

Applications with Bayesian Approach



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Outline

1 Missing Data in Longitudinal Studies

2 FMRI Analysis

3 Bayesian in Global Optimization

Clinical trial of recombinant human growth hormone (rhGH) for increasing muscle strength in the elderly (Daniels & Hogan 2008)

- The data come from a randomized clinical trial conducted to examine the effects of recombinant human growth hormone (rhGH) therapy for building and maintaining muscle strength in the elderly.
- The study enrolled 161 participants and randomized them to one of four treatment arms: placebo (P), growth hormone only (G), exercise plus placebo (EP), and exercise plus growth hormone (EG).
- Various muscle strength measures were recorded at baseline, 6 months, and 12 months.
- Roughly 75% of randomized individuals completed all 12 months of followup, and most of the dropout was thought to be related to the unobserved responses at the dropout times.

Treatment	s	n_s	Month		
			0	6	12
EG	1	12	58 (26)		
	2	4	57 (15)	68 (26)	
	3	22	78 (24)	90 (32)	88 (32)
	All	38	69 (25)	87 (32)	88 (32)
G	1	6	68 (17)		
	2	5	77 (33)	81 (42)	
	3	30	67 (22)	64 (21)	63 (20)
	All	41	69 (23)	66 (25)	63 (20)
EP	1	7	65 (32)		
	2	2	87 (52)	86 (51)	
	3	31	65 (24)	81 (25)	73 (21)
	All	40	66 (26)	82 (26)	73 (21)
P	1	8	66 (29)		
	2	5	53 (19)	62 (31)	
	3	28	67 (23)	62 (20)	63 (19)
	All	41	65 (24)	62 (22)	63 (19)

The pattern mixture model

- For the mixture model specification, the full-data response distribution is a mixture over the follow-up times, factored as

$$p(y_{\text{mis}}, y_{\text{obs}}, s|z) = p(y_{\text{mis}}|y_{\text{obs}}, s, z)p(y_{\text{obs}}|s, z)p(s|z)$$

where s is the pattern and this model allows **missing not at random**.

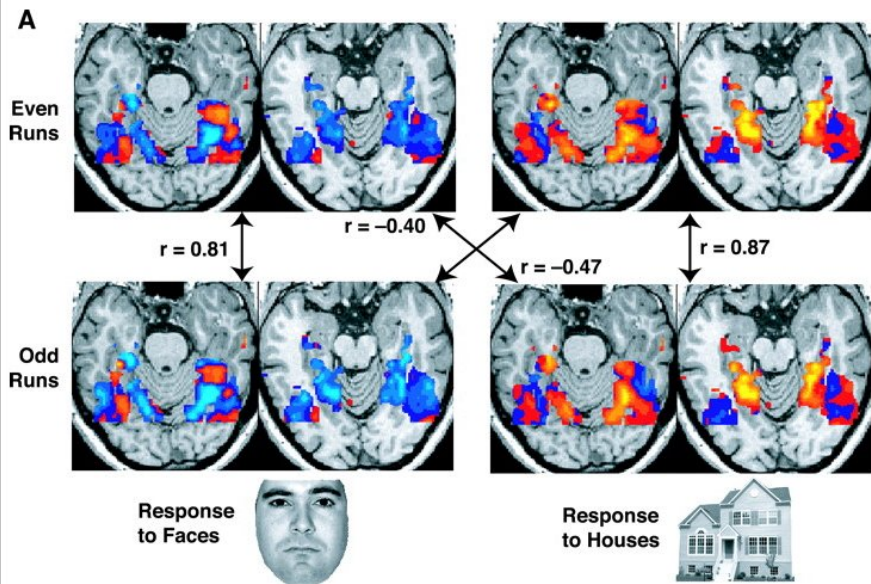
Table 10.1 *Growth hormone trial: posterior mean (s.d.) for quadriceps strength at each time point, stratified by treatment group. MVN = multivariate normal distribution assumed for joint distribution of responses; MAR = missing at random constraints; MNAR-1 = Δ assumed common across treatment groups; MNAR-2 = Δ assumed different by treatment group. Both MNAR analyses use uniform priors for Δ bounded away from zero. See Section 10.2.8 for details.*

Treatment	Month	MVN	Pattern Mixture Models		
			MAR	MNAR-1	MNAR-2
EP	0	65 (4.2)	66 (4.6)	66 (4.6)	66 (4.6)
	6	81 (4.4)	82 (4.7)	80 (4.9)	80 (4.9)
	12	73 (3.7)	73 (4.0)	70 (4.3)	69 (4.6)
EG	0	69 (4.2)	69 (4.4)	69 (4.4)	69 (4.4)
	6	81 (6.0)	81 (6.4)	78 (6.8)	78 (6.8)
	12	78 (6.3)	78 (6.7)	73 (7.4)	72 (8.1)
Difference at 12 mos.		5.7 (7.3)	5.4 (7.8)	3.1 (8.2)	2.6 (9.3)

Multilevel linear modelling for FMRI group analysis using Bayesian inference (Woolrich et al. 2004)

- Functional magnetic resonance imaging (FMRI) studies often involve the acquisition of data from multiple sessions and/or multiple subjects.
- A hierarchical approach can be taken to modelling such data with a general linear model (GLM) at each level of the hierarchy introducing different random effects variance components.
- Inferring on these models is nontrivial with frequentist solutions being unavailable. A solution is to use a Bayesian framework.

FMRI data



The two-level univariate GLM for FMRI

- Consider the familiar two-level univariate GLM for FMRI. For example, the model that in the first level deals with individual sessions for individual subjects, relating time series to activation, and in the second level deals with a group of subjects or sessions (or both), relating the combined individual activation estimates to some group parameter, such as mean activation level.
- The two-level model is

$$Y = X\beta_k + e_k$$

$$\beta_k = X_g\beta_g + e_g$$

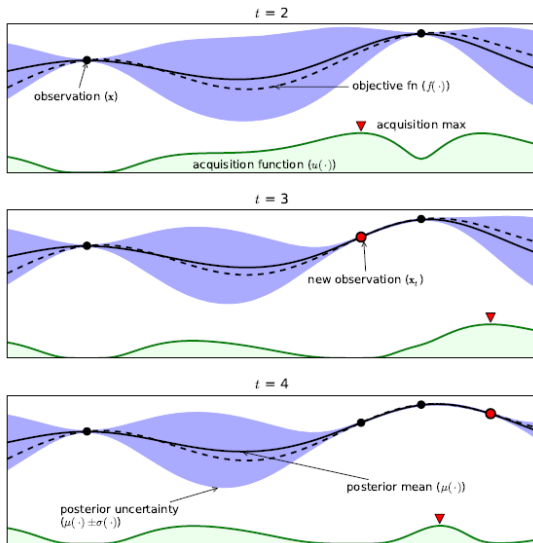
- Markov chain Monte Carlo (MCMC) is used to sample from the full joint posterior distribution

- Neuroeconomics is an interdisciplinary field that seeks to explain human decision making.
- It studies how economic behavior can shape our understanding of the brain, and how neuroscientific discoveries can constrain and guide models of economics
- There are several different techniques that can be utilized to understand the biological basis of economic behavior.
- Neural imaging is used in human subjects to determine which areas of the brain are most active during particular tasks. Some of these techniques, such as fMRI are best suited to giving detailed pictures of the brain which can give information about specific structures involved in a task (Volz et al. 2004).

- An enormous body of scientific literature has been devoted to the problem of optimizing a nonlinear function $f(x)$ over a compact set A . In the realm of optimization, this problem is formulated concisely as follows:

$$\max f(x)$$

- One typically assumes that the objective function $f(x)$ has a known mathematical representation, is convex, or is at least cheap to evaluate. Despite the influence of classical optimization on machine learning, many learning problems do not conform to these strong assumptions.



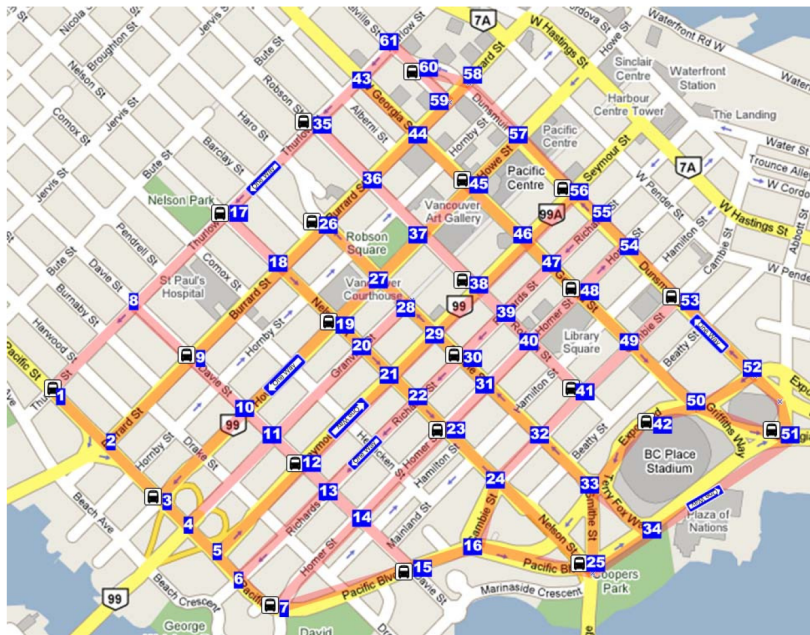
The Bayesian Optimization Approach(Brochu et al. 2010)

Algorithm 1 Bayesian Optimization

- 1: for $t = 1, 2, \dots$ do
 - 2: Find $\mathbf{x}_t$ by optimizing the acquisition function over the GP: $\mathbf{x}_t = \operatorname{argmax}_{\mathbf{x}} u(\mathbf{x}|\mathcal{D}_{1:t-1})$.
 - 3: Sample the objective function: $y_t = f(\mathbf{x}_t) + \varepsilon_t$.
 - 4: Augment the data $\mathcal{D}_{1:t} = \{\mathcal{D}_{1:t-1}, (\mathbf{x}_t, y_t)\}$ and update the GP.
 - 5: end for
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The Open Racing Car Simulator

- The Open Racing Car Simulator a 3D game engine that implements complex vehicle dynamics complete with manual and automatic transmission, engine, clutch, tire, suspension and aerodynamic models.



References

- Brochu, E., Cora, V. M. & De Freitas, N. (2010), 'A tutorial on bayesian optimization of expensive cost functions, with application to active user modeling and hierarchical reinforcement learning', *arXiv preprint arXiv:1012.2599* .
- Daniels, M. J. & Hogan, J. W. (2008), *Missing data in longitudinal studies: Strategies for Bayesian modeling and sensitivity analysis*, Chapman and Hall/CRC.
- Volz, K. G., Schubotz, R. I. & von Cramon, D. Y. (2004), 'Why am i unsure? internal and external attributions of uncertainty dissociated by fmri', *Neuroimage* **21**(3), 848–857.
- Woolrich, M. W., Behrens, T. E., Beckmann, C. F., Jenkinson, M. & Smith, S. M. (2004), 'Multilevel linear modelling for fmri group analysis using bayesian inference', *Neuroimage* **21**(4), 1732–1747.