

R-MarkDown-document: TNBC_TIL_analysis

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SECTION-1 Selection of a gene expression based TNBC cohort from TCGA

We use the `cgdsr` package to access data from the cBIO Portal.

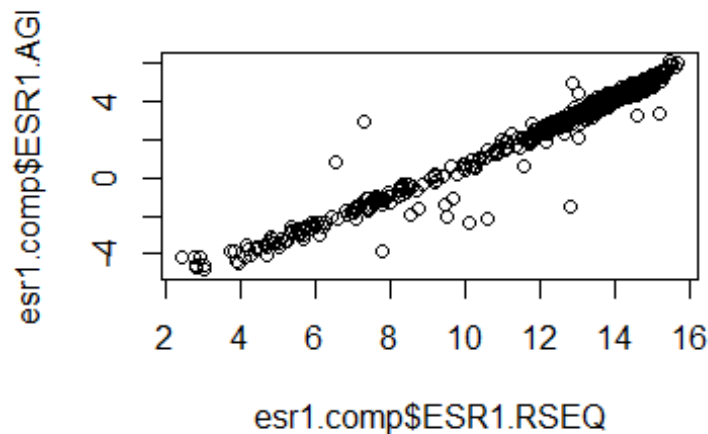
```
library("cgdsr")
cbiop <- CGDS("http://www.cbioportal.org/public-portal/")
# getCancerStudies(cbiop)$cancer_study_id
clidat = getClinicalData(cbiop, "brca_tcga_all")
```

1.1 Analysis of correlation of ESR1 gene expression from RNA-Seq and Agilent microarray platform

```
esr1.rseq = getProfileData(cbiop, "ESR1", "brca_tcga_rna_seq_v2_mrna",
"brca_tcga_all")
esr1.agi = getProfileData(cbiop, "ESR1", "brca_tcga_mrna", "brca_tcga_all")
```

```
# generate matrix of cases with both data for Agilent and RNA-Seq:
esr1.comp=as.data.frame(cbind(esr1.agi$ESR1, log2(esr1.rseq$ESR1+1))
                        [(!is.nan(esr1.agi$ESR1)) & (!is.nan(esr1.rseq$ESR1)), ])
colnames(esr1.comp)=c("ESR1.AGI", "ESR1.RSEQ")

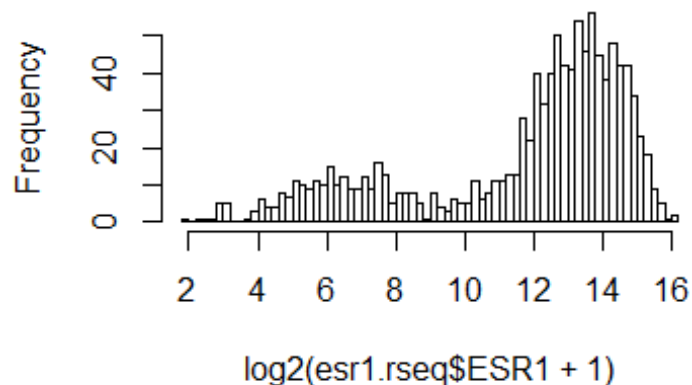
# correlation between Agilent and RNA-Seq:
plot(esr1.comp$ESR1.RSEQ, esr1.comp$ESR1.AGI)
```



```
cor(esr1.comp$ESR1.RSEQ, esr1.comp$ESR1.AGI)
## [1] 0.9821414

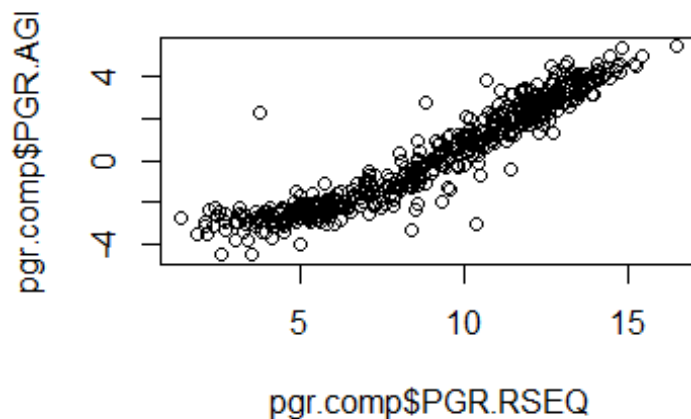
# bimodal distribution of RNA-Seq data
hist(log2(esr1.rseq$ESR1+1), breaks=80)
```

Histogram of $\log_2(\text{esr1.rseq\$ESR1} + 1)$



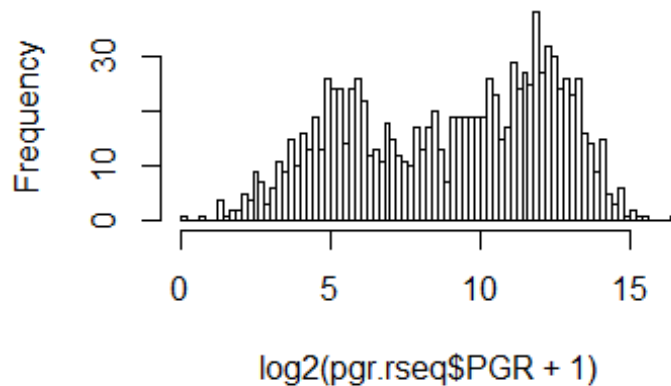
1.2 Analysis of correlation of PGR gene expression from RNA-Seq and Agilent microarray platform

```
pgr.rseq = getProfileData(cbiop, "PGR", "brca_tcga_rna_seq_v2_mrna",  
"brca_tcga_all")  
pgr.agi = getProfileData(cbiop, "PGR", "brca_tcga_mrna", "brca_tcga_all")  
  
# generate matrix of cases with both data for Agilent and RNA-Seq:  
pgr.comp=as.data.frame(cbind(pgr.agi$PGR, log2(pgr.rseq$PGR+1))  
[(!is.nan(pgr.agi$PGR)) & (!is.nan(pgr.rseq$PGR)), ])  
colnames(pgr.comp)=c("PGR.AGI", "PGR.RSEQ")  
# correlation between Agilent and RNA-Seq:  
plot(pgr.comp$PGR.RSEQ, pgr.comp$PGR.AGI)
```



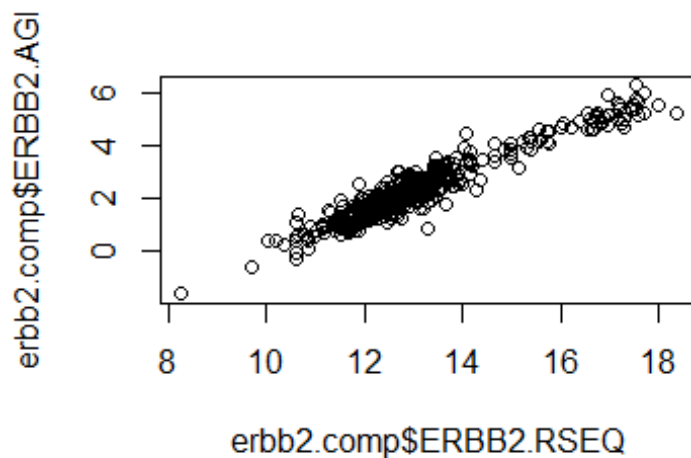
```
cor(pgr.comp$PGR.RSEQ, pgr.comp$PGR.AGI)  
## [1] 0.9499931  
  
# bimodal distribution of RNA-Seq data  
hist(log2(pgr.rseq$PGR+1), breaks=80)
```

Histogram of $\log_2(\text{pgr.rseq}\$PGR + 1)$



1.3 Analysis of correlation of HER2 gene expression from RNA-Seq and Agilent microarray platform

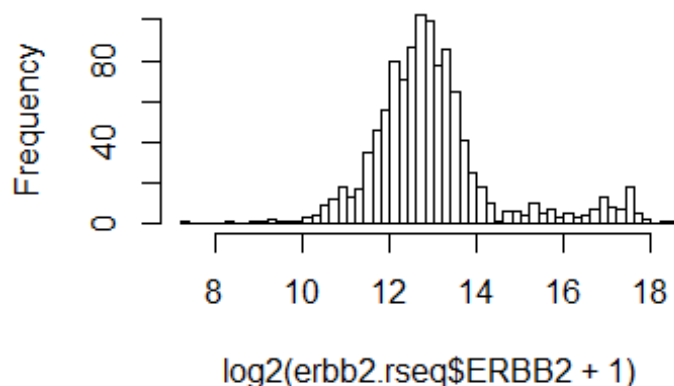
```
erbb2.rseq = getProfileData(cbiop, "ERBB2", "brca_tcga_rna_seq_v2_mrna",  
"brca_tcga_all")  
erbb2.agi = getProfileData(cbiop, "ERBB2", "brca_tcga_mrna", "brca_tcga_all")  
  
# generate matrix of cases with both data for Agilent and RNA-Seq:  
erbb2.comp = as.data.frame(cbind(erbb2.agi$ERBB2, log2(erbb2.rseq$ERBB2+1))  
[(!is.nan(erbb2.agi$ERBB2)) & (!is.nan(erbb2.rseq$ERBB2)), ])  
colnames(erbb2.comp) = c("ERBB2.AGI", "ERBB2.RSEQ")  
# correlation between Agilent and RNA-Seq:  
plot(erbb2.comp$ERBB2.RSEQ, erbb2.comp$ERBB2.AGI)
```



```
cor(erbb2.comp$ERBB2.RSEQ, erbb2.comp$ERBB2.AGI)
```

```
## [1] 0.9547622
# bimodal distribution of RNA-Seq data
hist(log2(erbb2.rseq$ERBB2+1), breaks=80)
```

Histogram of log2(erbb2.rseq\$ERBB2 +



1.4 Generate TNBC dataset

```
# Select tnbc/dnbc based on cutoffs from distribution of RNA-Seq
# define a logical selection vector
tnbc.group= !is.na(esr1.rseq) & !is.na(erbb2.rseq) &
  (log2(esr1.rseq$ESR1+1)<10) & (log2(erbb2.rseq$ERBB2+1)<14)
colnames(tnbc.group)="tnbc"
sum(na.omit(tnbc.group))

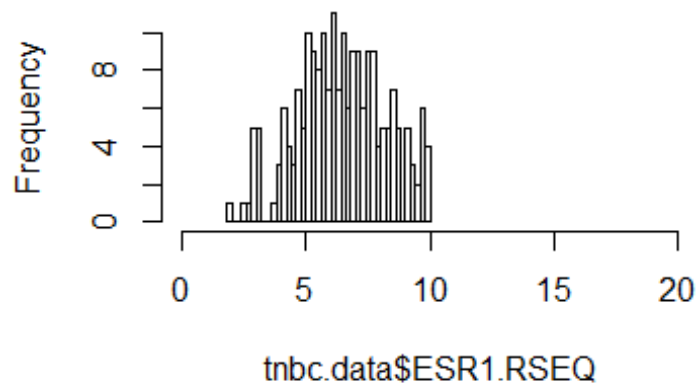
## [1] 208

# Generate tnbc dataset
tnbc.data= cbind(log2(esr1.rseq$ESR1+1)[tnbc.group],
  log2(pgr.rseq$PGR+1)[tnbc.group],
  log2(erbb2.rseq$ERBB2+1)[tnbc.group])
row.names(tnbc.data)= row.names(tnbc.group)[tnbc.group]
colnames(tnbc.data)=c("ESR1.RSEQ", "PGR.RSEQ", "ERBB2.RSEQ")

# Merge of Clinical data and tnbc dataset
# find subset in clidat corresponding to tnbc
clidat.sel=clidat[row.names(clidat)%in% row.names(tnbc.data),]
# merge tnbc.data and clinical data, left outer join:
tnbc.data= merge(tnbc.data, clidat.sel, by="row.names", all.x =TRUE)
# "merge" creates resorted dataframe with the row.names
# as a new first column "Row.names"
# rebuild structure (row.names):
row.names(tnbc.data)=tnbc.data$Row.names
tnbc.data=tnbc.data[,colnames(tnbc.data)!= "Row.names"]
```

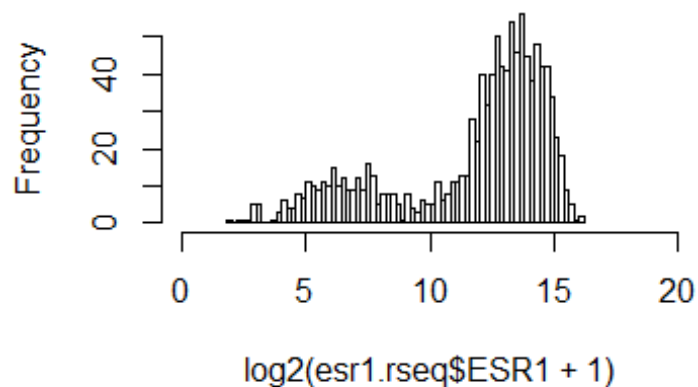
```
# check residual receptor expression in tnbc dataset:  
hist(tnbc.data$ESR1.RSEQ, xlim=c(0,20), breaks=40) # tnbc group
```

Histogram of tnbc.data\$ESR1.RSEQ



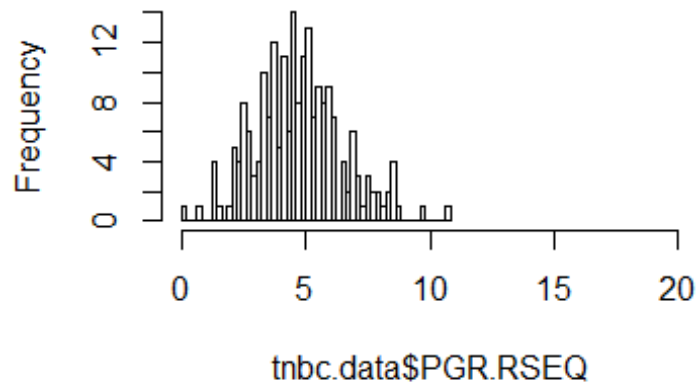
```
hist(log2(esr1.rseq$ESR1+1),xlim=c(0,20), breaks=80) # all samples
```

Histogram of $\log_2(\text{esr1.rseq\$ESR1} + 1)$



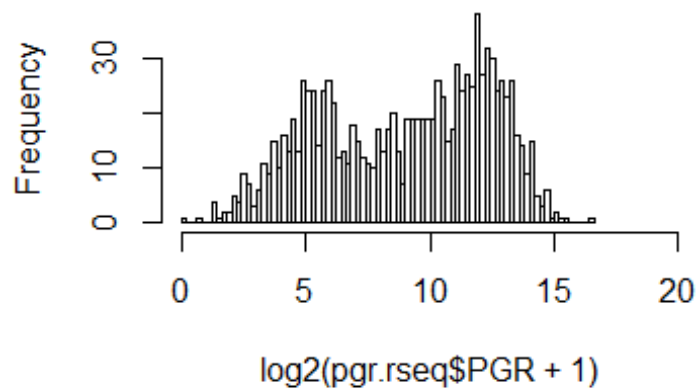
```
hist(tnbc.data$PGR.RSEQ, xlim=c(0,20), breaks=40) # tnbc group
```

Histogram of tnbc.data\$PGR.RSEQ



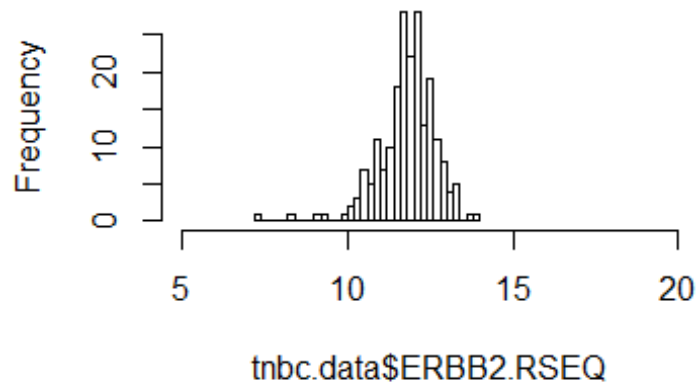
```
hist(log2(pgr.rseq$PGR+1),xlim=c(0,20), breaks=80) # all samples
```

Histogram of $\log_2(\text{pgr.rseq\$PGR} + 1)$



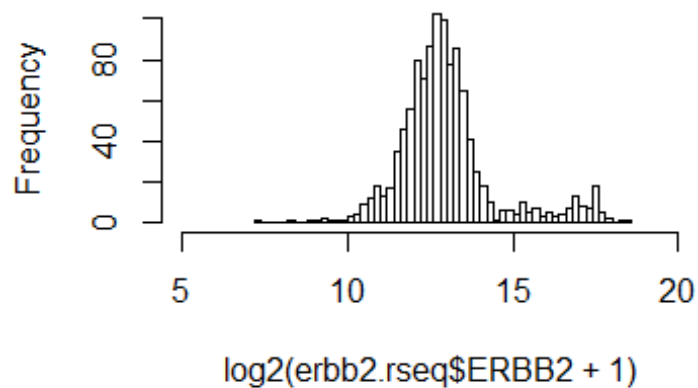
```
hist(tnbc.data$ERBB2.RSEQ, xlim=c(5,20), breaks=40) # tnbc group
```

Histogram of tnbc.data\$ERBB2.RSEQ



```
hist(log2(erbb2.rseq$ERBB2+1),xlim=c(5,20), breaks=80) # all samples
```

Histogram of log2(erbb2.rseq\$ERBB2 +

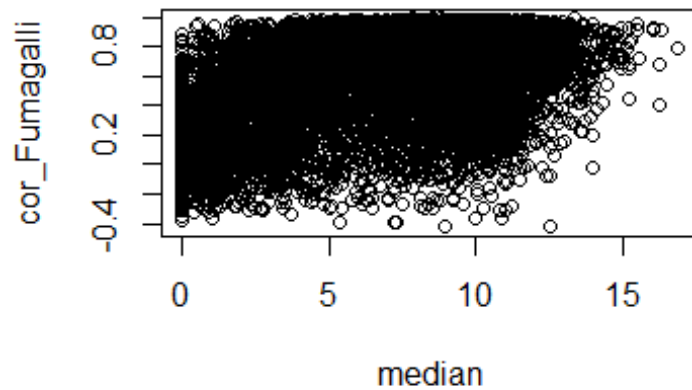


SECTION-2 Gene filtering in RNA-Seq data

```
# Spearman correlation values between RNA-Seq and Affymetrix microarray  
# for 16,097 Jetset probes for 57 paired frozen breast cancer samples  
# can be obtained from:  
# Suppl.Tab.S2 of Fumagalli et al. 2014, PubmedID 25412710
```

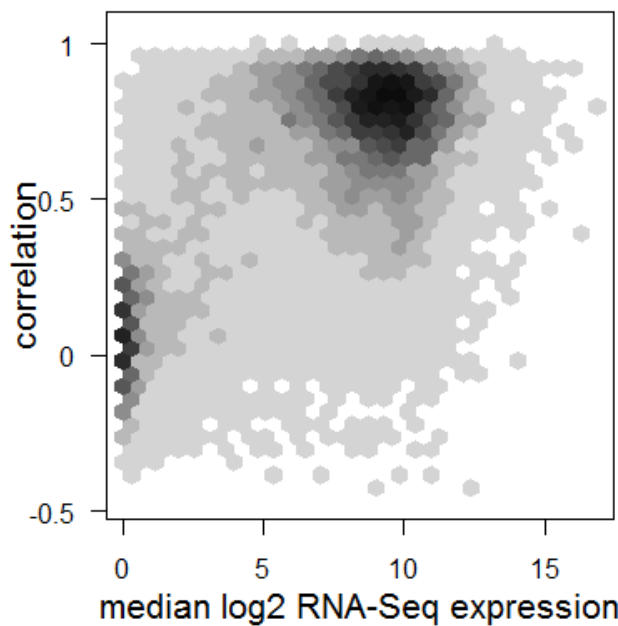
```
n208.FumagCorrel <-  
read.delim("2016_05_31_median_mean_n208RNASeq_vs_FumagalliCorrel.txt")
```

```
# Plot median expression vs Spearman correlation coefficient  
x=n208.FumagCorrel[,c(1,3)]  
plot(x)
```

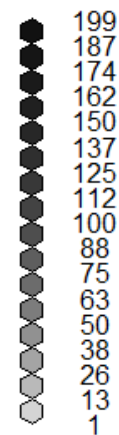



```
# Use hexbin plot to display the density of the scatter
library(hexbin)
plot(hexbin(x$median, x$cor_Fumagalli, xbins=30),
     xlab="median log2 RNA-Seq expression", ylab="correlation",
     main="Correlation (RNA-Seq vs. Affy) vs. \n median RNA-Seq expression")
```

Correlation (RNA-Seq vs. Affy) vs.
median RNA-Seq expression

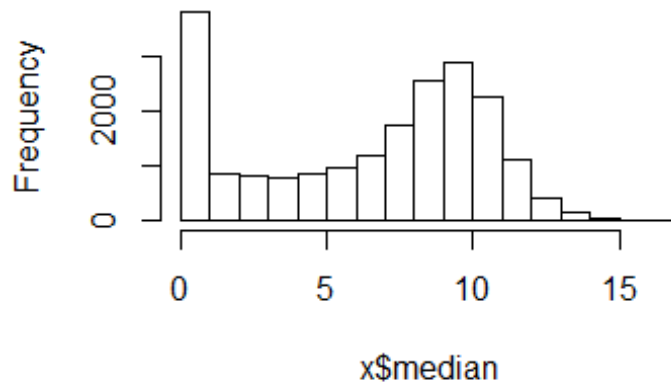


Counts



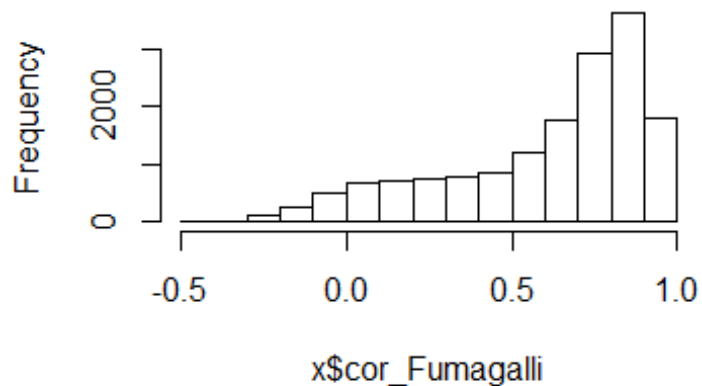
```
# Distribution of median expression values
hist(x$median)
```

Histogram of x\$median



```
# Distribution of Spearman correlation coefficients  
hist(x$cor_Fumagalli)
```

Histogram of x\$cor_Fumagalli



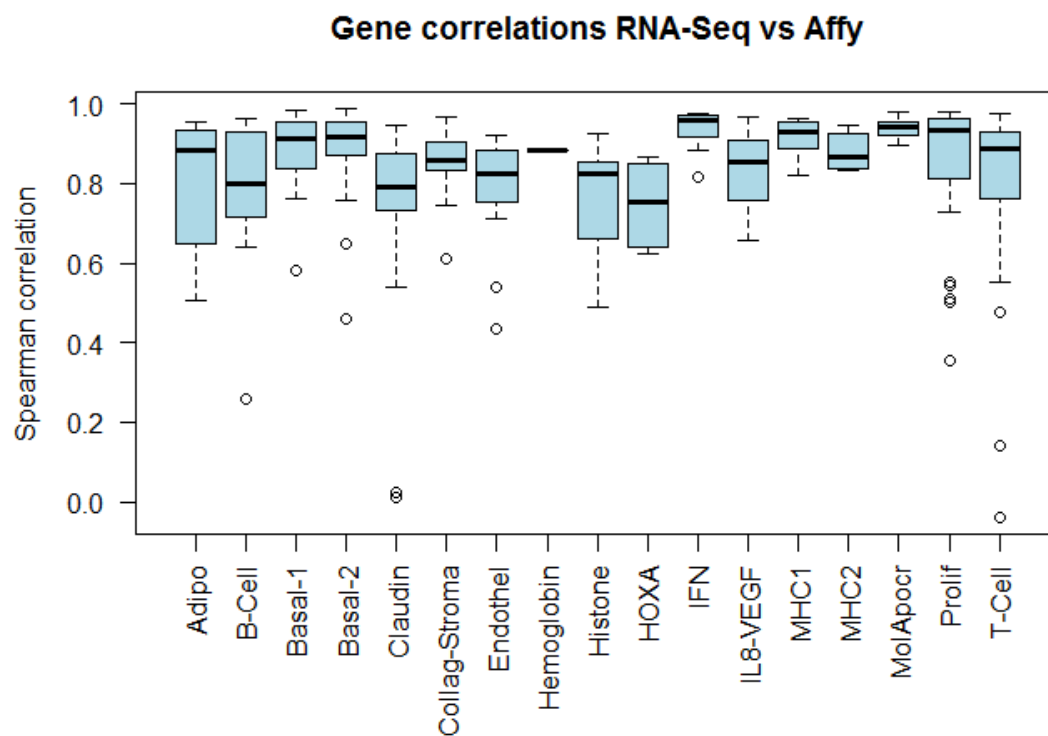
```
rm(x)
```

SECTION-3 Metagene construction

3.1 Metagene genes: RNA-Seq vs. Affy correlation

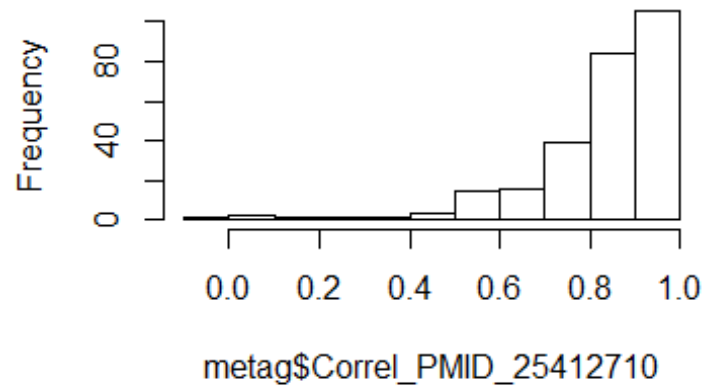
```
metag <- read.delim("2016_06_01_TNBC-metagenes_gene_list.txt")
```

```
par(las = 2) # labels always perpendicular to the axis  
par(mar=c(7,4,4,2)+0.1) # increase bottom margin  
boxplot(Correl_PMid_25412710~TNBCmetagene_RNA.Seq,  
        data=metag, notch=F, col="lightblue",  
        ylab="Spearman correlation",  
        main="Gene correlations RNA-Seq vs Affy" )
```

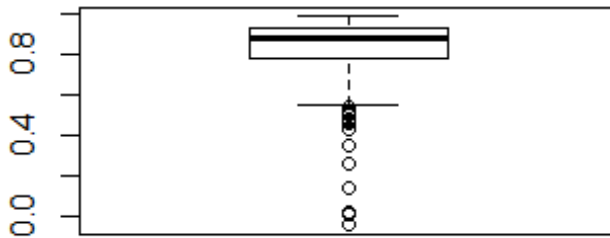


```
par(mar=c(5.1, 4.1, 4.1, 2.1))
hist(metag$Correl_PMD_25412710)
```

Histogram of metag\$Correl_PMD_25412710



```
boxplot(metag$Correl_PMD_25412710)
```



```
median(metag$Correl_PMID_25412710, na.rm=T)
```

```
## [1] 0.8831346
```

```
summary(metag$Correl_PMID_25412710, na.rm=T)
```

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.     Max.      NA's
## -0.04109  0.77800  0.88310  0.82610  0.93210  0.98810      35
```

3.2 Metagene calculation from RNA-Seq expression

```
# Load RNAseq data of 304 genes for 208 tnbc samples
```

```
# RNAseq data of 1218 TCGA BRCA can be downloaded from UCSC Xena browser  
(https://tcga.xenahubs.net/download/TCGA.BRCA.sampleMap/HiSeqV2)
```

```
n304genes <- read.table("n208tnbc_n304genes_RNAseq.csv", header=TRUE,  
sep=";")
```

```
# scale transposed expression data and re-transpose
```

```
n304.expr.sca= t(scale(t(n304genes[,5:212])))
```

```
colnames(n304.expr.sca)=colnames(n304genes[,5:212])
```

```
# calculate mean expression of each metag-cluster from scaled expression for  
17 metagenes
```

```
metag17=array(NA,dim=c(0,17))
```

```
for (i in 1:ncol(n304.expr.sca)) {
```

```
  mdf= as.data.frame(as.list(by(n304.expr.sca[,i],  
                                n304genes$MetagCluster17, mean)))
```

```
  rownames(mdf)=colnames(n304.expr.sca)[i]
```

```
  metag17=rbind(metag17, mdf)
```

```
}
```

```
rm(mdf)
```

```
# merge 17 metagene expression data with tnbc.data dataframe, left outer  
join:
```

```
tnbc.data.meta17= merge(tnbc.data, metag17, by="row.names", all.x =TRUE)
# "merge" command results in resorting of dataframe and loss of row.names
# but an additional new first column "Row.names"
# Assign new row.names from this additional column and then delete it
row.names(tnbc.data.meta17)=tnbc.data.meta17$Row.names
tnbc.data.meta17=tnbc.data.meta17[,colnames(tnbc.data.meta17)!= "Row.names"]
```

SECTION-4 MATH analysis of dispersion in mutant allele frequencies

*# Copy of maf file from TCGA
genome.wustl.edu_BRCA.IlluminaGA_DNASeq.Level_2.1.1.0.curated.somatic.maf.txt
(52MB) is available at <https://portal.gdc.cancer.gov/legacy-archive/files/50d6fb1d-5bb1-4a30-9e91-6d45bd9b1c3f>*

*# The required variant allele frequencies have been extracted in the smaller
file used here: "VAF-
table_genome.wustl.edu_BRCA.IlluminaGA_DNASeq.Level_2.1.1.0.curated.somatic.maf.txt"*

```
maf.download <- read.delim(
  "VAF-
table_genome.wustl.edu_BRCA.IlluminaGA_DNASeq.Level_2.1.1.0.curated.somatic.maf.txt")
```

```
all.maf = maf.download[,c("Hugo_Symbol", "Tumor_Sample_Barcode",
"tumor_vaf")]
```

```
TCGA_Sample=substr(all.maf$Tumor_Sample_Barcode, 1, 15)
```

```
all.maf = cbind(TCGA_Sample, all.maf)
```

calculate for each sample the median of tumor_vaf values
med=by(all.maf\$tumor_vaf, all.maf\$TCGA_Sample, median)

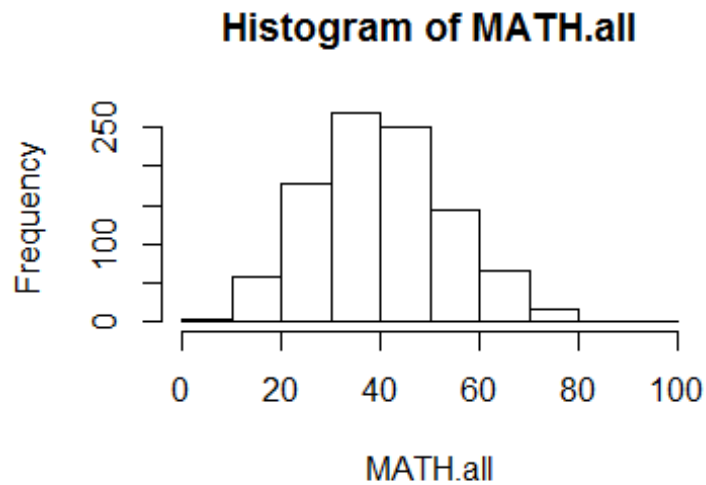
convert list to dataframe and transpose
med.df = t(as.data.frame(as.list(med)))
colnames(med.df)= "med.mut.AF"

calculate MAD (Median Absolute Deviation) for each sample
MAD=by(all.maf\$tumor_vaf, all.maf\$TCGA_Sample, mad)

convert list to dataframe and transpose
MAD.df= t(as.data.frame(as.list(MAD)))
colnames(MAD.df)= "MAD.mut.AF"

*# calculate MATH (Mutant Allele Tumor Heterogeneity) as $MATH=100*MAD/median$*
MATH.all =100 * MAD.df / med.df
colnames(MATH.all)= "MATH"

```
hist(MATH.all)
```



```
# Export MATH values:
```

```
# write.table(MATH.all, file="n982TCGA_MATH.txt",
#             row.names=TRUE, col.names = NA, quote=FALSE, sep="\t")
```

SECTION-5 Survival analysis

```
library("survival")
```

```
# Censor DFS at 120 months
```

```
dfs.120=tnbc.data.meta17$DFS_MONTHS
```

```
ev.120=tnbc.data.meta17$DFS_STATUS
```

```
for (i in 1:nrow(tnbc.data.meta17)) {
  if (is.na(tnbc.data.meta17$DFS_MONTHS[i]))
    {dfs.120[i]=NA ; ev.120[i]=NA}
  else
    { if (tnbc.data.meta17$DFS_MONTHS[i] > 120)
      {dfs.120[i]=120 ; ev.120[i]="DiseaseFree"}
      else {dfs.120[i]=tnbc.data.meta17$DFS_MONTHS[i] ;
ev.120=tnbc.data.meta17$DFS_STATUS}
    }
}
```

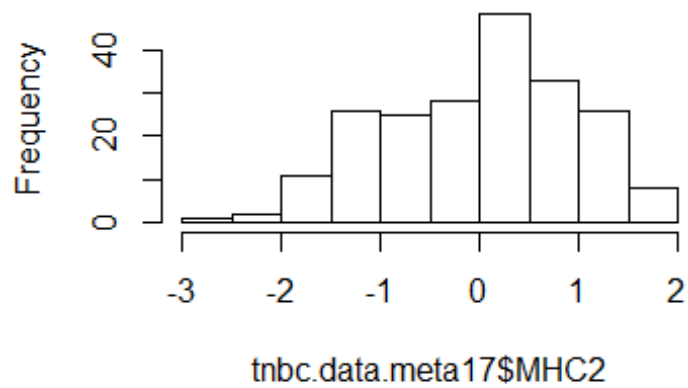
```
# Add censored DFS to dataframe
```

```
tnbc.data.meta17=cbind(tnbc.data.meta17, dfs.120, ev.120)
```

```
# Distributions of MHC2 metagene, B-Cell metagen, and IL8VEGF metagene
```

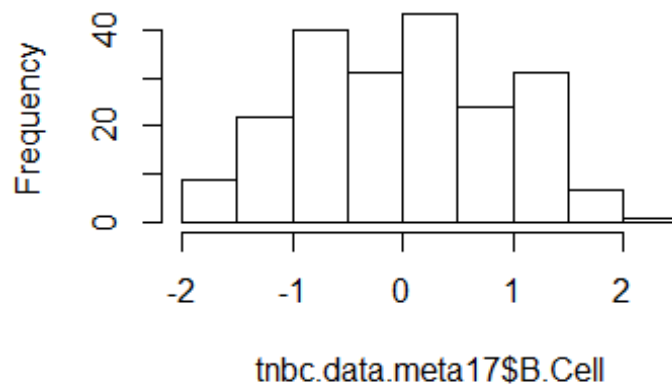
```
hist(tnbc.data.meta17$MHC2)
```

Histogram of tnbc.data.meta17\$MHC2



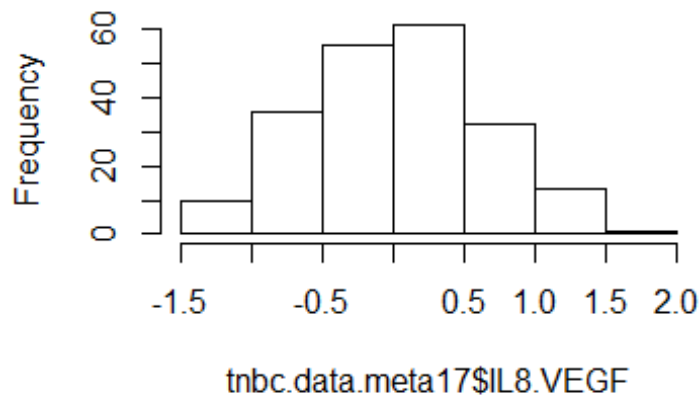
```
hist(tnbc.data.meta17$B.Cell)
```

Histogram of tnbc.data.meta17\$B.Cell



```
hist(tnbc.data.meta17$IL8.VEGF)
```

Histogram of tnbc.data.meta17\$IL8.VEGF



```
# Since no clear bimodality observed in distributions,
# we stay with previously established cutoffs for metagenes/signatures:
# MHC2 metagene: Upper quartile (Rody 2009, PMID 19272155)
# B-Cell metagene: Lower quartile (Rody 2011, PMID 21978456)
# IL8.VEGF metagene: Median split (Rody 2011, PMID 21978456)
```

5.1 MHC2/IL8VEGF signature

```
# Define upper quartile MHC2 metagene (based on Rody 2009, PMID 19272155)
MHC2.q4=tnbc.data.meta17$MHC2 > quantile(tnbc.data.meta17$MHC2, probs=0.75)
# Define below median IL8.VEGF metagene (cutoff from Rody 2011, PMID
21978456)
IL8.VEGF.q12=tnbc.data.meta17$IL8.VEGF < quantile(tnbc.data.meta17$IL8.VEGF,
probs=0.5)
# Define prognostic signature
MHC2.IL8.VEGF.sig = MHC2.q4 & IL8.VEGF.q12
```

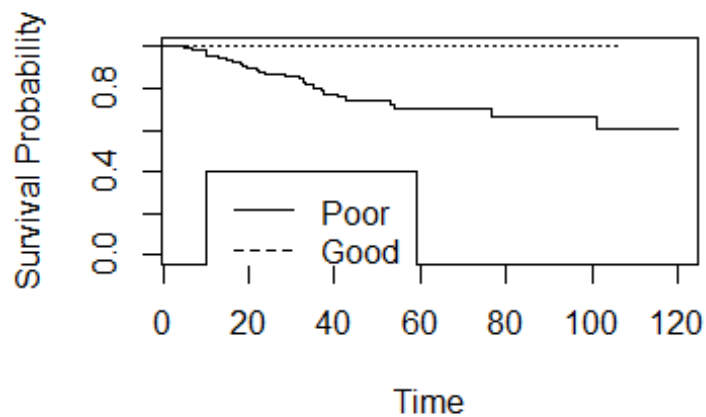
```
## Check MHC2.IL8.VEGF.sig in Survival analysis
time=tnbc.data.meta17$dfs.120
censor= (tnbc.data.meta17$ev.120 == "Recurred/Progressed")
strata= MHC2.IL8.VEGF.sig
test=survfit(Surv(time, censor)~strata,conf.type="none")
summary(test)

## Call: survfit(formula = Surv(time, censor) ~ strata, conf.type = "none")
##
## 14 observations deleted due to missingness
##           strata=FALSE
##    time n.risk n.event survival std.err
##    5.09   151      1    0.993 0.00660
##    6.80   149      1    0.987 0.00933
##    7.79   145      1    0.980 0.01149
##    9.89   138      1    0.973 0.01342
```



```
##      10.02      135      1      0.966 0.01513
##      10.28      134      1      0.958 0.01665
##      12.55      128      1      0.951 0.01812
##      12.71      126      1      0.943 0.01949
##      14.98      113      1      0.935 0.02103
##      16.10      109      1      0.926 0.02252
##      18.27      103      1      0.917 0.02403
##      18.50      102      1      0.908 0.02542
##      19.32       99      1      0.899 0.02677
##      21.91       89      1      0.889 0.02831
##      22.40       88      1      0.879 0.02974
##      23.95       82      1      0.868 0.03125
##      28.22       74      1      0.857 0.03295
##      31.90       69      1      0.844 0.03474
##      32.65       67      1      0.832 0.03643
##      33.31       63      1      0.818 0.03817
##      35.22       57      1      0.804 0.04011
##      36.79       53      1      0.789 0.04212
##      37.32       52      1      0.774 0.04396
##      40.70       47      1      0.757 0.04600
##      42.81       44      1      0.740 0.04807
##      53.02       37      1      0.720 0.05076
##      53.88       36      1      0.700 0.05315
##      76.54       21      1      0.667 0.06017
##     101.05       11      1      0.606 0.07957
##
##                                strata=TRUE
##      time n.risk n.event survival std.err
```

```
plot(test, lty=c(1,3), xlab="Time", ylab="Survival Probability")
legend(10, 0.4, c("Poor", "Good"), lty=c(1,2))
```



5.2 B-Cell/IL8VEGF signature

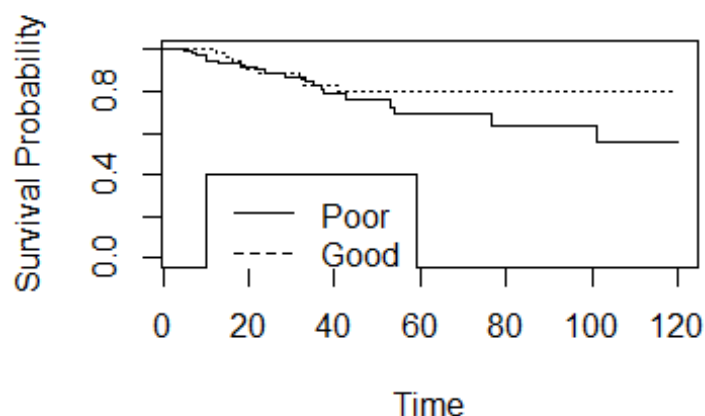
```
# Define B-Cell metagene above lowest quartile (cutoff from Rody 2011, PMID
21978456)
B.Cell.q234=tnbc.data.meta17$B.Cell > quantile(tnbc.data.meta17$B.Cell,
probs=0.25)
# Define below median IL8.VEGF metagene (cutoff from Rody 2011, PMID
21978456)
IL8.VEGF.q12=tnbc.data.meta17$IL8.VEGF < quantile(tnbc.data.meta17$IL8.VEGF,
probs=0.5)
# Define prognostic signature
B.Cell.IL8.VEGF.sig = B.Cell.q234 & IL8.VEGF.q12

## Check B.Cell.IL8.VEGF.sig in Survival analysis
time=tnbc.data.meta17$dfs.120
censor= (tnbc.data.meta17$ev.120 == "Recurred/Progressed")
strata= B.Cell.IL8.VEGF.sig
test=survfit(Surv(time, censor)~strata,conf.type="none")
summary(test)

## Call: survfit(formula = Surv(time, censor) ~ strata, conf.type = "none")
##
## 14 observations deleted due to missingness
##               strata=FALSE
##    time n.risk n.event survival std.err
##    5.09   108      1    0.991 0.00922
##    6.80   106      1    0.981 0.01303
##    7.79   102      1    0.972 0.01607
##    9.89    97      1    0.962 0.01877
##   10.02    95      1    0.952 0.02113
##   10.28    94      1    0.942 0.02320
##   12.71    89      1    0.931 0.02524
##   18.27    71      1    0.918 0.02808
##   21.91    62      1    0.903 0.03129
##   23.95    58      1    0.887 0.03440
##   28.22    52      1    0.870 0.03774
##   33.31    45      1    0.851 0.04156
##   35.22    41      1    0.830 0.04544
##   36.79    37      1    0.808 0.04944
##   37.32    36      1    0.785 0.05292
##   42.81    29      1    0.758 0.05761
##   53.02    22      1    0.724 0.06448
##   53.88    21      1    0.689 0.07002
##   76.54    13      1    0.636 0.08230
##  101.05     8      1    0.557 0.10355
##
##               strata=TRUE
##    time n.risk n.event survival std.err
##   12.6    61      1    0.984 0.0163
##   15.0    54      1    0.965 0.0241
##   16.1    52      1    0.947 0.0299
```

```
## 18.5      49      1      0.928 0.0350
## 19.3      45      1      0.907 0.0398
## 22.4      43      1      0.886 0.0441
## 31.9      34      1      0.860 0.0499
## 32.6      32      1      0.833 0.0551
## 40.7      27      1      0.802 0.0611
```

```
plot(test, lty=c(1,3), xlab="Time", ylab="Survival Probability")
legend(10, 0.4, c("Poor", "Good"), lty=c(1,2))
```



```
dir()
```

```
## [1] "2016_05_31_median_mean_n208RNASeq_vs_FumagalliCorrel.txt"
## [2] "2016_06_01_TNBC-metagenes_gene_list.txt"
## [3] "n208tnbc_n304genes_RNAseq.csv"
## [4] "TNBC_TIL_analysis_2017_05_18.Rmd"
## [5] "TNBC_TIL_analysis_2017_05_18_files"
## [6] "VAF-
table_genome.wustl.edu_BRCA.IlluminaGA_DNASeq.Level_2.1.1.0.curated.somatic.m
af.txt"
```

```
sessionInfo()
```

```
## R version 3.3.2 (2016-10-31)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 14393)
##
## locale:
## [1] LC_COLLATE=German_Germany.1252 LC_CTYPE=German_Germany.1252
## [3] LC_MONETARY=German_Germany.1252 LC_NUMERIC=C
## [5] LC_TIME=German_Germany.1252
##
## attached base packages:
## [1] stats      graphics  grDevices  utils      datasets  methods   base
##
```

```
## other attached packages:
## [1] survival_2.40-1 hexbin_1.27.1   cgdsr_1.2.5
##
## loaded via a namespace (and not attached):
## [1] Rcpp_0.12.9      lattice_0.20-34  digest_0.6.12
## [4] rprojroot_1.2    R.methodsS3_1.7.1 grid_3.3.2
## [7] backports_1.0.5  magrittr_1.5     evaluate_0.10
## [10] stringi_1.1.2    R.oo_1.21.0      Matrix_1.2-8
## [13] rmarkdown_1.3    splines_3.3.2    tools_3.3.2
## [16] stringr_1.2.0    yaml_2.1.14      htmltools_0.3.5
## [19] knitr_1.15.1
```