Does our DNA keep us awake?

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abstract

1 SNPs and insomnia

1.1 Introduction and goals

✠ Some intro about insomnia and its symptoms here

Every single-nucleotide polymorphism (SNP), together with the huge variety of external factors, can in principle affect the appearance of insomnia symptoms. It is extremely complicated to identify and untangle these causal mechanisms and interactions and to ascertain their degrees, although their causal graph (Pearl 2009) is easy to draw (fig.**). The interacting mechanisms represented by the arrows are difficult to study, and the external factors X are innumerable and largely unknown.

An indication of the causal strength of one or more SNPs on one or more symptoms can be obtained by replacing the causal graph with a corresponding simplified Bayesian network (Pearl 2009) of *conditional probabilities* (fig.**). The external factors X disappear from the graph but their presence is implicit in the probabilistic relation between the nodes; the latter also accounts for the complexity of the causal mechanisms and our uncertainty about them. This is the approach of genetic association studies ✠ ***ref.

The present work has two distinct goals:

First, we present evidence of a strong association between some SNPs located in *** and the three main insomnia symptoms ✠ name the relevant SNPs here?, within population sampled in***. Our results involve associations between each symptom and several SNPs indiviudally, and also associations between each symptom and *pairs* of SNPs; the latter result shows different kinds of interaction between the alleles of a SNP pair.

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Second, we give a detailed but intuitive discussion of the Bayesian method used to infer the associations described above. Similar methods have been used for other kinds of association studies, for example contextual text prediction (MacKay et al. 1995) and population-specific allele count (Lockwood et al. 2001). This method gives simple, clear, and intuitively understandable inferences about symptom-SNP associations; it is computationally fast; and it is easy to generalize to association studies of symptom *combinations* vs *multiple* SNPs, as we'll show in later sections.

The Method section of this work focus on explaining our Bayesian approach, but use the real data from which our results are derived. In the subsequent Result section we discuss the different relevant associations found.

1.2 The data

✠ description of our data here

2 Methods

2.1 Outline

Let's first focus on the simplest kind of association: between one particular SNP with two alleles a, b, and one symptom S. In an arbitrarily large population, consider the fraction $f_{S|a}$ of individuals that show symptom S among those having allele a, and the fraction $f_{S|b}$ among those having allele b. These are *conditional relative frequencies*. If these conditional frequencies are markedly different, then we can conclude that the SNP must have some causal relevance, however indirect, for the symptom.

✠ Add some remarks about the role of 'limit frequencies' and 'arbitrarily large population'. Relation to partial exchangeability and belief about next individual in an endless sequence.

We want to quantify our degree of belief about the values of such conditional frequencies in an arbitrarily large population, given (1) the conditional frequencies in a population sample, (2) our initial information or guesses about such frequencies. In formulae, we want to assign a numerical value to

$$\mathrm{p}(\text{conditional frequencies}|\,\text{sample data}, \text{initial information}).$$

Degrees of belief follow the probability calculus (Jeffreys 1983; Cox 1946; Jaynes 2003; Hailperin 1996), hence to quantify our belief we use

Bayes's theorem:

$$\mathrm{p}(\text{frequencies}|\,\text{data}, \text{initial info}) \propto$$
$$\mathrm{p}(\text{data}|\,\text{frequencies}, \text{initial info}) \times \mathrm{p}(\text{frequencies}|\,\text{initial info}). \quad (1)$$

The first degree of belief in the product above is given by a simple sampling formula, which we'll discuss shortly. The second can be modelled in several ways, but all will lead to the same final degrees of belief about the conditional frequencies, if the sample data are enough.

Once we have a quantified distribution of belief about the conditional frequencies in an arbitrarily large population, we can quantitatively estimate their difference and its significance in a variety of ways. The most direct approach is to calculate our belief about their difference; fig. 3 is a concrete example. The figure shows that we expect their difference to be 0.033, with an uncertainty of 0.012 as measured by the standard deviation. The expected difference is therefore 2.75 standard deviations away from zero, and this can be a way to quantify the significance of the difference. The belief distribution also says, for example, that the difference is 2.7% likely to be in the interval $[-0.01, 0.01]$; this isn't a meaningful measure of significance, though: any interval around zero is arbitrary since we're considering an arbitrarily large population.

✠ add something about dependence of broadness on sample size, and 'smoothing' as discussed by MacKay & Bauman Peto (1995 § 2.6).

The approach just outlined is not dichotomous, unlike a classical 'significance' test. Rather, we will find a graduation of cases: from conditional frequencies predicted to be clearly distinct, to conditional frequencies with uncertainties too large for drawing definite conclusions. These cases can be sorted, obtaining a sequence of SNPs with a decreasing belief of causal association with the symptom. How many of these SNPs are to be selected for further study depends on one's experimental and computational resources.

In the next sections we use formula (1) to estimate the limit frequencies given a sample of 6029 individuals from ✠ *** details here. We shall first focus on the conditional frequencies of each insomnia symptom given one SNP at a time. The inferences in this case are very simple, intuitive, and easily visualizable. In the subsequent sections we shall consider the study of each symptom given *pairs* of SNPs, and the study of all possible eight *symptom combinations* given one SNP at a time.

2.2 Inference: concrete calculation

In this section we do step by step the calculations outlined above. For definiteness we consider onset insomnia (O) and the SNP rs875994 with alleles a, b. The limit conditional frequencies are denoted $f_{\mathrm{O}|a}$ and $f_{\mathrm{O}|b}$. The sample data, denoted by D, consist of the number of individuals $F_{\mathrm{O}|a}$ that show symptom O among the sampled individuals having allele a, and the number $F_{\mathrm{O}|b}$ showing the same symptom among those having allele b. Our initial information consists in the number N_a of sampled individuals with allele a, and the number N_b with allele b. The total number of sampled individuals is therefore $N_a + N_b$. This initial information and our initial beliefs are denoted by I; the numbers N_a, N_b will often be indicated explicitly even though they're part of I.

Our belief about the joint conditional frequencies is expressed by the density function

$$\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} \,|\, D, I). \tag{2}$$

According to Bayes's theorem (1), the belief above is proportional to the product of $\mathrm{p}(D|\, f_{\mathrm{O}|a}, f_{\mathrm{O}|b}, I)$ and our initial belief $\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} \,|\, I)$. Let's consider these in turn.

In our hypothetical large population a fraction $f_{\mathrm{O}|a}$ of individuals having allele a shows symptom O, and a fraction $1 - f_{\mathrm{O}|a}$ doesn't show that symptom. Then, upon sampling N_a individuals with allele a, our belief that a fraction $F_{\mathrm{O}|a}$ of these will show symptom O and a fraction $1 - F_{\mathrm{O}|a}$ won't show this symptom is

$$\mathrm{p}(F_{\mathrm{O}|a} |\, f_{\mathrm{O}|a}, N_a, I) = {f_{\mathrm{O}|a}}^{N_a F_{\mathrm{O}|a}} \, (1 - f_{\mathrm{O}|a})^{N_a (1 - F_{\mathrm{O}|a})}, \tag{3}$$

and analogously for allele b. Our belief about obtaining data $D = (F_{\mathrm{O}|a}, F_{\mathrm{O}|b})$ is therefore

$$\mathrm{p}(D|\, f_{\mathrm{O}|a}, f_{\mathrm{O}|b}, N_a, N_b, I) = \prod_{x=a,b} {f_{\mathrm{O}|x}}^{N_x F_{\mathrm{O}|x}} \, (1 - f_{\mathrm{O}|x})^{N_x (1 - F_{\mathrm{O}|x})}. \tag{4}$$

Our initial degree of belief about the limit conditional frequencies is based on the following main assumption: we expect the frequencies conditional on the two alleles, $f_{\mathrm{O}|a}$ and $f_{\mathrm{O}|b}$, not to be wildly different. This is a conservative assumption. Therefore, if our updated belief conditional on the data will show clearly distinct conditional frequencies, it will be because the data have given enough evidence to overwhelm our initial conservative belief.

This initial belief is represented by a density qualitatively shown in fig. 1. Note how most of our belief's mass is concentrated along the diagonal of the coordinates $(f_{O|a}, f_{O|b})$. ✠ Say something about the rises at the edges of the diagonal. Mathematically we write this density as an integral:

$$\mathrm{p}(f_{O|a}, f_{O|b} \mid I) = \int_0^\infty \mathrm{d}\alpha \int_0^1 \mathrm{d}\nu \; \mathrm{p}(f_{O|a}, f_{O|b} \mid \alpha, \nu, I) \; \pi(\alpha, \nu \mid I) \tag{5}$$

with

$$\mathrm{p}(f_{O|a}, f_{O|b} \mid \alpha, \nu, I) \coloneqq \beta(f_{O|a} \mid \alpha, \nu) \; \beta(f_{O|b} \mid \alpha, \nu) \tag{6}$$

where $\beta(\cdot \mid \alpha, \nu)$ is a beta density with shape parameters $\alpha\nu$ and $\alpha(1-\nu)$:

$$\beta(f \mid \alpha, \nu) \coloneqq \frac{\Gamma(\alpha)}{\Gamma(\alpha\nu)\,\Gamma[\alpha(1-\nu)]} \; f^{\alpha\nu} \, (1-f)^{\alpha(1-\nu)}, \qquad \alpha > 0, \quad 0 \leqslant \nu \leqslant 1, \tag{7}$$

and π is a normalized density that we leave unspecified for the moment: several different choices for π will be used, to test how much our

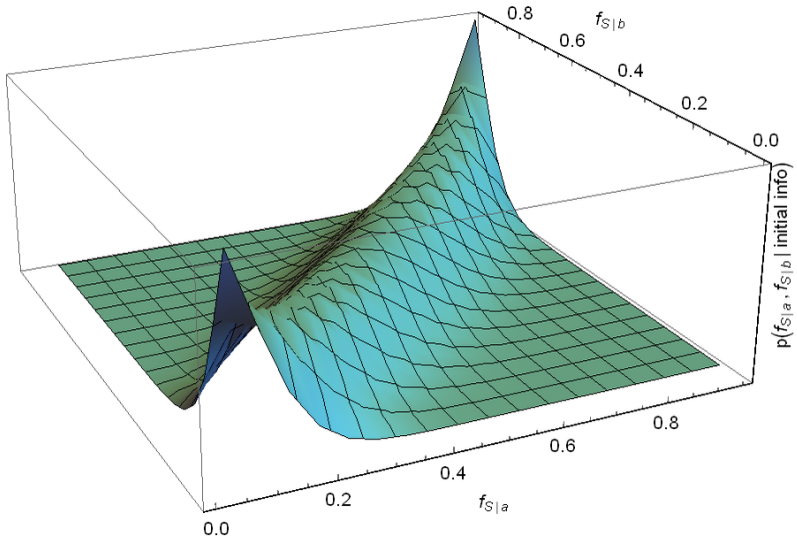

Figure 1 Qualitative plot of our initial belief

inferences depend on our initial belief. We discuss these choices in §*** together with the meaning of the parameters α, ν.

We express $\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, I)$ as an integral to emphasize that our initial beliefs about $f_{\mathrm{O}|a}$ and $f_{\mathrm{O}|b}$ are *not* disjoint, and to show how their mutual dependence comes about: by first considering two independent densities having the same parameters, and then mixing their product over these parameters.

This construction has the interesting consequence for our updated belief $\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, D, I)$. According to Bayes's theorem (1) combined with our initial belief (5) it is given by

$$\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, D, I) \propto \mathrm{p}(D|\, f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, I)\ \mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, I), \tag{8}$$

but, as shown in appendix A, it can also be written in the following way:

$$\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, D, I) = \int \mathrm{d}\alpha \int \mathrm{d}\nu\ \mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, \alpha, \nu, I)\ \pi(\alpha, \nu|\, D, I), \tag{9}$$

with the normalized density $\pi(\alpha, \nu|\, D, I)$ defined by

$$\pi(\alpha, \nu|\, D, I) \propto \pi(\alpha, \nu|\, I) \times \underbrace{\int \mathrm{d}f_{\mathrm{O}|a} \int \mathrm{d}f_{\mathrm{O}|b}\ \mathrm{p}(D|\, f_{\mathrm{O}|a}, f_{\mathrm{O}|b}, I)\ \mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, \alpha, \nu, I)}_{=:\ \mathrm{p}(D|\, \alpha, \nu, I)}. \tag{10}$$

It is as if α, ν were unknown parameters with initial belief density $\pi(\alpha, \nu|\, I)$, and our update for the frequencies proceeded by first updating our belief about the parameters, eq. (10), and then marginalizing them out, eq. (9). This is a so-called *hierarchic* model (Good 1980). This hierarchic way of thinking often helps in constructing densities that better represent our initial beliefs, and also leads to formulae that can be better approximated when exact computation is unfeasible. A point rarely emphasized in the literature, though, is that there is no mathematical difference between a hierarchic and a non-hierarchic model: we could forget about the integrals in formula (5) and about the update formula (9), and simply treat $\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, I)$ as the density depicted in fig. 1, with update (1). The results would be the same. Further discussion about the formulae above is given in §***.

With large sample sizes the density $\pi(\alpha, \nu|\, D, I)$ turns out to be so peaked with respect to $\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b}|\, \alpha, \nu, I)$ that it can be considered as a Dirac delta centred on the parameters α_{M}, ν_{M} that maximize it. We

thus obtain a good approximation of the updated belief (9) that doesn't involve parameter integration:

$$\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} | \, D, I) \approx \mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} | \, \alpha_{\mathrm{M}}, \nu_{\mathrm{M}}, I)$$
$$\text{with} \quad (\alpha_{\mathrm{M}}, \nu_{\mathrm{M}}) \coloneqq \arg\max_{\alpha,\nu} \pi(\alpha, \nu | \, D, I). \quad (11)$$

The maximum of $\pi(\alpha, \nu | \, D, I)$, or better of its logarithm, can easily be found with most optimization methods. The explicit expression to be optimized is discussed in appendix*** ✠ ref here to (MacKay 1996)

2.3 Choices of initial beliefs

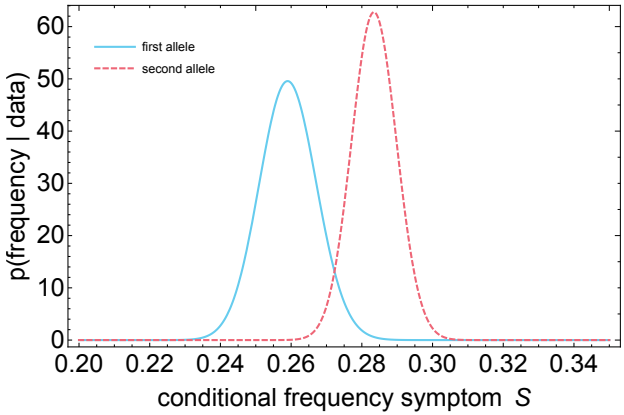

Figure 2 Example of distributions of belief

Appendices

A Derivation of Bayes's theorem in hierarcic form

We write Bayes's theorem (8) with our initial belief (5) written in full:

$$\mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} | D, I) \propto \int \mathrm{d}\alpha \int \mathrm{d}\nu \; \mathrm{p}(D | f_{\mathrm{O}|a}, f_{\mathrm{O}|b} | I) \; \mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} | \alpha, \nu, I) \; \pi(\alpha, \nu | I). \tag{12}$$

Multiplying and dividing within the integral with the expression

$$\mathrm{p}(D | \alpha, \nu, I) \coloneqq \int \mathrm{d}f_{\mathrm{O}|a} \int \mathrm{d}f_{\mathrm{O}|b} \; \mathrm{p}(D | f_{\mathrm{O}|a}, f_{\mathrm{O}|b}, I) \; \mathrm{p}(f_{\mathrm{O}|a}, f_{\mathrm{O}|b} | \alpha, \nu, I) \tag{13}$$

we obtain the alternative form (9)

Combining together the sampling formula (4), the expression of the beta density (7), and the update formula (10) we obtain

$$\pi(\alpha, \nu | D, I) \propto \pi(\alpha, \nu) \times$$
$$\left[\int \mathrm{d}f_{\mathrm{O}|a} \int \mathrm{d}f_{\mathrm{O}|b} \; \beta\left(f_{\mathrm{O}|a} \middle| \; \alpha + N_a, \tfrac{\alpha\nu + N_a F_{\mathrm{O}|a}}{\alpha + N_a}\right) \beta\left(f_{\mathrm{O}|b} \middle| \; \alpha + N_b, \tfrac{\alpha\nu + N_b F_{\mathrm{O}|b}}{\alpha + N_b}\right) \right] \tag{14}$$

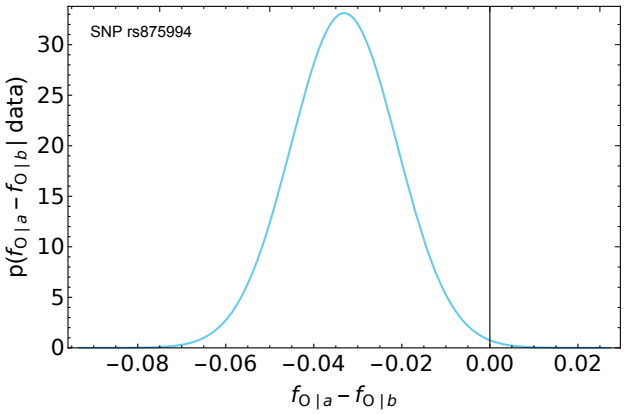

Figure 3 Distribution for the difference between the frequencies $f_{\mathrm{O}|a}$, $f_{\mathrm{O}|b}$ of onset insomnia (O) conditional on the two alleles of SNP rs875994

B Summary of the main formulae

We have a sample of size n. We check the subsample of individuals that have a particular allele, say Bx, for a particular gene, say rs697680_A. Suppose that in this subsample n_0 individuals *don't* show symptom A and n_1 *do* show symptom A. This also means that the size of our subsample (individuals with allele Bx) is $n \coloneqq n_0 + n_1$.

Our degree of belief about the frequency f_1 of symptom A among the individuals with allele Bx in an *infinite* population is a Beta distribution with parameters $n_0 + \theta_0$, $n_1 + \theta_1$, with $\theta \coloneqq \theta_0 + \theta_1$:

$$\mathrm{p}(f_1 | \, n_0, n_1, \theta_0, \theta_1) \, \mathrm{d}f_1 = \frac{\Gamma(n+\theta)}{\Gamma(n_0+\theta_0)\,\Gamma(n_1+\theta_1)} \, (1-f_1)^{n_0+\theta_0-1} \, {f_1}^{n_1+\theta_1-1} \, \mathrm{d}f_1 \quad (15)$$

This distribution has expected value and variance

$$\begin{aligned} \mathrm{E}(f_1 | \, n_0, n_1, \theta_0, \theta_1) &= \frac{n_1+\theta_1}{n+\theta}, \\ \mathrm{var}(f_1 | \, n_0, n_1, \theta_0, \theta_1) &= \frac{(n_0+\theta_0)\,(n_1+\theta_1)}{(n+\theta)^2\,(n+\theta+1)}. \end{aligned} \quad (16)$$

✠ Possible further developments: use of hyper-Dirichlet priors, use of graphical models to infer causal relationships (Pearl 2009)

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('de X' is listed under D, 'van X' under V, and so on, regardless of national conventions.)

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