



Size matters - sample size calculation with SAS and R



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Background



Comparison of Sample Size Computation



Conclusion

Background

SAS

- Programming tool of choice over many years
- PROC POWER is a useful function to determine sample sizes

R

- Open-source software becomes more popular
- Many flexible functions included in different packages (e.g. pwr, rpact and DoseFinding)

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Conclusion

Example 1

- Evaluate the efficacy of Treatment A versus Treatment B where main endpoint is a dichotomous variable (“Response” or “No response”)
- Assumptions:
 - Power: 80%, 2-sided significance level: 5%
 - Response rate Treatment A: 55%, response rate Treatment B: 45%
- Estimate the sample size needed to detect a difference in the response rate of 10%

Example 1

SAS

```
PROC POWER;  
  TWOSAMPLEFREQ TEST = PCHI  
  GROUPPROPORTIONS= (0.55 0.45)  
  ALPHA = 0.05  
  SIDES = 2  
  POWER = 0.80  
  NPERGROUP = .;  
RUN;
```

R

```
library("pwr")  
pwr.2p.test(h = ES.h(p1 = 0.55, p2 = 0.45),  
            n=NULL, power = 0.80,  
            alternative = "two.sided",  
            sig.level = 0.05)
```

Example 1

SAS

The POWER Procedure
Pearson Chi-square Test for Proportion Difference

Fixed Scenario Elements	
Distribution	Asymptotic normal
Method	Normal approximation
Number of Sides	2
Alpha	0.05
Group 1 Proportion	0.55
Group 2 Proportion	0.45
Nominal Power	0.8
Null Proportion Difference	0

Computed N per Group	
Actual Power	N per Group
0.801	392

R

Difference of proportion power calculation for binomial distribution (arcsine transformation)

```
h = 0.2003348
n = 391.1323
sig.level = 0.05
power = 0.8
alternative = two.sided
```

NOTE: same sample sizes

Example 2

- Evaluate the difference in the average change from baseline in a continuous variable between Treatment A and Treatment B.
- Assumptions:
 - Power: 80%, 2-sided significance level: 5%
 - Average change from baseline Treatment A: 15% with standard deviation of 1.5%
 - Average change from baseline Treatment B: 12% with standard deviation of 1.9%
- Estimate the sample size needed to detect a difference of 3% in the average change from baseline

Example 2

Pooled standard deviation

$$\sigma = \sqrt{\frac{\text{std}(\text{Treatment A})^2 + \text{std}(\text{Treatment B})^2}{2}} \approx 1.711724$$

Effect size (only for R)

$$d = \frac{\text{Difference in means}}{\text{Pooled standard deviation}} \approx 1.752619$$

SAS

```
proc power;  
  TWOSAMPLEMEANS  
  MEANDIFF = 3  
  STDDEV = 1.711724  
  ALPHA = 0.05  
  SIDES = 2  
  POWER = 0.8  
  NPERGROUP = .;  
run;
```

R

```
library("pwr")  
pwr.t.test(d = 1.752619, power = 0.80,  
           sig.level = 0.05, alternative = "two.sided")
```

Example 2

SAS

The POWER Procedure
Two-Sample t Test for Mean Difference

Fixed Scenario Elements	
Distribution	Normal
Method	Exact
Number of Sides	2
Alpha	0.05
Mean Difference	3
Standard Deviation	1.711724
Nominal Power	0.8
Null Difference	0

Computed N per Group	
Actual Power	N per Group
0.853	7

R

Two-sample t test power calculation

```
n = 6.234288  
d = 1.752619  
sig.level = 0.05  
power = 0.8  
alternative = two.sided
```

NOTE: n is number in *each* group

Example 3

- Evaluate the difference in survival times between Treatment A and Treatment B
- Assumptions:
 - Power: 80%, 2-sided significance level: 5%
 - Treatment A: 41% survival at five years (-> hazard of 0.178)
 - Treatment B: 60% survival at five years (-> hazard of 0.102)
 - Accrual time of two years
 - Follow-up time of six years

Example 3

SAS

```
proc power;  
  TWOSAMPLESURVIVAL TEST = logrank  
  GROUPSURVEXPHAZARDS = 0.178 | 0.102  
  FOLLOWUPTIME = 6  
  ACCRUALTIME = 2  
  POWER = 0.80  
  ALPHA = 0.05  
  SIDES = 2  
  NPERGROUP = . ;  
run;
```

R

```
library('rpact')  
getSampleSizeSurvival(alpha = 0.05, sided = 2, beta = 0.2,  
  lambda1 = 0.102, lambda2 = 0.178,  
  accrualTime = 2, followUpTime=6)
```

Example 3

SAS

The POWER Procedure Log-Rank Test for Two Survival Curves

Fixed Scenario Elements	
Method	Lakatos normal approximation
Form of Survival Curve 1	Exponential
Form of Survival Curve 2	Exponential
Number of Sides	2
Accrual Time	2
Follow-up Time	6
Alpha	0.05
Group 1 Survival Exponential Hazard	0.178
Group 2 Survival Exponential Hazard	0.102
Nominal Power	0.8
Number of Time Sub-Intervals	12
Group 1 Loss Exponential Hazard	0
Group 2 Loss Exponential Hazard	0

Computed N per Group	
Actual Power	N per Group
0.801	83

R

```

Design parameters:
  critical values           : 1.96
  Two-sided power         : FALSE
  Significance level       : 0.0500
  Type II error rate      : 0.2000
  Test                    : two-sided

User defined parameters:
  lambda(1)               : 0.102
  lambda(2)               : 0.178
  Accrual time            : 2.00

Default parameters:
  Theta H0                : 1
  Type of computation     : Schoenfeld
  Planned allocation ratio : 1
  kappa                   : 1
  Piecewise survival times : 0.00
  Follow up time          : 6.00
  Drop-out rate (1)       : 0.000
  Drop-out rate (2)       : 0.000
  Drop-out time           : 12.00

Sample size and output:
  Direction upper         : FALSE
  median(1)              : 6.8
  median(2)              : 3.9
  Hazard ratio            : 0.573
  Number of events        : 101.3
  Accrual intensity       : 83.0
  Number of events fixed  : 101.3
  Number of subjects fixed : 166
  Number of subjects fixed (1) : 83
  Number of subjects fixed (2) : 83
  Analysis times          : 8.00
  Study duration          : 8.00
  Lower critical values (treatment effect scale) : 0.677
  Upper critical values (treatment effect scale) : 1.476
  Local two-sided significance levels : 0.0500

Legend:
  (i): values of treatment arm i
  
```

Example 4

- Show a significant non-flat dose-response curve across three different doses of Treatment A and placebo for a binary endpoint (“Response” vs “No response”)
- Analysis will be performed using multiple comparison and modelling techniques (MCPMod)
- Assumptions:
 - Power: 80%, 2-sided significance level: 5%
 - linear comparator model
 - Response rate of 20% with placebo
 - Maximum response rate of Treatment A of 40%
 - Same number of patients in each dose group

Example 4

SAS

*<Manual implementation of
formula used for sample size
estimation>*

R

```
library('DoseFinding')
models <- Mods(doses = c(0,1,2,3), placEff=0.2, maxEff=0.4,
              linear = NULL)
sampSizeMCT(upperN=80, contMat = optContr(models, w=1),
            sigma = 1, altModels=models, alRatio = rep(1, 4),
            power = 0.8, alpha = 0.05)
```

Example 4

SAS

R

Sample size calculation

```
a1Ratio: 1 1 1 1
```

```
Total sample size: 280
```

```
Sample size per arm: 70 70 70 70
```

```
targFunc: 0.8005
```

Example 5

- For more complex study designs, there might be no formula for sample size computation at all or it might be very difficult to adapt existing formula to fit the needs
- Use a “guess and check” approach based on simulation-based power calculations:
 - Assume power of 80%
 - Select a sample size and run simulations to estimate the power (i.e. repeatedly simulate entire study and determine the power as the proportion of studies in which the null hypothesis is rejected)
 - If the power is estimated to be higher than 80%, select a new and lower sample size and estimate the power again
 - Repeat until the estimated power approximately equals 80%

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Background



Comparison of Sample Size Computation



Conclusion

Conclusion

SAS

- For simple and standard study designs, proc power is an efficient procedure for sample size calculation
- Limitations when it comes to more complex study designs

R

- For simple and standard study designs, efficient functions for sample size calculation are available from the pwr, rpact and DoseFinding package
- Flexible solutions for complex study designs

Thank you for your attention

Fenja Seither
fenja.seither@mainanalytics.de

