Designing Longitudinal Studies with Repeated
Measures:
the Case of Salivary Cortisol in the Multi-Ethnic
Study of Atherosclerosis

Applications

References

Introduction

Methods

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APHA Conference 10/31/2011



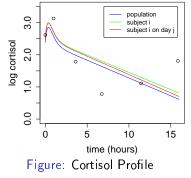
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 - The following personal financial relationships with commercial interests relevant to this presentation existed during the past 12 months: No relationships to disclose.

 This research is supported by Nation Institutes of Health Grant R21 DA024273.



- MESA Stress is a large scale epidemiology study which explores the association between stress and cardiovascular disease.
- Incoporate salivary cortisol as an <u>objective</u> and <u>field-friendly</u> measure for stress.



• Multi-level variability and sampling of nonlinear response.

 Introduction
 Methods
 Applications
 Summary
 References

 Models for the Cortisol Profile
 Image: Summary
 References
 Image: Summary
 References

For subject i on day j, we measure the salivary cortisol

$$y_{ijk} = f(t_k, \theta_{ij}) + \epsilon_{ijk}$$

- $\epsilon_{ijk} \sim N(0, \sigma^2)$: independent measurement error
- $\theta_{ij}|\theta_i \stackrel{iid}{\sim} MVN(\theta_i, \Sigma^d)$: parameter specific to subject *i* on day *j*
- $\theta_i \stackrel{iid}{\sim} MVN(\theta, \Sigma^s)$: parameter specific to subject *i*
- Piecewise Linear Model (Hajat et al., 2010):

$$f(t;\theta)=\theta_0+\theta_1t+\theta_2(t-0.5h)_++\theta_3(t-2h)_+$$

• Nonlinear Model (Stroud et al., 2004):

$$f(t;\theta) = \theta_0 + \theta_1 t + \theta_2 t \exp(-\theta_3 t)$$

Introduction	Methods	Applications	Summary	References
Continue E				
Cortisol Fe	eatures			

Features	G	References
Baseline	$f(0, \theta)$	Kumari et al. (2009)
Cortisol Awakening Response	$f(0.5, \theta) - f(0, \theta)$	Pruessner et al. (1997)
Evening Decline	$\frac{1}{16-10}(f(16,\theta)-f(10,\theta))dt$	Adam (2006)
Area Under the Curve Prediction	$\int_0^{16} f(t,\theta) dt \\ f(t,\theta)$	Badrick et al. (2007) Powell et al. (2002)

Table: Cortisol Features

Optimal Design to Estimate Cortisol Features

Identify the optimal design (n, m, d, T) that minimizes

- the variance of a single cortisol feature
- the weighted sum of variances of several cortisol features

Components of the optimal design (n, m, d, T):

- n: the total number of subjects
- m: the number of days for sampling
- *d*: the number of samples per day
- $T = (t_1, \ldots, t_d)$: the daily sampling schedule

Introduction	Methods	Applications	Summary	References
Existing A	pproaches			

There have been some research on the optimal schedule in the context of PD/PK:

Retout et al. (2002)

- Maximizes the determinant of the information matrix of the parameters
- It is the reciprocal of the size of the confidence region.

Stroud et al. (2001)

- Minimizes the pre-posterior prediction error
- Employs a Bayesian adaptive strategy for the sampling schedule given previous data.

We will take a different perspective:

- Focus on the variance of estimating the cortisol features.
- Analyze the implication of between-subject and between-day variability on multi-level sampling.

Computing the Variance of Cortisol Feature G

Denote the MLE of G by \hat{G} and the information matrix by $I(\theta)$

- $\sqrt{n}(\hat{G}-G)
 ightarrow N(0,
 abla G'I^{-1}(heta)
 abla G)$ by the delta method
- We can show that under some conditions

$$I(\theta) = \nabla f(T, \theta)' \Sigma \nabla f(T, \theta)$$

where

$$\Sigma = egin{pmatrix} \Sigma^s + \Sigma^d & \Sigma^s & \cdots & \Sigma^s \ \Sigma^s & \Sigma^s + \Sigma^d & \ddots & \ dots & dots & dots & \Sigma^s \ \Sigma^s & \cdots & \Sigma^s & \Sigma^s + \Sigma^d \end{pmatrix}$$

Roy et al. (2007) shows that

$$I(\theta)^{-1} = \Sigma^{s} + \frac{1}{m} (\Sigma^{d} + \sigma^{2} (X'(T)X(T))^{-1})$$

Computing the Variance of Cortisol Feature G

$$Var(\hat{G}) = \frac{1}{n} \nabla G' I(\theta) \nabla G$$

=
$$\underbrace{\frac{\nabla G' \Sigma^{s} \nabla G}{n}}_{\text{subject}} + \underbrace{\frac{\nabla G' \Sigma^{d} \nabla G}{nm}}_{\text{day}} + \underbrace{\frac{\sigma^{2} \nabla G' (X'(T)X(T))^{-1} \nabla G'}{nm}}_{\text{schedule within day}}$$

Clear Interpretation for each component

- $\nabla G' \Sigma^s \nabla G$: the between subject variability for G
- $\nabla G' \Sigma^d \nabla G$: the between day variability for G
- σ²∇G'(X'(T)X(T))⁻¹∇G': the estimation variance assuming no between-subject / between-day variability

Properties of Optimal Design

Optimal schedule, T

- minimizes $\nabla G'(X'(T)X(T))^{-1}\nabla G'$
- No knowledge of the variability components is required.

Optimal number of days, m

• When total number of samples is fixed, more subjects (fewer days) is almost always more efficient.

 $Var(\hat{G}(\alpha n, m, d, T)) \leq Var(\hat{G}(n, \alpha m, d, T))$ " = " if $\nabla G' \Sigma^s \nabla G = 0$

• When the total cost is fixed, the optimal *m* depends on the <u>cost ratio</u> and within-between variability ratio.

Introduction	Methods	Applications	Summary	References
Bayesian D)esign			

- The optimal design depends on unknown parameters.
- Incorporate the uncertainty by considering expected variance (Atkinson et al., 2007)
- Assuming θ and $\Sigma^{s},\Sigma^{d},\sigma^{2}$ are independent

$$E(Var(\hat{G})) = \int Var(\hat{G})dp(\theta, \Sigma^{s}, \Sigma^{d}, \sigma^{2})$$

= $tr(E(\nabla G' \nabla G)(\frac{E(\Sigma^{s})}{n} + \frac{E(\Sigma^{d})}{n \cdot m}))$
 $+ \frac{E(\sigma^{2})}{n \cdot m}E(\nabla G'(X'(T)X(T))^{-1}\nabla G)$

- Simple to compute
- Results on the previous slide still hold
- Only the mean, not the full distribution of $\Sigma^s, \Sigma^d, \sigma^2$ is required.

Application to MESA Stress Study

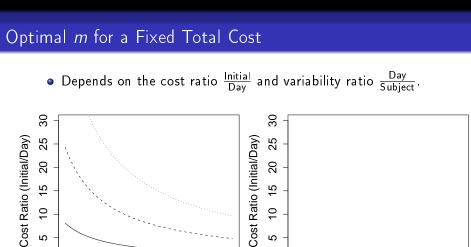
Context: Determine the optimal design for 2nd-stage data collection.

- The estimates and prior distributions are generated from the existing MESA data.
- # of samples per day: d = 4..7
- # of days: m = 1..5
- Times points of the daily schedule T are chosen from $\{0, 0.5, \ldots, 16\}$

Introduction	Methods	Application	15	Summa	ry	Ref	erences
Optimal	Design						
					Varian	ce	
d		Schedules		1 Day 2	2 Day 3 Day	/ 4 Day	5 Day
4	0 0	0	0	82.7	67.6 62.6	60	58.6
5	0 0	0 0	0	76.6	64.6 60.6	58.6	57.4
6	0 0 0 0		0 0	73.4	63 59.5	57.8	56.7
7	00 00	0	00	71.4	62 58.8	57.2	56.3
	0 1 2 3 4 5 6	7 8 9 10 11 12 13	14 15 16				
		Figure: A	UC		Varian	ce	
d		Schedules		1 Day 2	2 Day 3 Day	/ 4 Day	5 Day
4	00 0		0	0.562 0	0.281 0.188	0.141	0.113
5	000 0		0	0.419 0	0.212 0.140	0.106 (0.0854
6	000 00		0	0.369 0	0.183 0.122	0.0935 0	0.0738
7	000 000		0	0.333 0	0.169 0.112	0.0847	0.0676
	0 1 2 3 4 5 6	7 8 9 10 11 12 13	14 15 16				
		Figure: C.	AR				
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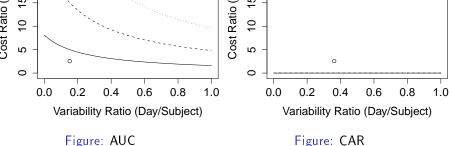
• $\nabla {\cal G}' \Sigma^s \nabla {\cal G} = 0.00033 \approx 0$ for CAR

• Expanding the days of sampling is almost as good as expanding subject.



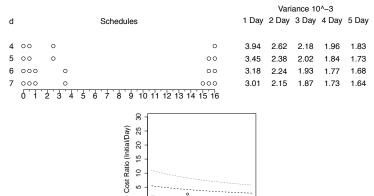
Applications

Introduction





 Minimize the weighted average of variance of Baseline, CAR, Evening Decline and AUC



Variability Ratio (Day/Subject)

0.0 0.2 0.4 0.6 0.8 1.0

Summary

- We discussed the properties of the optimal design for longitudinal study.
- The key is the closed form solution of $Var(\hat{G})$.
- We applied these results to MESA Stress Study.
- The results also hold for arbitrary levels of variabilities.

Future Work

- More flexible ways to model variabilities.
- Optimal designs for joint modeling of salivary cortisol and CVD outcome.

Introduction	Methods	Applications	Summary	References
Thank you!				

Introduction	Methods	Applications	Summary	References
Reference				

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