02-512 Assignment 06

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(a) The variables we are trying to find are the rate of infection, λ_1 and the rate of recovery, λ_2.

We can run the CTMM as a simulation and compare it with real data. The output of the simulation will be sequence of states over time where each state will be (S_t, I_t, R_t).

Let (Sr_t, Ir_t, Rr_t) be the real data. One possible objective function to minimize is

$$L(\lambda_1, \lambda_2) = \sum_{realdatapoints} (S_t - Sr_t)^2 + (I_t - Ir_t)^2 + (R_t - Rr_t)^2$$

You can use steepest/gradient descent, Newton-Raphson's method, or a similar algorithm to find parameters yielding a local minimum. Rather than analytically computing the gradient, you'd have to approximate it using finite difference methods. Performance may be a concern, depending on how long the simulation has to run for.

(b) Let G be the growth rate, x_1 be the conc of nutrient 1 x_2 be the conc of nutrient 2.

$$G = \theta_1 x_1^2 + \theta_2 x_1 + \theta_3 x_2^2 + \theta_4 x_2 + \theta_5$$

Where $\vec{\theta}$ are the parameters we're trying to estimate.

Let $Gr(x_1, x_2)$ be the experimenally determined growth rate.

One possible objective function to minimize is

$$L(x_1, x_2) = \sum (Gr(x_1, x_2) - G(x_1, x_2))^2$$

You can use steepest descent once again, like in part a.

(c) Call parameters we are estimating, f_B and f_b, which are the frequencies of the B allele and b allele respectively.

Let B be the number of people observed with brown eyes, and b be the number of people observed with blue eyes.

The likelihood function is as follows:

$$Pr(B = B, b = b | p = p) =$$

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(a) Say there are m biomarkers. Let $\vec{\theta}$ be an $m + 1$ dimensional vector of parameters.

Let $\mu = \theta_{m+1} + \sum_{i=1}^{m} \theta_i x_i$ in the following

$$L(\mu, \sigma^2; \theta) = \frac{1}{2\pi\sigma^2} \left(\frac{1}{e}\right)^{\frac{\sum_{i=1}^{n}(x_i-\mu)^2}{2\sigma^2}}$$

(b) Say there are m biomarkers. Let $\vec{\theta}$ be an $2m+1$ dimensional vector of parameters.

Let $\mu = \theta_{2m+1} + \sum_{i=1}^{m} \theta_i x_i^2 + \sum_{i=m+1}^{2m} \theta_i x_i$ in the same likelihood function from part a.

(c) Performance, over/underfitting.

(d) Metropolis

(e) Sampling vs solving

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Given two points $(t1, x1), (t2, x2)$, the eqn of a line for general t, x is as follows:

$$t - t2 = (x2 - x1)/(t2 - t1) * (x - x2)$$

The the following is the piecewise linear function interpolation, found by plugging in values from the table into the above equation:

If $0 \leq t < 2$, $t - 2 = (5/2)(x - 5)$
If $2 \leq t < 5$, $t - 5 = ((6 - 5)/(5 - 2))(x - 6)$
If $5 \leq t < 8$, $t - 8 = ((10 - 6)/(8 - 5))(x - 10)$
If $8 \leq t \leq 10$, $t - 10 = ((20 - 10)/(8 - 10))(x - 20)$

(b) Let $(t_1, x_1) = (0, 0), (t_2, x_2) = (2, 5), ..., (t_5, x_5) = (10, 20)$

Let [5] be short notation for $1, 2, 3, 4, 5$.

Then:

$$x = \sum_{i=1}^{5} \frac{\prod_{j \in [5]: j \neq i}(t - t_j)}{\prod_{j \in [5]: j \neq i}(t_i - t_j)} x_i$$

(c) We have 4 quadratic equations of the form

$$S_{i,i+1}(t) = c_{i,0} + c_{i,1}t + c_{i,2}t^2$$

for i = 1 to i = 4. The derivative of each equation is of the form

$$\frac{dS_{i,i+1}}{dt} = c_{i,1} + 2c_{i,2}t$$

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Given the constraints of the problem, we can solve for all $3 * 4 = 12$ parameters by expressing the constraints as equations:

$S_{1,2}(0) = 0$
$S_{1,2}(2) = 5$

$S_{2,3}(2) = 5$
$S_{2,3}(5) = 6$

$S_{3,4}(5) = 6$
$S_{3,4}(8) = 10$

$S_{4,5}(8) = 10$
$S_{4,5}(10) = 20$

Constraints for the derivative continuity:
$\frac{dS_{1,2}}{dt}(2) = \frac{dS_{2,3}}{dt}(2)$ $\frac{dS_{2,3}}{dt}(5) = \frac{dS_{3,4}}{dt}(8)$ $\frac{dS_{3,4}}{dt}(8) = \frac{dS_{4,5}}{dt}(10)$

Additional constraint:
$\frac{dS_{1,2}}{dt}(0) = 0$

Now we have 12 parameters and 12 constraints, we represent it as a linear system and solve using a gaussian elimination.

$$\begin{pmatrix} a & b & c \\ d & e & f \\ g & h & i \end{pmatrix}$$

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(a)

If b_i is 0, there are no boojum on island i. Based on this observation, we note the following:

$$Pr(b_i = 0|f) = (1-f)^{s_i}$$
$$Pr(b_i = 1|f) = 1 - Pr(b_i = 0|f) = 1 - (1-f)^{s_i}$$
$$Pr(b|f) = \prod_{i=1}^{n} Pr(b_i = b_i)$$

(b)

$$\hat{f} = \frac{\sum_{i=1}^{n} y_i}{\sum_{i=1}^{n} s_i}$$

(c)

$$E[y_i] = b_i * \hat{f} * s_i$$

(d)

Submitted online

(e)

TODO