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# Sample Size Calculation for Longitudinal Studies

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#### Introduction

Motivation Special considerations

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#### Examples

Example 1: Time-averaged difference Example 2: Difference in rate of change

#### Possible Extensions

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Motivation				

## Make sample size calculations more accessible

- Permit researchers to experiment easily with many different scenarios
- Emphasize relationship between sample size calculation and actual analysis of the data

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Special conside	erations	0	0000	

Longitudinal studies involve special considerations

- Correlation between data points for a given individual
- Sample attrition (drop-out)
- Effect(s) of interest often have complicated form (e.g., nonlinear across time)
- Effects of other covariates

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Underlying mode	I			

# Statistical model

Let  $Y_i = (y_{i1}, \ldots, y_{in_i})^T$  be an  $n_i \times 1$  vector of outcome values for the *i*th subject  $(i = 1, \ldots, m)$ , and  $X_i = (x_{i1}, \ldots, x_{in_i})^T$  be a corresponding  $n_i \times p$  matrix of covariate values.

$$egin{array}{rcl} Y_i &=& X_ieta+\epsilon_i\ \epsilon_i &\sim& (0,V) \end{array}$$

Note:

• Within-subject correlation  $R = V/\sigma^2$ 

•  $\epsilon_i$  and  $\epsilon_j$  are independent for all  $i \neq j$ 

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Underlying mo	del			

Generalized least squares estimator

$$\hat{\beta}_{GLS} = \left(\sum_{i=1}^{m} X_i' V^{-1} X_i\right)^{-1} \left(\sum_{i=1}^{m} X_i' V^{-1} Y_i\right)$$
$$\operatorname{Var}(\hat{\beta}_{GLS}) = \left(\sum_{i=1}^{m} X_i' V_i^{-1} X_i\right)^{-1}$$
$$= f(X, R, \sigma^2)$$

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Use of -xtgee-				

Steps in using -xtgee- to calculate variance

- 1. Create a *pseudo-dataset* containing X and Y for m subjects
- 2. Enter the correlation matrix R
- 3. Use -xtgee- command with fixed correlation R and dispersion parameter  $\sigma^2$

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Example 1: Ti	ime-averaged difference			

# Time-averaged difference between two groups

#### Suppose:

- > 2 groups of equal size (m/2 subjects each)
- All subjects measured at n = 3 time points (no drop-out)
- Constant within-subject correlation  $\rho = 0.5$

• 
$$\sigma^2 = 1$$

► We want 90% power to detect a difference *d* of 0.25 at the two-sided 0.05 level.

$$m = (4\sigma^2/nd^2)(1 + (n-1)\rho)(z_{\alpha/2} + z_\beta)^2$$
  
= 448 (224 per group)

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Example 1: Time-averaged difference

## Create pseudo-dataset and enter correlation matrix

```
. input g t
            g
                      t
 1.01
 2.02
 3.03
  4 1 1
 5 1 2
 6.13
 7. end
. expand 224
(1338 observations created)
. bys t (g): gen id = _n
. gen y = uniform()
. mat R = J(3,3,0.5) + I(3)*(1-0.5)
. mat list R
symmetric R[3,3]
   c1 c2 c3
r1
   1
r2 .5 1
r3 .5 .5 1
```

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Example 1: Time-averaged difference					

### Use -xtgee- to calculate variance

```
. xtgee y g, i(id) t(t) corr(fixed R) scale(1)
```

```
Iteration 1: tolerance = 2.308e-16
```

GEE population-averaged n	model	Number of obs	=	1344
Group and time vars:	id t	Number of groups	s =	448
Link:	identity	Obs per group: m	nin =	3
Family:	Gaussian	a	avg =	3.0
Correlation:	fixed (specified)	n	nax =	3
		Wald chi2(1)	=	0.01
Scale parameter:	1	Prob > chi2	=	0.9266
y   Coef	. Std. Err. z	P> z  [95% (	Conf.	Interval]
g  007108 _cons   .504199	9 .0771517 -0.09 7 .0545545 9.24	0.92715832 0.000 .39727	235 749	.1441056

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Example 1: Ti	me-averaged difference			

### Use -sampsi- to calculate power

. sampsi 0 0.25, alpha(0.05) n1(1) sd1(0.0771517) onesample

Estimated power for one-sample comparison of mean to hypothesized value

Test Ho: m = 0, where m is the mean in the population

Assumptions:

alpha = 0.0500 (two-sided) alternative m = .25 sd = .077152 sample size n = 1

Estimated power:

power = 0.8998

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# Difference in rate of change between two groups

- 10% drop-out per time point
- Constant within-subject correlation  $\rho = 0.8$
- Linear change in each group over time
- We want to compute power for detecting a 0.25 difference in the rate of change over entire study.

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Example 2: D	ifference in rate of change			

## Create pseudo-dataset and enter correlation matrix

. xtdes, i	(id) t(t)							
id:	1, 2,	, 448				n =		448
t:	1, 2,	, 3				Т =		3
	Delta(t)	= 1; (3-1)	+1 = 3					
	(id*t uni	quely ider	ntifies	each obs	ervation)			
Distributi	on of T_i:	min	5%	25%	50%	75%	95%	max
	_	1	1	3	3	3	3	3
Freq.	Percent	Cum.	Patter	n 				
364	81.25	81.25	111					
44	9.82	91.07	1					
40	8.93	100.00	11.					
448	100.00	+- 	XXX					

. mat R = J(3,3,0.8) + I(3)\*(1-0.8)

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Example 2: Di	ifference in rate of change			

#### Use -xtgee- to calculate variance

```
. xi: xtgee y i.g*t, i(id) t(t) corr(fixed R) scale(1)
                       (naturally coded; _Ig_0 omitted)
i.g
          _Ig_0-1
i.g*t
           IgXt #
                           (coded as above)
Iteration 1: tolerance = .00579064
Iteration 2: tolerance = 4.388e-16
GEE population-averaged model
                                     Number of obs = 1216
Group and time vars:
                            id t Number of groups = 448
Link:
                         identity Obs per group: min = 1
Family:
                          Gaussian
                                                 avg = 2.7
Correlation:
                fixed (specified)
                                                 max =
                                                            3
                                     Wald chi2(3) =
                                                          0.18
                                  Prob > chi2 = 0.9808
Scale parameter:
                                1
        y | Coef. Std. Err. z P>|z| [95% Conf. Interval]
     _Ig_1 | -.0121577 .1075186 -0.11 0.910 -.2228903 .1985749
        t | .007212 .0229825 0.31 0.754 -.0378328 .0522568
    _IgXt_1 | -.002222 .0325021 -0.07 0.945 -.065925 .061481
     _cons | .5004684 .0760271 6.58 0.000 .351458 .6494789
```

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Example 2: Di	fference in rate of change			

### Use -sampsi- to calculate power

- . loc d = 0.25/3
- . sampsi 0 'd', alpha(0.05) n1(1) sd1(0.0325021) onesample

```
Estimated power for one-sample comparison of mean to hypothesized value
```

Test Ho: m = 0, where m is the mean in the population

Assumptions:

alpha = 0.0500 (two-sided) alternative m = .083333 sd = .032502 sample size n = 1

Estimated power:

power = 0.7271

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## Extensions of the basic method

Generalized linear models

$$Var(\hat{\beta}) = f(X, \beta, R, \phi)$$

#### Effects of other covariates

Note: For random X, may need to increase size of pseudo-dataset and then scale up variance estimate accordingly.