data = read.csv(file = "M:/A Master of Science in Marketing Sciences/Mathematical Models in Marketing (Kohli)/latent/data\_ipad.csv",head = TRUE)

attach(data)

summary(data)

## Modelling Step 1: Set up Training Set and Dev Set

random\_factor = sample(1:15,137,replace = TRUE)

determinant\_factor = (1:137)\*15 - 15

## The index for Dev Set is the summation of Random and Deterministic.

index = random\_factor + determinant\_factor

dev = data[which(choice\_set\_id %in% index) ,]

train = data[which(!(choice\_set\_id %in% index)) ,]

## Model 1: Fit an aggregate model without any segment

## In the training set,

X1\_train = subset(train, alternative\_id\_in\_set == 1)

X2\_train = subset(train, alternative\_id\_in\_set == 2)

X3\_train = subset(train, alternative\_id\_in\_set == 3)

## In the test set,``

X1\_test = subset(dev, alternative\_id\_in\_set == 1)

X2\_test = subset(dev, alternative\_id\_in\_set == 2)

X3\_test = subset(dev, alternative\_id\_in\_set == 3)

## The dependent variable

train\_choice = X1\_train$choice

test\_choice = X1\_test$choice

train\_set = cbind(X1\_train[,5:22],X2\_train[,5:22],X3\_train[,5:22])

test\_set = cbind(X1\_test[,5:22],X2\_test[,5:22],X3\_test[,5:22])

## The parameters for the first segment

par1 = rnorm(18)

## The parameters for the second segment

par2 = rnorm(18)

## The parameters for the third segment

par3 = rnorm(18)

## The parameters for the fourth segment

par4 = rnorm(18)

## The parameters for the fifth segment

par5 = rnorm(18)

## The parameter for the likelihood that a randomly chosen individual belongs to segment 1

p5 = exp(rnorm(5))

p5 = p5/sum(p5)

## The combined parameters are

par\_5 = t(cbind(t(par1),t(par2),t(par3),t(par4),t(par5),t(p5[1:4])))

N = 1918

ll\_5 <- function(beta)

{

res = 0

## To calculate the likelohood for the first segment

M11 = as.matrix(train\_set)[,1:18] %\*% beta[1:18]

M12 = as.matrix(train\_set)[,19:36] %\*% beta[1:18]

M13 = as.matrix(train\_set)[,37:54] %\*% beta[1:18]

M1 = cbind(exp(M11),exp(M12),exp(M13))

## The likelihood for each of the three alternatives in the first segment

M1 = M1 / rowSums(M1)

M21 = as.matrix(train\_set)[,1:18] %\*% beta[19:36]

M22 = as.matrix(train\_set)[,19:36] %\*% beta[19:36]

M23 = as.matrix(train\_set)[,37:54] %\*% beta[19:36]

M2 = cbind(exp(M21),exp(M22),exp(M23))

## The likelihood for each of the three alternatives in the second segment

M2 = M2 / rowSums(M2)

M31 = as.matrix(train\_set)[,1:18] %\*% beta[37:54]

M32 = as.matrix(train\_set)[,19:36] %\*% beta[37:54]

M33 = as.matrix(train\_set)[,37:54] %\*% beta[37:54]

M3 = cbind(exp(M31),exp(M32),exp(M33))

## The likelihood for each of the three alternatives in the third segment

M3 = M3 / rowSums(M3)

M41 = as.matrix(train\_set)[,1:18] %\*% beta[55:72]

M42 = as.matrix(train\_set)[,19:36] %\*% beta[55:72]

M43 = as.matrix(train\_set)[,37:54] %\*% beta[55:72]

M4 = cbind(exp(M41),exp(M42),exp(M43))

## The likelihood for each of the three alternatives in the fourth segment

M4 = M4 / rowSums(M4)

M51 = as.matrix(train\_set)[,1:18] %\*% beta[73:90]

M52 = as.matrix(train\_set)[,19:36] %\*% beta[73:90]

M53 = as.matrix(train\_set)[,37:54] %\*% beta[73:90]

M5 = cbind(exp(M51),exp(M52),exp(M53))

## The likelihood for each of the three alternatives in the fourth segment

M5 = M5 / rowSums(M5)

## Given that the consumer belongs to Segment 1, what is the probability for him to choose Alternative i?

prob\_1 = M1[cbind(seq(1,length(train\_choice)),train\_choice)]

## Given that the consumer belongs to Segment 2, what is the probability for him to choose Alternative i?

prob\_2 = M2[cbind(seq(1,length(train\_choice)),train\_choice)]

## Given that the consumer belongs to Segment 3, what is the probability for him to choose Alternative i?

prob\_3 = M3[cbind(seq(1,length(train\_choice)),train\_choice)]

## Given that the consumer belongs to Segment 4, what is the probability for him to choose Alternative i?

prob\_4 = M4[cbind(seq(1,length(train\_choice)),train\_choice)]

## Given that the consumer belongs to Segment 5, what is the probability for him to choose Alternative i?

prob\_5 = M5[cbind(seq(1,length(train\_choice)),train\_choice)]

## This transformation guarantees that the likelihood for each segment is within the range of (0,1)

probability\_1 = beta[91]

probability\_2 = beta[92]

probability\_3 = beta[93]

probability\_4 = beta[94]

for (i in 1:137)

{

MP = c()

MP[i] = probability\_1 \* cumprod(prob\_1[(14\*(i-1)+1):(14\*i)])[14] + probability\_2 \* cumprod(prob\_2[(14\*(i-1)+1):(14\*i)])[14] + probability\_3 \* cumprod(prob\_3[(14\*(i-1)+1):(14\*i)])[14] + probability\_4 \* cumprod(prob\_4[(14\*(i-1)+1):(14\*i)])[14] + (1 - probability\_1 - probability\_2 - probability\_3 - probability\_4) \* cumprod(prob\_4[(14\*(i-1)+1):(14\*i)])[14]

res = res -log(MP[i])

}

return (res)

}

ML\_5 = nlm(ll\_5,par\_5,hessian = TRUE)

mode = ML\_5$estimate

SE = sqrt(diag(solve(ML\_5$hessian)))

Tvalue = mode/SE

ll = 2\*ML\_5$minimum

Result\_5 = cbind(Estimate = mode, SE= SE, Tvalue = Tvalue, minusll = ll)

round(Result\_5,2)

## This is the estimates for pi\_i(the market share of the first segment)

pi\_1 = ML\_5$estimate[91]

pi\_2 = ML\_5$estimate[92]

pi\_3 = ML\_5$estimate[93]

pi\_4 = ML\_5$estimate[94]

## Concise Expression

## The likelihood for each of the three alternatives in the first segment

M11 = as.matrix(train\_set)[,1:18] %\*% ML\_5$estimate[1:18]

M12 = as.matrix(train\_set)[,19:36] %\*% ML\_5$estimate[1:18]

M13 = as.matrix(train\_set)[,37:54] %\*% ML\_5$estimate[1:18]

M1 = cbind(exp(M11),exp(M12),exp(M13))

M1 = M1 / rowSums(M1)

## M11 is the probability for individual i's actual choice in Segment 1

M11 = M1[cbind(1:(137\*14),train\_choice[1:(137\*14)])]

## The likelihood for each of the three alternatives in the second segment

M21 = as.matrix(train\_set)[,1:18] %\*% ML\_5$estimate[19:36]

M22 = as.matrix(train\_set)[,19:36] %\*% ML\_5$estimate[19:36]

M23 = as.matrix(train\_set)[,37:54] %\*% ML\_5$estimate[19:36]

M2 = cbind(exp(M21),exp(M22),exp(M23))

M2 = M2 / rowSums(M2)

## M11 is the probability for individual i's actual choice in Segment 2

M12 = M2[cbind(1:(14\*137),train\_choice[1:(14\*137)])]

## The likelihood for each of the three alternatives in the third segment

M31 = as.matrix(train\_set)[,1:18] %\*% ML\_5$estimate[37:54]

M32 = as.matrix(train\_set)[,19:36] %\*% ML\_5$estimate[37:54]

M33 = as.matrix(train\_set)[,37:54] %\*% ML\_5$estimate[37:54]

M3 = cbind(exp(M31),exp(M32),exp(M33))

M3 = M3 / rowSums(M3)

## M11 is the probability for individual i's actual choice in Segment 2

M13 = M3[cbind(1:(14\*137),train\_choice[1:(14\*137)])]

## The likelihood for each of the three alternatives in the fourth segment

M41 = as.matrix(train\_set)[,1:18] %\*% ML\_5$estimate[55:72]

M42 = as.matrix(train\_set)[,19:36] %\*% ML\_5$estimate[55:72]

M43 = as.matrix(train\_set)[,37:54] %\*% ML\_5$estimate[55:72]

M4 = cbind(exp(M41),exp(M42),exp(M43))

M4 = M4 / rowSums(M4)

## M11 is the probability for individual i's actual choice in Segment 2

M14 = M4[cbind(1:(14\*137),train\_choice[1:(14\*137)])]

## The likelihood for each of the three alternatives in the fourth segment

M51 = as.matrix(train\_set)[,1:18] %\*% ML\_5$estimate[55:72]

M52 = as.matrix(train\_set)[,19:36] %\*% ML\_5$estimate[55:72]

M53 = as.matrix(train\_set)[,37:54] %\*% ML\_5$estimate[55:72]

M5 = cbind(exp(M51),exp(M52),exp(M53))

M5 = M5 / rowSums(M5)

## M11 is the probability for individual i's actual choice in Segment 2

M15 = M5[cbind(1:(14\*137),train\_choice[1:(14\*137)])]

## The individual-level estimates of segment membership using Bayes Rule

## What is the orobability for each individual to belong to Segment 1?

prob <- rep(0,137\*4)

prob = matrix(prob, 137,4)

for (i in 1:137)

{

prob[i,1] = (pi\_1 \* (cumprod(M11[(1+(i-1)\*14):(14 \* i)])[14]))/((pi\_1 \* cumprod(M11[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_2 \* cumprod(M12[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_3 \* cumprod(M13[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_4 \* cumprod(M14[(1+(i-1)\*14):(14 \* i)])[14]) + ((1 - pi\_2 - pi\_1 - pi\_3 - pi\_4) \* cumprod(M15[(1+(i-1)\*14):(14 \* i)])[14]))

prob[i,2] = (pi\_2 \* (cumprod(M12[(1+(i-1)\*14):(14 \* i)])[14]))/((pi\_1 \* cumprod(M11[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_2 \* cumprod(M12[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_3 \* cumprod(M13[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_4 \* cumprod(M14[(1+(i-1)\*14):(14 \* i)])[14]) + ((1 - pi\_2 - pi\_1 - pi\_3 - pi\_4) \* cumprod(M15[(1+(i-1)\*14):(14 \* i)])[14]))

prob[i,3] = (pi\_3 \* (cumprod(M13[(1+(i-1)\*14):(14 \* i)])[14]))/((pi\_1 \* cumprod(M11[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_2 \* cumprod(M12[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_3 \* cumprod(M13[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_4 \* cumprod(M14[(1+(i-1)\*14):(14 \* i)])[14]) + ((1 - pi\_2 - pi\_1 - pi\_3 - pi\_4) \* cumprod(M15[(1+(i-1)\*14):(14 \* i)])[14]))

prob[i,4] = (pi\_4 \* (cumprod(M14[(1+(i-1)\*14):(14 \* i)])[14]))/((pi\_1 \* cumprod(M11[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_2 \* cumprod(M12[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_3 \* cumprod(M13[(1+(i-1)\*14):(14 \* i)])[14]) + (pi\_4 \* cumprod(M14[(1+(i-1)\*14):(14 \* i)])[14]) + ((1 - pi\_2 - pi\_1 - pi\_3 - pi\_4) \* cumprod(M15[(1+(i-1)\*14):(14 \* i)])[14]))

}

## The vector prob is the probability for each individual to choose Segment 1

##########################################

# ## Another Method which is theoretical correct but practically infeasible

# cumprod(M11[(1+(2-1)\*14):(14+(2-1)\*14)])[14]

# cum\_M11 = cumprod(M11)

# cum\_M12 = cumprod(M12)

# cumprod(M11)[14]/(cumprod(M11)[14]+cumprod(M12)[14])

#

# a <- 1:(137\*14)

# b\_11 <- cum\_M11[seq(14, 137\*14, 14)]

# b\_11\_tmp <- t(cbind(1,t(b\_11)))

# b\_11\_tem = b\_11\_tmp[1:137]

# b\_11/b\_11\_tem

##########################################

## \*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*\*

## Then I am going to do the Cross-Validation

## The expected probability for each alternative in Segment 1

## Segment 1 -- Choice 1

X1\_predict\_11 = as.matrix(X1\_test)[,5:22] %\*% ML\_5$estimate[1:18]

## Segment 1 -- Choice 2

X2\_predict\_12 = as.matrix(X2\_test)[,5:22] %\*% ML\_5$estimate[1:18]

## Segment 1 -- Choice 3

X3\_predict\_13 = as.matrix(X3\_test)[,5:22] %\*% ML\_5$estimate[1:18]

## The expected probability for each alternative in Segment 2

## Segment 2 -- Choice 1

X1\_predict\_21 = as.matrix(X1\_test)[,5:22] %\*% ML\_5$estimate[19:36]

## Segment 2 -- Choice 2

X2\_predict\_22 = as.matrix(X2\_test)[,5:22] %\*% ML\_5$estimate[19:36]

## Segment 2 -- Choice 3

X3\_predict\_23 = as.matrix(X3\_test)[,5:22] %\*% ML\_5$estimate[19:36]

## The expected probability for each alternative in Segment 3

## Segment 3 -- Choice 1

X1\_predict\_31 = as.matrix(X1\_test)[,5:22] %\*% ML\_5$estimate[37:54]

## Segment 3 -- Choice 2

X2\_predict\_32 = as.matrix(X2\_test)[,5:22] %\*% ML\_5$estimate[37:54]

## Segment 3 -- Choice 3

X3\_predict\_33 = as.matrix(X3\_test)[,5:22] %\*% ML\_5$estimate[37:54]

## The expected probability for each alternative in Segment 4

## Segment 4 -- Choice 1

X1\_predict\_41 = as.matrix(X1\_test)[,5:22] %\*% ML\_5$estimate[55:72]

## Segment 4 -- Choice 2

X2\_predict\_42 = as.matrix(X2\_test)[,5:22] %\*% ML\_5$estimate[55:72]

## Segment 4 -- Choice 3

X3\_predict\_43 = as.matrix(X3\_test)[,5:22] %\*% ML\_5$estimate[55:72]

## The expected probability for each alternative in Segment 5

## Segment 5 -- Choice 1

X1\_predict\_51 = as.matrix(X1\_test)[,5:22] %\*% ML\_5$estimate[73:90]

## Segment 5 -- Choice 2

X2\_predict\_52 = as.matrix(X2\_test)[,5:22] %\*% ML\_5$estimate[73:90]

## Segment 5 -- Choice 3

X3\_predict\_53 = as.matrix(X3\_test)[,5:22] %\*% ML\_5$estimate[73:90]

predict\_51 = cbind(exp(X1\_predict\_11),exp(X2\_predict\_12),exp(X3\_predict\_13))

predict\_52 = cbind(exp(X1\_predict\_21),exp(X2\_predict\_22),exp(X3\_predict\_23))

predict\_53 = cbind(exp(X1\_predict\_31),exp(X2\_predict\_32),exp(X3\_predict\_33))

predict\_54 = cbind(exp(X1\_predict\_41),exp(X2\_predict\_42),exp(X3\_predict\_43))

predict\_55 = cbind(exp(X1\_predict\_51),exp(X2\_predict\_52),exp(X3\_predict\_53))

## predict\_51 is the predicted probability for each individual to choose each alternative given that he belongs to Segment 1

predict\_51 = predict\_51/rowSums(predict\_51)

## predict\_52 is the predicted probability for each individual to choose each alternative given that he belongs to Segment 2

predict\_52 = predict\_52/rowSums(predict\_52)

## predict\_53 is the predicted probability for each individual to choose each alternative given that he belongs to Segment 3

predict\_53 = predict\_53/rowSums(predict\_53)

## predict\_54 is the predicted probability for each individual to choose each alternative given that he belongs to Segment 4

predict\_54 = predict\_54/rowSums(predict\_54)

## predict\_55 is the predicted probability for each individual to choose each alternative given that he belongs to Segment 5

predict\_55 = predict\_54/rowSums(predict\_55)

## The vector prob is the probability for each individual to choose Segment 1

## We can use the posterior segment membership probability to estimate the probability that individual i chooses alternative j

predict\_5 = prob[,1] \* predict\_51 + prob[,2] \* predict\_52 + prob[,3] \* predict\_53 + prob[,4] \* predict\_54 + (1 - prob[,1] - prob[,2] - prob[,3] - prob[,4]) \* predict\_55

prediction\_5 = max.col(predict\_5)

## The performance of the model without segments is evaluated by the proportion of correct predictions.

performance\_5 = sum(prediction\_5 == test\_choice)/length(test\_choice)

performance\_5

Result\_5

> performance\_5

[1] 0.6350365

> Result\_5

Estimate SE Tvalue minusll

[1,] 2.05069048 0.29776468 6.88695005 2694.005

[2,] 4.82674027 0.25841512 18.67824218 2694.005

[3,] 2.62984406 0.25064769 10.49219343 2694.005

[4,] 1.61428335 0.25974755 6.21481656 2694.005

[5,] 0.12193542 0.23616391 0.51631689 2694.005

[6,] 0.45570374 0.25416357 1.79295459 2694.005

[7,] 0.47205196 0.28297212 1.66819247 2694.005

[8,] -0.63007259 0.20898901 -3.01485998 2694.005

[9,] -0.17296000 0.24144444 -0.71635527 2694.005

[10,] -0.65425252 0.25195483 -2.59670560 2694.005

[11,] -0.18245490 0.26703237 -0.68326883 2694.005

[12,] 0.32935071 0.30346268 1.08530877 2694.005

[13,] 0.33908931 0.27115727 1.25052634 2694.005

[14,] 0.46378152 0.17154370 2.70357651 2694.005

[15,] 0.27004382 0.26669523 1.01255588 2694.005

[16,] 0.49599209 0.24489839 2.02529745 2694.005

[17,] 0.22176353 0.29438182 0.75331938 2694.005

[18,] 0.39685285 0.38370606 1.03426267 2694.005

[19,] -0.15769336 0.31986185 -0.49300459 2694.005

[20,] -1.18585880 0.30363573 -3.90553119 2694.005

[21,] -0.81790717 0.27486834 -2.97563252 2694.005

[22,] -0.34091343 0.30433329 -1.12019765 2694.005

[23,] -1.47025773 0.25879874 -5.68108543 2694.005

[24,] -0.88964599 0.26454640 -3.36291101 2694.005

[25,] -3.02264887 0.28174119 -10.72845915 2694.005

[26,] -1.60251709 0.26651359 -6.01289081 2694.005

[27,] 2.64147605 0.25382759 10.40657573 2694.005

[28,] -2.68305587 0.29811706 -9.00000769 2694.005

[29,] -1.38539326 0.22652000 -6.11598646 2694.005

[30,] -0.33486302 0.22189749 -1.50908879 2694.005

[31,] -3.87802283 0.20022836 -19.36799970 2694.005

[32,] 4.18940574 0.18833838 22.24403651 2694.005

[33,] 1.17328269 0.19947486 5.88185747 2694.005

[34,] -2.27635546 0.34487512 -6.60052107 2694.005

[35,] -2.89739503 0.58101620 -4.98677148 2694.005

[36,] 3.66654299 0.90545433 4.04939584 2694.005

[37,] 1.02375681 0.25597599 3.99942516 2694.005

[38,] 0.74167649 0.24755117 2.99605323 2694.005

[39,] 0.53212014 0.21133588 2.51788831 2694.005

[40,] 0.30810436 0.22701742 1.35718374 2694.005

[41,] 0.24803614 0.18757326 1.32234274 2694.005

[42,] 0.65056986 0.17823631 3.65004110 2694.005

[43,] 0.57976404 0.19088349 3.03726664 2694.005

[44,] 0.12956592 0.18822560 0.68835444 2694.005

[45,] 0.50285265 0.18147764 2.77087939 2694.005

[46,] 0.44098133 0.19836594 2.22306983 2694.005

[47,] 0.51079608 0.14902391 3.42761157 2694.005

[48,] 1.08826079 0.14559623 7.47451210 2694.005

[49,] 0.10035019 0.15026775 0.66780922 2694.005

[50,] 0.02308246 0.14987185 0.15401462 2694.005

[51,] -0.74765328 0.24402531 -3.06383504 2694.005

[52,] -1.60867564 0.22805644 -7.05384869 2694.005

[53,] -3.41498883 0.25038072 -13.63918472 2694.005

[54,] -5.31977159 0.26082634 -20.39583750 2694.005

[55,] -0.76666718 0.29980192 -2.55724574 2694.005

[56,] 0.19457073 0.32999814 0.58961159 2694.005

[57,] -0.41636147 0.27045525 -1.53948373 2694.005

[58,] -0.19333723 0.31196793 -0.61973431 2694.005

[59,] 0.39379506 0.24294958 1.62089208 2694.005

[60,] 0.93016743 0.24686165 3.76797051 2694.005

[61,] 0.70542705 0.30806417 2.28987051 2694.005

[62,] 0.09241609 0.24770396 0.37309087 2694.005

[63,] 0.75399973 0.25583097 2.94725745 2694.005

[64,] 0.98145850 0.30600796 3.20729725 2694.005

[65,] 0.28917304 0.16641194 1.73769409 2694.005

[66,] 0.68824692 0.22183218 3.10255672 2694.005

[67,] 0.27400129 0.18077530 1.51570095 2694.005

[68,] 0.03137626 0.20817804 0.15071838 2694.005

[69,] -0.18975070 0.24756631 -0.76646412 2694.005

[70,] -0.01410414 0.28272355 -0.04988667 2694.005

[71,] -0.04848347 0.25806885 -0.18787030 2694.005

[72,] -0.57003830 0.28244150 -2.01825262 2694.005

[73,] -0.36021882 0.04468928 -8.06051921 2694.005

[74,] -0.24038056 0.04127790 -5.82346947 2694.005

[75,] -0.26180527 0.04219556 -6.20456951 2694.005

[76,] 0.54130779 0.29776468 1.81790464 2694.005

[77,] -1.00979211 0.25841512 -3.90763548 2694.005

[78,] 0.05253509 0.25064769 0.20959735 2694.005

[79,] 0.23690336 0.25974755 0.91205233 2694.005

[80,] -0.21291041 0.23616391 -0.90153661 2694.005

[81,] 0.50689926 0.25416357 1.99438204 2694.005

[82,] 2.39339145 0.28297212 8.45804677 2694.005

[83,] 1.86218461 0.20898901 8.91044289 2694.005

[84,] 1.58501281 0.24144444 6.56471021 2694.005

[85,] 1.06522643 0.25195483 4.22784680 2694.005

[86,] -2.60941042 0.26703237 -9.77188789 2694.005

[87,] -1.67921773 0.30346268 -5.53352305 2694.005

[88,] 0.10867626 0.27115727 0.40078683 2694.005

[89,] 0.36669578 0.17154370 2.13762309 2694.005

[90,] 0.70079215 0.26669523 2.62768912 2694.005

[91,] 2.15309922 0.24489839 8.79180631 2694.005

[92,] -6.42299995 0.29438182 -21.81860298 2694.005

[93,] 3.54596404 0.38370606 9.24135528 2694.005

[94,] 0.46581800 0.31986185 1.45630996 2694.005

> performance\_5

[1] 0.5693431

> Result\_5

Estimate SE Tvalue minusll

[1,] -0.05655540 0.882652339 -0.06407438 2510.201

[2,] -2.74461846 NaN NaN 2510.201

[3,] -2.95890267 0.376374860 -7.86158424 2510.201

[4,] 4.30963382 0.327639630 13.15357921 2510.201

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Estimate SE Tvalue minusll

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> performance\_5

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> Result\_5

Estimate SE Tvalue minusll

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