



ISLET / R / islet.est.R

haoharryfeng 0.99.6

8b8e137 · 2 years ago ⌂ History

Code Blame 213 lines (170 loc) · 7.11 KB

Raw 📄 ⬇ ✎ ⌵ 🗨

```

1
2   ###function to implement EM algorithm by block of genes in ISLET algorithm
3   #function here for unix and windows, using lapply, no parallel computing
4   #Y is a GxN matrix for gene expression
5   islet.solve.block<-function(Y, datuse){
6       #exp_case = as.matrix(datuse@exp_case)
7       #exp_ctrl = as.matrix(datuse@exp_ctrl)
8       X <- datuse@X
9       A <- datuse@A
10      K <- datuse@K
11      NU <- datuse@NU
12      NS <- datuse@NS
13      # para<-datuse@para
14
15      #initialization of parameters parameter estimation storage
16      B_est<-NULL
17      Sig0_est <- NULL
18      SigU_est <- NULL
19      E_U_est <- NULL
20      llk <- NULL
21      ##

```

$$\Sigma_u = \begin{bmatrix} \sigma_1^2 & & \\ & \ddots & \\ & & \sigma_k^2 \end{bmatrix} \in \mathbb{R}^+$$

$$\dim = (NU \times K) \times (NU \times K)$$

$$\beta \quad 300 \times 300$$

$$\sigma_0$$

$$\Sigma_u$$

$$\dim(A) = NS \times (NU \times K)$$

$$\dim(u) = (NU \times K) \times 1$$

$$X = \begin{pmatrix} \theta_{111} & \theta_{112} & \dots & \theta_{11K} & z_1\theta_{111} & z_1\theta_{112} & \dots & z_1\theta_{11K} \\ \theta_{121} & \theta_{122} & \dots & \theta_{12K} & z_1\theta_{121} & z_1\theta_{122} & \dots & z_1\theta_{12K} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \theta_{1T_11} & \theta_{1T_12} & \dots & \theta_{1T_1K} & z_1\theta_{1T_11} & z_1\theta_{1T_12} & \dots & z_1\theta_{1T_1K} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \theta_{J11} & \theta_{J12} & \dots & \theta_{J1K} & z_J\theta_{J11} & z_J\theta_{J12} & \dots & z_J\theta_{J1K} \\ \theta_{J21} & \theta_{J22} & \dots & \theta_{J2K} & z_J\theta_{J21} & z_J\theta_{J22} & \dots & z_J\theta_{J2K} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ \theta_{JT_11} & \theta_{JT_12} & \dots & \theta_{JT_1K} & z_J\theta_{JT_11} & z_J\theta_{JT_12} & \dots & z_J\theta_{JT_1K} \end{pmatrix}_{N \times 2K}$$

mization (EM) algorithm, although other viable approaches exist. Here, to facilitate the setup of the EM algorithm, we first define the “observed” and the “missing” data: $\mathbf{w} = (\mathbf{y}, \mathbf{u}) := (\mathbf{w}_{obs}, \mathbf{w}_{mis})$, where $\mathbf{w}_{obs} := \mathbf{y}$ is the observed data of admixed gene expression, and $\mathbf{w}_{mis} := \mathbf{u}$ is the missing data of individual-level deviance from the group mean. Then, we have the conditional distribution $\mathbf{w}_{obs} | \mathbf{w}_{mis} = \mathbf{y} | \mathbf{u} \sim N(\mathbf{X}\boldsymbol{\beta} + \mathbf{A}\mathbf{u}, \sigma_0^2 \mathbf{I})$ and marginal distribution $\mathbf{w}_{mis} = \mathbf{u} \sim N(\mathbf{0}, \Sigma_u)$. Here, Σ_u is a block-diagonal matrix $\Sigma_u = \text{diag}(\sigma_1^2 \mathbf{I}_J, \sigma_2^2 \mathbf{I}_J, \dots, \sigma_K^2 \mathbf{I}_J)$. By calculating the variance-covariance matrix of \mathbf{w}_{mis} and \mathbf{w}_{obs} , we have the following multivariate normal distribution:

$$\begin{pmatrix} \mathbf{w}_{obs} \\ \mathbf{w}_{mis} \end{pmatrix} = N \left[\begin{pmatrix} \mathbf{X}\boldsymbol{\beta} \\ \mathbf{0} \end{pmatrix}, \begin{pmatrix} \mathbf{A}\Sigma_u\mathbf{A}' + \sigma_0^2 \mathbf{I} & \mathbf{A}\Sigma_u \\ \Sigma_u' \mathbf{A}' & \Sigma_u \end{pmatrix} \right] \quad (6)$$

The EM algorithm calculation will then follow naturally.

E-step:

$$E[\mathbf{u} | \mathbf{w}_{obs} = \mathbf{y}] = \Sigma_u \mathbf{A}' V^{-1} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) \quad \text{sig}$$

$$E[\mathbf{s}' \mathbf{s} | \mathbf{w}_{obs} = \mathbf{y}] = \text{tr}(\mathbf{A}\Sigma_p \mathbf{A}') + (\mathbf{A}\boldsymbol{\mu}_p + \mathbf{X}\boldsymbol{\beta} - \mathbf{y})' (\mathbf{A}\boldsymbol{\mu}_p + \mathbf{X}\boldsymbol{\beta} - \mathbf{y})$$

$$E[\mathbf{u}'_k \mathbf{u}_k | \mathbf{w}_{obs} = \mathbf{y}] = \text{tr}(\Sigma_{p_k}) + \boldsymbol{\mu}'_{p_k} \boldsymbol{\mu}_{p_k}$$

Here, $\mathbf{s} = \mathbf{A}\mathbf{u} + \mathbf{X}\boldsymbol{\beta} - \mathbf{y}$, $V := \mathbf{A}\Sigma_u \mathbf{A}' + \sigma_0^2 \mathbf{I}$, Σ_{p_k} is the k th diagonal block of matrix Σ_p , and $\boldsymbol{\mu}_{p_k}$ is the k th sub-vector in $\boldsymbol{\mu}_p$.

22 Y<-t(Y) after this step, $\dim(Y) = N \times G$

23 G<-ncol(Y)

24 # Y=log2(Y+1)

25 #####1. Initialization of parameters

26 #1.1 cell type profiles AND csDE B parameters

27 #B_0 = solve(X,Y)

28 B_0 <- Matrix::tcrossprod(Matrix::tcrossprod(solve(Matrix::crossprod(X)), X), t(Y))

29 #1.2 error terms

30 # sig <- mean((Y-X*%B_0)^2)

31 sig <- colMeans((Y-X*%B_0)^2)

32 #sig <- 20

33 NU: # of subject

34 #1.3 missing values

35 U_0 <- rep(0, NU*K)

50 x 6 = 300

36 B_t <- B_0

37 #sig_t = rep(sig, 7)

38 U_t <- U_0

39 #sig0_t <- rep(sig, G)

40 #sigK_t <- rep(sig, K)

41 sig0_t <- sig #rep(sig, G)

42 sigK_t <- matrix(rep(sig, each=K), nrow=K)

43 iem <- 1

44 diff1 <- 100

45 diff2 <- 100

46 pp <- 1

47

48 1个list. 有G个element.

49 #Sig_U = diag(rep(sigK_t, each = NU))

50 Sig_p<-lapply(seq_len(G), function(x, A, sig0_t, sigK_t, NU, Y, X, B_t){

51 invSig_U<-Matrix::bdiag(diag(rep(1/sigK_t[, x], each=NU)))

Σ_u

$$\Sigma_u = \text{diag}(\sigma_1^2 I_J, \sigma_2^2 I_J, \dots, \sigma_K^2 I_J).$$

$$Y = X\beta + Au + \epsilon$$

$N \times G$ $N \times 2K$ (4k for slope) $N \times Q$ ($Q=JK$)
 $2K \times G$ $Q \times G$
 gene1 ... gene G
 celltype1 for subject 1 ~ 50
 $U = \begin{bmatrix} u_{11} \\ u_{21} \\ \vdots \\ u_{J1} \\ u_{12} \\ \vdots \\ u_{JK} \end{bmatrix}$

• Sig_p	list [500]	List of length 500
• [[1]]	list [2]	List of length 2
• Sig	S4 [300 x 300] (Matrix::dsCM	S4 object of class dsCMMatrix
• U	S4 [300 x 1] (Matrix::dgeMatr	S4 object of class dgeMatrix

$$X \in [0,1)^{N \times 2K}$$

for each gene g of subject j:
 $u \in \mathbb{R}^{K \times 1}$

$$\text{crossprod}(x, y) = x^T y$$

$$\text{tcrossprod}(x, y) = x y^T$$

1-50: CT1 for subject 1-50

$$\Sigma = \left(\frac{A^T A}{\sigma_0^2} + \Sigma_u^{-1} \right)^{-1}$$

$$A^T A / \sigma_0^2 + \Sigma_u^{-1}$$

```
Sig<-solve( Matrix::crossprod(A)/sig0_t[x]+invSig_U)
```

```
U<- Matrix::tcrossprod( Matrix::tcrossprod(Sig, A),
```

```
BiocGenerics::t(Y[, x] - Matrix::tcrossprod(X,
```

```
BiocGenerics::t(B_t[, x])))
```

```
)/sig0_t[x]
```

```
return(list(Sig=Sig, U=U))
```

```
}, A, sig0_t, sigK_t, NU, Y, X, B_t)
```

```
E_Up<-do.call(cbind, lapply(Sig_p, function(x)x$U))
```

```
while(iem<15){
```

```
#   cat("iteration=", iem, "\n")
```

```
iem <- iem + 1
```

```
####2. E-step
```

```
#observed data COV(Y) = V
```

```
#V = A%*%Sig_U%*%t(A) + diag(rep(sig0_t, 5*600))
```

```
#2.1 E[U|Y]: missing data [U|Y] given observed data
```

```
#invV = solve(V)
```

```
# E_U = mu_p = t(Sig_U) %*% t(A) %*% invV %*% (Y - X %*% B_t)
```

```
# Sig_p = Sig_U - crossprod(Sig_U,t(A)) %*% invV %*% A %*% Sig_U
```

```
# Estimate from last iteration
```

```
E_U <- E_Up
```

```
mu_p <- E_Up
```

```
E_U_frame <- as.data.frame(as.matrix(E_U))
```

```
#2.2 E[t(S)S|Y]
```

```
E_StS <- lapply(seq_len(G), function(x, A, Sig_p, mu_p, X, B_t, Y){
```

```
  sum( Matrix::diag(Matrix::tcrossprod( Matrix::tcrossprod(A, Sig_p[[x]]$Sig), A))) +
```

```
  sum(( Matrix::tcrossprod(A, BiocGenerics::t(mu_p[, x])) +
```

```
    Matrix::tcrossprod(X, BiocGenerics::t(B_t[, x])) - Y[, x])^2)},
```

```
  A, Sig_p, mu_p, X, B_t, Y)
```

```
E_StS <-unlist(E_StS)
```

• E_Up

Dim

• Dimnames

x

factors

JK G

S4 [300 x 500] (Matrix::dgm)

integer [2]

list [2]

double [150000]

list [0]

S4 object of class dgeMatrix

300 500

List of length 2

-97.90 -303.88 -79.14 243.73 -2.02 -79.58 ...

List of length 0

E-step:

$$E[\mathbf{u}|\mathbf{w}_{obs} = \mathbf{y}] = \Sigma_u \mathbf{A}' \mathbf{V}^{-1} (\mathbf{y} - \mathbf{X} \boldsymbol{\beta})$$

$$E[\mathbf{s}'\mathbf{s}|\mathbf{w}_{obs} = \mathbf{y}] = \text{tr}(\mathbf{A} \Sigma_p \mathbf{A}') + (\mathbf{A} \boldsymbol{\mu}_p + \mathbf{X} \boldsymbol{\beta} - \mathbf{y})' (\mathbf{A} \boldsymbol{\mu}_p + \mathbf{X} \boldsymbol{\beta} - \mathbf{y})$$

$$E[\mathbf{u}'_k \mathbf{u}_k | \mathbf{w}_{obs} = \mathbf{y}] = \text{tr}(\Sigma_{p_k}) + \boldsymbol{\mu}'_{p_k} \boldsymbol{\mu}_{p_k}$$

Here, $\mathbf{s} = \mathbf{A} \mathbf{u} + \mathbf{X} \boldsymbol{\beta} - \mathbf{y}$, $\mathbf{V} := \mathbf{A} \Sigma_u \mathbf{A}' + \sigma_0^2 \mathbf{I}$, Σ_{p_k} is the k th diagonal block of matrix Σ_p , and $\boldsymbol{\mu}_{p_k}$ is the k th sub-vector in $\boldsymbol{\mu}_p$.

```

92
93 #2.3 E[U_k^T U_k|Y]
94 mutra_split <- lapply(Sig_p, function(x){
95   sig_p<-split(diag(x$Sig), ceiling(seq_len(NU*K)/NU))
96   tra<-unlist(lapply(sig_p, sum))
97   return(tra)
98 })
99 mu_split <- split(E_U_frame, ceiling(seq_along(E_U_frame[, 1])/NU))
100
101 E_UkTuk <- do.call('cbind', mutra_split) + do.call('rbind', lapply(mu_split, colss))
102
103 ####3. M-step
104 #3.1 B
105 B_tp <- Matrix::tcrossprod( Matrix::tcrossprod(solve( Matrix::crossprod(X), X),
106   BiocGenerics::t(Y- Matrix::tcrossprod(A, BiocGenerics::t(E_U))) )
107
108 #make correction in case B[1:K]<0 or B_tp[(K+1):2K]<0
109 #important to bound the estimation to positive values
110
111 # B_tp[1:K,]=ifelse(B_tp[1:K,]<0,0,B_tp[1:K,])
112 # B_tp[-(1:K),]=ifelse(B_tp[1:K,]+B_tp[-(1:K),]<0,-B_tp[1:K,],B_tp[-(1:K),])
113
114
115 #3.2 sigma_0^2
116 sig0_tp <- E_StS/(NS)
117
118 #3.3 sigma_k^2
119 sigK_tp <- E_UkTuk/(NU)
120
121 ####4. Stopping criteria
122 diff1 <- sum(abs(B_tp - B_t)) + abs(sig0_tp - sig0_t) + sum(abs(sigK_tp - sigK_t))
123
124 n1 <- sum(abs(B_tp - B_t))/length(B_tp)
125 n2 <- sum(abs(B_tp))/length(B_tp)
126 pp <- n1/n2

```

$$(X^T X)^{-1}$$

M-step:

For the $(t + 1)^{th}$ iteration given the t^{th} iteration:

$$\hat{\beta}^{(t+1)} = (X'X)^{-1}X'(y - AE_{\eta^{(t)}}(\mathbf{u}^{(t)}))$$

```

127 #       cat("B_sum_val=", n2, "\n")
128 #       cat("B_change_val=", n1, "\n")
129 #       cat("B_change_prop=", pp*100,"% \n")
130
131 #####5. Update params
132 B_t<-B_tp
133 sig0_t <- sig0_tp
134 sigK_t <- sigK_tp
135
136 Sig_p<-lapply(seq_len(G), function(x, A, sig0_t, sigK_t, NU, Y, X, B_t){
137   Sig_U<- Matrix::bdiag(diag(rep(sigK_t[, x], each=NU)))
138   invSig_U<-Matrix::bdiag(diag(rep(1/sigK_t[, x], each=NU)))
139   Sig<-solve( Matrix::crossprod(A)/sig0_t[x]+invSig_U)
140   U<- Matrix::tcrossprod(Matrix::tcrossprod(Sig, A),
141                           t(as.matrix(Y[, x] -
142                               Matrix::tcrossprod(X, BiocGenerics::t(B_t[, x]))))
143                           )/sig0_t[x]
144   return(list(Sig_U=Sig_U, Sig=Sig, U=U))
145 }, A, sig0_t, sigK_t, NU, Y, X, B_t)
146 Sig_p_all<-NULL
147 E_Up<-do.call(cbind, lapply(Sig_p, function(x)x$U))
148
149 diff2 <- sum(abs(E_Up - E_U))/(length(E_U)*mean(colMeans(Y))^2)
150 #       cat("Random effect diff2=", diff2, "\n")
151
152 }
153 # Estimate of fixed effect ★
154 B_est<-cbind(B_est, B_t)
155 # Estimate of random effect
156 E_U_est<-cbind(E_U_est, E_Up)
157 # Estimate of variance Sigma_U, Sigma_0
158 Sig0_est <- cbind(Sig0_est, sig0_t)
159 SigU_est <- cbind(SigU_est, sigK_t)
160
161 #calculate LLK (log-likelihood)

```

$$\hat{\sigma}_0^{2(t+1)} = \frac{E_{\eta^{(t)}}[\mathbf{s}'\mathbf{s}|\mathbf{w}_{obs} = \mathbf{y}]}{N}$$

$$\hat{\sigma}_k^{2(t+1)} = \frac{E_{\eta^{(t)}}[\mathbf{u}'_k\mathbf{u}_k|\mathbf{w}_{obs} = \mathbf{y}]}{J}$$

The E-step and M-step above are repeated until convergence. The details of modeling and algorithm is available in Additional file 5.

```

162 llk<-lapply(seq_len(G), function(x){
163   Sig<- Matrix::tcrossprod( Matrix::tcrossprod(A, Sig_p[[x]]$Sig_U), A)+
164   Matrix::bdiag(diag(sig0_t[x], nrow = nrow(A)))
165   l<- Matrix::determinant(Sig)$modulus+
166   Matrix::tcrossprod(Matrix::crossprod(Y[, x]-
167     Matrix::tcrossprod(X, BiocGenerics::t(B_t[, x])), solve(Sig)),
168     BiocGenerics::t(Y[, x]-
169       Matrix::tcrossprod(X, BiocGenerics::t(B_t[, x])))) )
170   return(-as.numeric(l))
171 })

```

```

172
173 llk<-unlist(llk)

```

```

174
175 #compile return list  $m_k + \alpha_k$   $\beta_k$ : fixed group effect

```

```

176 case.m <- B_est[seq_len(K), ]+B_est[K+seq_len(K), ]
177 ctrl.m <- B_est[seq_len(K), ]

```

```

178
179
180 #(2) the individual value for case and control, for all cell types. 2 matrices of NU by K.

```

```

181 rel <- split(as.data.frame(as.matrix(E_U_est)), ceiling(seq_along(E_U_est[, 1])/NU))

```

```

182
183
184 case.indv <- lapply(seq_len(K), function(k){rel[[k]][seq_len(datuse@case_num), ] +
185    $\beta$  matrix(rep(case.m[k, ], each=datuse@case_num, nrow=datuse@case_num)) case-num:
186   ctrl.indv <- lapply(seq_len(K), function(k){rel[[k]][-seq_len(datuse@case_num), ] + # of case subject
187     matrix(rep(ctrl.m[k, ], each=datuse@ctrl_num, nrow=datuse@ctrl_num))})

```

```

188 names(case.indv) <- names(rel)

```

```

189 names(ctrl.indv) <- names(rel)

```

```

190

```

```

191 #(3) Variance for K cell types. 1 vector of length K.

```

```

192 #'SigU_est' is already to be rendered.

```

```

193

```

```

194 #(4) Variance for grand residuals. 1 scalar.

```

```

195 #'Sig0_est' is already to be rendered.

```

```

196

```

```
197     #(5) the model likelihood. 1 scalar.
198     #'llk' is already to be rendered.
199
200     #compile return list
201     rval <- list(
202         case.m=case.m,
203         ctrl.m=ctrl.m,
204         case.indv=case.indv,
205         ctrl.indv=ctrl.indv,
206         var.k=SigU_est,
207         var.0=Sig0_est,
208         LLK=llk)
209     return(rval)
210
211     message("Complete: parameter estimation from ISLET is complete.")
212 }
```

ISLET / R / islet.solve.R


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[Code](#)
[Blame](#)
 70 lines (58 loc) · 2.38 KB

[Raw](#)






```

1
2   ###function to run ISLET, using parallel computing
3
4   isletSolve<-function(input, BPPARAM=bpparam() ){
5       # islet.solve only runs on the model without age effect.
6       if(input@type == 'slope'){
7           stop('Input should be prepared by dataPrep()')
8       }
9
10      #make Yall a list
11      G <- nrow(input@exp_case)
12      Yall<-as.matrix(cbind(input@exp_case, input@exp_ctrl))
13      aval.nworkers<-BPPARAM$workers
14      block.size<-max(ceiling(G/aval.nworkers), 5)
15      Yall.list <- split(as.data.frame(Yall), ceiling(seq_len(G)/block.size))
16
17
18      # if(.Platform$OS.type == "unix") {
19      ## do some parallel computation under Unix
20      #     multicoreParam <- MulticoreParam(workers = ncores)
21      res <- bplapply(X=Yall.list, islet.solve.block, datuse=input, BPPARAM=BPPARAM)

```

```

> BPPARAM=bpparam()
> BPPARAM
class: MulticoreParam
bpisup: FALSE; bpnworkers: 6; bptasks: 0; bpjobname: BPJOB
bplog: FALSE; bpthreshold: INFO; bpstopOnError: TRUE
bpRNGseed: ; bptimeout: NA; bpprogressbar: FALSE
bpexportglobals: TRUE; bpexportvariables: FALSE; bpforceGC: FALSE
bpfallback: TRUE
bplogdir: NA
bpresultdir: NA
cluster type: FORK

```

```


> aval.nworkers<-BPPARAM$workers
> block.size<-max(ceiling(G/aval.nworkers), 5)
> aval.nworkers
[1] 6
> block.size
[1] 834
> G
[1] 5000

```

Yall.list

- 1
- 2
- 3
- 4
- 5
- 6

List of length 6

list [6]  List of length 6

list [834 x 250] (S3: data.frame) A data.frame with 834 rows and 250 columns

list [834 x 250] (S3: data.frame) A data.frame with 834 rows and 250 columns

list [834 x 250] (S3: data.frame) A data.frame with 834 rows and 250 columns

list [834 x 250] (S3: data.frame) A data.frame with 834 rows and 250 columns

list [834 x 250] (S3: data.frame) A data.frame with 834 rows and 250 columns

list [830 x 250] (S3: data.frame) A data.frame with 830 rows and 250 columns

G x NS

 NS: # of sample
 NU: # of subject

基因组

1, 2, 3, 4, 5, 6 的列名均不同

见page 1-7


```

22 # }
23 # else {
24   ## This will be windows
25   ## Use serial param or do not use any parallel functions, just use 'lapply'
26   ## result should be of the same "type" from both the if and else statements.
27 #   nworkers<-length(Yall.list)
28 #   cl <- makeCluster(nworkers)
29
30   ## Remove clusterExport(), clusterEvalQ() if use devtools::install() to build package
31 #   clusterExport(cl,list('colss'))
32 #   clusterEvalQ(cl,{
33 #     library(Matrix)
34 #     library(BiocGenerics)}})
35
36 #   res <-parLapply(cl, X=Yall.list, islet.solve.block, datuse=input)
37 #   stopCluster(cl)
38 #
39 # }
40
41 # Organize estimated individual reference
42 K<-input@K      C(1,2,...,50)
43 SubjectID<-unique(input@SubjectID)
44 case_num<-input@case_num
45 case.indv.merge<-lapply(seq_len(K), function(k){
46   case.indv.all<-lapply(res, '[[', 3)  提取 res 的第3个元素, 相当于 [[3]]
47   case.indv.ctk<-t(do.call(cbind, lapply(case.indv.all, '[[', k)))
48   case.indv.ctk<-ifelse(as.matrix(case.indv.ctk)<0, 0, case.indv.ctk)
49   dimnames(case.indv.ctk)<-list(rownames(input@exp_case), SubjectID[seq_len(case_num)])
50   return(case.indv.ctk)  gene_names
51 })
52 ctrl.indv.merge<-lapply(seq_len(K), function(k){
53   ctrl.indv.all<-lapply(res, '[[', 4)
54   ctrl.indv.ctk<-t(do.call(cbind, lapply(ctrl.indv.all, '[[', k)))
55   ctrl.indv.ctk<-ifelse(as.matrix(ctrl.indv.ctk)<0, 0, ctrl.indv.ctk)
56   dimnames(ctrl.indv.ctk)<-list(rownames(input@exp_ctrl), SubjectID[-seq_len(case_num)])

```

```

#compile return list
rval <- list(
  case.m=case.m,
  ctrl.m=ctrl.m,
  case.indv=case.indv,
  ctrl.indv=ctrl.indv,
  var.k=SigU_est,
  var.0=Sig0_est,
  LLK=llk)
return(rval)

```

```
57     return(ctrl.indv.ctk)
58   })
59
60   names(case.indv.merge)<-input@CT
61   names(ctrl.indv.merge)<-input@CT
62   llk<-unlist(lapply(res, '[', 7))
63
64   rval<-outputSol(case.ind.ref=case.indv.merge,
65                   ctrl.ind.ref=ctrl.indv.merge,
66                   mLLK=llk)
67
68   return(rval)
69 }
```

```
caseEst<-function(res.sol){
  est <- res.sol@case.ind.ref
  return(est)
}

ctrlEst<-function(res.sol){
  est <- res.sol@ctrl.ind.ref
  return(est)
}
```

```
N25_age.ref <- readRDS("N25_ref_0_0.rds")
caseVal <- caseEst(N25_age.ref)
ctrlVal <- ctrlEst(N25_age.ref)
```

N25_age.ref	S4 (ISLET::outputSol)	S4 object of class outputSol
case.ind.ref	list [6]	List of length 6
B-cells	double [5000 x 25]	1968 0 566 3473 6020 0 2035 0 547 3406 5788 0 1612 0 585 3411 ...
CD4	double [5000 x 25]	0.0 0.0 5242.0 4223.7 0.0 0.0 0.0 0.0 5125.7 4053.3 0.0 ...
CD8	double [5000 x 25]	5071 0 1535 2855 4692 522 4788 0 1264 2724 4171 534 4297 0 1299 27...
NK	double [5000 x 25]	9488.65 0.00 1376.65 0.00 1590.27 76.19 9418.68 0.00 1017.64 0.00 ...
Neutrophils	double [5000 x 25]	10538 254 0 0 3234 256 10612 256 0 0 2459 279 10897 ...
Monocytes	double [5000 x 25]	3648.872 282.819 324.877 0.000 432.233 235.798 4116.368 300.163 50....
ctrl.ind.ref	list [6]	List of length 6
B-cells	double [5000 x 25]	8611.35 0.00 0.00 950.40 1633.46 136.96 8275.63 0.00 0.00 ...
CD4	double [5000 x 25]	13037 180 0 776 0 0 13201 218 0 742 0 0 12907 ...
CD8	double [5000 x 25]	12630 0 1057 0 3289 0 11783 0 1161 0 2578 0 11525 ...
NK	double [5000 x 25]	0.00 22.66 2097.96 0.00 2401.11 1136.82 0.00 8.09 2160.48 0.00 ...
Neutrophils	double [5000 x 25]	0 892 590 1607 1167 204 0 883 669 1553 923 220 0 876 633 1601 ...
Monocytes	double [5000 x 25]	2510 0 3814 816 9475 377 2473 0 3850 781 9207 383 2378 0 3855 810 ...
mLLK	double [5000]	-4368 -3070 -3680 -3682 -4044 -3212 ...

caseVal	list [6]	List of length 6
B-cells	double [5000 x 25]	2920 0 5053 7317 10854 0 3024 0 5033 7161 10605 0 2554 ...
CD4	double [5000 x 25]	7040.09 0.00 8077.24 9397.88 280.51 0.00 7038.60 0.00 7879.73 8997.4...
CD8	double [5000 x 25]	11345 0 3885 8104 9141 2365 11024 0 3407 7821 8488 2423 10471 ...
NK	double [5000 x 25]	7972.8 0.0 1139.8 262.1 2998.0 674.7 8079.7 0.0 677.1 0.0 2514.4 77 ...
Neutrophils	double [5000 x 25]	13584 1177 1780 786 3981 702 14249 1170 1279 170 3164 797 14306 1 ..
Monocytes	double [5000 x 25]	10521.9 1303.8 276.1 0.0 2517.8 891.9 10954.2 1459.2 53.2 0.0 ...