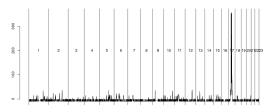
Local IBD inference

Ida Moltke, Naples, April 2018



chromozomes

Outline

- 1. Introduction
 - Goal
 - Motivation
- 2. Inferring local IBD sharing between pairs of individuals
 - Current solutions
 - An HMM based solution
 - Example of use: disease mapping
- 3. Exercises

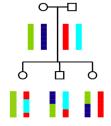
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Goal

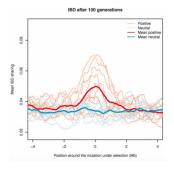
- ▶ We want to infer tracts of IBD sharing along the genome
- ► For example:



► For unphased data: to infer if individuals share 0, 1, 2 alleles IBD locally

Motivation

▶ Can be used for population genetic analyses, e.g. detection of selection:



► Can be used for disease mapping (will return to this later if time allows)

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Current solutions

There are several methods for doing this:

- ► Non-probabilistic, including but not limited to:
 - ► GERMLINE (Gusev et al., 2009)
 Finds stretches of identity above a certain (user defined) length
- ► Probabilistic, including but not limited to:
 - ► BEAGLE (Browning et al., 2010-2016)
 - ► Relate (Albrechtsen et. al., 2009)

We will look at a fairly simple probabilistic solution (a simple version of Relate)

Intuition behind

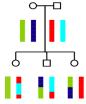
Info source 1: genotypes and allele frequencies (as before!):

- If alleles are not identical they cannot be IBD
- ▶ If alleles are identical it could be due to either IBD or chance
- ▶ If an allele is frequent, identity will occur often simply by chance
- ▶ If an allele is rare, identity will occur rarely by chance
- So the rarer the allele, the more identity makes us believe the individuals are IBD

Intuition behind

Info source 2: The length of the stretches of identity (new!)

▶ IBD is broken up by recombination and thus comes in consecutive regions, hence so will IBD 0, 1 and 2

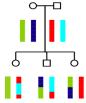


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- ▶ In fact, often very unlikely to see long stretches of identity by chance

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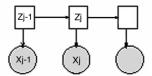


- ▶ Identity that occurs by chance does not have this property.
- ▶ In fact, often very unlikely to see long stretches of identity by chance
- ▶ The more distantly related, the shorter IBD tracts are expected to be

An HMM based solution

Using a Hidden Markov Model (HMM)

- We use these observations for inference based on a HMM
- ▶ Similar to the model we just looked at! E.g. has 2 variables per locus j:
 - 1. an observed variable, G_j (here genotype data, e.g. (AA,aa)).
 - 2. a hidden variable, Z_j (here number of alleles shared IBD in locus j).
- ▶ What is different: we no longer assume the loci are independent
- ▶ Instead Z_j depends on Z_{j-1} :



► Mathematical formulation for *L* loci:

$$P(G,Z) = P(Z)P(G|Z) = P(Z_1) \Big(\prod_{j=2}^{L} P(Z_j|Z_{j-1}) \Big) \Big(\prod_{j=1}^{L} P(G_j|Z_j) \Big)$$
 with $G = (G_1, G_2,, G_L)$ and $Z = (Z_1, Z_2,, Z_L)$.

Emission probabilities $(P(G_j|Z_j))$

▶ $P(G_j|Z_j)$ is exactly the same as before:

G_j	$Z_j=0$	$Z_j = 1$	$Z_j=2$	
AA,AA	f_A^4	f_A^3	p_A^2	$\forall A$
AA,aa	$2f_A^2f_a^2$	0	0	$A \neq a$
AA,Aa	$4f_A^3f_a$	$2f_A^2f_a$	0	$A \neq a$
Aa,Aa	$2f_A^2f_a^2$	$f_A^2 f_a + f_A f_a^2$	$2f_Af_a$	$A \neq a$

- ► Captures connection between IBD, genotypes and allele frequencies:
 - that alleles have to be identical to be IBD
 - that the rarer an allele, the more will observing identity make us believe the individuals are IBD

Transition probabilities $(P(Z_j|Z_{j-1}))$

The probability of a change in IBD state from locus j-1 to j:

- \blacktriangleright We let these depend on the distance between markers, d, and R
- ► E.g. we set

$$P(Z_j = 0|Z_{j-1} = 1) = (1 - e^{-ad})k_0$$

where a is a non-negative parameter of the model

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- ▶ Dependence on the distance *d*:
 - ► The larger *d* is, the larger is the probability of a change
 - ▶ Reflects that the probability of recombination increases with *d*
 - Captures the fact that IBD occurs in tracts that are broken up by recombination

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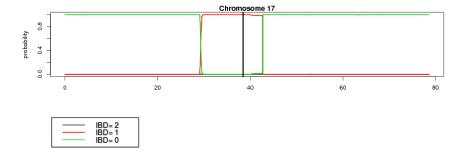
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- ▶ Dependence on the distance *d*:
 - ► The larger *d* is, the larger is the probability of a change
 - Reflects that the probability of recombination increases with d
 - Captures the fact that IBD occurs in tracts that are broken up by recombination
- ▶ Dependence on the distance R (in the example k_0):
 - ► The larger k_0 is (so the more distantly related), the higher is the probability of a change to sharing 0 alleles IBD ($Z_i = 0$)
 - ► Captures that more distantly related tend to have shorter IBD tracts

The inference

- ► We can now use standard inference methods for HMMs
- ▶ We can e.g. (using the forward-backward algorithm) get the posterior probability of the 3 possible states $P(Z_j|G)$:

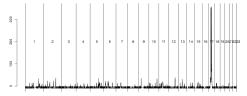


Example of use: disease mapping

- Individuals with a disease caused by the same mutation are IBD in a region harbouring the mutation
- ► Can identify such mutations by finding regions where cases tend to be IBD

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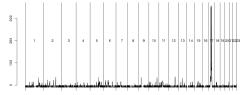
- ► Individuals with a disease caused by the same mutation are IBD in a region harbouring the mutation
- Can identify such mutations by finding regions where cases tend to be IBD
- ► E.g. in Albrechtsen et al. 2009:
 - ► 7 Danish seemingly unrelated Danish individuals with breast cancer
 - ► All individuals genotyped for 225,000 SNPs across the genome
 - ▶ Used an HMM to infer IBD 0,1,2 along the then for all pairs
 - ► Looked for excess IBD sharing in cases (vs. controls)



▶ 1 region and here all cases carried same cancer causing mutation

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- ▶ 1 region and here all cases carried same cancer causing mutation
- ► So mapping can be done w. very few individuals (and SNPs) (<<GWAS)

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Exercises

Go to http://popgen.dk/ida/Naples2018/web/ and solve exercises 3 & 4 (run the exercises on the server logged in with ssh -Y)