Marketing Homework 3

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# Binary Data Regression Models for Bank Customer Attrition

# Q1

bankRetentionData = read.csv('Bank\_Retention\_Data.csv')

bankRetentionData$TractID = as.factor(bankRetentionData$TractID)

Logistic Regression

churnlogit <- glm(bankRetentionData$Churn ~ bankRetentionData$Age + bankRetentionData$Income + bankRetentionData$HomeVal + bankRetentionData$Tenure + bankRetentionData$DirectDeposit + bankRetentionData$Loan + bankRetentionData$Dist + bankRetentionData$MktShare, data = bankRetentionData, family = binomial(link = "logit"))  
summary(churnlogit)

##   
## Call:  
## glm(formula = bankRetentionData$Churn ~ bankRetentionData$Age +   
## bankRetentionData$Income + bankRetentionData$HomeVal + bankRetentionData$Tenure +   
## bankRetentionData$DirectDeposit + bankRetentionData$Loan +   
## bankRetentionData$Dist + bankRetentionData$MktShare, family = binomial(link = "logit"),   
## data = bankRetentionData)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.2054 -0.6823 -0.5328 -0.3401 2.6266   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.606224 0.296596 -2.044 0.040960 \*   
## bankRetentionData$Age -0.016103 0.004150 -3.881 0.000104 \*\*\*  
## bankRetentionData$Income 0.107067 0.015985 6.698 2.11e-11 \*\*\*  
## bankRetentionData$HomeVal -0.026059 0.005477 -4.758 1.95e-06 \*\*\*  
## bankRetentionData$Tenure -0.029709 0.006549 -4.536 5.73e-06 \*\*\*  
## bankRetentionData$DirectDeposit -0.465836 0.110617 -4.211 2.54e-05 \*\*\*  
## bankRetentionData$Loan 0.099376 0.124380 0.799 0.424310   
## bankRetentionData$Dist 0.267618 0.061958 4.319 1.57e-05 \*\*\*  
## bankRetentionData$MktShare -0.082440 0.325551 -0.253 0.800089   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 2355.9 on 2504 degrees of freedom  
## Residual deviance: 2189.4 on 2496 degrees of freedom  
## AIC: 2207.4  
##   
## Number of Fisher Scoring iterations: 5

Probit Regression

churnprobit <- glm(bankRetentionData$Churn ~ bankRetentionData$Age + bankRetentionData$Income + bankRetentionData$HomeVal + bankRetentionData$Tenure + bankRetentionData$DirectDeposit + bankRetentionData$Loan + bankRetentionData$Dist + bankRetentionData$MktShare, data = bankRetentionData, family = binomial(link = "probit"))  
summary(churnprobit)

##   
## Call:  
## glm(formula = bankRetentionData$Churn ~ bankRetentionData$Age +   
## bankRetentionData$Income + bankRetentionData$HomeVal + bankRetentionData$Tenure +   
## bankRetentionData$DirectDeposit + bankRetentionData$Loan +   
## bankRetentionData$Dist + bankRetentionData$MktShare, family = binomial(link = "probit"),   
## data = bankRetentionData)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.1714 -0.6886 -0.5374 -0.3252 2.7140   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.397967 0.168825 -2.357 0.0184 \*   
## bankRetentionData$Age -0.009050 0.002314 -3.910 9.22e-05 \*\*\*  
## bankRetentionData$Income 0.059194 0.008871 6.673 2.51e-11 \*\*\*  
## bankRetentionData$HomeVal -0.014360 0.002922 -4.914 8.90e-07 \*\*\*  
## bankRetentionData$Tenure -0.016430 0.003550 -4.628 3.69e-06 \*\*\*  
## bankRetentionData$DirectDeposit -0.263070 0.062851 -4.186 2.84e-05 \*\*\*  
## bankRetentionData$Loan 0.057756 0.070224 0.822 0.4108   
## bankRetentionData$Dist 0.154712 0.036313 4.261 2.04e-05 \*\*\*  
## bankRetentionData$MktShare -0.045443 0.184547 -0.246 0.8055   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 2355.9 on 2504 degrees of freedom  
## Residual deviance: 2188.6 on 2496 degrees of freedom  
## AIC: 2206.6  
##   
## Number of Fisher Scoring iterations: 6

From the summary tables, we see that

* Age
* Income
* HomeVal
* Tenure
* DirectDeposit
* Dist

are statistically significant.

*β*1, *β*2*, β*3, *β*4, *β*5, *β*7 are statistically significant in both models because their p-values are less than 0.05

cat("AIC : ")

## AIC :

AIC(churnlogit)

## [1] 2207.358

AIC(churnprobit)

## [1] 2206.626

cat("BIC : ")

## BIC :

BIC(churnlogit)

## [1] 2259.793

BIC(churnprobit)

## [1] 2259.06

Probit is slightly better as it’s AIC, BIC values are lower.

# Q2

library(lme4)

## Warning: package 'lme4' was built under R version 3.6.2

## Loading required package: Matrix

churnrandom <- glmer(Churn ~ (1|TractID) + Age + Income + HomeVal + Tenure + DirectDeposit + Loan + Dist + MktShare, data = bankRetentionData, family=binomial)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =  
## control$checkConv, : Model failed to converge with max|grad| = 0.00217238  
## (tol = 0.001, component 1)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unidentifiable: very large eigenvalue  
## - Rescale variables?

summary(churnrandom)

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula:   
## Churn ~ (1 | TractID) + Age + Income + HomeVal + Tenure + DirectDeposit +   
## Loan + Dist + MktShare  
## Data: bankRetentionData  
##   
## AIC BIC logLik deviance df.resid   
## 2208.7 2266.9 -1094.3 2188.7 2495   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.0912 -0.5118 -0.3895 -0.2447 5.3475   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## TractID (Intercept) 0.01994 0.1412   
## Number of obs: 2505, groups: TractID, 26  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.564391 0.305963 -1.845 0.0651 .   
## Age -0.016479 0.004178 -3.944 8.00e-05 \*\*\*  
## Income 0.107015 0.016078 6.656 2.81e-11 \*\*\*  
## HomeVal -0.026706 0.005691 -4.693 2.69e-06 \*\*\*  
## Tenure -0.029231 0.006564 -4.453 8.46e-06 \*\*\*  
## DirectDeposit -0.461463 0.111004 -4.157 3.22e-05 \*\*\*  
## Loan 0.099944 0.124635 0.802 0.4226   
## Dist 0.266979 0.063386 4.212 2.53e-05 \*\*\*  
## MktShare 0.007963 0.373360 0.021 0.9830   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) Age Income HomeVl Tenure DrctDp Loan Dist   
## Age -0.647   
## Income -0.221 0.055   
## HomeVal -0.206 -0.060 -0.534   
## Tenure 0.014 -0.285 -0.075 0.077   
## DirectDepst -0.175 0.012 -0.050 0.081 -0.115   
## Loan -0.073 0.073 -0.007 -0.059 -0.105 -0.083   
## Dist -0.324 0.000 -0.012 -0.150 -0.013 -0.008 -0.012   
## MktShare -0.359 -0.006 -0.031 0.060 -0.140 0.005 -0.008 0.260  
## convergence code: 0  
## Model failed to converge with max|grad| = 0.00217238 (tol = 0.001, component 1)  
## Model is nearly unidentifiable: very large eigenvalue  
## - Rescale variables?

cat("AIC : ")

## AIC :

AIC(churnrandom)

## [1] 2208.686

cat("BIC : ")

## BIC :

BIC(churnrandom)

## [1] 2266.947

From the summary table, we see that

* Age
* Income
* HomeVal
* Tenure
* DirectDeposit
* Dist

are still statistically significant.

*β*1, *β*2*, β*3, *β*4, *β*5, *β*7 are still statistically significant because their p-values are less than 0.05

# Q3

library(MCMCpack)

## Warning: package 'MCMCpack' was built under R version 3.6.3

## Loading required package: coda

## Warning: package 'coda' was built under R version 3.6.3

## Loading required package: MASS

## Warning: package 'MASS' was built under R version 3.6.2

## ##  
## ## Markov Chain Monte Carlo Package (MCMCpack)

## ## Copyright (C) 2003-2020 Andrew D. Martin, Kevin M. Quinn, and Jong Hee Park

## ##  
## ## Support provided by the U.S. National Science Foundation

## ## (Grants SES-0350646 and SES-0350613)  
## ##

churnmcmchlogit = MCMChlogit(bankRetentionData$Churn ~ bankRetentionData$Age + bankRetentionData$Income + bankRetentionData$HomeVal + bankRetentionData$Tenure + bankRetentionData$DirectDeposit + bankRetentionData$Loan + bankRetentionData$Dist + bankRetentionData$MktShare, data = bankRetentionData, group = 'TractID', random=~1, r=2, R=1, burnin=10000, mcmc=20000, thin=20)

##   
## Running the Gibbs sampler. It may be long, keep cool :)  
##   
## \*\*\*\*\*\*\*\*\*\*:10.0%, mean accept. rate=0.444  
## \*\*\*\*\*\*\*\*\*\*:20.0%, mean accept. rate=0.489  
## \*\*\*\*\*\*\*\*\*\*:30.0%, mean accept. rate=0.458  
## \*\*\*\*\*\*\*\*\*\*:40.0%, mean accept. rate=0.528  
## \*\*\*\*\*\*\*\*\*\*:50.0%, mean accept. rate=0.504  
## \*\*\*\*\*\*\*\*\*\*:60.0%, mean accept. rate=0.534  
## \*\*\*\*\*\*\*\*\*\*:70.0%, mean accept. rate=0.547  
## \*\*\*\*\*\*\*\*\*\*:80.0%, mean accept. rate=0.440  
## \*\*\*\*\*\*\*\*\*\*:90.0%, mean accept. rate=0.605  
## \*\*\*\*\*\*\*\*\*\*:100.0%, mean accept. rate=0.398

summary(churnmcmchlogit$mcmc[,1:9])

##   
## Iterations = 10001:29981  
## Thinning interval = 20   
## Number of chains = 1   
## Sample size per chain = 1000   
##   
## 1. Empirical mean and standard deviation for each variable,  
## plus standard error of the mean:  
##   
## Mean SD Naive SE  
## beta.(Intercept) -0.25947 0.0815724 2.580e-03  
## beta.bankRetentionData$Age -0.01804 0.0007226 2.285e-05  
## beta.bankRetentionData$Income 0.12285 0.0030567 9.666e-05  
## beta.bankRetentionData$HomeVal -0.03213 0.0006686 2.114e-05  
## beta.bankRetentionData$Tenure -0.03938 0.0019498 6.166e-05  
## beta.bankRetentionData$DirectDeposit -0.63830 0.0324330 1.026e-03  
## beta.bankRetentionData$Loan 0.27031 0.0337348 1.067e-03  
## beta.bankRetentionData$Dist 0.24827 0.0170810 5.401e-04  
## beta.bankRetentionData$MktShare -0.22866 0.1150054 3.637e-03  
## Time-series SE  
## beta.(Intercept) 0.0452272  
## beta.bankRetentionData$Age 0.0003740  
## beta.bankRetentionData$Income 0.0019092  
## beta.bankRetentionData$HomeVal 0.0004355  
## beta.bankRetentionData$Tenure 0.0017056  
## beta.bankRetentionData$DirectDeposit 0.0241419  
## beta.bankRetentionData$Loan 0.0274172  
## beta.bankRetentionData$Dist 0.0096881  
## beta.bankRetentionData$MktShare 0.0840372  
##   
## 2. Quantiles for each variable:  
##   
## 2.5% 25% 50% 75%  
## beta.(Intercept) -0.40488 -0.31840 -0.27135 -0.19533  
## beta.bankRetentionData$Age -0.01918 -0.01868 -0.01817 -0.01744  
## beta.bankRetentionData$Income 0.11867 0.12046 0.12197 0.12492  
## beta.bankRetentionData$HomeVal -0.03312 -0.03271 -0.03224 -0.03178  
## beta.bankRetentionData$Tenure -0.04248 -0.04139 -0.03895 -0.03752  
## beta.bankRetentionData$DirectDeposit -0.68343 -0.66094 -0.64954 -0.61730  
## beta.bankRetentionData$Loan 0.22642 0.24463 0.25666 0.30730  
## beta.bankRetentionData$Dist 0.22056 0.23051 0.25124 0.26070  
## beta.bankRetentionData$MktShare -0.43719 -0.33105 -0.20048 -0.13206  
## 97.5%  
## beta.(Intercept) -0.09033  
## beta.bankRetentionData$Age -0.01674  
## beta.bankRetentionData$Income 0.12881  
## beta.bankRetentionData$HomeVal -0.03095  
## beta.bankRetentionData$Tenure -0.03695  
## beta.bankRetentionData$DirectDeposit -0.57135  
## beta.bankRetentionData$Loan 0.33526  
## beta.bankRetentionData$Dist 0.28204  
## beta.bankRetentionData$MktShare -0.06770

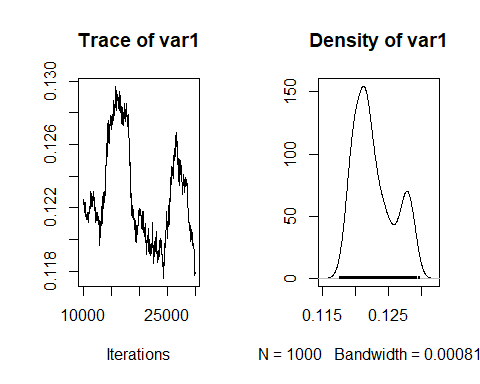
From the summary table, we see that

* Age
* Income
* HomeVal
* Tenure
* DirectDeposit
* Loan
* Dist
* MarketShare

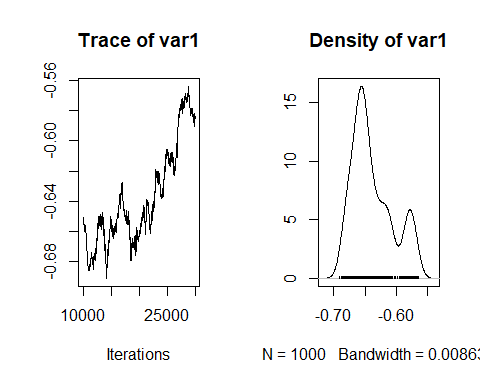
are statistically significant at the 5% level

*β*1, *β*2*, β*3, *β*4, *β*5, *β*6, *β*7, *β*8 are statistically significant at the 5% level.

plot(churnmcmchlogit$mcmc[,3])



plot(churnmcmchlogit$mcmc[,6])



# Count Data Analysis for Shopping Mall Visits

# Q4

mallVisitData = read.csv('Mall\_visit.csv')

mallVisitData$customerID = as.factor(mallVisitData$customerID)

visit.poisson = glm(Visit ~ Discount + Target + Income + Distant + Gender, data=mallVisitData, family = poisson(link = "log"))  
summary(visit.poisson)

##   
## Call:  
## glm(formula = Visit ~ Discount + Target + Income + Distant +   
## Gender, family = poisson(link = "log"), data = mallVisitData)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.5136 -0.9896 -0.7675 0.5602 3.8721   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.4143685 0.0343574 -41.166 < 2e-16 \*\*\*  
## Discount 0.0007975 0.0002693 2.962 0.00306 \*\*   
## Target -0.0275468 0.0179415 -1.535 0.12469   
## Income 0.0049092 0.0001252 39.216 < 2e-16 \*\*\*  
## Distant -0.0469158 0.0036635 -12.806 < 2e-16 \*\*\*  
## Gender 0.0448540 0.0179698 2.496 0.01256 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for poisson family taken to be 1)  
##   
## Null deviance: 26722 on 24999 degrees of freedom  
## Residual deviance: 24853 on 24994 degrees of freedom  
## AIC: 45274  
##   
## Number of Fisher Scoring iterations: 6

From the summary table, we see that

* Discount,
* Distant,
* Income,
* Gender

are statistically significant.

*β*1, *β*3, *β*4, *β*5 are still statistically significant because their p-values are less than 0.05

cat("AIC : ")

## AIC :

AIC(visit.poisson)

## [1] 45274.32

cat("BIC : ")

## BIC :

BIC(visit.poisson)

## [1] 45323.08

# Q5

library(lme4)  
visit.poisson.random = glmer(Visit ~ (1|customerID) + Discount + Target + Income + Distant + Gender, data = mallVisitData, family = poisson)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =  
## control$checkConv, : Model failed to converge with max|grad| = 0.00178329  
## (tol = 0.001, component 1)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unidentifiable: very large eigenvalue  
## - Rescale variables?

summary(visit.poisson.random)

## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: poisson ( log )  
## Formula:   
## Visit ~ (1 | customerID) + Discount + Target + Income + Distant +   
## Gender  
## Data: mallVisitData  
##   
## AIC BIC logLik deviance df.resid   
## 44695.9 44752.8 -22340.9 44681.9 24993   
##   
## Scaled residuals:   
## Min 1Q Median 3Q Max   
## -1.2248 -0.6673 -0.5086 0.6231 5.9048   
##   
## Random effects:  
## Groups Name Variance Std.Dev.  
## customerID (Intercept) 0.09248 0.3041   
## Number of obs: 25000, groups: customerID, 500  
##   
## Fixed effects:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.4612139 0.0570247 -25.624 < 2e-16 \*\*\*  
## Discount 0.0008835 0.0002700 3.273 0.00107 \*\*   
## Target -0.0269294 0.0179820 -1.498 0.13424   
## Income 0.0049041 0.0002231 21.984 < 2e-16 \*\*\*  
## Distant -0.0473146 0.0067025 -7.059 1.67e-12 \*\*\*  
## Gender 0.0458270 0.0333825 1.373 0.16982   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Correlation of Fixed Effects:  
## (Intr) Discnt Target Income Distnt  
## Discount -0.125   
## Target -0.155 -0.012   
## Income -0.707 -0.003 -0.002   
## Distant -0.560 -0.004 0.004 0.039   
## Gender -0.255 0.000 0.001 -0.038 -0.030  
## convergence code: 0  
## Model failed to converge with max|grad| = 0.00178329 (tol = 0.001, component 1)  
## Model is nearly unidentifiable: very large eigenvalue  
## - Rescale variables?

From the summary table, we see that

* Discount,
* Distant,
* Income

are statistically significant. Gender is no more significant

*β*1, *β*3, *β*4 are statistically significant because their p-values are less than 0.05

cat("AIC : ")

## AIC :

AIC(visit.poisson.random)

## [1] 44695.9

cat("BIC : ")

## BIC :

BIC(visit.poisson.random)

## [1] 44752.78

# Q6

library(MASS)  
visit.nb <- glm.nb(Visit ~ Discount + Target + Income + Distant + Gender, data=mallVisitData)  
summary(visit.nb)

##   
## Call:  
## glm.nb(formula = Visit ~ Discount + Target + Income + Distant +   
## Gender, data = mallVisitData, init.theta = 10.82765227, link = log)  
##   
## Deviance Residuals:   
## Min 1Q Median 3Q Max   
## -1.4760 -0.9787 -0.7623 0.5435 3.6554   
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -1.4140463 0.0350814 -40.308 <2e-16 \*\*\*  
## Discount 0.0007957 0.0002764 2.878 0.0040 \*\*   
## Target -0.0275706 0.0184075 -1.498 0.1342   
## Income 0.0049096 0.0001281 38.328 <2e-16 \*\*\*  
## Distant -0.0470039 0.0037561 -12.514 <2e-16 \*\*\*  
## Gender 0.0449952 0.0184358 2.441 0.0147 \*   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for Negative Binomial(10.8277) family taken to be 1)  
##   
## Null deviance: 25524 on 24999 degrees of freedom  
## Residual deviance: 23738 on 24994 degrees of freedom  
## AIC: 45248  
##   
## Number of Fisher Scoring iterations: 1  
##   
##   
## Theta: 10.83   
## Std. Err.: 2.18   
##   
## 2 x log-likelihood: -45234.17

From the summary table, we see that

* Discount,
* Distant,
* Income,
* Gender

are statistically significant.

*β*1, *β*3, *β*4, *β*5 are statistically significant because their p-values are less than 0.05

cat("AIC : ")

## AIC :

AIC(visit.nb)

## [1] 45248.16

cat("BIC : ")

## BIC :

BIC(visit.nb)

## [1] 45305.05

Best model is random effects model with AIC of 44695 (lowest)

# Q7

library(MCMCpack)  
mallVisitData.mcmc <- MCMChpoisson(fixed=Visit ~ Discount + Target + Distant + Income + Gender, data=mallVisitData, random=~1, group="customerID", burnin=10000, mcmc=20000, thin=20, r=1, R=diag(1))

##   
## Running the Gibbs sampler. It may be long, keep cool :)  
##   
## \*\*\*\*\*\*\*\*\*\*:10.0%, mean accept. rate=0.456  
## \*\*\*\*\*\*\*\*\*\*:20.0%, mean accept. rate=0.447  
## \*\*\*\*\*\*\*\*\*\*:30.0%, mean accept. rate=0.431  
## \*\*\*\*\*\*\*\*\*\*:40.0%, mean accept. rate=0.415  
## \*\*\*\*\*\*\*\*\*\*:50.0%, mean accept. rate=0.386  
## \*\*\*\*\*\*\*\*\*\*:60.0%, mean accept. rate=0.369  
## \*\*\*\*\*\*\*\*\*\*:70.0%, mean accept. rate=0.429  
## \*\*\*\*\*\*\*\*\*\*:80.0%, mean accept. rate=0.322  
## \*\*\*\*\*\*\*\*\*\*:90.0%, mean accept. rate=0.420  
## \*\*\*\*\*\*\*\*\*\*:100.0%, mean accept. rate=0.397

summary(mallVisitData.mcmc$mcmc[,1:6])

##   
## Iterations = 10001:29981  
## Thinning interval = 20   
## Number of chains = 1   
## Sample size per chain = 1000   
##   
## 1. Empirical mean and standard deviation for each variable,  
## plus standard error of the mean:  
##   
## Mean SD Naive SE Time-series SE  
## beta.(Intercept) -1.4657682 0.0358470 1.134e-03 7.743e-03  
## beta.Discount 0.0009947 0.0002054 6.497e-06 3.099e-05  
## beta.Target -0.0276942 0.0177249 5.605e-04 3.572e-03  
## beta.Distant -0.0485401 0.0044378 1.403e-04 1.008e-03  
## beta.Income 0.0048980 0.0001143 3.616e-06 1.938e-05  
## beta.Gender 0.0484992 0.0205758 6.507e-04 4.346e-03  
##   
## 2. Quantiles for each variable:  
##   
## 2.5% 25% 50% 75% 97.5%  
## beta.(Intercept) -1.5284016 -1.4943879 -1.4665657 -1.438243 -1.401021  
## beta.Discount 0.0005916 0.0008572 0.0009947 0.001139 0.001394  
## beta.Target -0.0609695 -0.0403323 -0.0283693 -0.014381 0.004982  
## beta.Distant -0.0568009 -0.0518336 -0.0480617 -0.045343 -0.040486  
## beta.Income 0.0046961 0.0048143 0.0048823 0.004976 0.005144  
## beta.Gender 0.0097694 0.0346725 0.0477855 0.063028 0.088967

Without Random effects:

* Discount,
* Distant,
* Income  
  Gender

are significant. Target is insignificant.

With Random effects:

* Discount,
* Target,
* Distant,
* Income  
  Gender

are significant.

plot(mallVisitData.mcmc$mcmc[,3])

