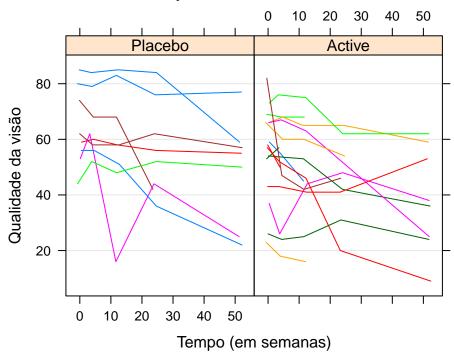
Modelos de Regressão Linear Mistos para dados discretos: Uma abordagem utilizando MCMC através do Stan integrado ao R.

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The Stan project develops a probabilistic programming language that implements full Bayesian statistical inference via Markov Chain Monte Carlo, rough Bayesian inference via 'variational' approximation, and (optionally penalized) maximum likelihood estimation via optimization. In all three cases, automatic differentiation is used to quickly and accurately evaluate gradients without burdening the user with the need to derive the partial derivatives.



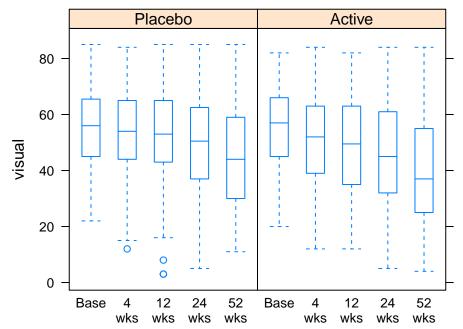
```
Placebo Active
                 119
                        121
  Baseline
  4wks
                 117
                        114
  12wks
                 117
                        110
   24wks
                 112
                        102
   52wks
                 105
   [1] "Placebo" "Active"
                             "Placebo" "Active"
                                                  "Placebo" "Active"
            P:n A:n
                       P:Mean
                                 A:Mean P:Mdn A:Mdn
## Baseline 119 121 55.33613 54.57851
                                         56.0
```

```
## 4wks 117 114 53.96581 50.91228 54.0 52.0

## 12wks 117 110 52.87179 48.67273 53.0 49.5

## 24wks 112 102 49.33036 45.46078 50.5 45.0

## 52wks 105 90 44.43810 39.10000 44.0 37.0
```

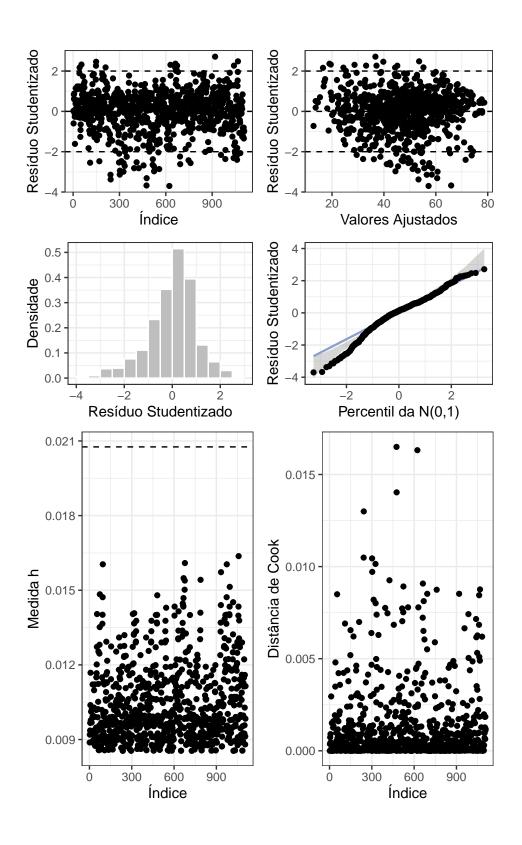


```
visual0 visual4 visual12 visual24 visual52
## visual0 220.3055 206.7096 196.2439 193.3099 152.7141
## visual4 206.7096 246.2204 224.7933 221.2677 179.2284
## visual12 196.2439 224.7933 286.2072 257.7738 222.6830
## visual24 193.3099 221.2677 257.7738 334.4456 285.2327
## visual52 152.7141 179.2284 222.6830 285.2327 347.4311
            visual0 visual4 visual12 visual24 visual52
                               0.78
## visual0
             1.00
                     0.89
                                         0.71
                                                 0.55
## visual4
              0.89
                       1.00
                                0.85
                                         0.77
                                                  0.61
              0.78
                       0.85
                                1.00
                                         0.83
                                                  0.71
## visual12
## visual24
               0.71
                       0.77
                                0.83
                                         1.00
                                                  0.84
## visual52
               0.55
                       0.61
                                0.71
                                         0.84
                                                  1.00
```

1 MODELO NORMAL INDEPENDENTE HOMOCEDASTICO

```
##
## Call:
## lm(formula = lm.form, data = armd)
##
## Residuals:
## Min    1Q Median   3Q Max
## -45.210 -6.459   1.532   7.512   33.283
```

```
##
## Coefficients:
                            Estimate Std. Error t value Pr(>|t|)
##
                             0.83037 0.02842 29.213 < 2e-16 ***
## visual0
## time.f4wks
                             8.07531
                                       1.94341 4.155 3.58e-05 ***
## time.f12wks
                             7.08066
                                       1.94066
                                                 3.649 0.00028 ***
## time.f24wks
                             3.63022
                                       1.95316
                                                1.859 0.06342 .
## time.f52wks
                            -1.74643
                                       1.98952 -0.878 0.38029
                                       1.62894 -1.444 0.14900
## time.f4wks:treat.fActive -2.35278
## time.f12wks:treat.fActive -3.70852
                                       1.64378 -2.256 0.02432 *
## time.f24wks:treat.fActive -3.44915
                                       1.69399 -2.036 0.04205 *
## time.f52wks:treat.fActive -4.47345
                                       1.77811 -2.516 0.01206 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 12.38 on 858 degrees of freedom
## Multiple R-squared: 0.9432, Adjusted R-squared: 0.9426
## F-statistic: 1583 on 9 and 858 DF, p-value: < 2.2e-16
## [1] 12.37649
##
                                 2.5 %
                                           97.5 %
## visual0
                             0.7745832 0.8861617
## time.f4wks
                             4.2609239 11.8897036
                             3.2716615 10.8896534
## time.f12wks
## time.f24wks
                            -0.2033236 7.4637556
## time.f52wks
                            -5.6513208 2.1584611
## time.f4wks:treat.fActive -5.5499518 0.8443996
## time.f12wks:treat.fActive -6.9348245 -0.4822195
## time.f24wks:treat.fActive -6.7740045 -0.1243018
## time.f52wks:treat.fActive -7.9634126 -0.9834943
## Analysis of Variance Table
##
## Response: visual
##
                  Df Sum Sq Mean Sq F value
                                                 Pr(>F)
## visual0
                  1 2165776 2165776 14138.9886 < 2.2e-16 ***
## time.f
                   4 14434
                              3608
                                     23.5574 < 2.2e-16 ***
## time.f:treat.f
                 4
                       2703
                                676
                                        4.4109 0.001555 **
## Residuals 858 131426
                                 153
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



2 MODELO MISTO FREQUENTISTA

```
## Linear mixed-effects model fit by REML
   Data: armd
   Log-restricted-likelihood: -3288.986
##
   Fixed: lme.form
       (Intercept)
                           visual0
                                               time
                                                       treat.fActive
         9.28807837
                                       -0.21221595
                        0.82643987
                                                         -2.42200012
##
## time:treat.fActive
##
        -0.04959058
##
## Random effects:
## Formula: ~1 | subject
   (Intercept) Residual
## StdDev: 8.978212 8.627514
## Number of Observations: 867
## Number of Groups: 234
                                            DF t-value p-value
                       Value Std.Error
                    9.288078 2.681889 631.000000 3.4633 0.0005698 ***
## (Intercept)
                    ## visual0
## time
                   ## treat.fActive
                   -2.422000 1.499967 231.000000 -1.6147 0.1077402
## time:treat.fActive -0.049591 0.033562 631.000000 -1.4776 0.1400155
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## subject 2
## Conditional variance covariance matrix
## 1 2 3 4
## 1 74.434 0.000 0.000 0.000
## 2 0.000 74.434 0.000 0.000
## 3 0.000 0.000 74.434 0.000
## 4 0.000 0.000 0.000 74.434
   Standard Deviations: 8.6275 8.6275 8.6275 8.6275
                   2
           1
                            3
## 1 1.0000000 0.5199116 0.5199116 0.5199116
## 2 0.5199116 1.0000000 0.5199116 0.5199116
## 3 0.5199116 0.5199116 1.0000000 0.5199116
## 4 0.5199116 0.5199116 0.5199116 1.0000000
       AIC
                BIC
                       AICc
                             SABIC
                                     HQCIC -2log.lik
  6833.788 6881.438 6833.998 6846.091 6848.200 6813.788
##
                                        HQCIC -2log.lik
##
       AIC
                BIC
                        AICc
                                SABIC
  6591.971 6625.286 6592.026 6597.137 6597.444 6577.971
##
```

3 MODELO MISTO BAYESIANO

Segundo Manly (1997) a ideia básica por trás da Inferência Bayesiana é mudar as probabilidades para os parâmetros tomando valores númericos particulares para novas probabilidades como um resultado da coleta de mais dados, com essa mudança sendo alcançada através do Teorema de Bayes. Como um exemplo da abordagem Bayesiana, suponha que temos interesse no valor de um parâmetro θ de uma determinada população, e que antes de qualquer informação ser observada é de alguma forma possível afirmar que θ deve assumir um dos valores entre $\theta_1, \theta_1, \ldots, \theta_n$ e que a probabilidade de o valor ser θ_i é $\pi(\theta_i)$. Suponha também que alguns dados novos são coletados e a probabilidade de observar estes dados é $\pi(dados|\theta_i)$ se de fato $\theta=\theta_i$

```
## SAMPLING FOR MODEL 'matrixModel' NOW (CHAIN 1).
## Chain 1:
## Chain 1: Gradient evaluation took 0.000595 seconds
## Chain 1: 1000 transitions using 10 leapfrog steps per transition would take 5.95 seconds.
## Chain 1: Adjust your expectations accordingly!
## Chain 1:
## Chain 1:
## Chain 1: Iteration:
                          1 / 2000 [
                                      0%]
                                             (Warmup)
                        200 / 2000 [ 10%]
## Chain 1: Iteration:
                                             (Warmup)
## Chain 1: Iteration:
                        400 / 2000 [ 20%]
                                             (Warmup)
## Chain 1: Iteration:
                        600 / 2000 [ 30%]
                                             (Warmup)
## Chain 1: Iteration: 800 / 2000 [ 40%]
                                             (Warmup)
## Chain 1: Iteration: 1000 / 2000 [ 50%]
                                             (Warmup)
## Chain 1: Iteration: 1001 / 2000 [ 50%]
                                            (Sampling)
## Chain 1: Iteration: 1200 / 2000
                                    [ 60%]
                                            (Sampling)
## Chain 1: Iteration: 1400 / 2000
                                    [ 70%]
                                             (Sampling)
## Chain 1: Iteration: 1600 / 2000
                                    [ 80%]
                                             (Sampling)
## Chain 1: Iteration: 1800 / 2000 [ 90%]
                                             (Sampling)
## Chain 1: Iteration: 2000 / 2000 [100%]
                                             (Sampling)
## Chain 1:
## Chain 1:
             Elapsed Time: 30.2139 seconds (Warm-up)
## Chain 1:
                           16.0806 seconds (Sampling)
## Chain 1:
                            46.2946 seconds (Total)
## Chain 1:
##
## SAMPLING FOR MODEL 'matrixModel' NOW (CHAIN 2).
## Chain 2:
## Chain 2: Gradient evaluation took 0.000438 seconds
## Chain 2: 1000 transitions using 10 leapfrog steps per transition would take 4.38 seconds.
## Chain 2: Adjust your expectations accordingly!
## Chain 2:
## Chain 2:
## Chain 2: Iteration:
                          1 / 2000 [ 0%]
                                             (Warmup)
## Chain 2: Iteration:
                        200 / 2000 [ 10%]
                                             (Warmup)
## Chain 2: Iteration: 400 / 2000 [ 20%]
                                             (Warmup)
                        600 / 2000 [ 30%]
## Chain 2: Iteration:
                                             (Warmup)
## Chain 2: Iteration:
                        800 / 2000 [ 40%]
                                             (Warmup)
## Chain 2: Iteration: 1000 / 2000 [ 50%]
                                             (Warmup)
## Chain 2: Iteration: 1001 / 2000 [ 50%]
                                             (Sampling)
## Chain 2: Iteration: 1200 / 2000 [ 60%]
                                             (Sampling)
```

```
## Chain 2: Iteration: 1400 / 2000 [ 70%]
                                            (Sampling)
## Chain 2: Iteration: 1600 / 2000 [ 80%]
                                            (Sampling)
## Chain 2: Iteration: 1800 / 2000 [ 90%]
                                            (Sampling)
## Chain 2: Iteration: 2000 / 2000 [100%]
                                            (Sampling)
## Chain 2:
## Chain 2: Elapsed Time: 30.4907 seconds (Warm-up)
## Chain 2:
                           15.9974 seconds (Sampling)
## Chain 2:
                           46.4881 seconds (Total)
## Chain 2:
## SAMPLING FOR MODEL 'matrixModel' NOW (CHAIN 3).
## Chain 3:
## Chain 3: Gradient evaluation took 0.000988 seconds
## Chain 3: 1000 transitions using 10 leapfrog steps per transition would take 9.88 seconds.
## Chain 3: Adjust your expectations accordingly!
## Chain 3:
## Chain 3:
## Chain 3: Iteration:
                         1 / 2000 [ 0%]
                                            (Warmup)
## Chain 3: Iteration: 200 / 2000 [ 10%]
                                            (Warmup)
## Chain 3: Iteration: 400 / 2000 [ 20%]
                                           (Warmup)
## Chain 3: Iteration: 600 / 2000 [ 30%]
                                           (Warmup)
## Chain 3: Iteration: 800 / 2000 [ 40%]
                                           (Warmup)
## Chain 3: Iteration: 1000 / 2000 [ 50%]
                                           (Warmup)
## Chain 3: Iteration: 1001 / 2000 [ 50%]
                                           (Sampling)
## Chain 3: Iteration: 1200 / 2000 [ 60%]
                                           (Sampling)
## Chain 3: Iteration: 1400 / 2000 [ 70%]
                                           (Sampling)
## Chain 3: Iteration: 1600 / 2000 [ 80%]
                                           (Sampling)
## Chain 3: Iteration: 1800 / 2000 [ 90%]
                                           (Sampling)
## Chain 3: Iteration: 2000 / 2000 [100%]
                                            (Sampling)
## Chain 3:
## Chain 3: Elapsed Time: 28.8419 seconds (Warm-up)
## Chain 3:
                           15.6728 seconds (Sampling)
## Chain 3:
                           44.5147 seconds (Total)
## Chain 3:
##
## SAMPLING FOR MODEL 'matrixModel' NOW (CHAIN 4).
## Chain 4: Gradient evaluation took 0.000217 seconds
## Chain 4: 1000 transitions using 10 leapfrog steps per transition would take 2.17 seconds.
## Chain 4: Adjust your expectations accordingly!
## Chain 4:
## Chain 4:
                         1 / 2000 [ 0%]
## Chain 4: Iteration:
                                            (Warmup)
## Chain 4: Iteration: 200 / 2000 [ 10%]
                                            (Warmup)
## Chain 4: Iteration: 400 / 2000 [ 20%]
                                            (Warmup)
## Chain 4: Iteration: 600 / 2000 [ 30%]
                                            (Warmup)
## Chain 4: Iteration: 800 / 2000 [ 40%]
                                            (Warmup)
## Chain 4: Iteration: 1000 / 2000 [ 50%]
                                            (Warmup)
## Chain 4: Iteration: 1001 / 2000 [ 50%]
```

(Sampling)

Manly, Bryan F. J. 1997. Randomization, Bootstrap and Monte Carlo Methods in Biology. Chapman & Hall.