

Messina E3: Messina vs ? on APGI

March 22, 2015

1 Preparation

```
library(plyr)
library(ggplot2)

## Loading required package:  methods

library(messina)

## Loading required package:  survival
## Loading required package:  splines

library(maxstat)
library(doMC)

## Loading required package:  foreach
## Loading required package:  iterators
## Loading required package:  parallel

paropts = list(.options.multicore = list(preschedule = FALSE))
```

2 Data preparation

```
load("../biosurv/data/07_data_for_SIS.rda")
APGI.x = x.diag_dsd
APGI.y = y.diag_dsd
APGI.samps = samps.diag_dsd
APGI.feats = data.frame(symbol = rownames(APGI.x))

temp = NA
temp = ls()
rm(list = temp[!(temp %in% c("APGI.x", "APGI.y", "APGI.samps", "APGI.feats"))])

load("../biosurv/data/15_validation.rda")
rm(GSE28735.lingex, GSE21501.lingex)
GSE28735.x = GSE28735.gex
GSE21501.x = GSE21501.gex
GSE28735.feats = GSE28735.feats
GSE21501.feats = GSE21501.feats
rm(GSE28735.gex, GSE21501.gex, GSE28735.feats, GSE21501.feats)
```

```

load("../biosurv/data/validation/tcga-clin-gex.20141118.rda")
TCGA.x = data.merged$paad$gex$Illuminahiseq_rnaseqv2
rownames(TCGA.x) = gsub("\\|.*", "", rownames(TCGA.x))
TCGA.x = TCGA.x[rownames(TCGA.x) != "?",]
TCGA.x = log2(TCGA.x + 1)
temp.time = as.numeric(as.character(data.merged$paad$clin$days_to_death))
temp.time[is.na(temp.time)] = as.numeric(as.character(data.merged$paad$clin$days_to_last_followup[is.na(
TCGA.y = Surv(temp.time, data.merged$paad$clin$vital_status == "Dead")
TCGA.feats = data.frame(symbol = rownames(TCGA.x))
rm(data.merged)

keepMostVariableGeneMeasurement = function(gex, feats, ids)
{
  sds = apply(gex, 1, sd, na.rm = TRUE)
  perm = order(-sds)
  gex = gex[perm,,drop = FALSE]
  feats = feats[perm,,drop = FALSE]
  ids = ids[perm]
  drop = duplicated(ids) | is.null(ids)
  gex = gex[!drop,,drop = FALSE]
  feats = feats[!drop,,drop = FALSE]
  ids = ids[!drop]
  list(gex = gex, feats = feats, ids = ids)
}

# Now moved to the validation function
# regularizeX = function(x)
# {
#   require(robustbase)
#   location = apply(x, 1, median, na.rm = TRUE)
#   scale = apply(x, 1, scaleTau2, na.rm = TRUE)
#   (x - location) / scale
# }

temp = keepMostVariableGeneMeasurement(APGI.x, APGI.feats, APGI.feats$symbol)
APGI.x = temp$gex
APGI.feats = temp$feats
temp = keepMostVariableGeneMeasurement(GSE28735.x, GSE28735.feats, GSE28735.feats$Gene.symbol)
GSE28735.x = temp$gex
GSE28735.feats = temp$feats
temp = keepMostVariableGeneMeasurement(GSE21501.x, GSE21501.feats, GSE21501.feats$Gene.symbol)
GSE21501.x = temp$gex
GSE21501.feats = temp$feats

GSE28735.y = Surv(GSE28735.samp$time, GSE28735.samp$event)
GSE21501.y = Surv(GSE21501.samp$time, GSE21501.samp$event)

# APGI.xreg = regularizeX(APGI.x)
# GSE28735.xreg = regularizeX(GSE28735.x) # This one validated for survsigs
# GSE21501.xreg = regularizeX(GSE21501.x)

```

```

# Temporary testing measure. Probably will be used in real application, but somewhat defeats
# the whole purpose of Messina for testing, so should be removed when comparing vs other methods.
# temp.sel = apply(APGI.x, 1, sd) >= 1 & grepl("^D", rownames(APGI.x))
# APCI.x = APCI.x[temp.sel,,drop = FALSE]
# APCI.feats = APCI.feats[temp.sel,,drop = FALSE]

# messinaSurv(APGI.x, APCI.y, messinaSurvObj.CoxCoef(round(log(2), 3)), parallel = TRUE, silent = FALSE)
# messinaSurv(APGI.x, APCI.y, messinaSurvObj.Tau(0.6), parallel = TRUE, silent = FALSE, seed = 20150321)
# messinaSurv(APGI.x, APCI.y, messinaSurvObj.RelTau(0.7), parallel = TRUE, silent = FALSE, seed = 20150321)

registerDoMC(32)

library(plyr)
APGI.messina.cc2 = messinaSurv(APGI.x, APCI.y, messinaSurvObj.CoxCoef(round(log(2), 3)), parallel = TRUE)

## Performance bootstrapping...
## Final training...

APGI.messina.cc3 = messinaSurv(APGI.x, APCI.y, messinaSurvObj.CoxCoef(round(log(3), 3)), parallel = TRUE)

## Performance bootstrapping...
## Final training...

APGI.messina.tau6 = messinaSurv(APGI.x, APCI.y, messinaSurvObj.Tau(0.6), parallel = TRUE, silent = FALSE)

## Performance bootstrapping...
## Final training...

APGI.messina.tau7 = messinaSurv(APGI.x, APCI.y, messinaSurvObj.Tau(0.7), parallel = TRUE, silent = FALSE)

## Performance bootstrapping...
## Final training...

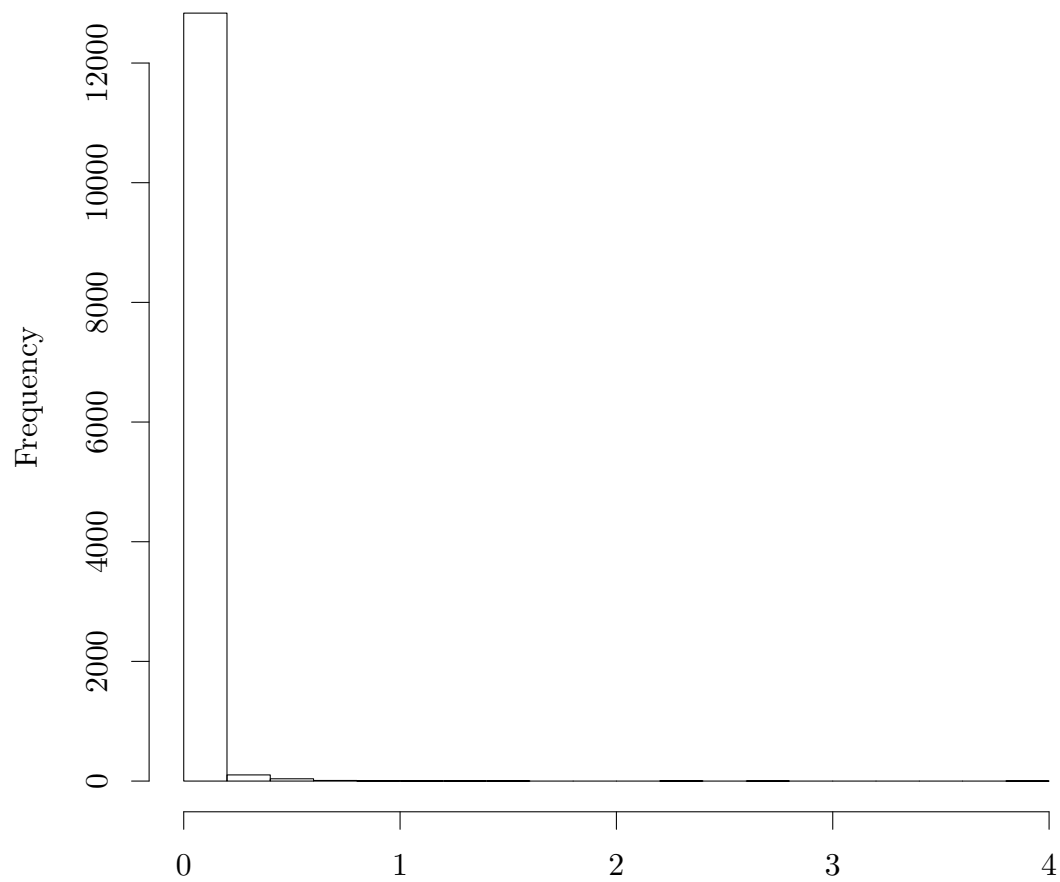
APGI.messina = APCI.messina.cc2
APGI.maxstat = alply(APGI.x, 1, function(x1) {
  data = data.frame(time = APCI.y[,1], event = APCI.y[,2], x = x1)
  test = try(maxstat.test(Surv(time, event) ~ x, data = data, smethod = "LogRank", pmethod = "HL"))
  result = list(p.value = NA, threshold = NA)
  if (class(test) != "try-error")
  {
    result$p.value = test$p.value
    result$threshold = test$estimate
  }
  result
}, .parallel = TRUE)

print(dim(APGI.x))

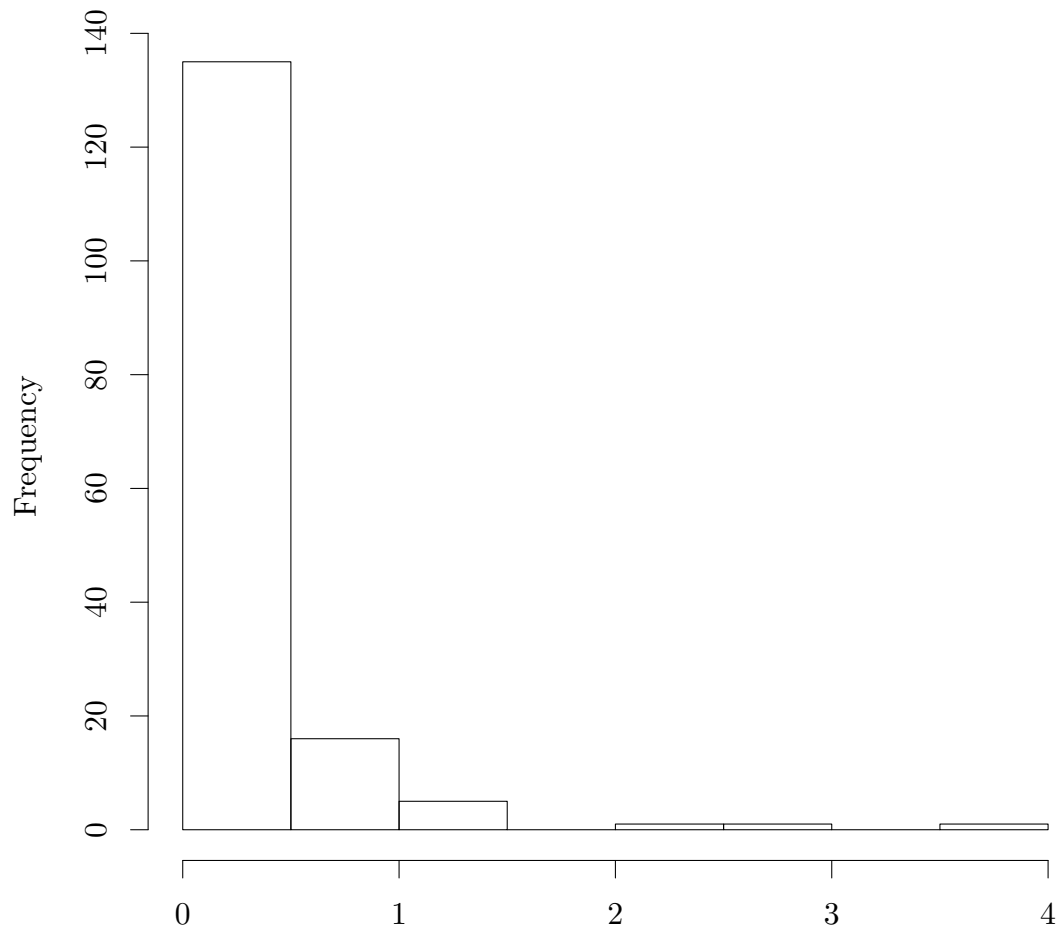
## [1] 13000 110

hist(APGI.messina@fits@summary$margin, main = "", xlab = "")

```



```
hist(APGI.messina@fits@summary$margin[APGI.messina@fits@summary$passed == TRUE], main = "", xlab = "")
```



```
sum(APGI.messina@fits@summary$passed == TRUE)
## [1] 159

mean(APGI.messina@fits@summary$passed == TRUE)
## [1] 0.01223

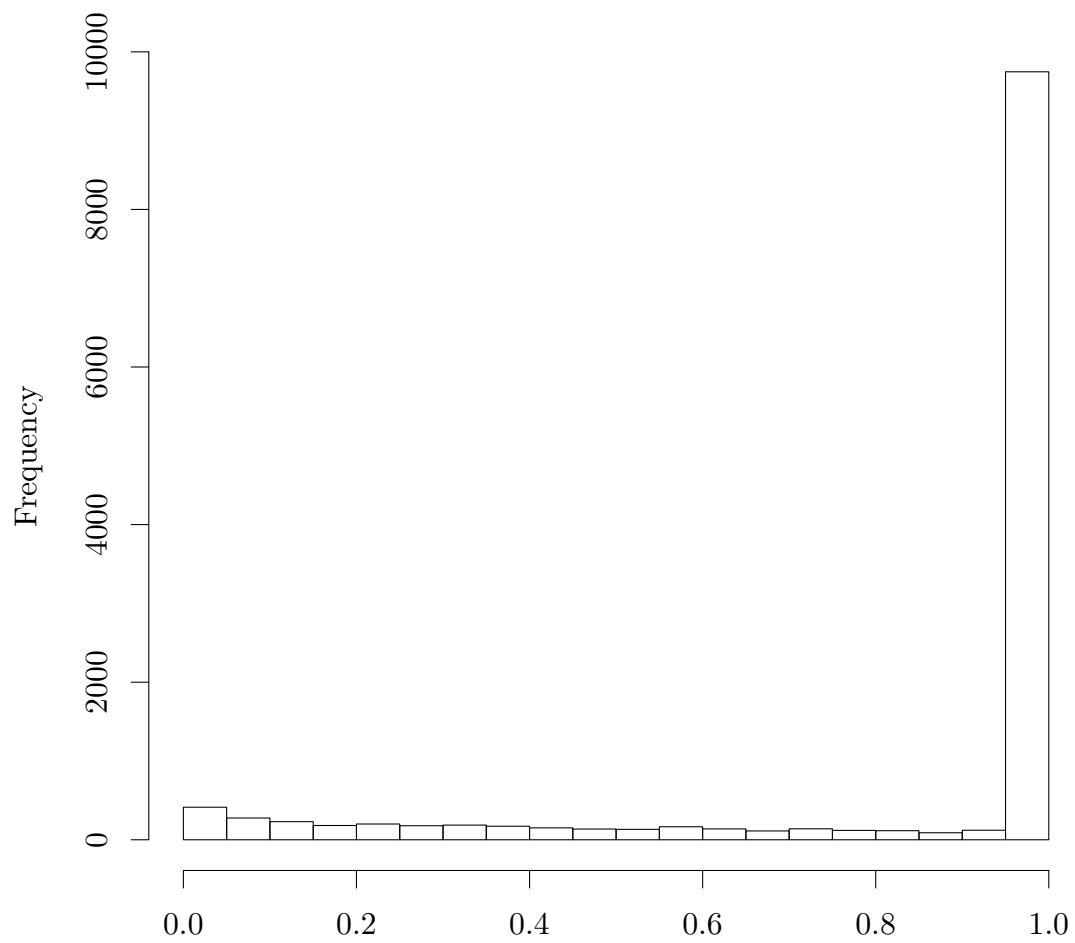
sum(APGI.messina@fits@summary$margin >= 1)
## [1] 11

mean(APGI.messina@fits@summary$margin >= 1)
## [1] 0.0008462

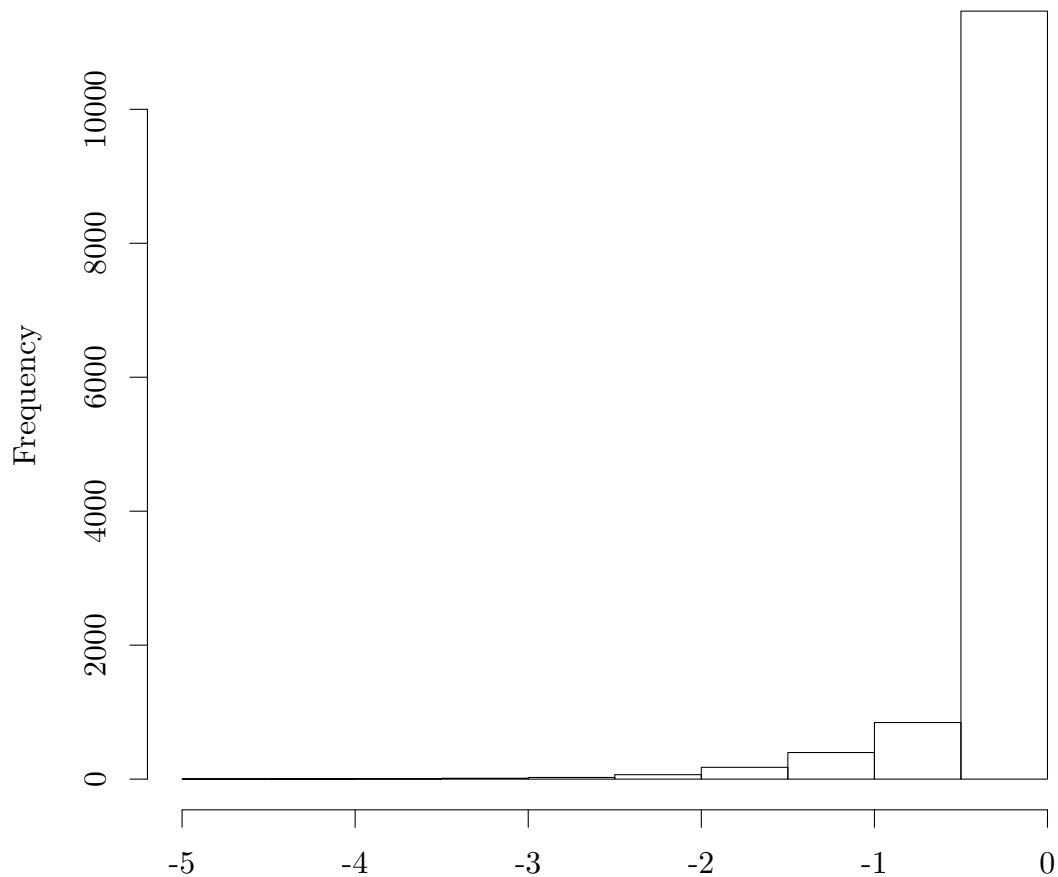
sum(APGI.messina@fits@summary$margin >= 1 & APGI.messina@fits@summary$passed == TRUE)
## [1] 8

mean(APGI.messina@fits@summary$margin >= 1 & APGI.messina@fits@summary$passed == TRUE)
## [1] 0.0006154

hist(sapply(APGI.maxstat, function(x) x$p.value), main = "", xlab = "")
```



```
hist(log10(sapply(APGI.maxstat, function(x) x$p.value)), main = "", xlab = "")
```



```
sum(sapply(APGI.maxstat, function(x) x$p.value) < 0.05, na.rm = TRUE)
## [1] 413

sum(sapply(APGI.maxstat, function(x) x$p.value) < 0.05, na.rm = TRUE) / length(APGI.maxstat)
## [1] 0.03177
```

```
doValidation = function(train.features, train.x, train.threshold, train.merit, min_merit, test.features,
{
  require(robustbase)

  sel.merit = train.merit >= min_merit
  sel.val_avail = train.features %in% test.features
  sel = sel.merit & sel.val_avail
  print(fisher.test(table(sel.merit, sel.val_avail)))

  val.train.features = train.features[sel]
  val.train.x = train.x[sel,,drop=FALSE]
  val.train.threshold = train.threshold[sel]
  val.train.merit = train.merit[sel]
  val.perm = match(val.train.features, test.features)
  val.test.features = test.features[val.perm]
  val.test.x = test.x[val.perm,,drop=FALSE]

  stopifnot(val.test.features == val.train.features)
```

```

# Translate the threshold on the training x to an approximate equivalent
# on the test x, by normalization
locscale.train = apply(val.train.x, 1, function(x) scaleTau2(x[!is.na(x)], mu.too = TRUE))
loc.train = locscale.train[1,]
scale.train = locscale.train[2,]

locscale.test = apply(val.test.x, 1, function(x) scaleTau2(x[!is.na(x)], mu.too = TRUE))
loc.test = locscale.test[1,]
scale.test = locscale.test[2,]

val.test.threshold = (val.train.threshold - loc.train) / scale.train * scale.test + loc.test

val.chisq = mapply(function(row_index, threshold) {
  x = val.test.x[row_index,]
  xd = x > threshold
  if (all(xd) || all(!xd)) { return(NA) }
  fit = survdiff(test.y ~ xd)
  fit$chisq
}, 1:length(val.test.threshold), val.test.threshold)

result = data.frame(merit = val.train.merit, threshold.train = val.train.threshold, threshold.test = val.test.threshold)
rownames(result) = val.test.features
result = result[order(-result$merit),]
result
}

val.GSE28735.messina = doValidation(as.character(APGI.feats$symbol), APCI.x, APCI.messina@fits@summary$)

## Loading required package: robustbase
##
## Attaching package: 'robustbase'
##
## The following object is masked from 'package:survival':
##
## heart

##
## Fisher's Exact Test for Count Data
##
## data: table(sel.merit, sel.val_avail)
## p-value = 0.003805
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
## 1.552 28.453
## sample estimates:
## odds ratio
## 6.109

val.GSE28735.maxstat = doValidation(as.character(APGI.feats$symbol), APCI.x, sapply(APGI.maxstat, function(x) {
  ##
  ## Fisher's Exact Test for Count Data
  ##
  ## data: table(sel.merit, sel.val_avail)

```



```

## p-value < 2.2e-16
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
## 2.431 3.653
## sample estimates:
## odds ratio
## 2.982

val.GSE21501.messina = doValidation(as.character(APGI.feats$symbol), APCI.x, APCI.messina@fits@summary$

##
## Fisher's Exact Test for Count Data
##
## data: table(sel.merit, sel.val_avail)
## p-value = 1.561e-05
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
## 3.835 176.208
## sample estimates:
## odds ratio
## 18.54

val.GSE21501.maxstat = doValidation(as.character(APGI.feats$symbol), APCI.x, sapply(APGI.maxstat, function(x)

##
## Fisher's Exact Test for Count Data
##
## data: table(sel.merit, sel.val_avail)
## p-value = 1.805e-10
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
## 1.649 2.540
## sample estimates:
## odds ratio
## 2.051

val.TCGA.messina = doValidation(as.character(APGI.feats$symbol), APCI.x, APCI.messina@fits@summary$thres

##
## Fisher's Exact Test for Count Data
##
## data: table(sel.merit, sel.val_avail)
## p-value = 1
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
## 0.2236 Inf
## sample estimates:
## odds ratio
## Inf

val.TCGA.maxstat = doValidation(as.character(APGI.feats$symbol), APCI.x, sapply(APGI.maxstat, function(x)

##
## Fisher's Exact Test for Count Data
##

```

```
## data: table(sel.merit, sel.val_avail)
## p-value = 0.08234
## alternative hypothesis: true odds ratio is not equal to 1
## 95 percent confidence interval:
## 0.961 2.318
## sample estimates:
## odds ratio
## 1.46

## Error in if (all(xd) || all(!xd)) {: missing value where TRUE/FALSE needed

val.GSE28735.messina

##      merit threshold.train threshold.test   chisq
## KRT6A 3.999          9.503          4.754 1.638186
## ANGPTL4 2.716          8.900          3.754 0.670894
## DHRS9 1.468          8.965          4.404 0.007037
## FGG 1.365          8.585          13.796      NA
## PPY 1.098         11.931          4.068 2.536840
## LOX 1.051          7.686          6.841 0.494314
## IL20RB 1.043          6.971          4.060 0.435502

val.GSE21501.messina

##      merit threshold.train threshold.test   chisq
## KRT6A 3.999          9.503          3.3849 0.2333
## ANGPTL4 2.716          8.900          0.7529 0.1246
## KRT6C 2.333          7.458          40.3387      NA
## IGFBP1 1.474          7.070         -4.0458 2.3645
## DHRS9 1.468          8.965          1.9614 3.9596
## FGG 1.365          8.585          9.7976      NA
## PPY 1.098         11.931          3.8380 0.3419
## LOX 1.051          7.686         -0.5062 0.1867
## IL20RB 1.043          6.971          1.7140 0.6682

val.GSE28735.maxstat

##      merit threshold.train threshold.test   chisq
## ANGPTL4 4.835          8.356          3.527 1.217e+00
## KRT6A 4.450          8.915          4.503 2.180e+00
## LOX 4.225          7.502          6.609 5.419e-01
## PYGL 3.837          8.829          7.074 2.251e+00
## ST6GAL1 3.803          9.542          6.145 1.230e+00
## FAM189A2 3.630          6.455          4.052 3.197e-03
## KLHL5 3.511          8.978          6.464 2.728e+00
## ADM 3.394          8.820          4.730 1.088e+00
## E2F7 3.373          6.507          3.854 4.938e+00
## SMOX 3.165          7.190          4.852 2.650e-02
## KIF20A 3.123          7.250          3.584 2.396e+00
## CAPN6 3.073          6.516          4.094 7.537e-01
## IL20RB 2.994          6.505          3.492 6.901e-01
## P4HA1 2.882          9.080          7.426 3.618e-02
## FYN 2.854          8.079          6.086 5.064e-01
## AURKA 2.850          7.727          3.628 5.199e-01
## TCEA3 2.791          8.955          4.898 3.547e+00
```

## LOXL4	2.778	7.628	3.985 4.353e-03
## LDHA	2.744	11.922	9.716 6.056e-01
## CKAP2L	2.693	7.047	3.898 3.238e+00
## PPY	2.628	11.966	4.074 2.537e+00
## TREM1	2.588	6.546	5.146 3.641e-01
## PLOD1	2.541	10.492	5.802 6.070e-02
## CDC20	2.506	8.806	4.385 7.903e-01
## PFKP	2.483	9.183	5.636 7.701e-02
## ERFFI1	2.364	10.222	8.463 2.657e-02
## RGS5	2.303	8.665	6.941 1.157e-01
## TPX2	2.283	7.213	4.613 2.342e+00
## P4HA2	2.267	9.209	6.579 2.345e+00
## SLC15A1	2.242	6.716	5.053 4.828e-01
## DPY19L1	2.227	9.183	6.364 3.403e-02
## MME	2.227	6.441	4.645 1.425e-01
## ATF7IP2	2.212	7.139	5.793 4.623e-02
## PAEP	2.186	6.304	5.022 2.214e-01
## EPHX2	2.173	7.223	3.637 7.331e-01
## KYNU	2.169	7.161	5.370 9.540e-04
## FOXM1	2.166	6.884	4.573 5.998e+00
## NAMPT	2.159	7.988	10.049 3.699e-01
## PLOD2	2.155	10.451	7.593 3.300e+00
## UPP1	2.130	9.094	4.411 1.248e+00
## KCTD10	2.119	7.907	6.094 3.352e-04
## ZNF185	2.105	7.420	3.933 1.060e+00
## EDIL3	2.105	6.400	8.217 5.409e-03
## NEK2	2.103	8.167	4.426 5.032e-01
## LCP1	2.100	8.702	6.629 6.413e+00
## GAPDH	2.086	11.336	9.814 1.951e+00
## ARSD	2.085	9.970	6.440 2.866e+00
## KIF2C	2.080	6.839	3.953 3.629e+00
## ENO2	2.069	7.557	5.422 3.748e-02
## COL12A1	2.052	8.689	8.314 5.723e-02
## VSNL1	2.052	6.712	4.221 2.337e-03
## ENTHD1	2.044	6.345	3.130 1.851e-01
## CADPS2	2.043	7.892	5.795 3.026e+00
## ASPM	1.993	7.916	5.271 9.366e-02
## ASAP1	1.993	9.917	7.260 4.509e-02
## SPATA18	1.952	7.197	5.264 2.207e+00
## KRT18	1.943	12.487	7.917 6.325e-01
## POLQ	1.938	6.758	3.609 5.093e+00
## FAM3D	1.933	9.474	6.136 2.076e+00
## CD109	1.929	6.370	5.959 2.207e-01
## UBE2C	1.927	9.305	5.228 1.843e+00
## OCLN	1.922	7.722	7.186 5.277e-01
## WNK2	1.915	6.293	3.922 2.774e+00
## TGFBI	1.912	12.180	8.229 2.750e+00
## SPOCK1	1.903	8.915	5.387 7.009e+00
## CD300A	1.885	6.707	5.248 1.331e-01
## RAVR2	1.856	7.583	5.856 7.799e-01
## P2RY8	1.856	7.349	4.024 1.079e-02
## A4GNT	1.846	6.439	3.549 1.023e+00
## RIMKLB	1.825	7.221	6.093 7.238e-03
## ADAM23	1.824	6.394	4.155 7.598e-03

## FST	1.820	7.155	4.557	1.088e+00
## CA8	1.819	6.429	3.264	1.650e+00
## CEP55	1.819	7.985	4.831	1.431e+00
## IL1A	1.813	6.266	2.599	1.460e-01
## ANLN	1.811	7.020	4.871	3.439e+00
## DCBLD2	1.806	10.689	8.544	7.788e+00
## PLA2G10	1.795	9.726	4.000	4.374e+00
## KLHL13	1.791	6.430	3.543	6.677e-01
## STAG3L4	1.784	6.532	4.970	3.087e-01
## GOLM1	1.777	6.547	8.986	NA
## F3	1.770	9.228	7.930	4.135e-02
## NTS	1.760	6.317	2.643	1.702e+00
## TPI1	1.759	10.890	6.342	4.913e-01
## PTGES	1.757	7.540	4.722	7.838e-06
## IGKV10RY-1	1.755	11.809	7.375	2.201e-03
## SNAI2	1.753	8.469	6.705	7.687e-02
## NFIA	1.727	7.914	5.845	1.255e+00
## COL7A1	1.726	8.066	4.932	2.645e+00
## FGD6	1.724	6.426	6.617	9.292e-01
## MCM4	1.721	7.948	5.209	1.214e+00
## TUBA1C	1.720	11.899	6.920	1.285e-02
## MELK	1.713	7.288	4.752	2.117e+00
## C5orf46	1.700	6.858	2.836	NA
## COL17A1	1.700	10.742	6.042	7.886e-01
## PDLIM7	1.691	8.030	6.383	6.057e-01
## PTTG1	1.674	9.067	4.939	1.004e+00
## DSG2	1.663	10.999	7.174	6.084e+00
## COL1A2	1.658	12.989	11.330	1.470e+00
## SYNE2	1.657	8.782	7.637	1.589e-01
## SERPINH1	1.646	10.187	6.735	2.134e+00
## PHLDA1	1.643	9.269	6.348	1.132e+00
## CTSE	1.642	11.677	9.666	1.154e+00
## ADH1A	1.635	8.432	4.306	3.482e+00
## WEE1	1.635	7.480	7.084	1.675e+00
## CHEK1	1.623	6.501	4.403	2.718e+00
## GSDMC	1.618	6.409	3.565	4.329e+00
## SLC2A1	1.615	10.218	7.422	3.749e-03
## SERPINB3	1.614	6.324	2.770	1.020e-02
## DHRS9	1.609	8.430	4.046	2.091e-01
## PPP1R3C	1.597	8.282	5.976	3.812e+00
## FLRT3	1.596	9.224	5.713	3.404e+00
## CCNB2	1.594	7.685	4.108	1.338e+00
## CORO1A	1.593	8.375	5.960	4.792e-03
## RHOF	1.591	6.800	4.881	5.617e-01
## GRAMD3	1.587	7.707	5.612	7.763e-03
## IL33	1.583	7.299	4.397	2.122e-03
## AQP1	1.577	7.146	5.848	7.817e-02
## VEGFA	1.573	7.090	6.212	1.095e-02
## ANGPTL2	1.563	9.897	5.866	1.308e+00
## SEMA4A	1.562	7.304	4.697	1.226e-01
## GCNT1	1.562	8.263	6.462	2.802e-01
## CCL19	1.560	9.155	6.111	2.032e-01
## CACHD1	1.555	6.709	5.075	4.289e-03
## NCAPG	1.544	7.323	5.149	4.495e-01

## FCGR2B	1.536	7.007	4.506	2.784e-02
## BOC	1.528	6.805	5.509	3.207e+00
## CNIH3	1.513	6.461	4.149	9.764e-01
## IL1R2	1.508	8.252	5.522	3.305e+00
## ITGA5	1.505	8.100	5.330	7.701e-02
## ITM2A	1.504	9.660	5.222	7.935e-01
## SLC9A9	1.502	7.348	6.777	2.790e-02
## TM4SF19	1.496	6.269	4.532	1.245e+00
## JAG1	1.488	9.130	8.263	4.872e+00
## FN1	1.486	6.406	11.169	2.450e-02
## NRP2	1.484	6.606	8.615	NA
## TNNI2	1.480	6.303	4.497	3.223e-01
## APOL1	1.469	6.456	7.103	6.062e-02
## KANK4	1.468	7.979	4.247	2.105e-01
## RFX2	1.463	6.427	5.086	5.510e-01
## DSC2	1.458	6.704	7.468	8.154e+00
## KRT17	1.449	10.862	6.923	1.492e+00
## ANKLE2	1.448	7.795	6.781	1.866e+00
## PRC1	1.445	8.324	5.413	2.803e+00
## PPP2R2C	1.443	6.859	3.662	4.825e+00
## KIF18A	1.440	6.472	3.550	1.717e+00
## NDRG2	1.438	8.691	6.250	2.768e+00
## LONRF2	1.437	6.411	4.445	4.865e-01
## SEMA3A	1.432	7.328	6.924	1.541e+00
## ARHGAP26	1.426	6.622	7.091	3.126e+00
## ZBED2	1.424	6.267	4.047	1.361e+00
## PCF11	1.422	6.970	5.972	5.690e+00
## IGJ	1.420	9.761	10.380	1.711e-02
## RGS16	1.419	6.813	5.669	4.387e+00
## HRASLS2	1.418	7.346	3.576	1.641e-01
## AHCYL2	1.417	8.620	7.190	4.483e+00
## TLE4	1.417	8.089	5.644	1.763e-02
## CDA	1.416	6.859	4.461	1.855e-01
## DNASE1	1.415	6.346	3.864	6.021e-01
## DKK1	1.413	9.728	5.287	1.032e+00
## CD38	1.405	7.104	6.298	7.484e-01
## MALL	1.405	10.388	6.245	3.778e-01
## GIMAP2	1.400	7.313	5.276	2.303e+00
## GPC3	1.399	7.457	6.106	8.675e-01
## SH3RF1	1.391	8.535	6.363	4.798e+00
## DUOXA2	1.384	7.261	4.065	3.746e+00
## FRMD6	1.379	9.411	7.018	1.674e+00
## KNTC1	1.365	7.209	5.133	2.333e+00
## TMSB10	1.364	13.721	10.239	9.794e-01
## KPNA2	1.356	6.543	6.121	6.968e-01
## CST6	1.354	8.451	4.027	1.272e+00
## CCNB1	1.353	7.364	5.563	3.176e-01
## CD79A	1.350	7.991	4.204	1.653e+00
## RAP1GAP	1.346	9.590	3.821	2.320e-01
## CENPF	1.346	7.209	5.142	5.130e-01
## SOD2	1.341	8.755	7.349	NA
## MIF	1.334	12.328	7.195	2.992e-01
## GBE1	1.331	7.564	6.499	1.296e+00
## MEOX1	1.331	6.748	4.334	3.263e-02

## KIF14	1.322	6.914	3.835	3.222e+00
## TRNP1	1.319	10.665	5.963	4.984e-03
## FGG	1.319	8.010	10.996	NA
## MUC16	1.312	6.930	3.937	1.296e-01
## DYNC2H1	1.312	7.510	6.309	4.117e+00
## MMP10	1.307	6.412	2.984	6.057e-01
## LETM2	1.306	6.642	4.413	6.681e-01

val.GSE21501.maxstat

##	merit	threshold.train	threshold.test	chisq
## ANGPTL4	4.835	8.356	0.19587	6.865e-01
## KRT6A	4.450	8.915	2.97484	2.615e-02
## LOX	4.225	7.502	-0.79221	1.058e+00
## KRT6C	4.215	6.392	5.59238	NA
## ST6GAL1	3.803	9.542	0.78319	5.739e-01
## FAM189A2	3.630	6.455	0.28808	7.248e-01
## ADM	3.394	8.820	-1.66023	7.681e+00
## E2F7	3.373	6.507	-2.26972	1.101e+01
## CAPN6	3.073	6.516	0.58777	1.934e+00
## IL20RB	2.994	6.505	0.27819	2.890e+00
## FGF13	2.837	6.400	-0.33980	2.197e+00
## TCEA3	2.791	8.955	0.67789	4.561e+00
## LOXL4	2.778	7.628	0.96728	4.499e-01
## TMEM26	2.688	6.692	0.77037	4.695e-02
## BIRC5	2.643	7.334	-1.61111	4.021e+00
## CD70	2.632	6.748	-0.60306	5.035e-01
## PPY	2.628	11.966	3.85564	7.804e-01
## TREM1	2.588	6.546	2.12235	4.167e+00
## IGFBP1	2.466	7.076	-4.02812	1.675e+00
## ERRFI1	2.364	10.222	0.59119	1.790e+01
## RGS5	2.303	8.665	4.26999	5.369e+00
## PHACTR3	2.275	6.884	1.98393	1.343e+00
## MME	2.227	6.441	-1.58576	2.189e-01
## PRDM16	2.206	6.605	3.97296	1.839e+00
## PAEP	2.186	6.304	0.77117	4.242e-01
## EPHX2	2.173	7.223	0.03016	4.564e-01
## KYNU	2.169	7.161	-1.99673	3.795e-01
## NAMPT	2.159	7.988	0.11528	1.970e+00
## PLOD2	2.155	10.451	0.06961	8.655e-02
## EDIL3	2.105	6.400	4.24471	1.304e+00
## NEK2	2.103	8.167	-1.80395	4.750e+00
## LCP1	2.100	8.702	-1.84614	2.896e+00
## COL12A1	2.052	8.689	1.83301	3.053e-01
## VSNL1	2.052	6.712	-1.64740	1.529e-01
## ENTHD1	2.044	6.345	1.75682	2.632e-01
## PCDH20	2.003	7.551	3.99419	1.354e+00
## ASPM	1.993	7.916	-0.07079	1.759e+00
## CATSPER1	1.956	6.371	0.89696	1.486e+00
## KRT18	1.943	12.487	0.25249	1.552e+00
## FAM3D	1.933	9.474	5.30834	6.346e+00
## CD109	1.929	6.370	-0.49431	4.737e-01
## UBE2C	1.927	9.305	-1.15748	2.006e+00
## OCLN	1.922	7.722	2.27334	3.056e+00

##	TGFBI	1.912	12.180	1.17508	7.810e-02
##	SPOCK1	1.903	8.915	-0.07385	3.241e-02
##	P2RY2	1.899	6.885	2.53729	5.626e-01
##	RAVER2	1.856	7.583	0.05711	4.701e-01
##	P2RY8	1.856	7.349	0.52845	1.882e+00
##	A4GNT	1.846	6.439	3.40057	8.431e-01
##	APOA4	1.823	6.333	-1.04560	3.747e-01
##	CEP55	1.819	7.985	-0.77283	1.442e-03
##	IL1A	1.813	6.266	-0.13329	2.483e-02
##	ANLN	1.811	7.020	-2.66571	1.547e-01
##	DCBLD2	1.806	10.689	0.63766	4.607e+00
##	PLA2G10	1.795	9.726	3.52033	1.519e-01
##	GOLM1	1.777	6.547	4.36321	3.484e+00
##	F3	1.770	9.228	3.33470	7.961e-01
##	NTS	1.760	6.317	-5.02906	1.450e+00
##	SNAI2	1.753	8.469	0.96462	2.333e+00
##	COL7A1	1.726	8.066	-0.65725	1.243e+00
##	FGD6	1.724	6.426	1.00560	2.874e-02
##	NFIX	1.713	9.904	1.57937	1.036e+00
##	C5orf46	1.700	6.858	1.16807	5.466e+00
##	COL17A1	1.700	10.742	4.24593	2.682e-01
##	VSTM2L	1.679	7.078	2.67464	2.975e-01
##	COL1A2	1.658	12.989	3.96788	4.629e-03
##	SERPINH1	1.646	10.187	0.16779	4.575e+00
##	CTSE	1.642	11.677	7.26038	3.184e+00
##	TNFRSF6B	1.638	7.634	3.32680	6.004e-01
##	ADH1A	1.635	8.432	2.32552	1.282e+00
##	CHEK1	1.623	6.501	-3.47669	7.154e-02
##	SLC2A1	1.615	10.218	-0.52907	5.130e-01
##	SERPINB3	1.614	6.324	0.71096	4.767e-01
##	DHRS9	1.609	8.430	1.56562	2.307e+00
##	PPP1R3C	1.597	8.282	0.52826	8.428e-05
##	FLRT3	1.596	9.224	3.15856	2.789e+00
##	CCNB2	1.594	7.685	-0.56249	1.099e+00
##	CXCR5	1.589	6.681	7.98854	NA
##	IL33	1.583	7.299	4.11799	2.212e-02
##	AQP1	1.577	7.146	3.32621	1.330e-01
##	TNFRSF17	1.573	7.032	12.81828	NA
##	VEGFA	1.573	7.090	-0.39754	2.750e-01
##	GCNT1	1.562	8.263	1.40450	6.109e-02
##	CCL19	1.560	9.155	5.98546	9.945e-01
##	ADRA1B	1.546	6.285	0.12758	3.060e+00
##	CAV2	1.540	8.562	1.61441	2.749e+00
##	FCGR2B	1.536	7.007	1.56740	9.048e-01
##	MRAP2	1.532	7.684	0.29126	2.912e-01
##	CCL3L3	1.524	6.799	1.79960	1.696e+00
##	CNIH3	1.513	6.461	0.57543	1.041e+00
##	IL1R2	1.508	8.252	3.85019	2.006e-01
##	ITM2A	1.504	9.660	-0.78323	1.336e+00
##	SLC9A9	1.502	7.348	3.46665	9.579e-02
##	FN1	1.486	6.406	0.04531	3.830e-01
##	SOX8	1.486	7.496	0.79012	5.370e-03
##	NRP2	1.484	6.606	5.28797	NA
##	TNNI2	1.480	6.303	-1.30119	7.253e+00

##	HES1	1.479	8.112	1.10294	4.000e-01
##	KCNH2	1.476	6.778	0.69336	2.375e+00
##	APOL1	1.469	6.456	0.79884	2.381e-02
##	KANK4	1.468	7.979	1.54307	1.052e-01
##	KRT17	1.449	10.862	1.84873	3.034e+00
##	PPP2R2C	1.443	6.859	-0.11054	1.115e-01
##	KIF18A	1.440	6.472	-2.19452	1.770e-01
##	LONRF2	1.437	6.411	-1.25358	1.612e+00
##	SEMA3A	1.432	7.328	0.13548	6.067e-01
##	ARHGAP26	1.426	6.622	1.86500	5.095e-01
##	ZBED2	1.424	6.267	2.24266	7.387e-01
##	SPOCD1	1.422	6.904	1.25823	5.807e+00
##	IGJ	1.420	9.761	1.21379	3.078e-01
##	RGS16	1.419	6.813	1.94034	2.366e-01
##	HRASLS2	1.418	7.346	4.41621	2.843e-01
##	AHCYL2	1.417	8.620	1.74374	4.884e+00
##	DNASE1	1.415	6.346	0.03199	5.313e-02
##	DKK1	1.413	9.728	0.52018	1.947e+00
##	CD38	1.405	7.104	2.18938	7.635e-01
##	MALL	1.405	10.388	3.83833	5.231e-01
##	FGF18	1.397	6.280	1.94601	3.342e-03
##	ZNF365	1.390	7.180	2.32667	3.166e-01
##	FRMD6	1.379	9.411	1.01822	1.170e-02
##	TK1	1.375	8.114	-1.37859	4.348e+00
##	CST6	1.354	8.451	4.65564	2.530e-01
##	CD79A	1.350	7.991	2.33695	7.925e-02
##	RAP1GAP	1.346	9.590	0.53578	8.878e-03
##	CENPF	1.346	7.209	-2.07887	2.536e+00
##	SOD2	1.341	8.755	-0.40747	6.928e-01
##	MEOX1	1.331	6.748	0.96369	5.732e-01
##	KIF14	1.322	6.914	-1.85459	3.210e-01
##	TRNP1	1.319	10.665	3.20514	9.527e-04
##	FGG	1.319	8.010	6.42581	NA
##	CBX1	1.317	6.644	0.09649	4.679e-01
##	MUC16	1.312	6.930	-1.13833	1.513e-01
##	DYNC2H1	1.312	7.510	0.47423	6.089e-03
##	GATA6	1.310	6.470	3.72622	2.664e+00
##	MMP10	1.307	6.412	1.44298	3.202e-02

val.TCGA.messina

##	merit	threshold.train	threshold.test	chisq
##	KRT6A	3.999	9.503	3.656 1.4483
##	ANGPTL4	2.716	8.900	3.336 0.2310
##	KRT6C	2.333	7.458	16.773 NA
##	CIDEC	2.269	8.021	3.192 2.0245
##	IGFBP1	1.474	7.070	3.788 NA
##	DHRS9	1.468	8.965	3.203 0.1557
##	FGG	1.365	8.585	10.219 NA
##	LYNX1	1.344	7.020	3.998 NA
##	PPY	1.098	11.931	3.969 0.3139
##	LOX	1.051	7.686	3.602 0.3011
##	IL20RB	1.043	6.971	2.975 4.0928

val.TCGA.maxstat


```
## Error in eval(expr, envir, enclos): object 'val.TCGA.maxstat' not found
```