}) \quad (1b)$$

$$F_4(X_1, X_2; X_3, X_4) = \frac{1}{S} \sum_{l=1}^S (x_{1l} - x_{2l})(x_{3l} - x_{4l}), \quad (1c)$$

The normalization by the number of SNPs S is assumed to be the same for all calculations and is thus omitted subsequently. Both F_3 and F_4 can be written as sums of F_2 -statistics:

$$2F_3(X_1; X_2, X_3) = F_2(X_1, X_2) + F_2(X_1, X_3) - F_2(X_2, X_3) \quad (2a)$$

$$2F_4(X_1, X_2; X_3, X_4) = F_2(X_1, X_3) + F_2(X_2, X_4) - F_2(X_1, X_4) - F_2(X_2, X_3) \quad (2b)$$

F -statistics have been primarily motivated in the context of trees and admixture graphs (Patterson et al., 2012). In a tree, the squared Euclidean distance $F_2(X_1, X_2)$ measures the length of the path between populations X_1 and X_2 (Figure 2A); F_3 represents the length of an external branch (Figure 2B) and F_4 the length of an internal branch, respectively (Figure 2C). Crucially, for branches that do not exist in the tree (as in Figure 2D), F_4 will be zero. The length of each branch can be thought of in units of genetic drift, and is non-negative (Patterson et al., 2012).

Thinking of F -statistics as branch lengths is useful for a number of applications, including building multi-population models (Patterson et al., 2012, Lipson et al., 2013), estimating admixture proportions (Petr et al., 2019, Harney et al., 2021) and finding the population most closely related to an unknown sample (“Outgroup”- F_3 -statistic).

Most commonly however, F_3 and F_4 are used as tests of treeness (Patterson et al., 2012): Negative F_3 -values correspond to a branch with negative genetic drift, which is not allowed under the null assumption of a tree-like population relationship. Similarly if four populations are related as a tree, then at least one of the F_4 statistics between the populations will be zero (Buneman, 1974, Patterson et al., 2012).

The most widely considered alternative model is an admixture graph (Patterson et al., 2012), an example is given in Figure 3A. Here, the *typically unobserved) population X_y is generated by a mixture of individuals from the ancestors of X_2 and X_3 . Over time, genetic drift will change X_y to X_x , which is the admixed population we observe. This will result in F_4 -statistics that are non-zero, and, in some cases, in negative F_3 -statistics (exact conditions can be found in Peter, 2016).

2.1.1 Geometric interpretation of F -statistics

An implicit assumption in the development of F -statistics is that population lineages are mostly discrete, and that gene flow is rare. Recently, Oteo-Garcia and Oteo (2021) showed re-deriving F -statistics in a geometric framework, showing that these assumptions are not necessary. Specifically, they interpret the populations X_i as points or vectors in the S -dimensional *allele frequency space* \mathbb{R}^S . In this case, the F -statistics can be thought of as inner (or dot) products, and they showed that all properties and tests related to treeness can be derived in this larger space. In particular the F -statistics can be written as

$$F_2(X_1, X_2) = \frac{1}{S} \sum_{l=1}^S (x_{1l} - x_{2l})^2 = \frac{1}{S} \langle X_1 - X_2, X_1 - X_2 \rangle = \frac{1}{S} \|X_1 - X_2\|^2 \quad (3a)$$

$$F_3(X_1; X_2, X_3) = \frac{1}{S} \sum_{l=1}^S (x_{1l} - x_{2l})(x_{1l} - x_{3l}) = \frac{1}{S} \langle X_1 - X_2, X_1 - X_3 \rangle \quad (3b)$$

$$F_4(X_1, X_2; X_3, X_4) = \frac{1}{S} \sum_{l=1}^S (x_{1l} - x_{2l})(x_{3l} - x_{4l}) = \frac{1}{S} \langle X_1 - X_2, X_3 - X_4 \rangle, \quad (3c)$$

where $\|\cdot\|$ denotes the Euclidean norm and $\langle \cdot, \cdot \rangle$ denotes the dot product. Some elementary properties of the dot product between vectors a, b, c that I will use later are

$$\langle a, b \rangle = \sum_i a_i b_i \quad (4a)$$

$$\langle a, b \rangle = \|a\| \|b\| \cos(\phi) \quad (4b)$$

$$\langle a, a \rangle = \|a\|^2 \quad (4c)$$

$$\langle a + c, b \rangle = \langle a, b \rangle + \langle c, b \rangle, \quad (4d)$$

where ϕ is the angle between a and b . The inner product is closely related to vector projections

$$proj_b a = \frac{\langle a, b \rangle}{\|b\|^2} b, \quad (5)$$

which is a vector colinear to b whose length measures how much vector a points in the direction of b . Thinking of F -statistics as projections also holds on trees: In e.g. a $F_4(X_1, X_4; X_2, X_3)$ -statistic (Figure 3C), the internal branch is precisely the intersection of the paths from X_1 to X_4 and from X_2 and X_3 . The external branches are independent populations, and so they are expected to drift orthogonally to each other.

The drawback of the geometric approach of Oteo-Garcia and Oteo (2021) is that we have to deal with an very high-dimensional space, as the number of SNPs is frequently in the millions. However,

138 it has been commonly observed that population structure is quite low-dimensional, and that the first
 139 few PCs provide a good approximation of the covariance structure in the data (Patterson et al., 2006).
 140 Therefore, we may hope that PCA could yield a reasonable approximation of the allele frequency
 141 space, and that F -statistics as measures of population structure may likewise be well-approximated
 142 by the first few PCs.

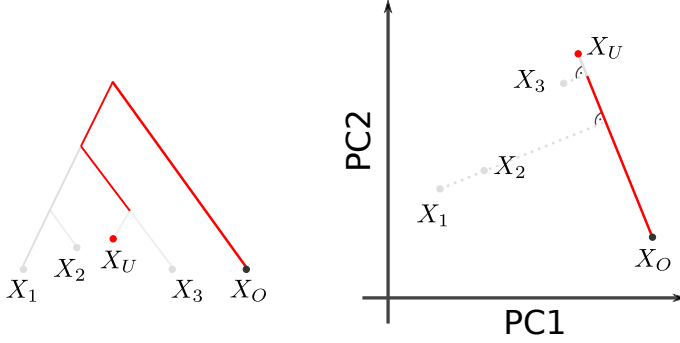


Figure 1: **Outgroup- F_3 -statistics**. The circle with a dot denotes a right angle.

143 2.2 Formal Definition of PCA

144 PCA is a common way of summarizing genetic data, and so a large number of variations of PCA exist,
 145 e.g. in how SNPs are standardized, how missing data is treated or whether we use individuals or
 146 populations as units of analysis. The version of PCA I use here is set up such that the similarities to
 147 F -statistics are maximized, and does *not* reflect how PCA is most commonly applied to genome-scale
 148 human genetic variation data sets. In particular, I assume that a PCA is performed on unscaled,
 149 estimated population allele frequencies, whereas many applications of PCA are based on individual-
 150 level sample allele frequency, scaled by the estimated standard deviation of each SNP (Patterson
 151 et al., 2006). The differences this causes will be addressed in the discussion.

152 Let us again assume we have allele frequency data as above, but let us now assume we aggregate
 153 the allele frequency vectors X_i of many populations in a matrix \mathbf{X} whose entry x_{il} reflects the allele
 154 frequency of the i -th population at the l -th genotype. If we have S SNPs and n populations, \mathbf{X} will
 155 have dimension $n \times S$. Since the allele frequencies are between zero and one, we can interpret each
 156 Population X_i of \mathbf{X} as a point in $[0, 1]^S$, the allele frequency or *data space*, which is a subset of \mathbb{R}^S .

157 One way PCA can be motivated is that it aims to find a K -dimensional subspace of the data
 158 space that retains most variation in the data. K is at most $n - 1$, in which case the data is simply
 159 rotated. However, the historical processes that generated genetic variation often result in *low-rank*
 160 data (Engelhardt and Stephens, 2010), so that $K \ll n$ explains a substantial portion of the variation;
 161 for visualization $K = 2$ is frequently used.

There are several algorithms that are used to perform PCAs, the most common one is based on
 singular value decomposition (e.g. Jolliffe, 2013). In this approach, we first mean-center \mathbf{X} , obtaining
 a centered matrix \mathbf{Y}

$$y_{il} = x_{il} - \mu_l$$

162 where μ_l is the mean allele frequency at the l -th locus.

163 PCA can then be written as

$$\mathbf{Y} = \mathbf{C}\mathbf{X} = (\mathbf{U}\mathbf{\Sigma})\mathbf{V}^T = \mathbf{P}\mathbf{L}, \quad (6)$$

164 where $\mathbf{C} = \mathbf{I} - \frac{1}{n}\mathbf{1}\mathbf{1}^T$ is a centering matrix that subtracts row means, with \mathbf{I} , $\mathbf{1}$ the identity matrix
 165 and a matrix of ones, respectively. For any matrix \mathbf{Y} , we can perform a singular value decomposition
 166 $\mathbf{Y} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$ which, in the context of PCA, is interpreted as follows: The matrix of principal

167 components $\mathbf{P} = \mathbf{U}\Sigma$ has size $n \times n$ and contains information about population structure. The SNP
 168 loadings $\mathbf{L} = \mathbf{V}^T$ form an orthonormal basis of size $n \times S$, its rows give the contribution of each
 169 SNP to each PC. It is often used to look for outliers, which might be indicative of selection (e.g ?).
 170 Alternatively, the PCs can also be obtained from an eigendecomposition of the covariance matrix
 171 $\mathbf{Y}\mathbf{Y}^T$. This can be motivated from (6):

$$\mathbf{Y}\mathbf{Y}^T = \mathbf{P}\mathbf{L}\mathbf{L}^T\mathbf{P}^T = \mathbf{P}\mathbf{P}^T, \quad (7)$$

172 since $\mathbf{L}\mathbf{L}^T = \mathbf{I}$.

173 2.3 Connection between PCA and F -statistics

174 2.3.1 Principal components from F -statistics

175 PCA, as defined above, and F -statistics are closely related. In fact, the principal components can
 176 be directly calculated from F -statistics using multidimensional scaling, which, for squared Euclidean
 177 (F_2)-distances, leads to an identical decomposition to PCA (Gower, 1966). Suppose we calculate the
 178 pairwise $F_2(X_i, X_j)$ between all n populations, and collect them in a matrix \mathbf{F}_2 . We can obtain the
 179 principal components from this matrix by double-centering it, so that its row and column means are
 180 zero, and perform an eigendecomposition of the resulting matrix:

$$\mathbf{P}\mathbf{P}^T = -\frac{1}{2}\mathbf{C}\mathbf{F}_2\mathbf{C}. \quad (8)$$

181 2.3.2 F -statistics in PCA-space

182 By performing a PCA, we rotate our data to reveal the axes of highest variation. However, the dot
 183 product is invariant under rotation, and F -statistics can be thought of as dot products (Oteo-Garcia
 184 and Oteo, 2021). What this means is that we are free to calculate F_2 either on the uncentered data
 185 \mathbf{X} , the centered data \mathbf{Y} or any other orthogonal basis such as the principal components \mathbf{P} . Formally,

$$\begin{aligned} F_2(X_i, X_j) &= \sum_{l=1}^L (x_{il} - x_{jl})^2 \\ &= \sum_{l=1}^L ((x_{il} - \mu_l) - (x_{jl} - \mu_l))^2 = F_2(Y_i, Y_j) \\ &= \sum_{k=1}^n (p_{ik} - p_{jk})^2 = F_2(P_i, P_j), \end{aligned} \quad (9)$$

186 A derivation of this change-of-basis is given in Appendix A, Equation A1. As F_3 and F_4 can be
 187 written as sums of F_2 -terms (Eqs. 2a, 2b), analogous relations apply.

In most applications, we do not use all PCs, but instead truncate to the first K PCs, which explain most of the between-population genetic variation. Thus,

$$\begin{aligned} F_2(P_i, P_j) &= \sum_{k=1}^K (p_{ik} - p_{jk})^2 + \sum_{k=K+1}^n (p_{ik} - p_{jk})^2 \\ &= \hat{F}_2^{(K)}(P_i, P_j) + \epsilon^{(K)}(P_i, P_j). \end{aligned} \quad (10)$$

188 In this notation, $\hat{F}_2^{(K)}$ is the approximation of F_2 with only the first K PCs considered, and $\epsilon^{(K)}$ is
 189 the corresponding approximation error. I will omit the superscript of \hat{F}_2 when the exact number of

190 PCs is not relevant. If we sum up the squared approximation errors over all pairs of populations in
 191 our sample, we obtain

$$\sum_{i,j} \epsilon^{(K)}(P_i, P_j)^2 = \sum_{i,j} \left(\hat{F}_2^{(K)}(P_i, P_j) - F_2^{(K)}(P_i, P_j) \right)^2 = \left\| \mathbf{F}_2 - \hat{\mathbf{F}}_2 \right\|_F^2, \quad (11)$$

192 where the Frobenius-norm $\|\cdot\|_F^2$ of a matrix is defined as the square root of the sum-of-squares of
 193 all its elements. This is precisely the function that is minimized in MDS (Jolliffe, 2013). In that
 194 sense, $\hat{\mathbf{F}}_2^{(K)}$ is the optimal low-rank approximation of \mathbf{F}_2 for any K in that it minimizes the sum of
 195 approximation errors of all F_2 -statistics.

196 2.3.3 F -statistics and samples projected onto PCA

197 One of the easiest ways of dealing with missing data in PCA is to calculate the principal components
 198 (equation 6) only on a subset of the data with no missingness, and then to *project* the lower quality
 199 samples with high missingness onto this PCA. The simplest way to do this is to note that

$$\mathbf{Y}\mathbf{L}^T = \mathbf{P}\mathbf{L}\mathbf{L}^T = \mathbf{P},$$

and so a new (centered) population Y_{new} can be projected onto an existing PCA simply by post-multiplying it with \mathbf{L}^T :

$$P_{\text{proj}} = Y_{\text{new}}\mathbf{L}^T;$$

the k -th entry of P_{proj} gives the coordinates of the new sample on the k -th PC. However, it is likely that Y_{new} lies outside the variation of the original samples. In this case, there is a projection error

$$\|Y_{\text{new}} - P_{\text{proj}}\mathbf{L}\|^2 = F_2(P_{\text{proj}}\mathbf{L}, Y_{\text{new}}).$$

200 If we project with missing data, a similar projection can be used where we remove the rows from
 201 Y_{new} and \mathbf{L} where data in Y_{new} is missing, and add a scaling factor (Patterson et al., 2006).

202 Thus, if we compare the F -statistic of a projected sample, we have

$$\begin{aligned} F_2(X_i, X_{\text{new}}) &= F_2(Y_i, Y_{\text{new}}) \\ &= F_2(P_i, P_{\text{proj}}) + F_2(P_{\text{proj}}\mathbf{L}, Y_{\text{new}}) \\ &= \hat{F}_2(P_i, P_j) + \epsilon(P_i, P_j) + F_2(P_{\text{proj}}\mathbf{L}, Y_{\text{new}}). \end{aligned} \quad (12)$$

203 The second row follows because the projection error and projection are orthogonal to each other.
 204 The main implication of equation 12 is that both truncation and projection introduce some error,
 205 and that $\hat{F}_2(P_i, P_j)$ will be a good approximation to $F_2(P_i, P_j)$ only if both errors are small.

206 3 Material & Methods

207 The theory outlined in the previous section suggests that F -statistics have a geometric interpretation
 208 in PCA-space, which can be approximated on PCA plots. In the next section I explore this connection
 209 in detail, and illustrate it on two sample data sets that I briefly introduce here. Both are based on
 210 the analyses by Lazaridis et al. (2014). The data is from the Reich lab compendium data set (v44.3),
 211 downloaded from <https://reich.hms.harvard.edu/allen-ancient-dna-resource-aadr-downloadable->
 212 using data on the ‘‘Human Origins’’-SNP set (597,573 SNPs). SNPs with missing data in any
 213 population are excluded. The code used to create all figures and analyses will be available on
 214 https://github.com/BenjaminPeter/fstats_pca.

215 **“World” data set** This data set is a subset of the “World Foci” data set of Lazaridis et al. (2014),
 216 where I removed samples which are not permitted for free reuse. These populations span the globe and
 217 roughly represents global human genetic variation (638 individuals from 33 population) As adjacent
 218 sampling locations are often thousands of kilometers apart, I speculate that gene flow between these
 219 populations may not be particularly common; and their structure may therefore be well-approximated
 220 by an admixture graph. A file with all individuals used and their assigned population is given in
 221 **Supplementary File 1.**

222 **Western Eurasian data set** This data set of 1,119 individuals from 62 populations contains
 223 present-day individuals from the Eastern Mediterranean, Caucasus and Europe. It is motivated
 224 by the analysis of Lazaridis et al. (2014), who used it as a basis of comparison for ancient genetic
 225 analyses of Western Eurasian individuals, and PCAs based on similar sets of samples have been used
 226 in many other ancient DNA studies (e.g. Haak et al., 2015). Genetic differentiation in this region is
 227 low and closely mirrors geography (Novembre et al., 2008). I thus speculate that gene flow between
 228 these populations is common (Ralph and Coop, 2013), and a discrete model such as a tree or an
 229 admixture graph might be a rather poor reflection of this data. A file with all individuals used and
 230 their assigned population is given in **Supplementary File 2.**

231 **Computing F -statistics and PCA** All computations are performed in R. I use `admixtools`
 232 2.0.0 (<https://github.com/uqrmaie1/admixtools>) to compute F -statistics. To obtain a PC-
 233 decomposition, I first calculate all pairwise F_2 -statistics, and then use equation 8 and the `eigen`
 234 function to obtain the PCs. The right-hand side matrix of equation 8 is supposed to have non-
 235 negative eigenvalues (i.e. $-\mathbf{CF}_2\mathbf{C}$ is positive-semidefinite). However as F_2 -statistics are estimates,
 236 some eigenvalues might be slightly negative, which would lead to imaginary PCs. I avoid this by
 237 using the `nearPD`-function in R that ensures all eigenvalues have the correct sign.

238 4 Results

239 The transformation from the previous section allows us to consider the geometry of F -statistics in
 240 PCA-space. The relationships we will discuss formally only hold if we use all PCs. However, the
 241 appeal of PCA is that frequently, only a very small number $K \ll n$ of PCs contain most information
 242 that is relevant for population structure, in which case the geometric interpretations become very
 243 simple. Thus, throughout the schematic figures, I assume that two PCs are sufficient to characterize
 244 population structure. In the data applications I evaluate how deviations of this assumption my
 245 manifest themselves in PCA plots.

246 4.1 F_2 in PC-space

247 The F_2 -statistic is an estimate of the squared allele-frequency distance between two populations.
 248 On a tree (Figure 2A) this corresponds to the branch between two populations. In allele-frequency
 249 space, it corresponds to the squared Euclidean distance, and thus reflects the intuition that closely
 250 related populations will fall close to each other on a PCA-plot, and have low pairwise F_2 -statistics.
 251 However, since F_2 can be written as a sum of squared (non-negative) terms for each PC (eq. 9),
 252 the distance on a PCA-plot will always be an underestimate of the full F_2 -distance. Thus, PCA
 253 might project two populations with high F_2 -distance very close to each other, which would indicate
 254 that these particular PCs are not suitable to understand and visualize the relationship between these
 255 particular populations. In converse, populations that are distant on a PCA-plot are guaranteed to
 256 also have a large F_2 -distance.

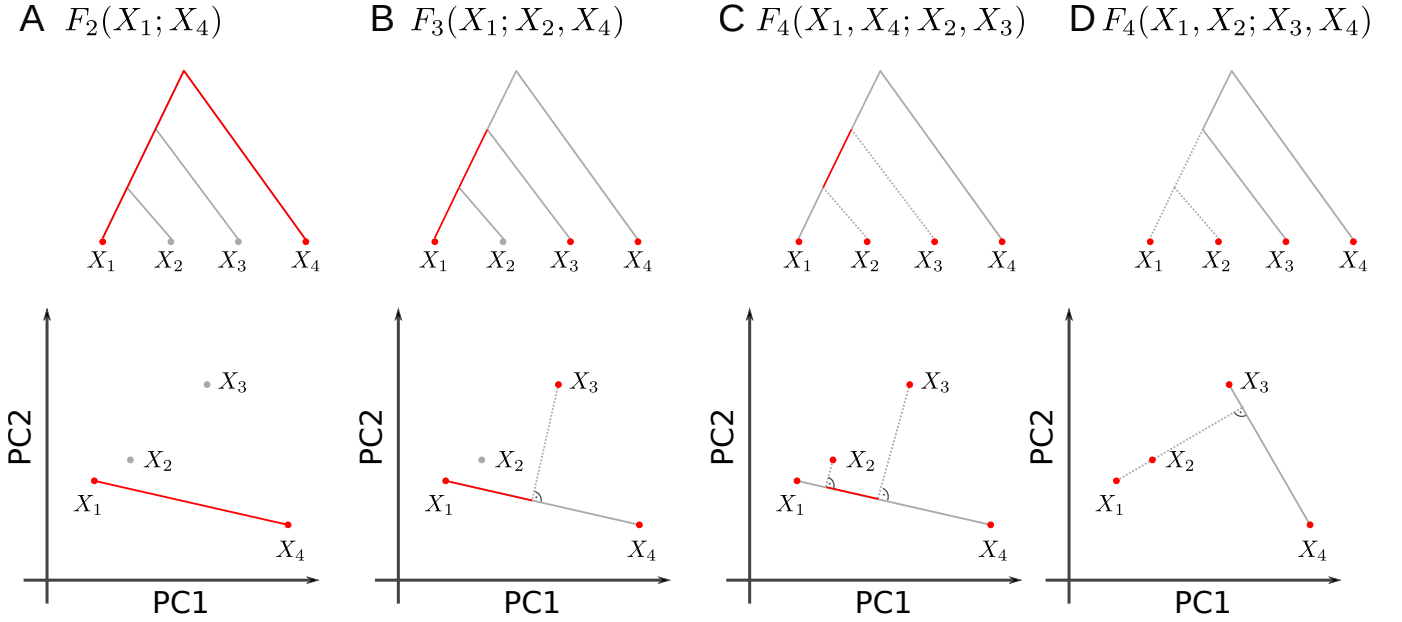


Figure 2: **Representation of F -statistics on trees and 2D-PCA-plots.** The schematics show four populations and their representation using a tree (top row) or a 2D-PCA plot (bottom row). A: F_2 represents the (squared) Euclidean distance between two tree leafs, and in PC-space. B: $F_3(X_1; X_2, X_4)$ corresponds to the external branch from X_1 to the internal node joining the populations, and is proportional to the orthogonal projection of $X_1 - X_3$ onto $X_1 - X_4$. C: $F_4(X_1, X_4; X_2, X_3)$ corresponds to the internal branch in the tree, or the orthogonal projection of $X_2 - X_3$ on $X_1 - X_4$. D: $F_4(X_1, X_2; X_3, X_4)$ The two paths from X_1 to X_2 and X_3 and X_4 are non-overlapping in the tree, which corresponds to orthogonal vectors in PCA-space.

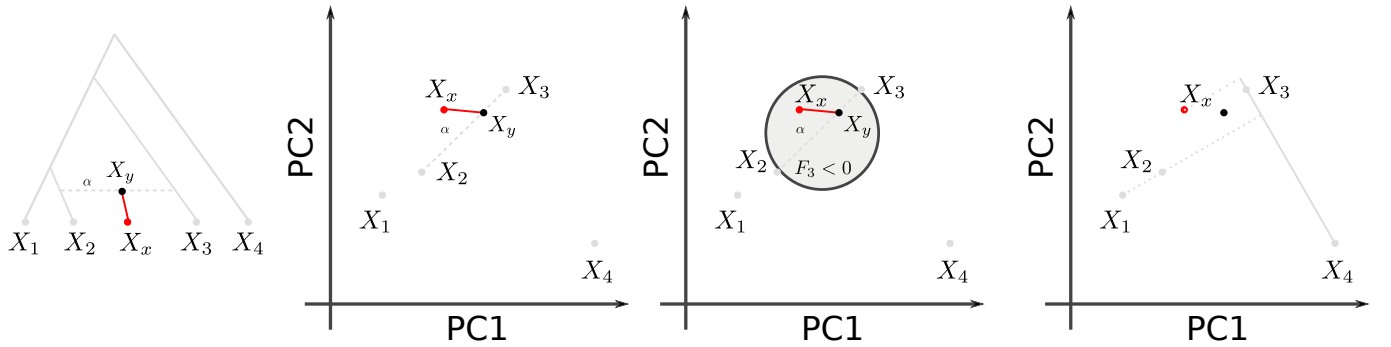


Figure 3: **Admixture representation on 2D-PCA-plot.** The schematics show four populations and their representation using an admixture graph (A) or a 2D-PCA plot. A: Admixture graph, with population X_y originating as an admixture of X_2 and X_3 , with X_2 contributing proportion α . Subsequent drift (red branch) will change allele frequency to sampled admixture population X_x . B: PCA representation of the scenario in A. X_y originates on the segment connecting X_2 and X_3 , and subsequent drift may move it in a random direction. C: $F_3(X_x; X_2, X_3)$ and negative region (light gray circle). $F_4(X_1, X_x; X_3, X_4)$ will no longer be zero (compare to Figure 2D).

257

4.2 When are admixture- F_3 statistics negative?

Consider again the admixture scenario in Figure 3A, where population X_y is the result of a mixture of X_2 and X_3 , and subsequent drift changes the allele frequencies of the admixed population from X_y to X_x . How is such a scenario displayed on a PCA? Since the allele frequencies of X_y are a linear combination of X_2 and X_3 , it will lie on the line segment connecting these two populations (Figure 3B), at a location predicted by the admixture proportions. Subsequent drift will change the allele

frequency of X_x , and so in general it might fall on a different point on a PCA-plot. An exception occurs when X_x (and no other populations related to X_x) are not part of the construction of the PCA, so that $X_x - X_y$ is orthogonal to all PCs, i.e.

$$\langle X_x - X_y, X_i - X_j \rangle = \langle X_x - X_y, P_i \rangle = 0$$

for all populations $i, j \leq n$. In this case, X_x and X_y project to the same point, and the location on the PCA can directly be used to predict the admixture proportions (McVean, 2009, Brisbin et al., 2012, Oteo-Garcia and Oteo, 2021). However, if either X_x , is included in the construction of the PCA, or if some gene flow occurred between X_x and any of the populations used to construct the PCA, X_x and X_y may project on different spots (Figure 3B).

Thus, a natural question to ask is given two source populations X_2, X_3 , can we use PCA to predict which populations might be considered admixed between them? One way to address this question is to consider the space for which F_3 is negative, i.e.

$$\begin{aligned} 2F_3(X_x; X_2, X_3) &= 2\langle X_x - X_2, X_x - X_3 \rangle \\ &= \|X_x - X_2\|^2 + \|X_x - X_3\|^2 - \|X_2 - X_3\|^2 < 0. \end{aligned} \quad (13)$$

By the Pythagorean theorem, $F_3 = 0$ if and only if X_2, X_3 and X_x form a right-angled triangle. The associated region where $F_3 = 0$ is a n -sphere (or a circle in two dimensions) with diameter $\overline{X_2 X_3}$ (The overline denotes a line segment). F_3 is negative when the triangle is obtuse, i.e. X_x could be considered admixed if it lies inside the n -ball with diameter $\overline{X_2 X_3}$ (Figure 2B, Equation A2).

F_3 on a 2D PCA-plot. If we project this n -ball on a two-dimensional plot, $\overline{X_2 X_3}$ will usually not align with the PCs; thus the ball may be somewhat larger than it appears on the plot. This geometry is perhaps easiest visualized on a globe. If we look at the globe from a view point parallel to the equator, both the north and south poles are visible at the very edge of the circle. But if we look at it from above the north pole, the north- and south-poles will be at the very same point.

Thus if $\hat{F}_3 \ll F_3$, the “true” circle will be bigger than what would be predicted from a 2D-plot, and populations that appear inside the circle on a PCA-plot may, in fact, have positive F_3 -statistics. This is because they are outside the n -ball in higher dimensions. The converse interpretation is more strict: if a population lies outside the circle on *any* 2D-projection, F_3 is guaranteed to be bigger than 0 (see Equation A4 in the Appendix).

Example As an example, I visualize the admixture statistic $F_3(X; \text{Basque, Turkish})$, on the first two PCs of the Western Eurasian data set (Figure 4A). In this case, the projected n -ball (light gray) and circle based on two dimensions (dark gray) have similar sizes. However, several populations that appear inside the circles (e.g. Sardinian, Finnish) have, in fact, positive F_3 -values, so they lie outside the n -ball. This reveals that the first two PCs do not capture all the genetic variation relevant for Southern European population structure. Consequently, approximating F_3 by the first two or ten PCs (Figure 4B) only gives a coarse approximation of F_3 , and from Figure 4C we see that many higher PCs contribute to F_3 statistics.

However, many populations, particularly from Western Asia and the Caucasus, fall outside the circle. This allows us to immediately conclude that their F_3 -statistics must be positive; and we should not consider them as a mixture between Basques and Turks.

4.3 Outgroup- F_3 -statistics as projections

A common application of F_3 -statistics is, given an unknown sample X_U , to find the most closely related population among a reference panel (X_i) (Raghavan et al., 2014). This is done using an *outgroup- F_3* -statistic $F_3(X_O; X_U, X_i)$, where X_O is an outgroup. The reason an outgroup is introduced is

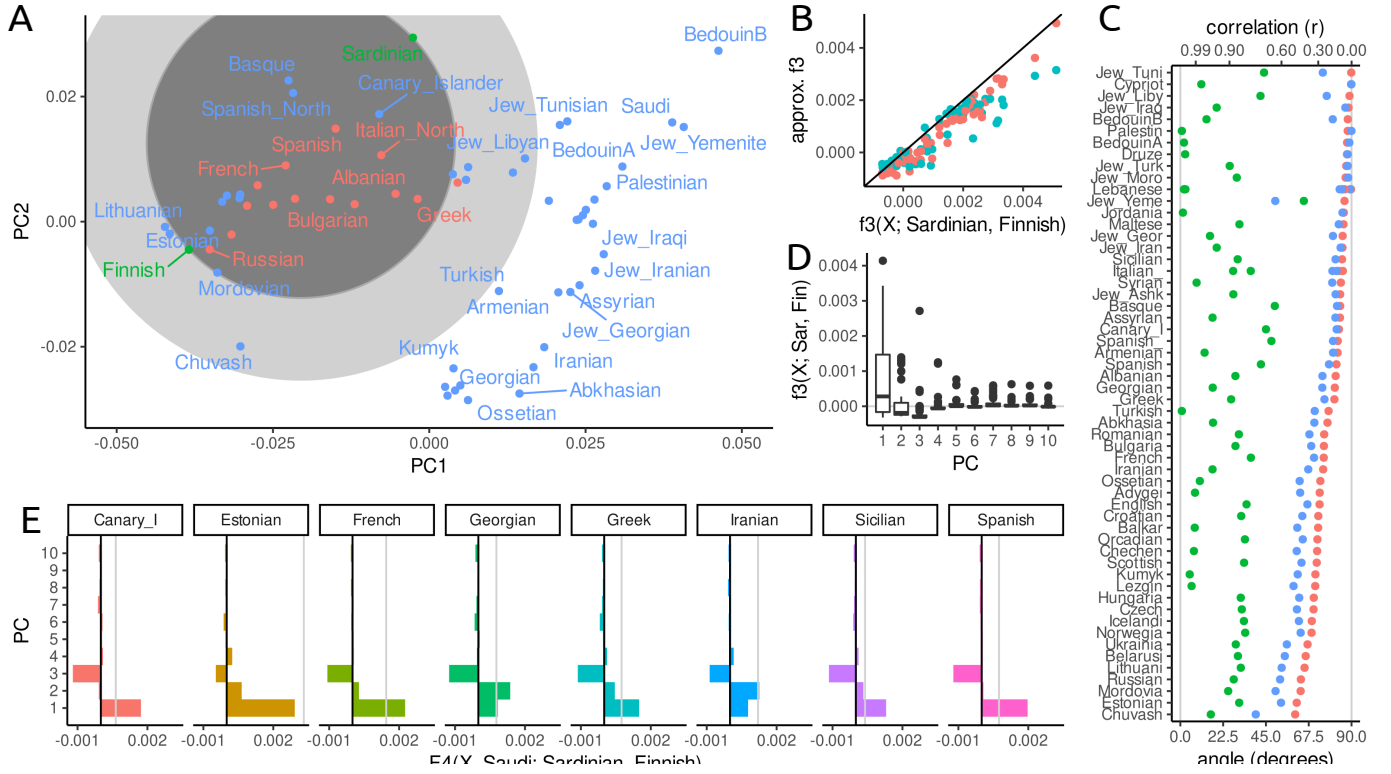


Figure 4: **PCA and F_3 -statistics** A: PCA of Western Eurasian data; the circle denotes the region for which $F_3(X; \text{Basque, Turkish})$ may be negative. Populations for which F_3 is negative are colored in red. B, E: F_3 approximated with two (blue) and ten (red) PCs versus the full spectrum. C, F: Contributions of PCs 1-10 to each F_3 -statistic. D: PCA of World data set, color indicates value of $F_3(\text{Mbuti; Mozabite, } X)$. The black line shows the projection axis Mbuti-Mozabite, the gray lines indicates the projected position of each population.

295 to account for differences in sample times and additional drift in the reference populations (1A) The
 296 outgroup- F_3 -statistic $F_3(X_O; X_U, X_3)$ represents the branch length from X_O to the common node
 297 between the three samples in the statistic, and the closer this node is to X_U , the longer the branch
 298 and hence the larger the F_3 -statistic.

To make sense of outgroup- F_3 -statistics in the PCA context, I use the association of F_3 -statistics to projections (Equation 5): On a PCA-plot, we can visualize this F_3 -statistic as the projection of the vector $X_i - X_O$ onto $X_U - X_O$:

$$\text{proj}_{X_U - X_O} X_i - X_O = F_3(X_O; X_U, X_i) \frac{X_U - X_O}{F_2(X_O; X_U)}.$$

299 On the right-hand-side terms only the F_3 term depends on the X_i . The fraction can be thought
 300 of as a normalizing constant, which justifies the argument that the F_3 -statistic and length of the
 301 projected vector are proportional to each other, and can thus be interpreted similarly. Thus, the
 302 outgroup- F_3 -statistic is largest for whichever X_i projects furthest along the axis from the outgroup
 303 to the unknown population; in the example in Figure 1B this is X_3 .

304 **Example** In Figure 4D, I use the World data set to visualize the outgroup- F_3 -statistic $F_3(\text{Mbuti; Gujarati, } X)$
 305 in i.e. a statistic that aims to find the population most closely related to Gujarati (from Western
 306 India), assuming the Mbuti are an outgroup to all populations. On a PCA, we can interpret this
 307 F_3 statistic as the projection of the line segment from Mbuti to population X_i onto the line through
 308 Mbuti and Gujarati (black line). For each population, the projection is indicated with a grey line. In
 309 the full data space, this line is always orthogonal to the segment Mbuti-Gujarati, but on the plot (i.e.

the subspace spanned by the first two PCs), this is not necessarily the case. The coloring is based on the F_3 -statistic calculated from all the data, with brighter values indicating higher F_3 -statistics. In this case, the first two PCs approximate the F_3 -statistic very well: Particularly the samples from East Asia, Siberia and the Americas project very close to orthogonally, suggesting that most of the genetic variation relevant for this analysis is captured by these first two PCs. We can quantify this and find that the first two PCs slightly underestimate the absolute value of F_3 (Figure 4E), but keep the relative ordering. I also find that many PCs, e.g. PCs 3-5, 7 and 10 have almost zero contribution to all F_3 -statistics (Figure 4F), and PCs 6, 8 and 9 having a similar non-zero contribution for almost all statistics, likely because these PCs explain within-African variation.

4.4 F_4 -statistics as angles

The interpretation of F_4 in PCA is similar to that of F_3 as a projection of one vector onto another, with the difference that now all four points may be distinct. F_4 -statistics that correspond to a branch in a tree (as in Figure 2C), can be interpreted as being proportional to the length of a projected segment on a PCA plot (Figure 2G), again with the caveat that we need to scale it by a constant. If the F_4 -statistic corresponds to a branch that does not exist in the tree, i.e it is a test statistic (Figure 2D), then, from the tree-interpretation, we expect $F_4(X_1, X_2; X_3, X_4) = 0$ implies that the vectors $X_1 - X_2$ and $X_3 - X_4$ are orthogonal to each other, or that the two populations map to the same point (Figure 2H). In the case of an admixture graph, this is no longer the case: Population X_x in Figure 3D does *not* map to the same point as X_1 or X_2 do, implying that statistics of the form $F_4(X_1, X_x; X_3, X_4) \neq 0$.

$$F_4(X_3, X'_3; X_4, X'_4) = 0.$$

Since F_4 is a covariance, its magnitude lacks an interpretation. Therefore, commonly correlation coefficients are used, as there, zero means independence and one means maximum correlation. For F_4 , we can write

$$\text{Cor}(X_1 - X_2, X_3 - X_4) = \frac{\langle X_1 - X_2, X_3 - X_4 \rangle}{\|X_1 - X_2\| \|X_3 - X_4\|} = \cos(\phi), \quad (14)$$

where ϕ is the angle between $X_1 - X_2$ and $X_3 - X_4$. Thus, independent drift events lead to $\cos(\phi) = 0$, so that the angle is 90 degrees, whereas an angle close to zero means $\cos(\phi) \approx 1$, which means most of the genetic drift on this branch is shared.

Example To illustrate the angle interpretation I again use the Western Eurasian data. The PCA-biplot shows two roughly parallel clines (Figure 4A), a European gradient (from Sardinian to Chuvash), and a Asian cline (from Arab to Caucasus populations). This is quantified in Figure 5A, where I plot the angle corresponding to $F_4(X, \text{Sardinian}; \text{Saudi, Georgian})$. For most European populations, using two PCs (green points) gives an angle close to zero, corresponding to a correlation coefficient between the two clines of $r > 0.9$. Just adding PC3 (blue), however, shows that the parallelism of the clines is spurious: Using three PCs or the full data (red) shows that most correlations are low. I arrive at a similar interpretation from the spectrum of these statistics (Figure 5B), which has high loadings for the first three PCs, with minimal contributions from the higher ones.

4.5 Other projections

So far, I used eq. 9 to interpret F -statistics on a PC-plot, but the argument holds for *any* orthonormal projection of the data space. This is useful in particular for estimates of admixture proportions, which are often done in a small reference space (Patterson et al., 2012, Petr et al., 2019, Harney et al., 2021, Oteo-Garcia and Oteo, 2021).

The simplest approach is the F_4 -ratio to infer the admixture sources of population X as

$$\alpha = \frac{F_4(R_1, R_2; X, A)}{F_4(R_1, R_2; B, A)} = \frac{\text{proj}_{R_1-R_2} X - A}{\text{proj}_{R_1-R_2} B - A}, \quad (15)$$

which can be interpreted as projecting $X - A$ and $B - A$ onto $R_1 - R_2$ and measuring their relative proportions (Oteo-Garcia and Oteo, 2021). **qpAdm** extends this approach to a higher-dimensional reference space and multiple potential source populations. One open practical question in many applications is which reference and putative source populations to use (Harney et al., 2021). The theory developed here suggests some possible visualizations that may address this issue.

4.5.1 Example

In the PCA on the world overview data set, I found a gradient from Africans to Europeans (Figure 4D). I focus on this cline using an alternative projection by using F -statistics of the form $F_4(X, Y; \text{Sardinian}, \text{Yoruba})$, which might e.g. be used in an F_4 -ratio. These F_4 -statistics are very well-approximated by the first two PCs, with a 99.2% correlation between F_4 and its approximation using the first two PCs (Figure 5C).

In Figure 5D, I show the projection $\langle X; \text{Sardinian}, \text{Yoruba} \rangle$ on the X -axis, which means that the horizontal difference between any pair of population is proportional to their F_4 -statistic relative to Sardinians and Yorubans. We can also ask what variation is not represented by performing a PCA on the residual of this projection, the first two residual PCs are given on the Y -axis and in the coloring. This visualization reveals that variation within Africans (with Mbuti, Biaka and Ju|'hoansi, top right) and the variation in East Asians and Americans are largely orthogonal to this projection axis, and so Sardinians and Yoruba would be poor references if we were interested in studying East Asian genetic variation.

The percentage of between-population variance explained by the Sardinia-Yoruba axis (24%) is much lower than that of the first PC (40%, Figure 5E). However, the cumulative variance explained by the first two axes is similar, with (52%) explained when adding residual PC1 to the projection, compared to 55% for the first two PCs. The advantage of specifying one axis is that it displays the orthogonal components more explicitly, reveals distinct structure in Africans and non-Africans and thus can be used to test assumptions of more complex models.

5 Discussion

Particularly for the analysis of human genetic variation with a large number of individuals with heterogeneous relationships, F -statistics are a powerful tool to describe population genetic diversity. Here, I show that the geometry of F -statistics (Oteo-Garcia and Oteo, 2021) leads to a number of simple interpretations of F -statistics on a PCA-plot.

Previous interpretation of PCA in the context of population genetic models have focused on explicit models such as trees (Cavalli-Sforza and Piazza, 1975), homogeneous spatial models (Novembre and Stephens, 2008) and discrete-population models (?). My interpretation here is different in that it puts more emphasis on the geometry itself, rather than directly interpreting the PCs. One consequence is that the results here are not impacted by sample ascertainment, sample sizes or number of principal components analyzed, which are common concerns in the interpretation of PCA. However, a very skewed sampling distribution will increase the likelihood that more or different PCs will have to be included in the analysis. From this perspective, one could envision a framework where F -statistics are used to decide which samples should be included to obtain a low-dimensional PCA-plot “representative” of the data.

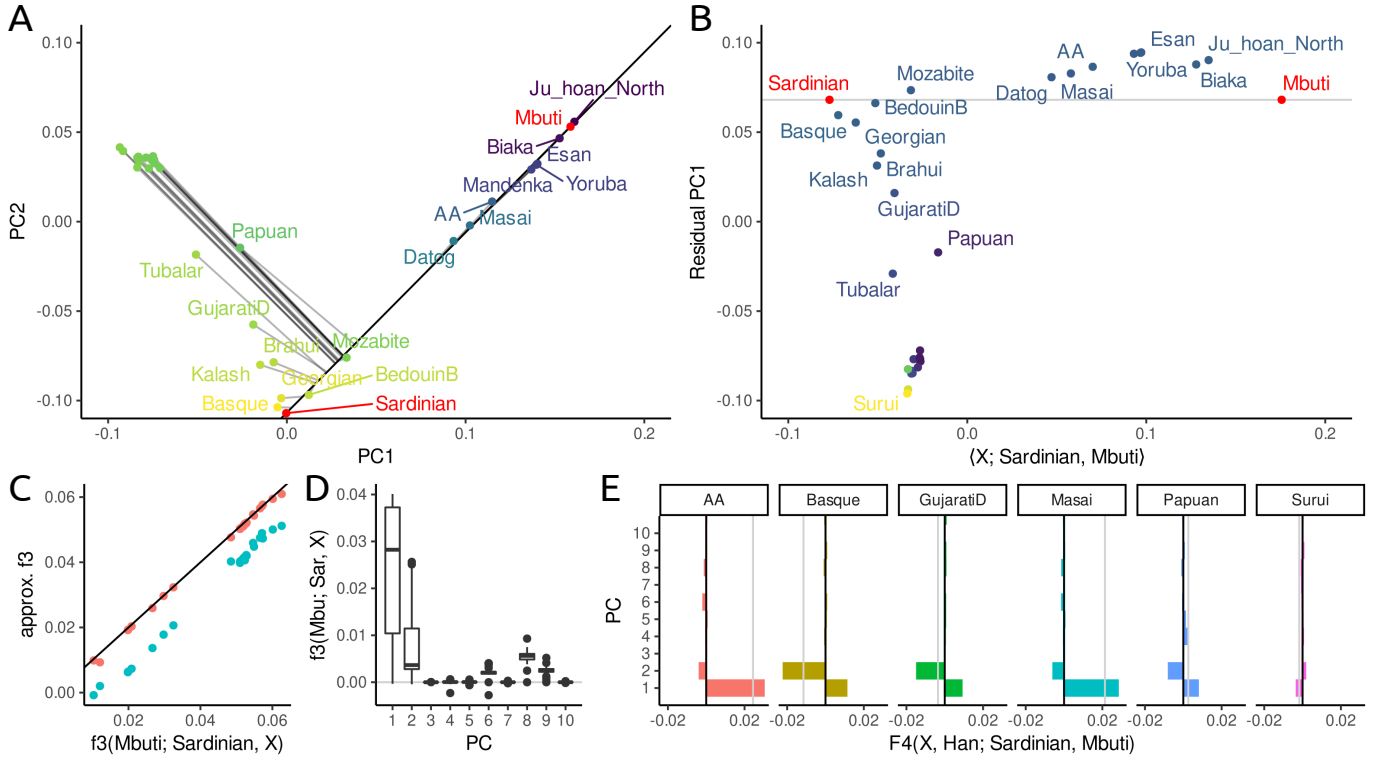


Figure 5: **PCA and F_4 -statistics** A: Projection angle and correlation coefficient r representation of $F_4(X, \text{Sardinian}; \text{Saudi, Georgian})$ (red) in the Western Eurasian data set, and approximations using two (green) and three (blue) PCs. B: Spectrum of select F_4 -statistics in the Western Eurasian data set. C: Spectrum of $F - 4$ -statistics in World data set. D: Scatterplot of F_3 -projection on Sardinian-Yoruba axis and residual PC1. E: Percent variance explained from of the projection based on F_3 in panel D and first nine residual PCs (light gray), compared with percent variance explained by first ten PCs (dark gray).

5.1 more PCs

This allows for direct and quantitative comparisons between F -statistic-based results and PCA bi-plots. As PCA is often ran in an early step in data analysis, this may aid in generation of hypotheses that can be more directly evaluated using generative models, typically using a lower number of populations. It also allows reconciling apparent contradictions between F -statistics and PCA-plots. In many cases, differences between the two data summaries will be due to variation on higher PCs. In this case, plotting additional PCs, or further subsetting the data to a more local set of populations seems prudent.

5.2 Assumptions

The other cause for disagreements between F -statistics and PCA are differences in assumptions. The version of PCA I used for my analyses was chosen such that the similarities to F -statistics are maximized. In particular, I assume here that i) we have no missing data, ii) SNPs are equally weighted and iii) that individuals can be grouped into populations and iv) we use estimated allele frequencies. In contrast, most data analyses have to grapple with missing data, SNP are often weighted according to their allele frequency and observed, individual-level genotypes are used as the basis of PCA.

408 5.2.1 missing data

409 The liability of PCA to missing data is a well-studied problem and a number of algorithms for
410 imputing have been proposed (e.g. Hastie et al., 2015, ?, Meisner et al., 2021). Calculating F -statistics
411 first is yet another way to impute data for PCA that works well if missingness is low (Meisner et al.,
412 2021). In contrast, missing data in F -statistics is handled by estimating a standard error using
413 resampling across the genome (Patterson et al., 2012), which does not distinguish between biological
414 and sampling variation. These strategies are distinct, but not unique to the relative approaches and a
415 PCA-like decomposition from F -statistics is commonly applied using MDS (e.g. Fu et al., 2016), and
416 a PCA-based approach to estimating F -statistics may provide higher accuracy than naive approaches
417 because it allows using data from related populations.

418 5.2.2 normalization

419 The normalization of SNPs is similarly a matter of convention. The F -statistic framework assumes
420 that each SNP is an identically-distributed (but not independent) random variable; and the same
421 would hold if SNPs were weighted. The drawback for individual F -statistics is that this adds a
422 dependency on additional samples (through the mean allele frequency) that may be unwanted for
423 individual F -statistics, but could be advantageous for tools that aim to do joint inference from many
424 F -statistics (Patterson et al., 2012, Harney et al., 2021). As genetic differentiation between human
425 populations is low, the normalization used may matter little in practice, but should be explored in
426 future work (Felsenstein, 1973).

427 5.2.3 estimated vs. observed allele frequencies

428 The third difference between F -statistics and standard PCA is on the usage of estimated allele
429 frequencies versus individual-based genotypes. The fact that PCA does not distinguish between
430 sample-based errors and the underlying structure is a well-known drawback of standard PCA, and
431 applying the theory presented here to individual-based PCA would result in F -statistics that incor-
432 porate some sampling noise. Probabilistic PCA is one class of approaches that aim to separate the
433 population structure from sampling noise (e.g. Agrawal et al., 2020). It seems likely that probabilistic
434 PCA would yield a representation of the data that corresponds more closely aligned with F -statistics
435 than regular PCA.

436 5.2.4 individual vs. population-based analyses

437 The final issue is that PCA is commonly run on individual-based data, whereas F -statistics often
438 group individuals into populations. This is not necessary; population-based PCA has been the
439 default in the past (Cavalli-Sforza et al., 1994), and F -statistics are often applied to individuals (e.g.
440 Green et al., 2010, Massilani et al., 2020, ?). Thus, more commonly the choice between individual-
441 based and population-based approaches is in the goal of an analysis. Grouping individuals into
442 populations introduces a major assumption, that can e.g. be justified using an individual-based
443 PCA. In particular, since F -statistics assume individuals are randomly drawn from a population,
444 they should form tight clusters on an individual-based PCA-plot, otherwise population substructure
445 becomes a possible alternative model for negative F_3 -statistics and non-zero F_4 -statistics (Peter,
446 2016).

447 5.2.5 summary

448 Thus, while the version of PCA used here differs from that proposed by Patterson et al. (2012),
449 the differences are largely due to conventions, or due to different goals for a particular analysis.
450 Particularly for studies where the description of population structure is a major focus, results might

451 be easier to interpret if conventions regarding missing data, normalization and estimation of allele
452 frequencies are used consistently between F -statistics and PCA.

453 5.3 broader scope

454 As F -statistics are motivated by trees, they assume that populations are discrete, related as a
455 graph, and that gene flow between populations is rare (Patterson et al., 2012, Harney et al., 2021).
456 However, in many regions, all humans populations are admixed to some degree (Pickrell and Reich,
457 2014), and in regions such as Europe, genetic diversity is distributed continuously (Novembre et al.,
458 2008, Novembre and Stephens, 2008). This provides a challenge for interpretation; as many F_3
459 and F_4 statistics may indicate gene flow. In my example (Figure 4A), most Southern European
460 populations are “admixed” between Basques and Turkish, but a more accurate model might be
461 one of continuous variation where Basque and Turkish lie on one of multiple gradients; which is
462 more directly visualized with PCA. There are a number of tools that have been developed that use
463 multiple F -statistics to build complex models, such as **qpGraph** (Lazaridis et al., 2014) and **qpAdm**
464 (Harney et al., 2021). One issue with these approaches is that they are usually restricted to at most
465 a few dozen populations. As ancient DNA data sets now commonly include thousands of individuals,
466 analysts are faced with the challenge of which data to include. A common approach is to sample a
467 large number of distinct models, and retain the ones that are compatible with the data. However, as
468 both **qpGraph** and **qpAdm** assume that gene flow is rare and discrete, selecting sets of populations that
469 did experience little gene flow will provide good fits. One example of this is the world foci data set
470 used here, which contains only 33 populations from across the world, and which is well-approximated
471 by two PCs. However, this ascertainment misses a large amount of variation; a more dense sampling
472 would show that in many places human genetic diversity is very gradual and multi-layered (Lazaridis
473 et al., 2014, Peter et al., 2020). The PCA-based interpretation offers an alternative that trades
474 interpretability for robustness. Particularly interpreting a (normalized) F_4 -statistic as a correlation
475 coefficient translates to generalized models of gene flow. Separating F -statistics in a sum of model
476 and residuals, and performing a PCA on the latter (such as in Figure 5D) is another way how we
477 can visualize F -statistics and evaluate the model fit.

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771 abstract.

A Derivations

Depending on a readers' background in linear algebra, these results may appear elementary; I include them here for reference and because they were not obvious to me at the onset of this project.

F-statistics are invariant under a change-of-basis

$$\begin{aligned}
F_2(X_i, X_j) &= \sum_{l=1}^S ((x_{il} - \mu_l) - (x_{jl} - \mu_l))^2 = F_2(Y_i, Y_j) \\
&= \sum_{l=1}^S \left(\sum_k L_{kl} P_{ik} - \sum_k L_{kl} P_{jk} \right)^2 \\
&= \sum_{l=1}^S \left(\sum_k L_{kl} (P_{ik} - P_{jk}) \right)^2 \\
&= \sum_{l=1}^S \left(\sum_k L_{kl}^2 (P_{ik} - P_{jk})^2 + 2 \sum_{k \neq k'} L_{kl} L_{k'l} (P_{ik} - P_{jk'})^2 \right) \\
&= \sum_k \underbrace{\left(\sum_{l=1}^S L_{kl}^2 \right)}_1 (P_{ik} - P_{jk})^2 + 2 \sum_{k \neq k'} \underbrace{\left(\sum_{l=1}^S L_{kl} L_{k'l} \right)}_0 (P_{ik} - P_{jk'})^2 \\
&= \sum_k (P_{ik} - P_{jk})^2
\end{aligned} \tag{A1}$$

In summary, the first row shows that F_2 on the centered data will give the same results (as distances are invariant to translations), in the second row we apply the PC-decomposition. The third row is obtained from factoring out L_{lk} . Row four is obtained by multiplying out the sum inside the square term for a particular l . We have k terms when for $\binom{k}{2}$ terms for different k 's. Row five is obtained by expanding the outer sum and grouping terms by k . The final line is obtained by recognizing that \mathbf{L} is an orthonormal basis; where dot products of different vectors have lengths zero.

Note that if we estimate F_2 , unbiased estimators are obtained by subtracting the population-heterozygosities H_i, H_j from the statistic. As these are scalars, they do not change above calculation.

The region of negative F_3 -statistics is a n -ball Without loss of generality, assume that $X_1 = (r, 0, 0, \dots)$ and $X_2 = (-r, 0, 0, \dots)$, and let us assume that X_x has coordinates (x_1, x_2, \dots, x_S) . Assuming $F_3(X_x; X_1, X_2) = 0$, equation 13 becomes

$$\begin{aligned}
2F_3(X_x; X_1, X_2) &= \|X_x - X_1\|^2 + \|X_x - X_2\|^2 - \|X_1 - X_2\|^2 = 0 \\
&= \left[(x_1 - r)^2 + \sum_{i=2}^S x_i^2 \right] + \left[(x_1 + r)^2 + \sum_{i=2}^S x_i^2 \right] - 4r^2 \\
&= 2 \left[\sum_{i=1}^S x_i^2 + r^2 + x_1 r - x_1 r \right] - 4r^2 \\
F_3(X_x; X_1, X_2) &= -r^2 + \sum_{i=1}^S x_i^2 = -r^2 + \|X_x\|^2 = 0,
\end{aligned} \tag{A2}$$

which is the equation of a n -sphere with radius r and center at the origin, as assumed from the placing of X_1 and X_2 . Now, assume that F_3 is negative, i.e. $F_3(X_x; X_1, X_2) = -k < 0$. Moving r^2 to the left we obtain

$$r^2 - k = \|X_x\|^2, \tag{A3}$$

786 which is another n -sphere with a smaller radius, showing that all points inside the n -sphere will have
787 negative F_3 -values.

If a population lies outside the circle of this n -Sphere in any 2D-projection, F_3 is positive
Assume the center of the n -sphere $C = \frac{X_1+X_2}{2} = (c_1, c_2, \dots, c_S)$, and $X_x = (x_1, x_2, \dots, x_S)$. Then,

$$\begin{aligned}
F_3(X_x; X_1, X_2) &= \|X_x - C\|^2 - r^2 \\
&= \underbrace{(x_1 - c_1)^2 + (x_2 - c_2)^2}_{> r^2} + \underbrace{\sum_{i=3}^S (x_i - c_i)^2}_{\geq 0} - r^2 \\
&> 0.
\end{aligned} \tag{A4}$$

788 The condition $(x_1 - c_1)^2 + (x_2 - c_2)^2 > r^2$ is satisfied whenever X_x is outside the circle obtained
789 from projecting the n -sphere on the first two dimensions. An analogous argument applies for any
790 low-dimensional representation.