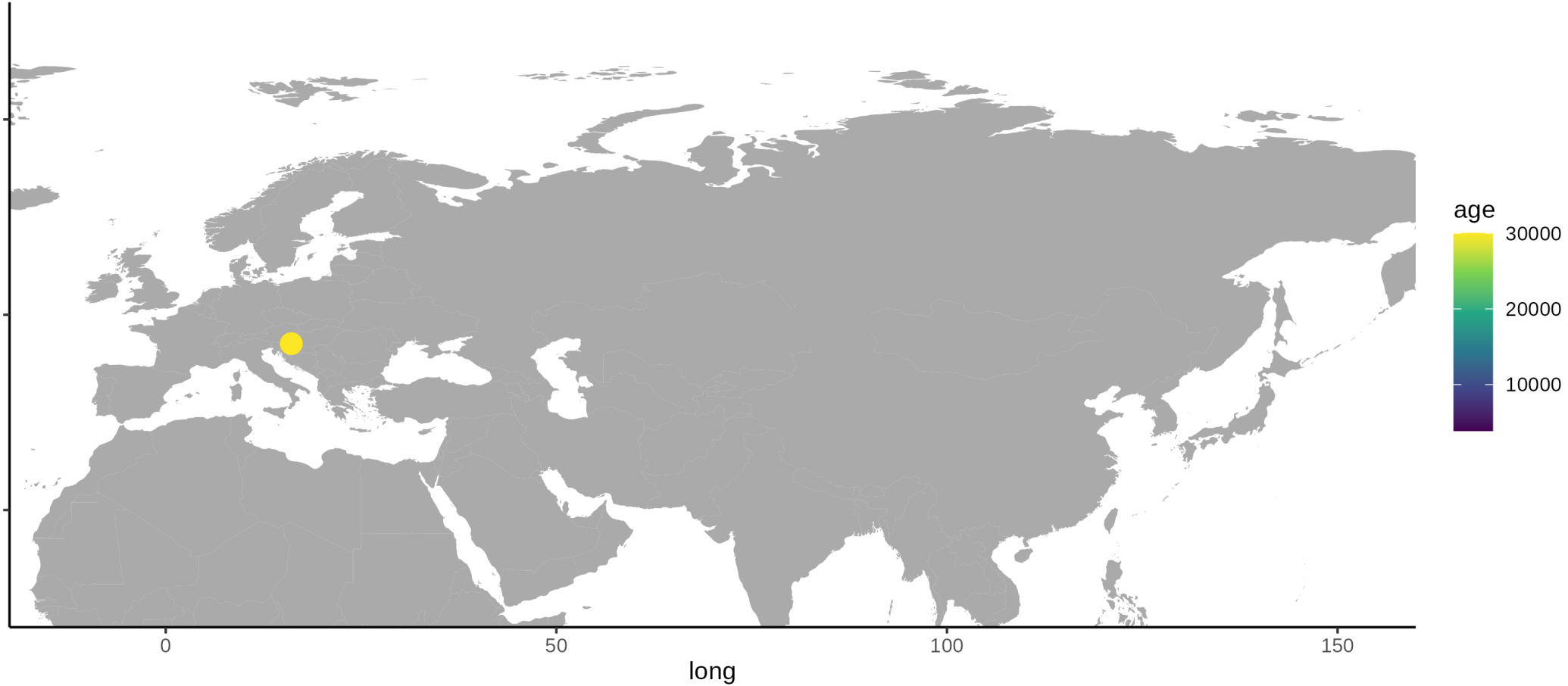


# F-statistics and Population Structure

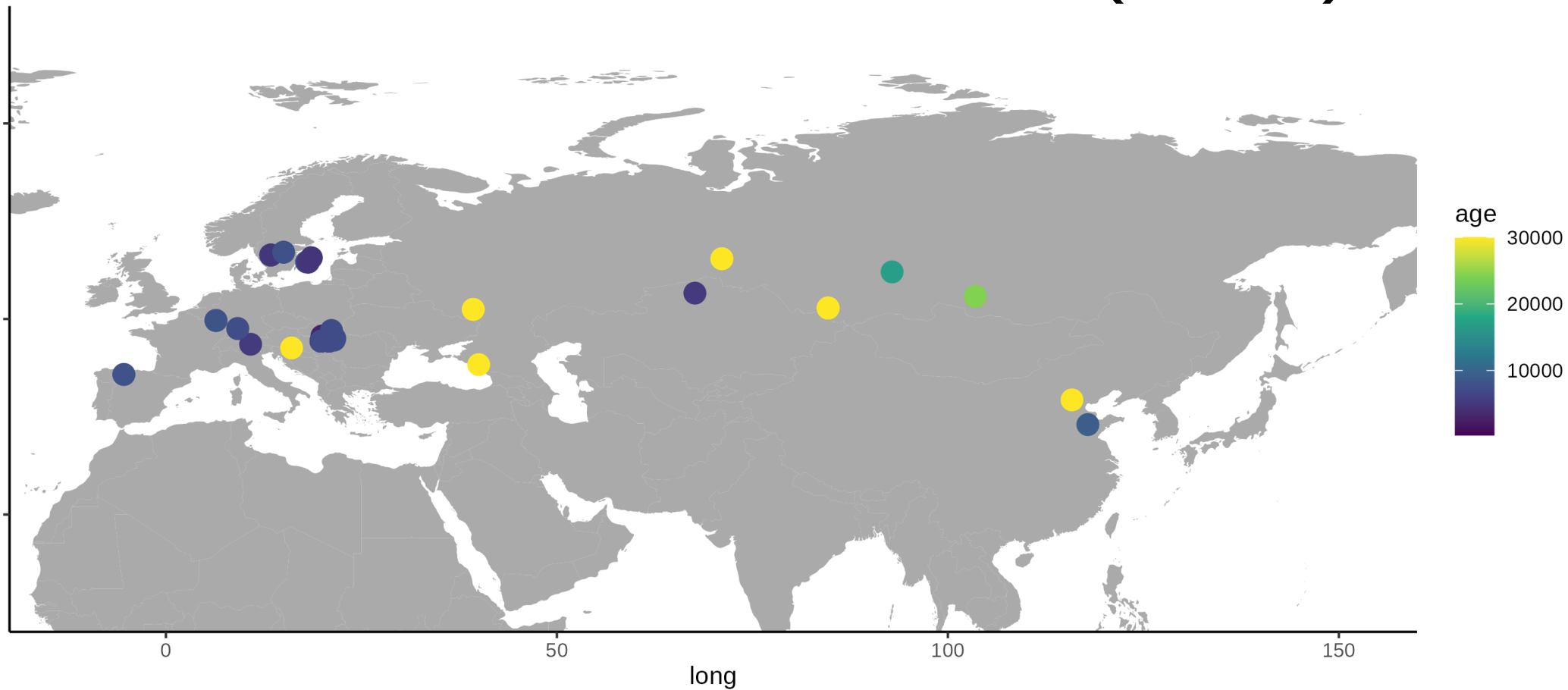
Benjamin Peter, MPI for Evolutionary Anthropology

# Hominin Ancient DNA (2010)



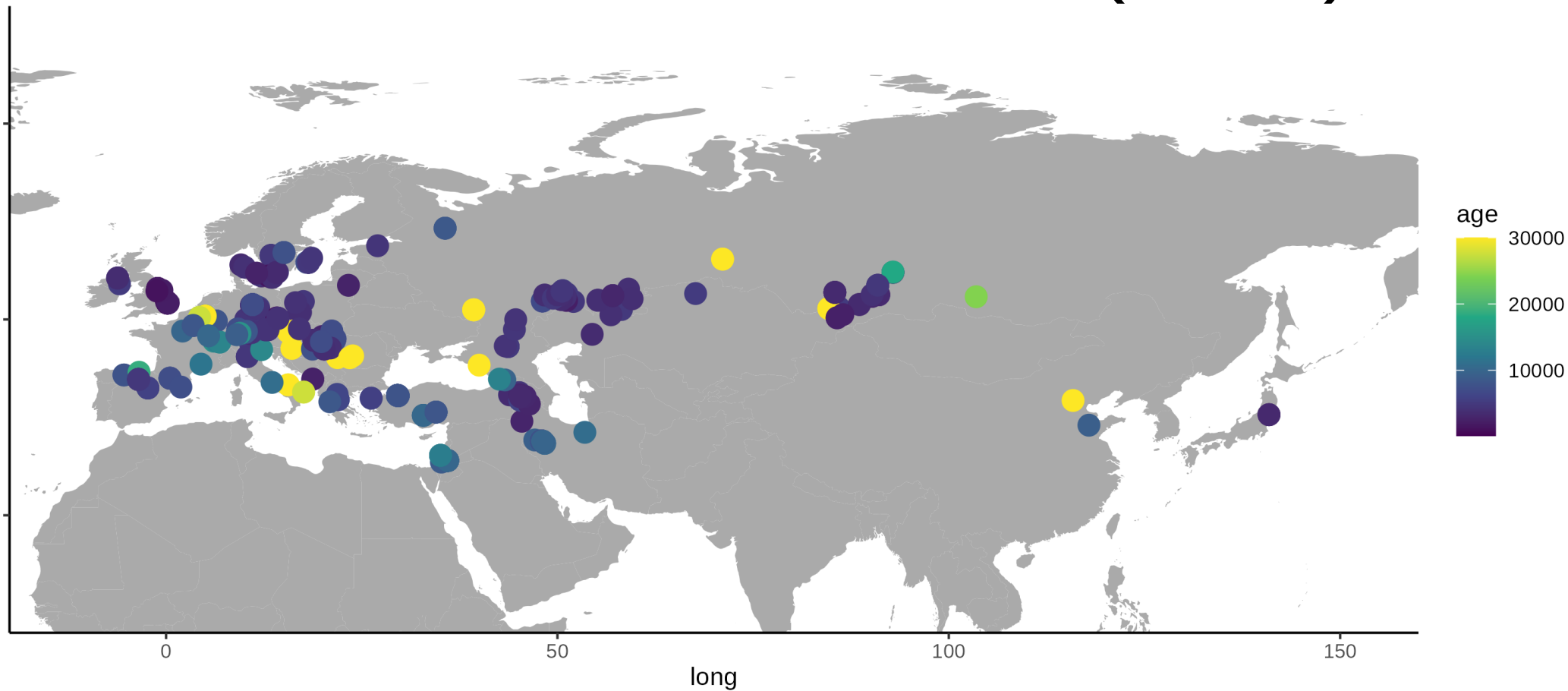
Data compiled by D. Reich et al.

# Hominin Ancient DNA (2014)



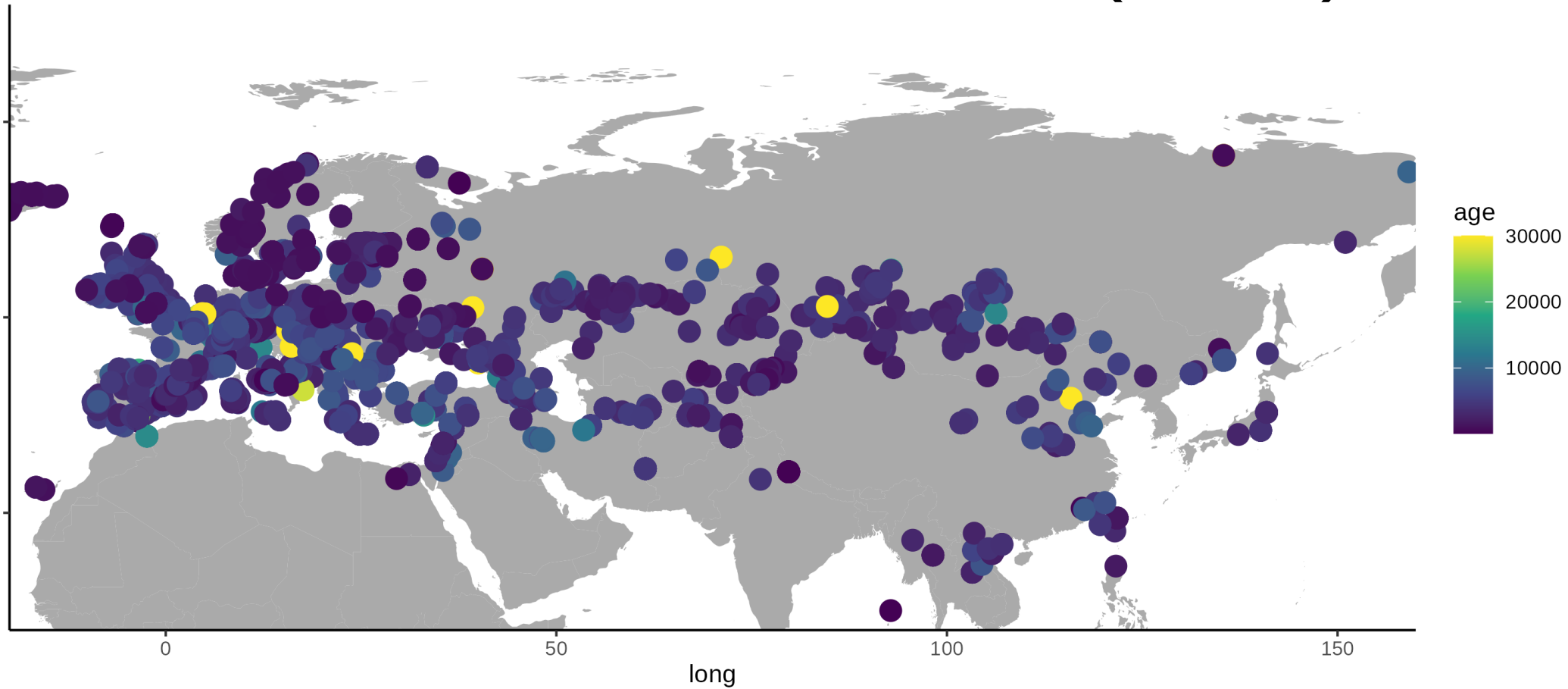
Data compiled by D. Reich et al.

# Hominin Ancient DNA (2016)



Data compiled by D. Reich et al.

# Hominin Ancient DNA (2020)



Data compiled by D. Reich et al.

# Main Reference

GENETICS | INVESTIGATION

## Admixture, Population Structure, and *F*-Statistics

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ORCID ID: 0000-0003-2526-8081 (B.M.P.)

<https://doi.org/10.1534/genetics.115.183913>

# Setup

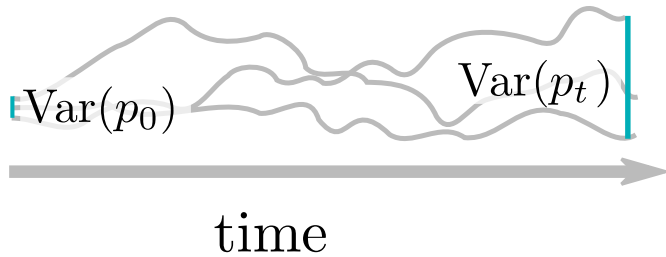
- Today: Theory of F-statistics and Computations
- Tomorrow: Using F-statistics to build more complex models

# Measuring Genetic Drift



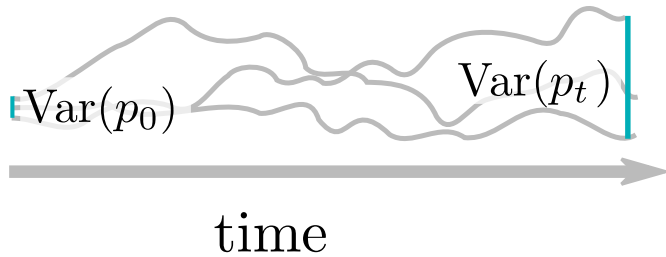
# Measuring Genetic Drift

Change in Allele Frequency

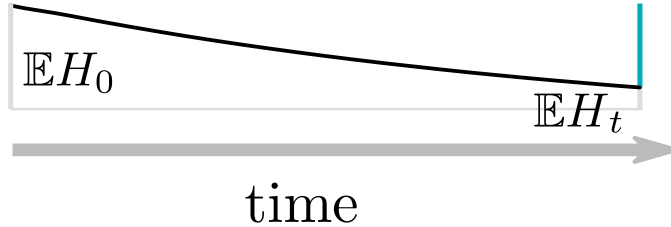


# Measuring Genetic Drift

Change in Allele Frequency

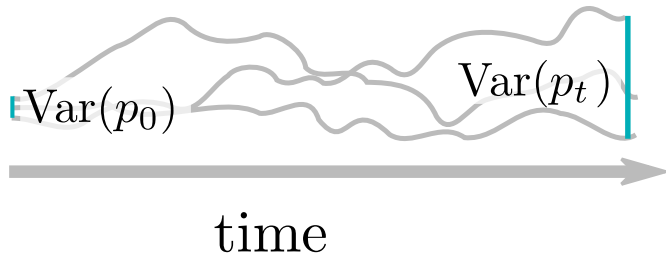


Decay of Heterozygosity

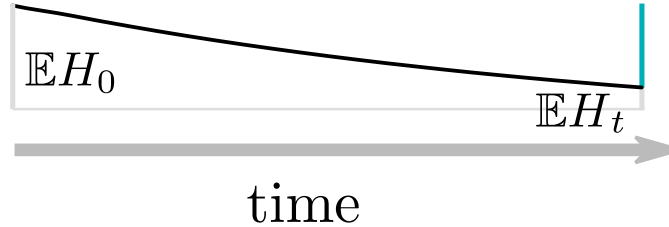


# Measuring Genetic Drift

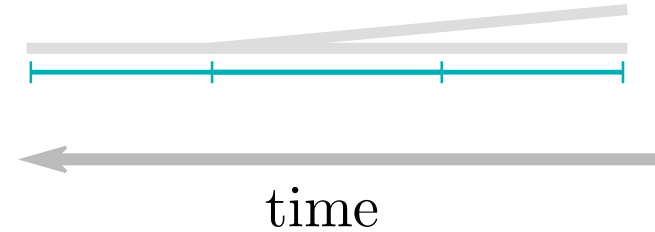
Change in Allele Frequency



Decay of Heterozygosity

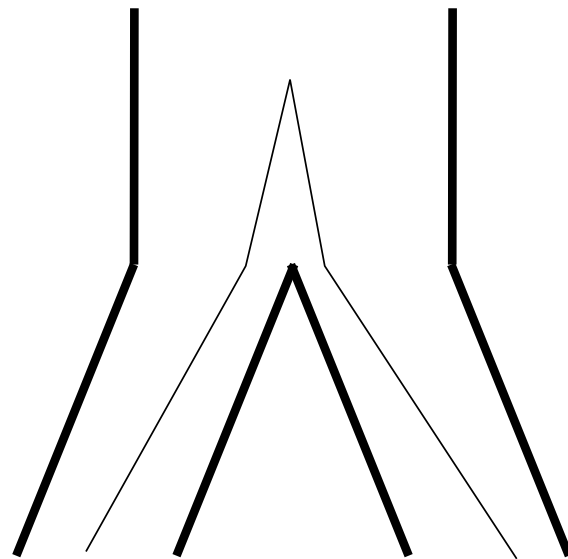
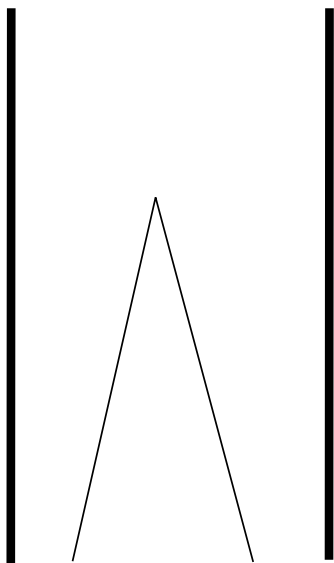


Coalescence rates



# Pairwise differences

$$\mathbb{E}[\pi] = 4N\mu = \theta \qquad \mathbb{E}[\pi_{12}] = t_{12} + 4N_{anc}\mu = t_{12} + \theta$$

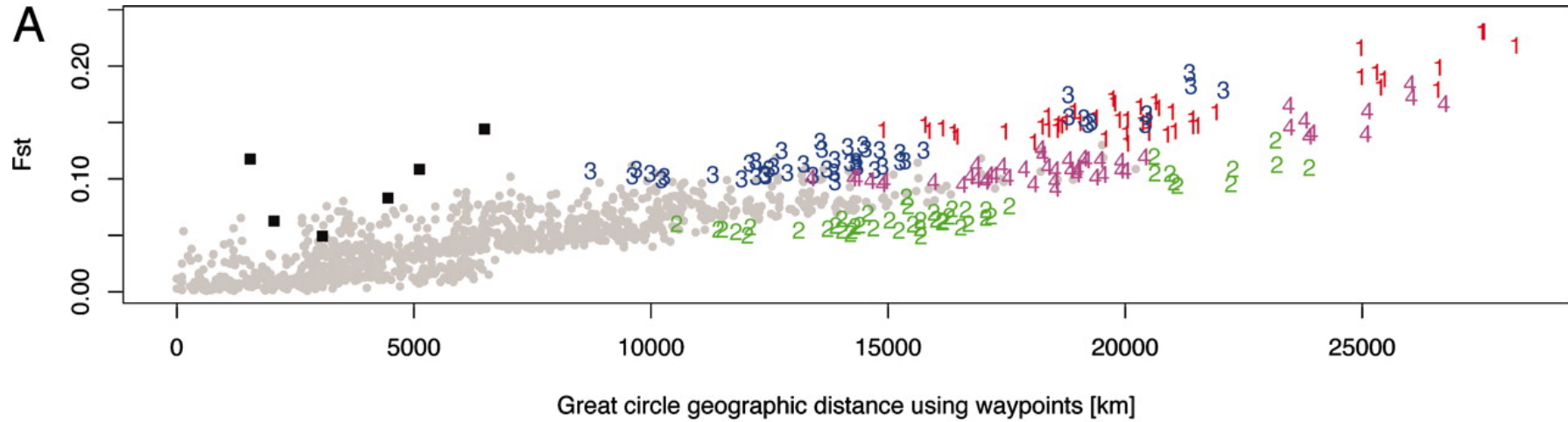


# Fixation Index $F_{ST}$

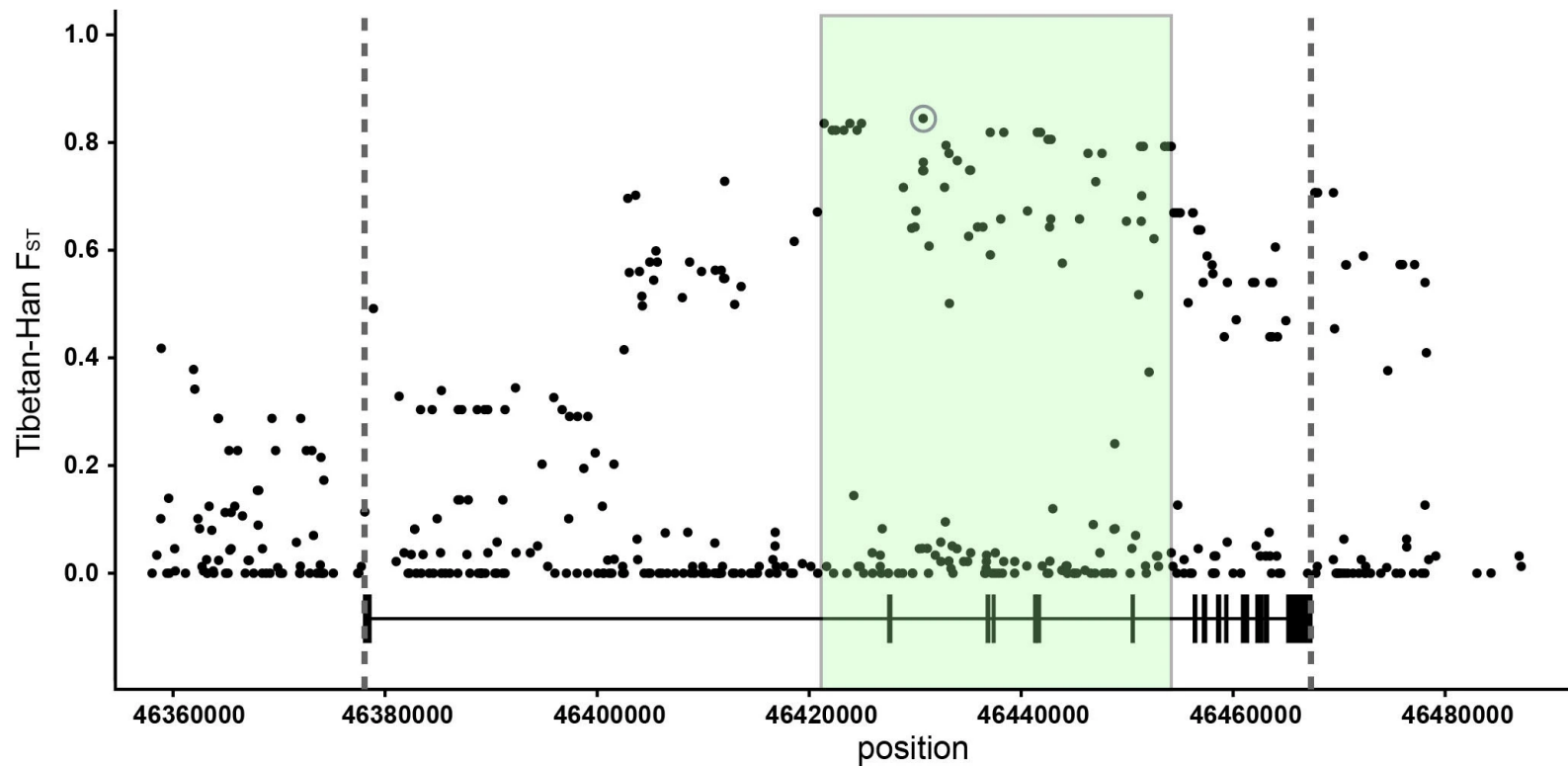
$$F_{ST}(P_1, P_2) = \frac{\pi_{12} - \frac{\pi_1 + \pi_2}{2}}{\pi_{12}}$$

- $F_{ST}$  is a correlation coefficient
- Between 0 and 1
- Hierarchical partitioning (AMOVA)
- Many estimators exist
  - Hudson (1991)
  - Weir & Cockerham (1984)

# Fixation Index $F_{ST}$



# $F_{ST}$ Outliers



# $F_2$ -statistic

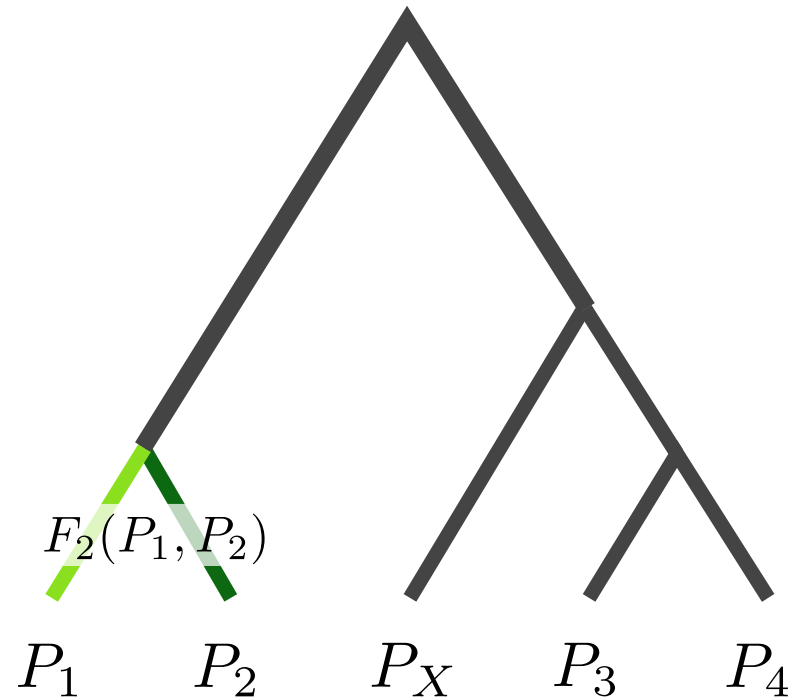
$$F_{ST}(P_1, P_2) = \frac{\pi_{12} - \frac{\pi_1 + \pi_2}{2}}{\pi_{12}}$$

$$\begin{aligned} F_2(P_1, P_2) &= 2\pi_{12} - \pi_1 - \pi_2 \\ &= \sum_l (p_{1l} - p_{2l})^2 \end{aligned}$$

- $F_{ST}$  is a correlation coefficient
- Between 0 and 1
- Hierarchical partitioning (AMOVA)
- Many estimators exist
  - Hudson (1991)
  - Weir & Cockerham (1984)
- $F_2$  is a covariance
- Bigger than 0
- Tree-additive
- Testing for treeness

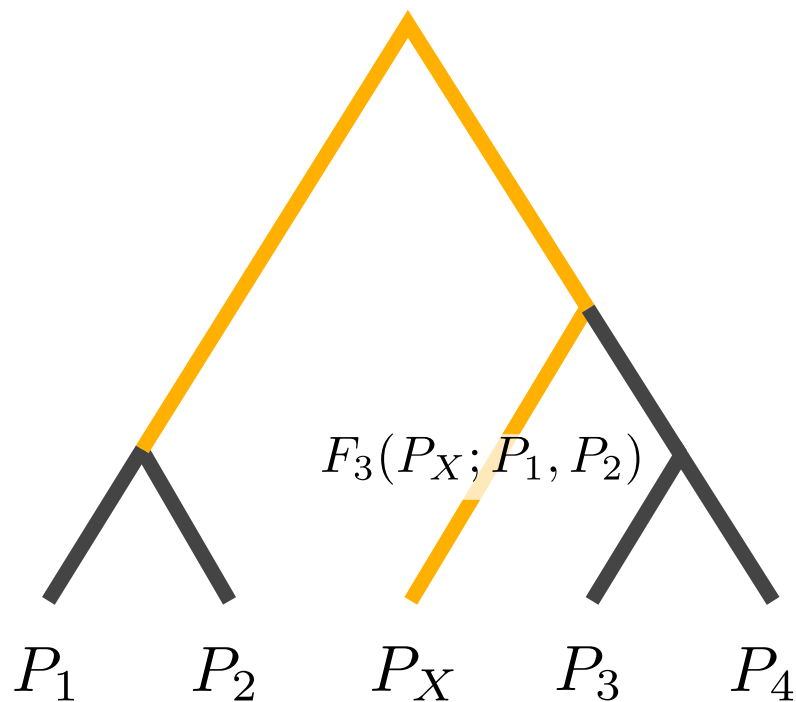


# Tree-additive



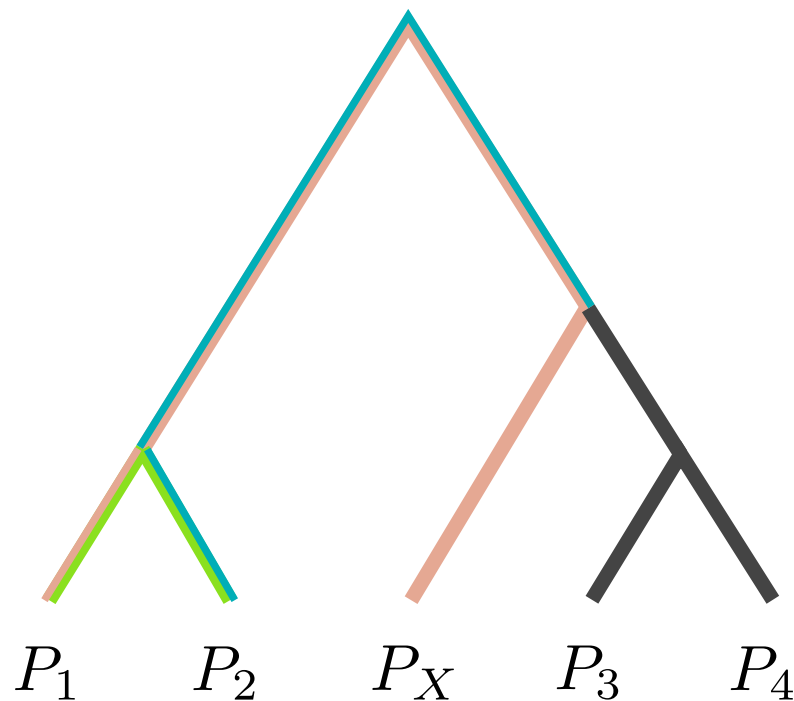
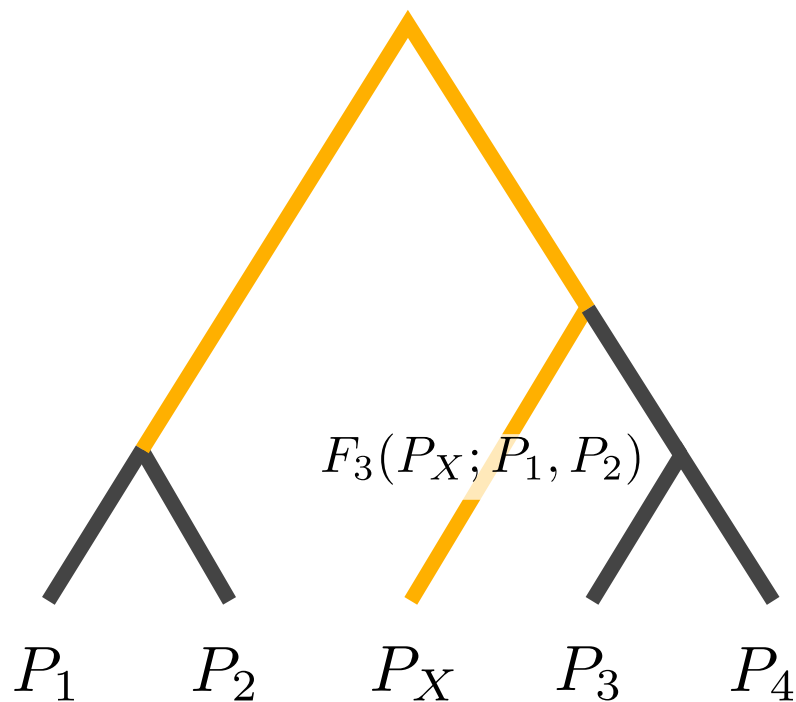
# $F_3$ -statistic

Given all  $F_2$ -values, how can we calculate the yellow branch length?



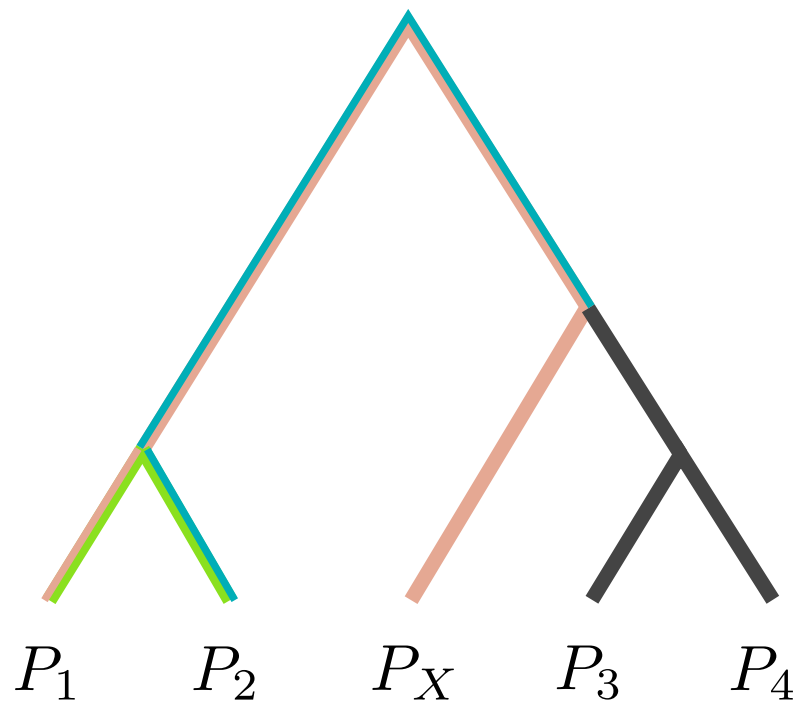
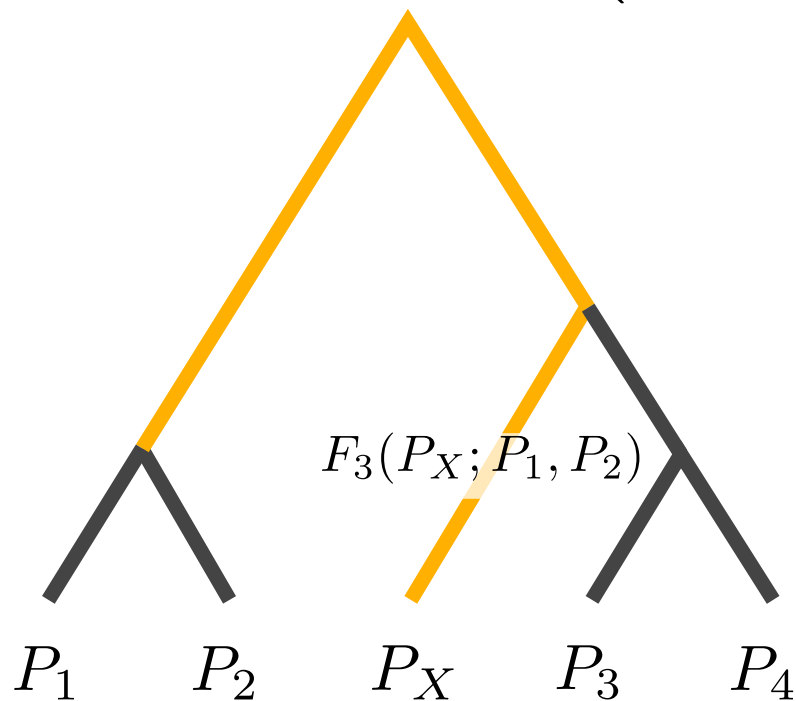
# $F_3$ -statistic

Given all F2-values, how can we calculate the yellow branch length?



# $F_3$ -statistic

$$F_3(P_X; P_1, P_2) = \frac{1}{2} \left( F_2(P_X, P_1) + F_2(P_X, P_2) - F_2(P_1, P_2) \right)$$



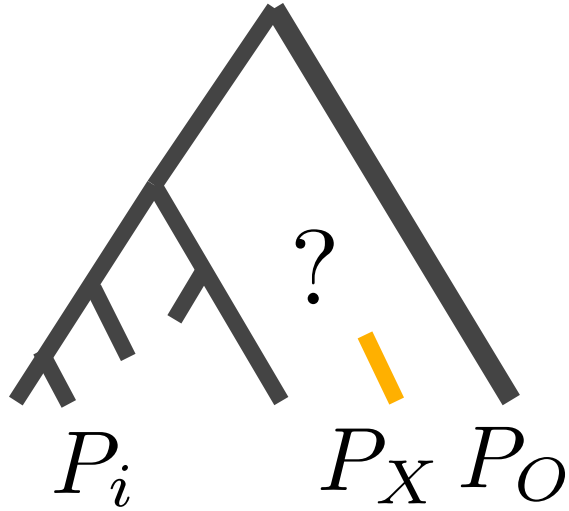
## $F_3$ -statistic equations

$$F_3(P_X; P_1, P_2) = \frac{1}{2} \left( F_2(P_X, P_1) + F_2(P_X, P_2) - F_2(P_1, P_2) \right)$$

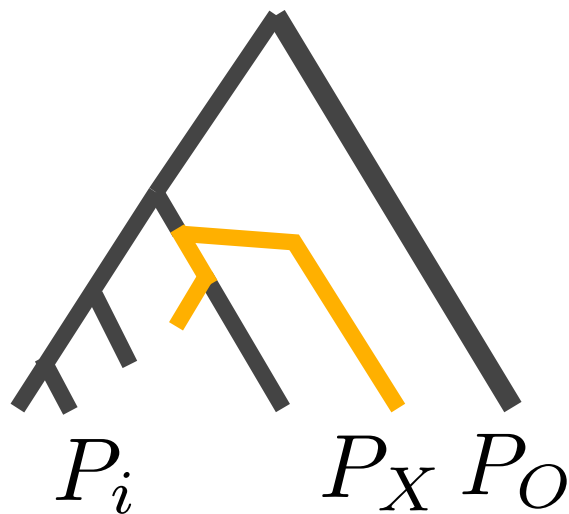
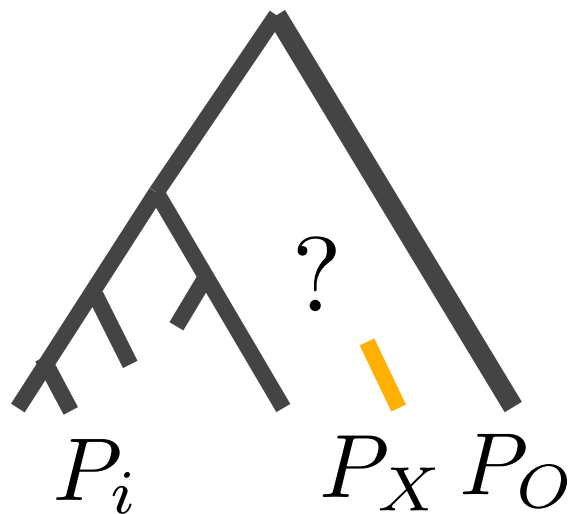
$$F_3(P_X; P_1, P_2) = \sum_l (p_{xl} - p_{x1})(p_{xl} - p_{x2})$$

$$F_3(P_X; P_1, P_2) = \pi_{1x} + \pi_{2x} - \pi_{12} - \pi_x$$

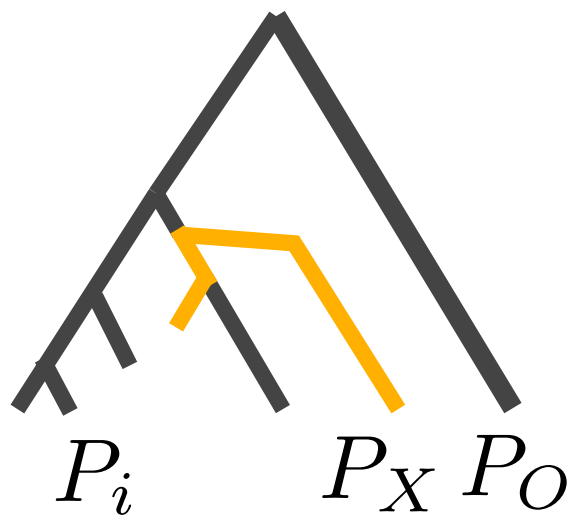
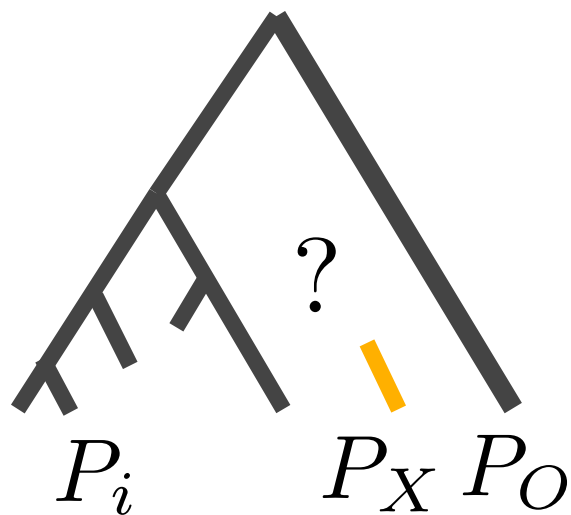
# Outgroup- $F_3$ -statistic



# Outgroup- $F_3$ -statistic



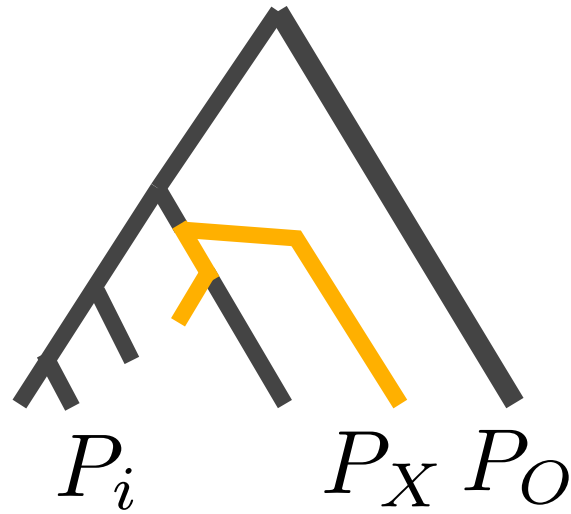
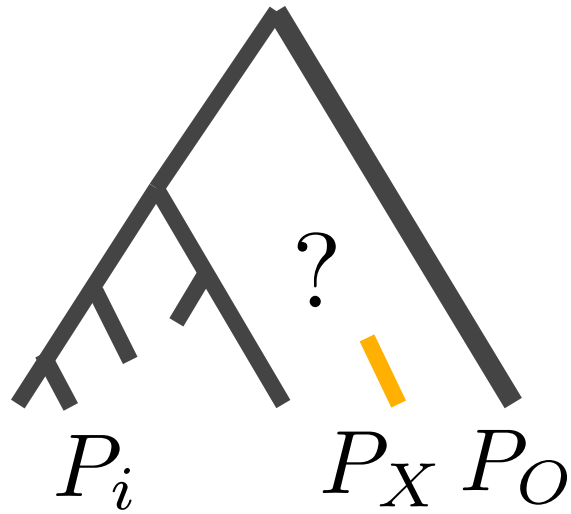
# Outgroup- $F_3$ -statistic



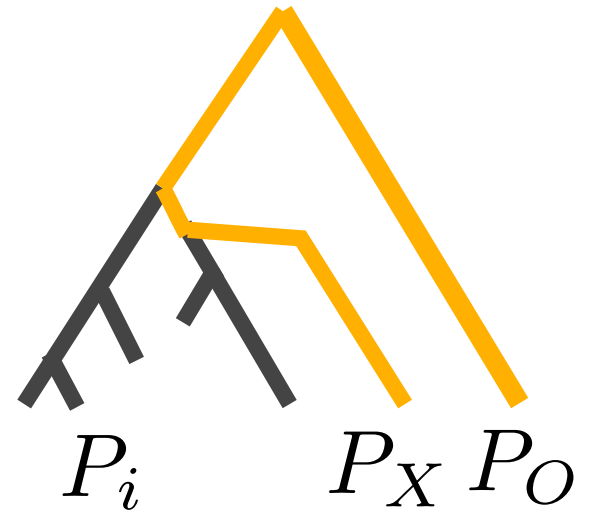
$$F_2(P_X, P_i)$$



# Outgroup- $F_3$ -statistic



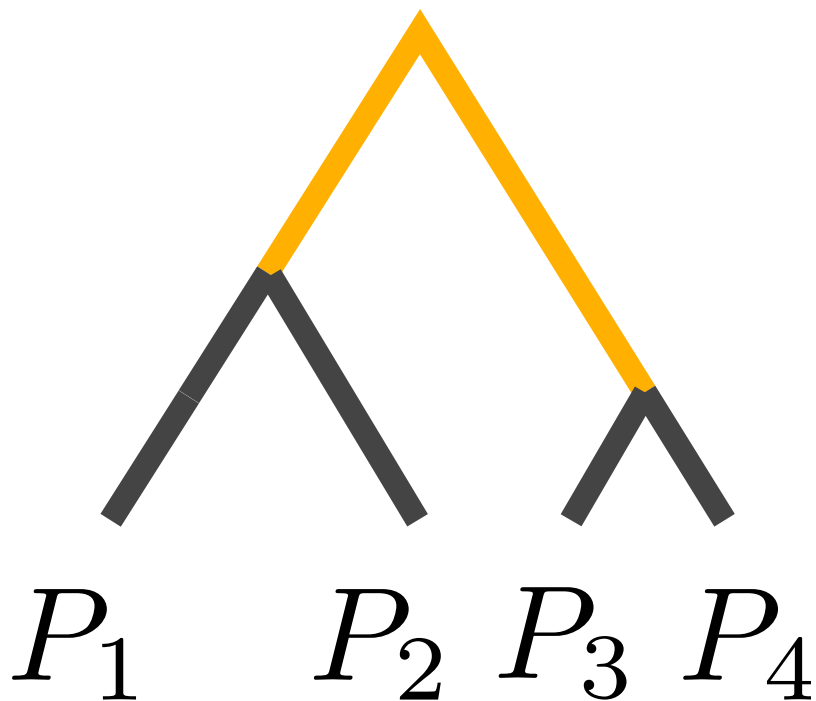
$$F_2(P_X, P_i)$$



$$F_3(P_O; P_X, P_i)$$

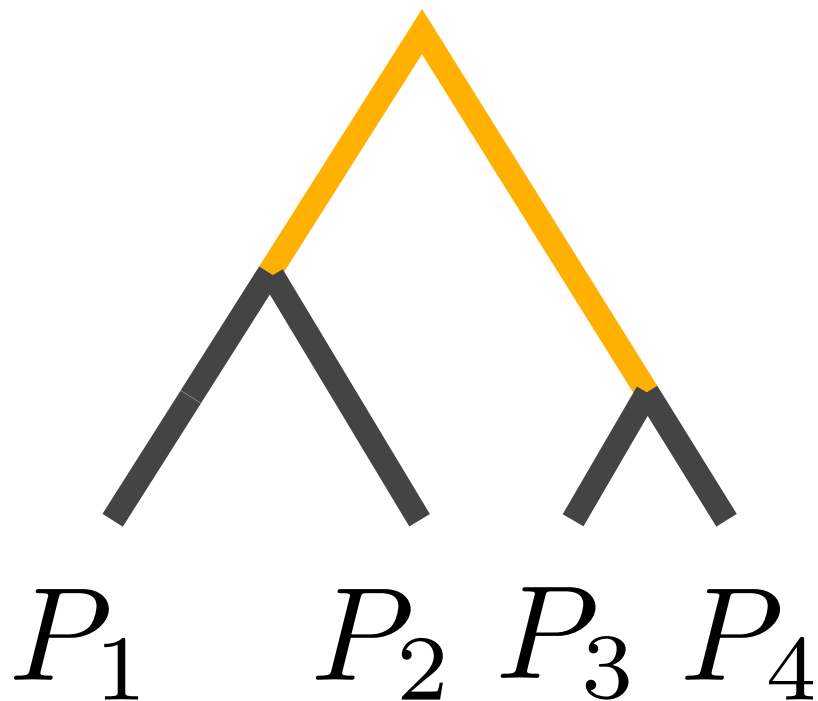
# (Branch)- $F_4$ -statistic

$$F_4^{(B)}(P_1, P_2; P_3, P_4) = \frac{1}{2} \left( F_2(P_1, P_3) + F_2(P_2, P_4) - F_2(P_1, P_2) - F_2(P_3, P_4) \right)$$



# (Branch)- $F_4$ -statistic

$$F_4^{(B)}(P_1, P_2; P_3, P_4) = \frac{1}{2} \left( F_2(P_1, P_3) + F_2(P_2, P_4) - F_2(P_1, P_2) - F_2(P_3, P_4) \right)$$

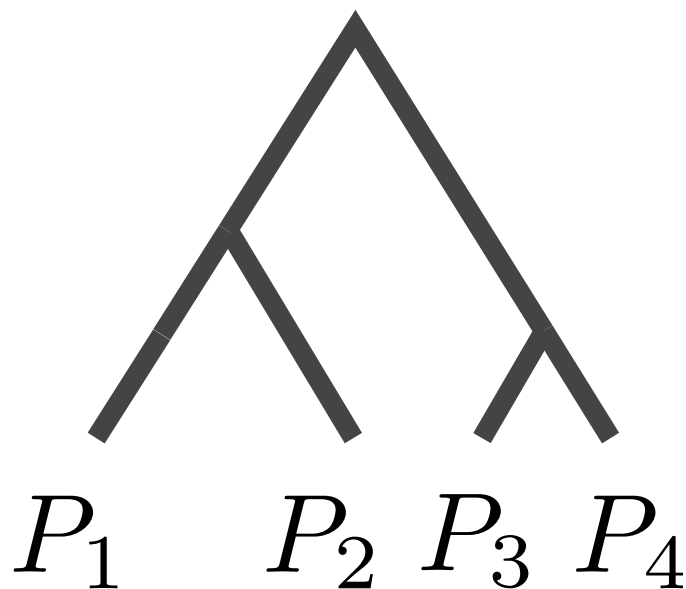


What if we reorder the arguments?

$$F_4^{(T)}(P_1, P_2; P_3, P_4) = F_4^{(B)}(P_1, P_4; P_3, P_2)$$

# (Treeness)- $F_4$ -statistic

$$F_4^{(T)}(P_1, P_2; P_3, P_4) = \frac{1}{2} \left( F_2(P_1, P_3) + F_2(P_2, P_4) - F_2(P_1, P_4) - F_2(P_2, P_3) \right)$$



# $F_4$ -statistic-equations

$$F_4^{(T)}(P_1, P_2; P_3, P_4) = \frac{1}{2} \left( F_2(P_1, P_3) + F_2(P_2, P_4) - F_2(P_1, P_4) - F_2(P_2, P_3) \right)$$

$$F_4^{(T)}(P_1, P_2; P_3, P_4) = \sum_l (p_{l1} - p_{l2})(p_{l3} - p_{l4})$$

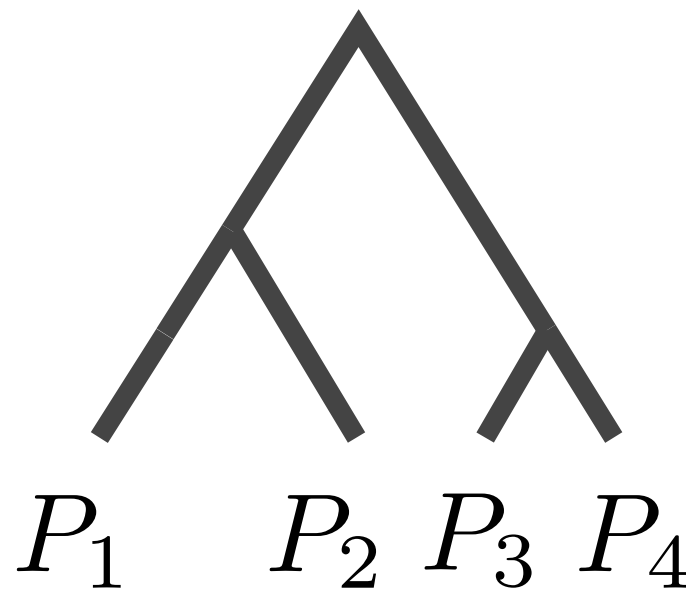
$$F_4^{(T)}(P_1, P_2; P_3, P_4) = \pi_{13} + \pi_{24} - \pi_{14} - \pi_{23}$$

# Testing Treeness

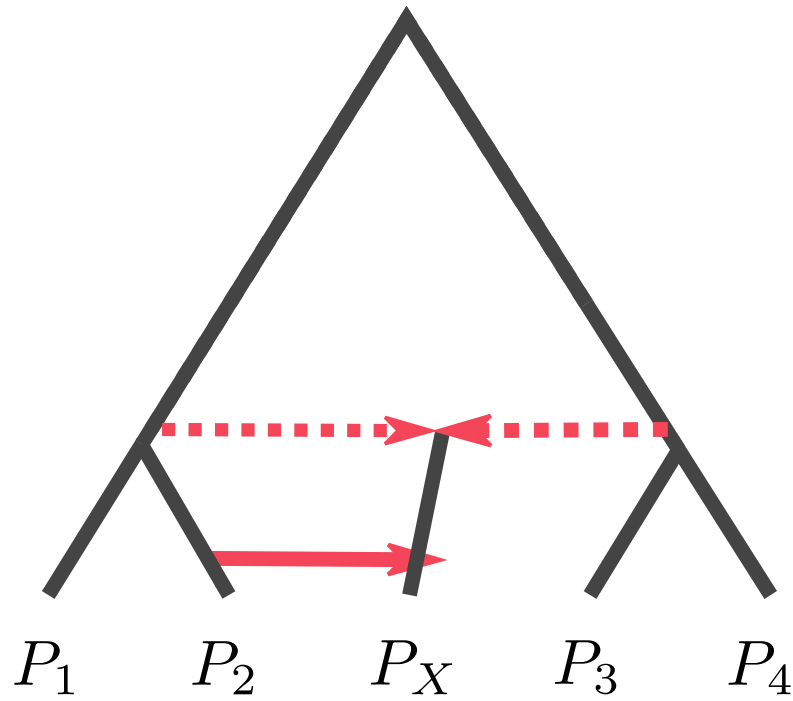
If data is generated from a tree:

$$F_3(P_3; P_1; P_2) \geq 0$$

$$F_4^{(T)}(P_1, P_2; P_3, P_4) = 0$$

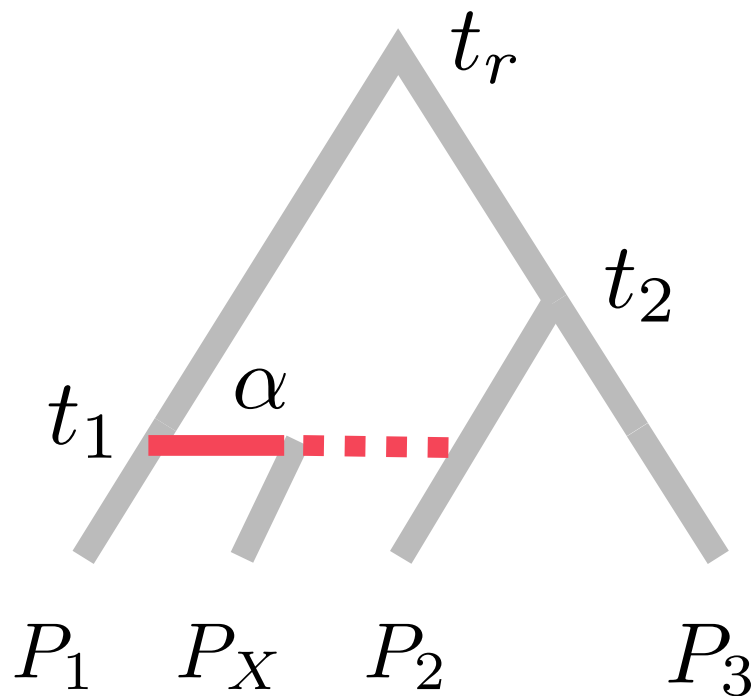


# Admixture Graphs



# F3 in an admixture graph

$$F_3(P_X; P_1, P_2) \approx \theta [t_1 - 2\alpha(1 - \alpha)t_r]$$

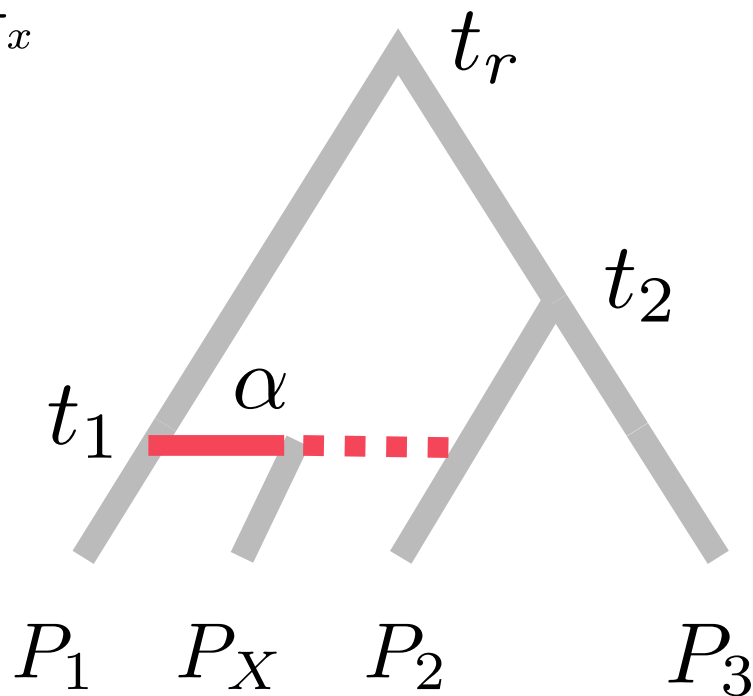




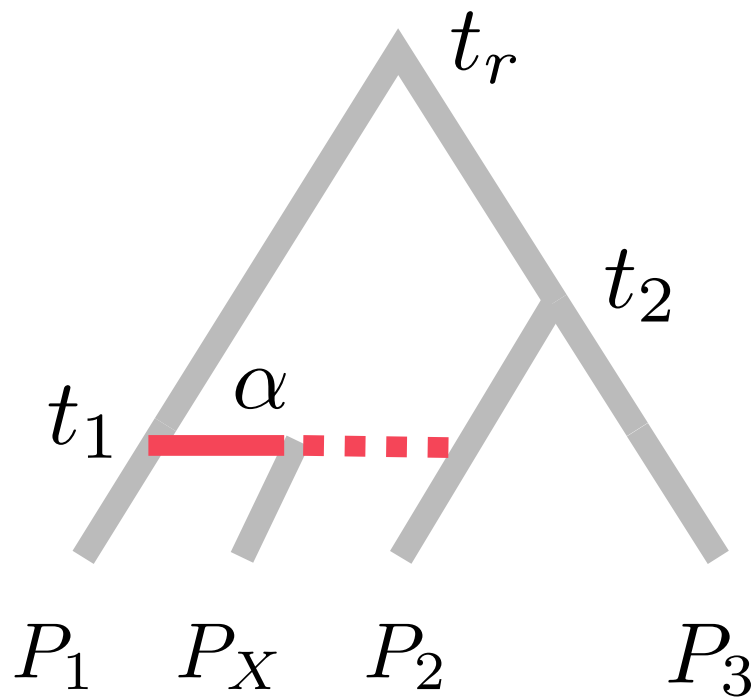
# F3 in an admixture graph

$$F_3(P_X; P_1, P_2) = \pi_{1x} + \pi_{2x} - \pi_{12} - \pi_x$$

$$F_3(P_X; P_1, P_2) \approx \theta [t_1 - 2\alpha(1 - \alpha)t_r]$$

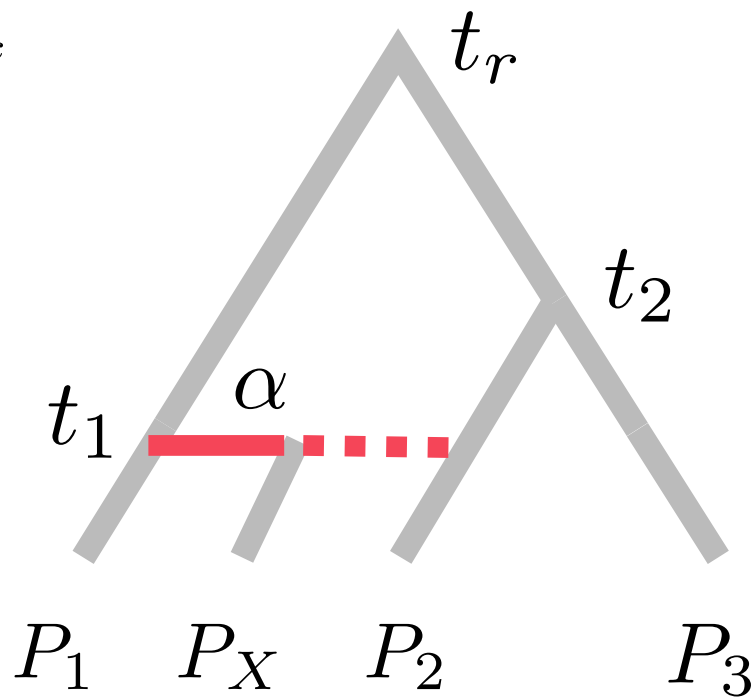


# F4 in an admixture graph



# F4 in an admixture graph

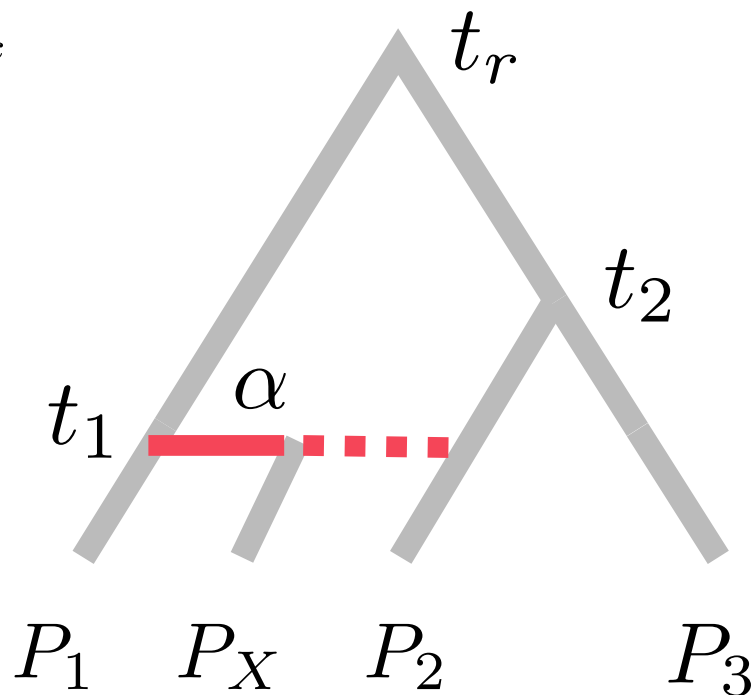
$$F_4^{(T)}(P_1, P_X; P_2, P_3) = \pi_{12} + \pi_{3x} - \pi_{13} - \pi_{2x}$$



# F4 in an admixture graph

$$F_4^{(T)}(P_1, P_X; P_2, P_3) = \pi_{12} + \pi_{3x} - \pi_{13} - \pi_{2x}$$

$$F_4^{(T)}(P_1, P_X; P_2, P_3) = (1 - \alpha)(t_2 - t_1) \neq 0$$

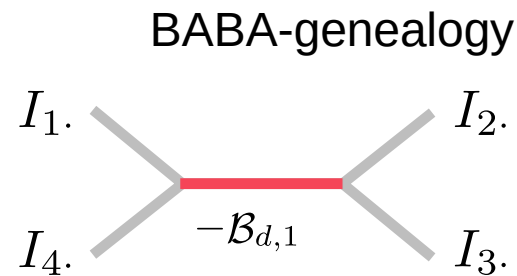
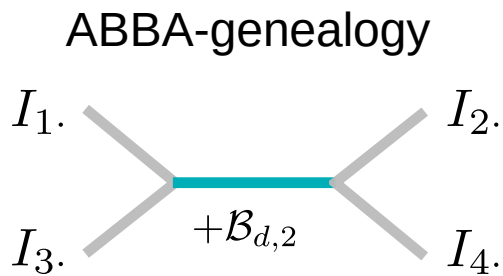
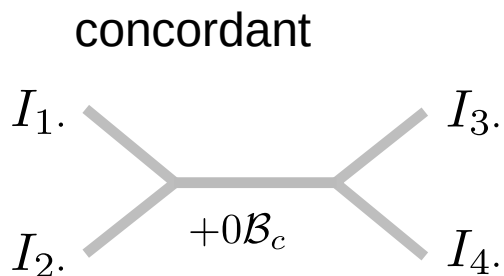
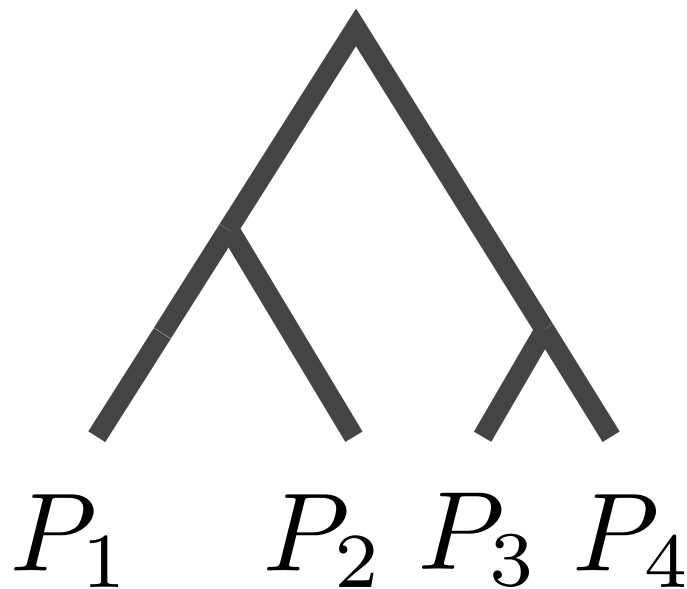


# D-statistic

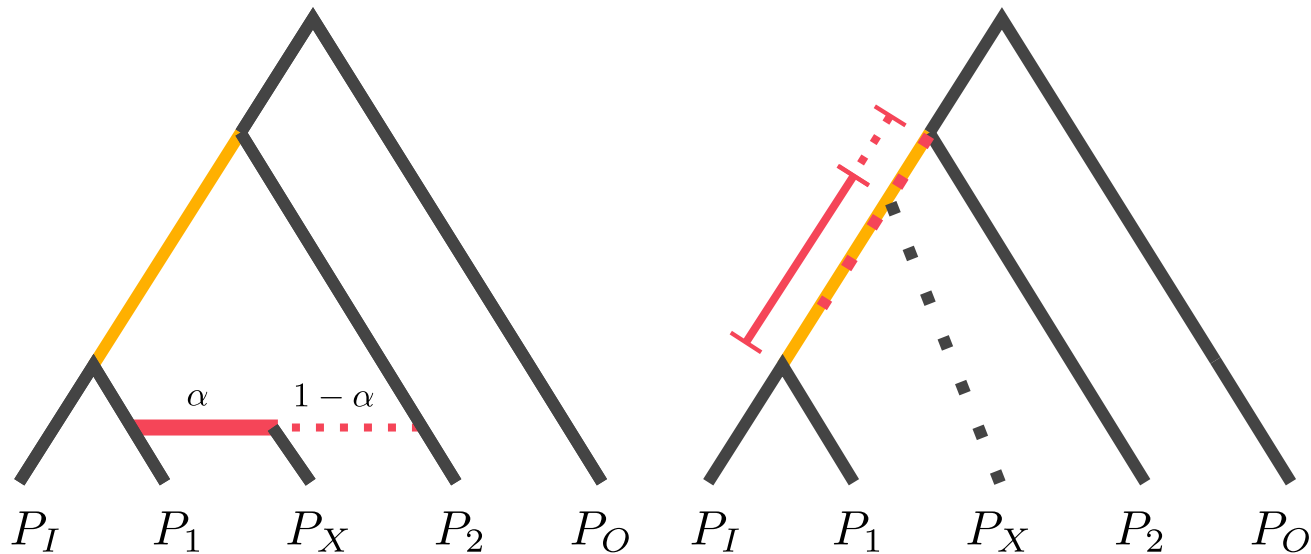
$$D = \frac{\text{ABBA} - \text{BABA}}{\text{BABA} + \text{ABBA}}$$

- D-statistic and F4 are closely related

$$F_4^{(T)}(P_1, P_2; P_3, P_4) = \pi_{13} + \pi_{24} - \pi_{14} - \pi_{23}$$

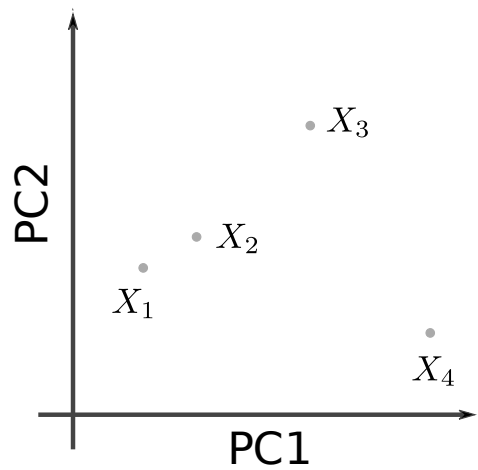
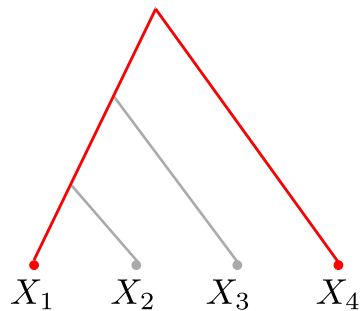


# F4-ratio

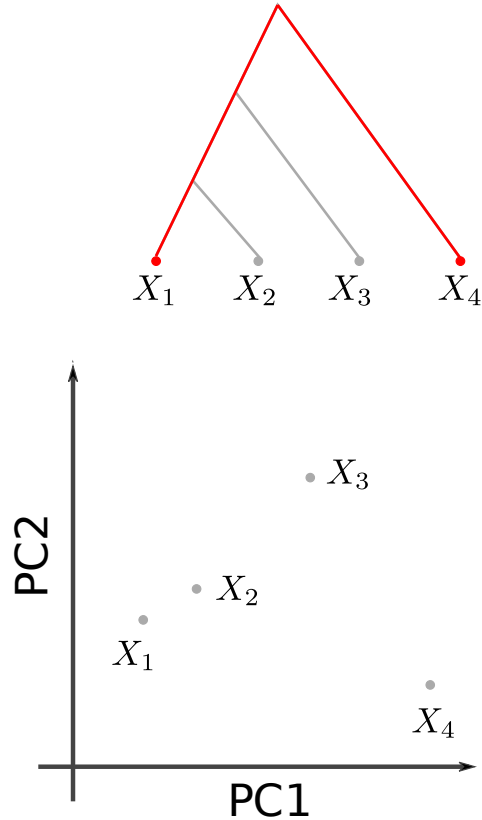


$$\alpha = 1 - \frac{F_4^{(B)}(P_I, P_1; P_X, P_O)}{F_4^{(B)}(P_I, P_1; P_2, P_O)}$$

**A**  $F_2(X_1; X_4)$



A  $F_2(X_1; X_4)$



## PHILOSOPHICAL TRANSACTIONS B

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Research



**Cite this article:** Peter BM. 2022 A geometric relationship of  $F_2$ ,  $F_3$  and  $F_4$ -statistics with principal component analysis. *Phil. Trans. R. Soc. B* **377**: 20200413. <https://doi.org/10.1098/rstb.2020.0413>

Received: 7 July 2021

Accepted: 12 February 2022

One contribution of 15 to a theme issue  
'Celebrating 50 years since Lewontin's  
analysis of genetic variation'

## A geometric relationship of $F_2$ , $F_3$ and $F_4$ -statistics with principal component analysis

Benjamin M. Peter

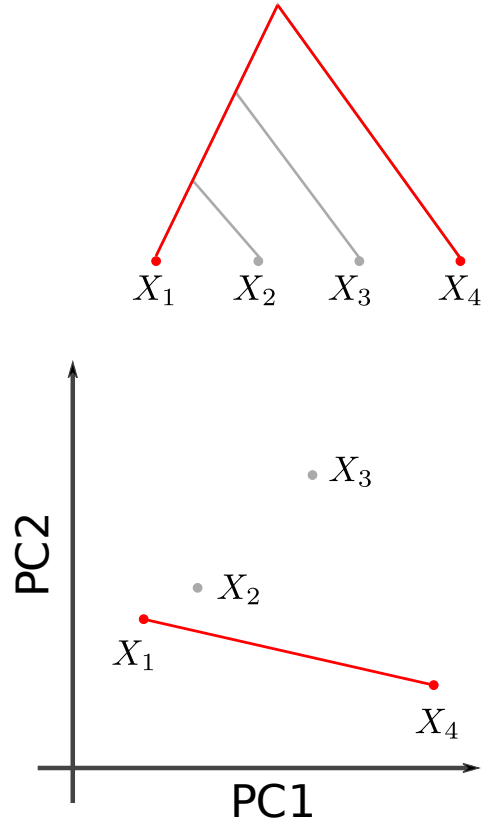
Max-Planck-Institute for Evolutionary Anthropology, Leipzig 04103, Germany

BMP, 0000-0003-2526-8081

Principal component analysis (PCA) and  $F$ -statistics *sensu* Patterson are two of the most widely used population genetic tools to study human genetic variation. Here, I derive explicit connections between the two approaches and show that these two methods are closely related.  $F$ -statistics have a simple geometrical interpretation in the context of PCA, and orthogonal projections are a key concept to establish this link. I show that for any pair of populations, any population that is admixed as determined by an  $F_3$ -statistic will lie inside a circle on a PCA plot. Furthermore, the  $F_4$ -statistic is closely related to an angle measurement, and will be zero if the differences between pairs of populations intersect at a right angle in PCA space. I illustrate my results on two examples, one of Western Eurasian, and one of global human diversity. In both examples, I find that the first few PCs are sufficient to approximate most  $F$ -statistics, and that PCA plots are effective at predicting



A  $F_2(X_1; X_4)$



## PHILOSOPHICAL TRANSACTIONS B

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Research



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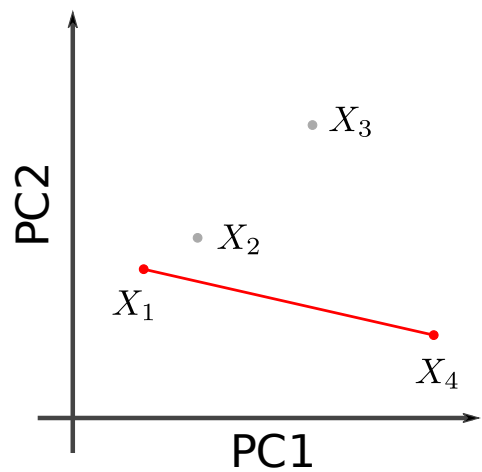
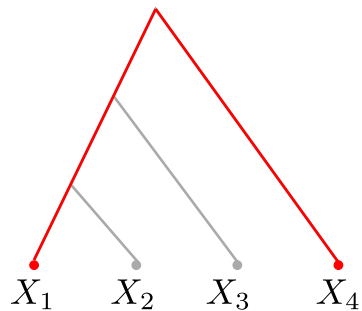
Benjamin M. Peter

Max-Planck-Institute for Evolutionary Anthropology, Leipzig 04103, Germany

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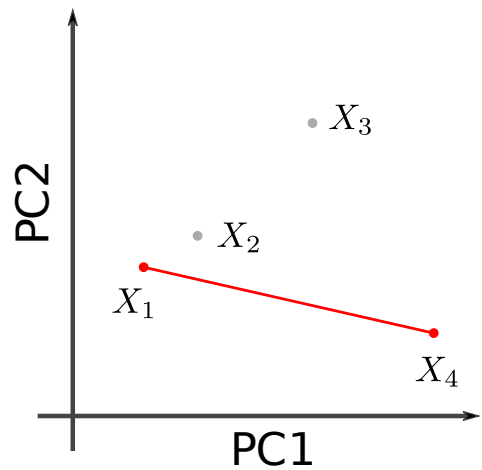
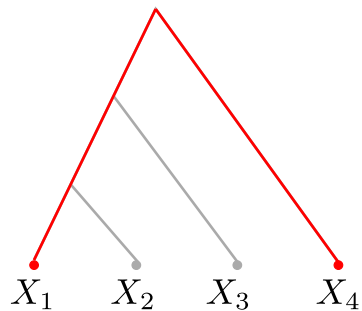
**A**  $F_2(X_1; X_4)$



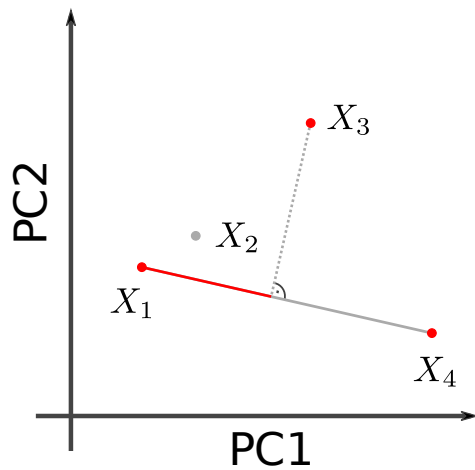
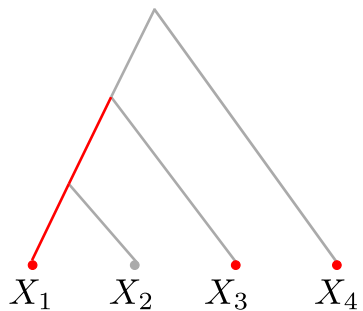
\* true if all PCs are used, optimal approximation otherwise

Peter (2022): doi 10.1098/rstb.2020.0413

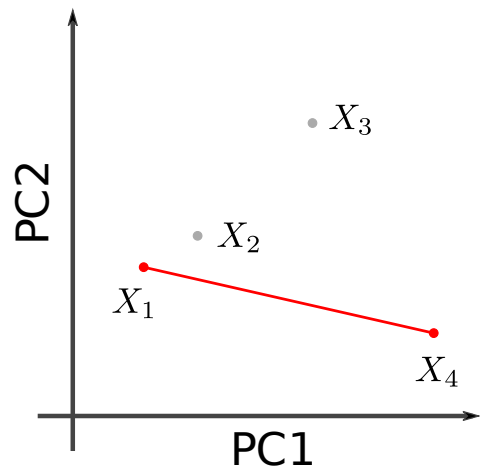
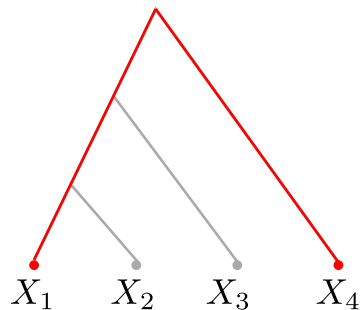
**A**  $F_2(X_1; X_4)$



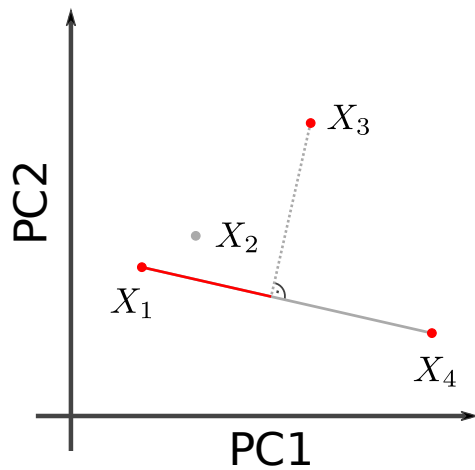
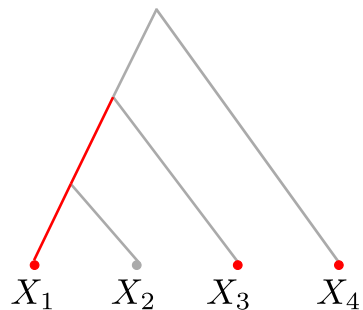
**B**  $F_3(X_1; X_3, X_4)$



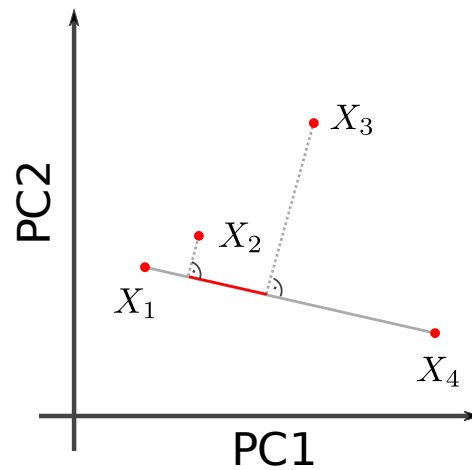
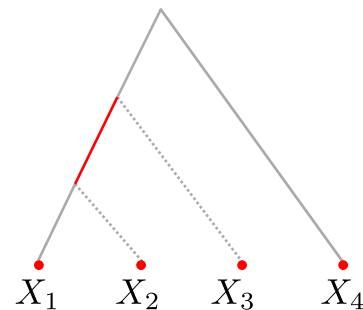
**A**  $F_2(X_1; X_4)$



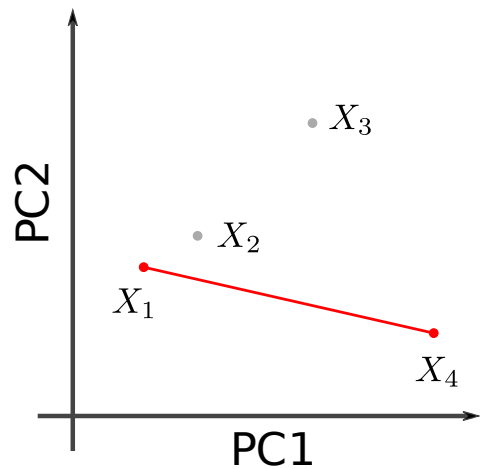
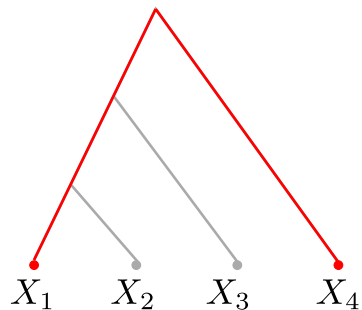
**B**  $F_3(X_1; X_3, X_4)$



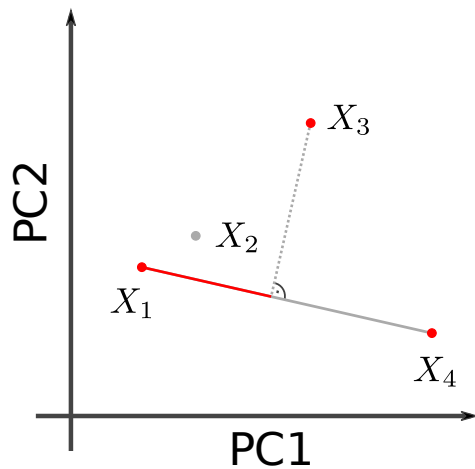
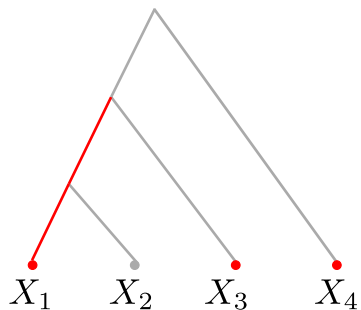
**C**  $F_4(X_1, X_4; X_2, X_3)$



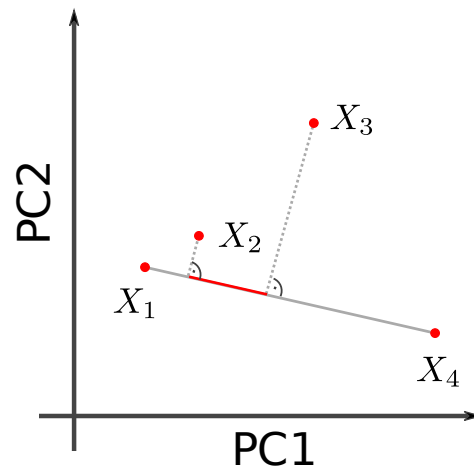
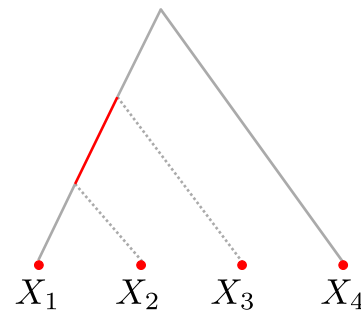
**A**  $F_2(X_1; X_4)$



**B**  $F_3(X_1; X_3, X_4)$



**C**  $F_4(X_1, X_4; X_2, X_3)$



**D**  $F_4(X_1, X_2; X_3, X_4)$

