ICeDT: Immune Cell Deconvolution in Tumor tissues

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Introduction

This workfolow demonstrate the usage of ICeDT and also evaluate its performance using a simulated dataset. library(ICeDT)

```
## Loading required package: alabama
## Loading required package: numDeriv
## Loading required package: gtools
dimX <- function(v){ if(is.null(dim(v))){r=length(v)} else{r=dim(v)}; r }</pre>
```

Simulate gene expressoin data

We simulate the expression of 250 genes from 135 bulk tumor samples as well as purified samples for 5 cell types, with 5 replicates per cell type.

```
set.seed(666)
data(mean_var_relation)
simData = simFunc(nS=135, nG=250, nrep=5, nCT=5, pctAb=20,
                  meanVar_Rel=mean_var_relation)
names(simData)
## [1] "MGene_Exp"
                       "PGene_Exp"
                                      "cellType"
                                                      "aberrant"
## [5] "rho"
                       "tumor_purity"
lapply(simData, dimX)
## $MGene_Exp
## [1] 250 135
## $PGene_Exp
## [1] 250 25
##
## $cellType
## [1] 25
##
## $aberrant
## [1] 250
## $rho
## [1]
         5 135
##
## $tumor_purity
## [1] 135
simData$tumor_purity[1:5]
```

```
## [1] 0.8513188 0.6029154 0.6582970 0.6808798 0.7493846
simData$PGene_Exp[1:2,1:7]
##
               tumor
                            tumor
                                          tumor
                                                       tumor
                                                                     tumor
## [1,] 7.931848e-05 2.859189e-04 3.817089e-05 1.096758e-04 1.080461e-04
## [2,] 2.574509e-05 7.253033e-05 3.896733e-05 2.049412e-05 8.703739e-05
##
               CT2
                          CT2
## [1,] 3034.01723 3893.93296
## [2,]
          61.96612
                     33.01001
```

Estimate signature matrix

A sigmature matrix refers to a matrix of expected cell type specific expression for a set of genes across several cell types. These genes are usually selected due to their cell type-specific expression pattern.

We have simulated gene expression of tumor as well as four other cell types. However, in practice, we do not know the expression from tumor samples. Thus we only use the expression of non-tumor cell types when estimating signature matirx.

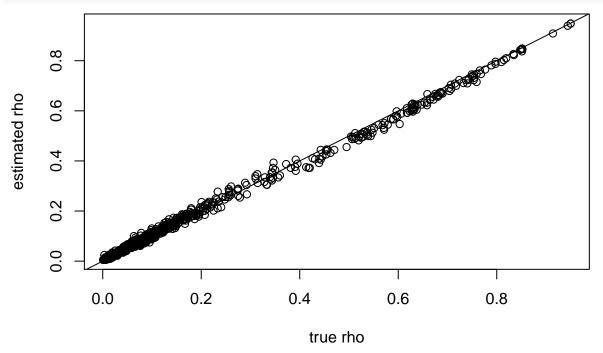
```
X = simData$PGene_Exp
dim(X)
## [1] 250
            25
X[1:2,1:7]
               tumor
                             tumor
                                          tumor
                                                        tumor
## [1,] 7.931848e-05 2.859189e-04 3.817089e-05 1.096758e-04 1.080461e-04
## [2,] 2.574509e-05 7.253033e-05 3.896733e-05 2.049412e-05 8.703739e-05
##
               CT2
                           CT2
## [1,] 3034.01723 3893.93296
## [2,]
          61.96612
                     33.01001
X = X[,which(colnames(X) != "tumor")]
refE = refEstimate(X)
lapply(refE, dimX)
## $refMat
## [1] 250
             4
##
## $refVar
## [1] 250
##
## $ctMu
## [1] 250
##
## $ctVar
## [1] 250
refE$refMat[1:2,]
               CT2
                           CT3
                                       CT4
                                                  CT5
##
## [1,] 3869.36411 992.272995 3102.820206 849.60168
## [2,]
          78.45819
```

7.470082 59.98775

7.947046

```
refE$refVar[1:2,]
## [1,] 0.09148839 0.1196739 0.2716482 0.1365715
## [2,] 0.22901550 0.1410654 0.3117909 0.4490935
refE$ctMu[1:2,]
             CT2
                      CT3
                               CT4
## [1,] 8.200511 6.83614 7.957212 6.678798
## [2,] 4.244652 1.96588 1.882645 3.948717
refE$ctVar[1:2,]
##
                         CT3
                                   CT4
## [1,] 0.1206693 0.1277156 0.1657092 0.1319400
## [2,] 0.2358273 0.2138398 0.2565212 0.2908468
refVar is cell type-specific variance estiamte without borrowing information across cell types, while ctVar is
the estimates after borrowing information across cell types. They have strong correlation.
cor(c(refE$refVar), c(refE$ctVar))
## [1] 0.8844
cell type composition estimation
Y = simData$MGene_Exp
Z = refE$refMat
ice1 = ICeDT(Y = Y, Z = Z, tumorPurity = NULL, refVar = NULL)
## Iter 1: max diff of rho: 0.526962138400084
## Iter 11: max diff of rho: 0.00552148595219343
## Iter 21: max diff of rho: 0.00228034794013091
## ....
lapply(ice1, dimX)
## $rho
## [1]
         5 135
##
## $sigma2C
## [1] 135
##
## $sigma2A
## [1] 135
##
## $cProp
## [1] 135
##
## $cProb
## [1] 250 135
```

```
plot(simData$rho, ice1$rho, xlab="true rho", ylab="estimated rho")
abline(0,1)
```



Session information

```
sessionInfo()
```

```
## R version 3.5.0 (2018-04-23)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS 10.14.3
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRlapack.dylib
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
## attached base packages:
## [1] stats
                graphics grDevices utils
                                               datasets methods
                                                                   base
##
## other attached packages:
## [1] ICeDT_0.99.1
                         gtools_3.8.1
                                           alabama_2015.3-1 numDeriv_2016.8-1
##
## loaded via a namespace (and not attached):
  [1] Rcpp_0.12.18
                        digest_0.6.15
                                        rprojroot_1.3-2 backports_1.1.2
  [5] magrittr_1.5
                        evaluate 0.11
                                        stringi 1.2.4
                                                        rmarkdown 1.10
                                        yam1_2.2.0
## [9] tools_3.5.0
                        stringr_1.3.1
                                                        compiler_3.5.0
## [13] htmltools_0.3.6 knitr_1.20
```