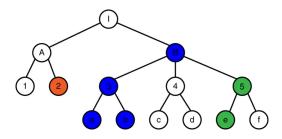
# **TreeWAS**

Exploring hierarchical phenotypic data in genomic datasets

Lino Ferreira 6<sup>th</sup> December 2019



Some genomic datasets organise phenotypic information in a **tree of** diseases.

How can we use this greater resolution to **estimate associations more accurately** without sacrificing statistical power?

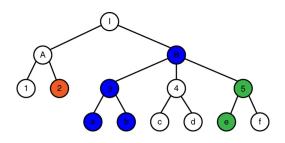
 Model the correlation structure of the genetic effects across different phenotypes

### ANALYSIS

# genetics

#### Bayesian analysis of genetic association across treestructured routine healthcare data in the UK Biobank

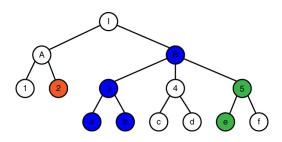
 $Adrian\ Cortes^{1,2,10},\ Calliope\ A\ Dendrou^{1-3,10},\ Allan\ Motyer^{4},\ Luke\ Jostins^1,\ Damjan\ Vukcevic^{4,5},\ Alexander\ Dilthey^{1,6},\ Peter\ Donnelly^{1,7},\ Stephen\ Leslie^{4,5},\ Lars\ Fugger^{2,3,8,11}\ \&\ Gil\ McVean^{1,9,11}$ 



Each node *j* is a binary indicator of disease modelled through **logistic regression**:

logit 
$$(\mathbb{P}(Z_j = 1)) = \beta_j^0 + \beta_j^1 \mathbb{I}(\text{heterozygous}) + \beta_j^2 \mathbb{I}(\text{homozygous})$$

The  $\beta$  coefficients evolve down the tree in a Markov process.



## The $\beta$ coefficients evolve down the tree in a Markov process:

- Parent coefficients inherited with probability  $e^{-\theta}$
- · Otherwise drawn from mixture prior:
  - Null with probability  $\pi_1$
  - · Otherwise drawn from joint mean-zero normal

Use dynamic programming to determine the marginal posterior probability that each coefficient is non-zero and estimate its effect size.

Achieve an increase in power of more than 20%.