

Multinomial Regression for Correlated Data Using the Bootstrap in R

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August 9, 2015

Purpose

- ▶ Multinomial logistic regression: Useful for outcomes with >2 levels without inherent order
- ▶ Model fits ($\#$ levels - 1) coefficients for each variable
- ▶ Some methods exist in R, including:
 - ▶ VGAM package: `vglm()` with `family = multinomial()`
 - ▶ multgee package: `nomLORgee()`
- ▶ To our knowledge, neither method allows us to easily get SEs/confidence intervals for predicted probabilities

Proposed Method: Clustered Bootstrapped Multinomial Regression

- ▶ Given data set with N subjects and m_n records per subject, use clustered bootstrap sampling to create B data sets
 - ▶ Sample N subject IDs with replacement
 - ▶ Take all m_n records from each sampled ID
- ▶ Fit multinomial model on each of B data sets

Proposed Method: Clustered Bootstrapped Multinomial Regression

- ▶ *Coefficients*: Estimates = means of B estimates
- ▶ *CIs*: Percentile method; (2.5^{th} , 97.5^{th})
- ▶ *P-values*: Wald test
- ▶ *Predicted probability* of an outcome level: Estimates straightforward; for CIs, use method in Liu's *Survival Analysis: Models and Applications* Appendix B
- ▶ Functions collected in **ClusterBootMultinom** package on Github (github.com/jenniferthompson/ClusterBootMultinom)

Motivating Example

- ▶ Cohort of critically ill patients with data collected daily in the ICU
- ▶ Outcome: Mental status, assessed daily while in hospital; could be normal, delirious or comatose
- ▶ Cannot assume that coma is worse than delirium
- ▶ Exposure: Levels of a biomarker measured on study days 1, 3, and 5, if patient remained in the hospital
- ▶ Most confounders also measured daily in the ICU
- ▶ **Main question:** After adjusting for confounders, are biomarker levels associated with mental status on the day following biomarker measurement?
- ▶ Final data: 767 unique patients with ≥ 1 day of complete data; 1946 total patient-days

Create Data Sets

```
# library(devtools)
# install_github(
#   'jenniferthompson/ClusterBootMultinom')

library(ClusterBootMultinom)

## Set number of bootstraps
nboot <- 25
```

Using `create.sampdata()`,

- ▶ Create B (here, 25) data sets, plus extra in case of nonconvergence
- ▶ Each has all records from 767 IDs sampled with replacement from set of original IDs

```
boot.datasets <-
  create.sampdata(org.data = our.data,
                  id.var = 'id',
                  n.sets = ceiling(nboot * 1.25))
```

Run Models on Bootstrapped Data Sets

Using `multi.bootstrap()`:

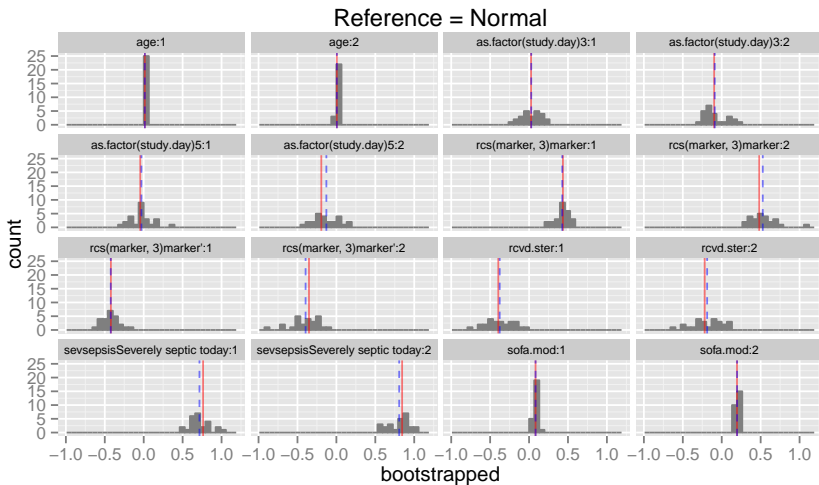
- ▶ Run model on original data set
- ▶ If that model converges, run same model on bootstrapped data sets until B converged models
- ▶ Save errors and warnings to .txt file
- ▶ To calculate CIs for predicted probabilities for all outcome levels, run models twice, using highest & lowest outcome levels as reference

```
## mod.formula <-  
##   as.formula(mental.tmw ~ age + rcvd.ster +  
##     sevsepsis + sofa.mod + as.factor(study.day) +  
##     rcs(marker, 3))
```

Run Models on Bootstrapped Data Sets

```
## Run with Normal as reference level
boot.models.n <-
  multi.bootstrap(
    org.data = our.data,
    ## original data set
    data.sets = boot.datasets,
    ## list of bootstrapped data sets
    ref.outcome = grep('Normal',
                       levels(our.data$mental.tmw)),
    ## outcome level to use as reference
    multi.form = mod.formula,
    ## model formula
    n.boot = nboot,
    ## number of successful model fits desired
    xvar = 'Marker')
    ## text for status updates
```


Check Distribution of Coefficients using `boot.coef.plot()`

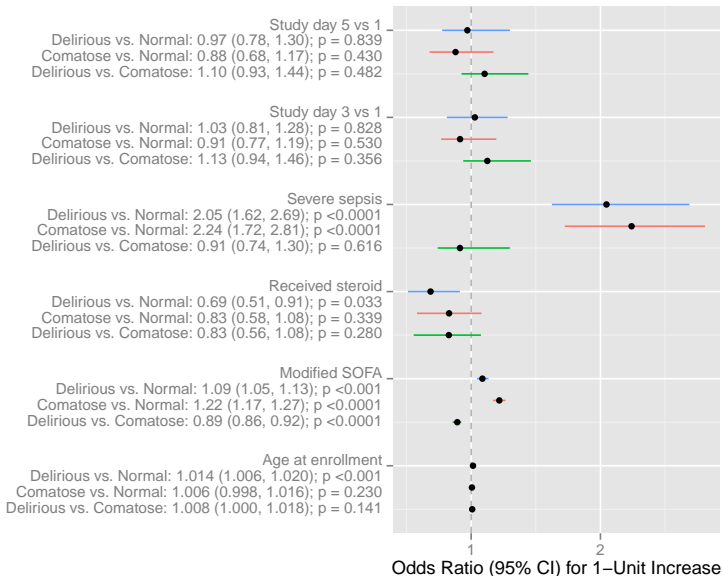


Calculate Odds Ratios

Use `multi.plot.ors()` to show ORs, 95% CIs for each outcome comparison.

```
## Plot odds ratios and CIs for non-biomarker variables
covariate.ors <-
  multi.plot.ors(
    coef.list = list(boot.matrix.n, boot.matrix.c),
    ## List of matrices with bootstrapped coeffs
    label.data = or.labels,
    ## data frame containing labels for each variable
    remove.vars = 'marker',
    ## this plot is just for confounders
    round.vars = 'age', round.digits = 3,
    ## round results for age to 3 instead of 2 places
    out.strings.list = list(out.comp.n, out.comp.c),
    ## list of strings describing comparisons
    delete.row = 'Normal vs. Comatose')
    ## One comparison will be redundant
```

covariate.ors\$or.plot



Create Design Matrices

To get predicted probabilities for outcomes vs. a continuous covariate, we need to adjust all other covariates to specific values.

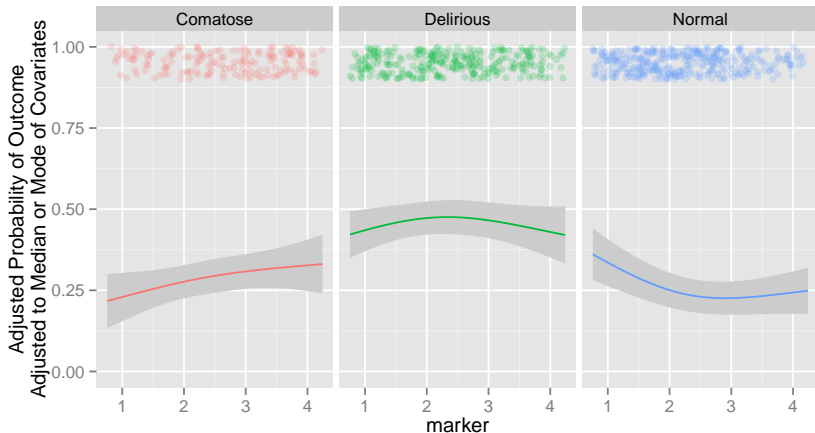
- ▶ Pass `multi.plot.probs()` [# outcome levels - 1] numeric vectors
- ▶ Functions assume covariate in question is **last** variable in model formula; its X values will become columns at the end of design matrices
- ▶ Example has $\beta_{0,2}$ + 6 other β per outcome level, excluding biomarker; set each to median/mode, representing “average” patient

```
##           [,1] [,2]      [,3]      [,4] [,5] [,6] [,7] [,8] [,9] [,10] [,11] [,12] [,13] [,14]
## design.out1    1    0 60.84873 0.00000    0    0    1    0    6    0    0    0    0    0
## design.out2    0    1 0.00000 60.84873    0    0    0    1    0    6    0    0    0    0
```

Calculate & Plot Predicted Probabilities, CIs of Each Mental Status by Marker Level

```
## Predicted probabilities for
## outcome levels vs. biomarker
marker.prob.results <-
  multi.plot.probs(
    xval = 'marker',
    data.set = our.data,
    design.mat = list(design.out1, design.out2),
    mod.objs = list(boot.models.n$org.model,
                    boot.models.c$org.model),
    coef.list = list(boot.matrix.n,
                     boot.matrix.c),
    vcov.list = list(boot.vcov.n,
                     boot.vcov.c))
```

```
marker.prob.results$prob.line.plot
```



Bootstrapped Wald P-Values:
Delirious vs. Normal: $p < 0.0001$
Comatose vs. Normal: $p = 0.004$
Delirious vs. Comatose: $p = 0.187$

Simulation Study

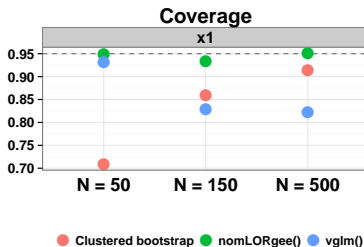
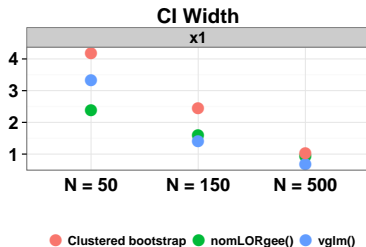
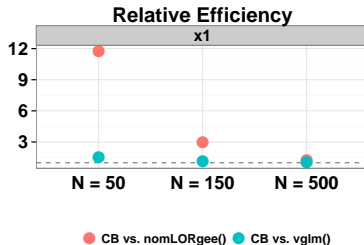
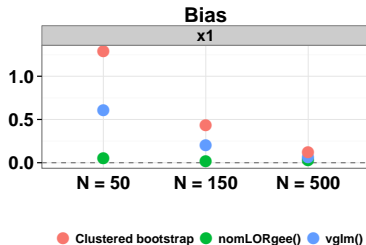
- ▶ Compared our method with
 1. `vg1m()` from VGAM, without accounting for correlation
 2. `nomLORgee()` from multgee package, which accounts for correlation
- ▶ Simulated 1000 data sets with correlated multinomial data, based on example from SimCorMultRes package
 - ▶ data sets included ID, time (cluster size = 3), one $X \sim N(2.5, 3)$, outcome with $I = 4$ levels
 - ▶ all $\beta_{0i, \dots, I-1} = 1$, all $\beta_{1i, \dots, I-1} = 2$
 - ▶ correlation within patient = 0.9
 - ▶ $N = 50, 150, 500$

Model Convergence

Proportions of models which did not converge:

Method	N = 50	N = 150	N = 500
nomLORgee()	0.49	0.18	0.08
vglm()	0.14	0.01	0.01
Clustered bootstrap	0.33	0.03	0.01

Bias, Relative Efficiency & CIs



Future Work & Acknowledgements

- ▶ Future directions
 - ▶ Additional CI methods
 - ▶ Extending package to include more nonlinear terms, other flexibilities
- ▶ Clinical investigators & coauthors:
 - ▶ Tim Girard, MD, MSCI
 - ▶ Pratik Pandharipande, MD, MSCI
 - ▶ Wes Ely, MD, MPH
- ▶ R package resources:
 - ▶ Hilary Parker - Writing an R Package from Scratch
 - ▶ Hadley Wickham - devtools, roxygen2, *R Packages*
 - ▶ Karl Broman - R package primer
 - ▶ Jeremy Stephens, VUMC computer systems analyst
- ▶ Email: `jennifer.l.thompson@vanderbilt.edu`
- ▶ Package: `github.com/jenniferthompson/ClusterBootMultinom`