

SIS NMF Final: Diagnosis to DSD

March 21, 2015

1 Preparation

```
options(java.parameters = "-Xmx4G")

library(survival)
library(energy)
library(NMF)
library(nnlS)

library(bnlearn)

library(glmulti)
library(glmnet)

library(RColorBrewer)
library(gplots)

library(xtable)
library(stargazer)

load("image.rda")
```

2 Cohort characteristics

```
cpvs.diag_dsd$Path.TumourLocation[cpvs.diag_dsd$Path.TumourLocation == ""] = NA
cpvs.diag_dsd$Path.Nodes.Regional.Involved.Fraction = cpvs.diag_dsd$Path.Nodes.Regional.Involved / cpvs.diag_dsd$Path.Nodes.Regional.Total
cpvs.diag_dsd$Treat.Surgery.ExcisionStatus.Coarse = ordered(ifelse(cpvs.diag_dsd$Treat.Surgery.ExcisionStatus == "1", "1", "2"), "1or2", "3or4")
cpvs.diag_dsd$Path.Grade.Coarse = ordered(ifelse(cpvs.diag_dsd$Path.Grade %in% c("1", "2"), "1or2", "3or4"), "1or2", "3or4")
cpvs.diag_dsd$Path.TumourLocation.Coarse = factor(ifelse(cpvs.diag_dsd$Path.TumourLocation %in% c("Head", "Neck", "Trunk", "Extremities", "Other"), "Head/Neck", "Trunk/Extremities", "Other"))

summary(cpvs.diag_dsd)
```

| ## | Patient.ID | Patient.Gender | Patient.Ethnicity |
|----|------------------|----------------|-----------------------------------|
| ## | Length:110 | Female:50 | Asian : 5 |
| ## | Class :character | Male :60 | Asian, White/Caucasian : 0 |
| ## | Mode :character | | Black/African : 0 |
| ## | | | Black/African, White/Caucasian: 0 |
| ## | | | White/Caucasian :104 |
| ## | | | NA's : 1 |

```

##
## Patient.Country History.LastFollowup.Date
## Australia :110 Min. :2007-06-29
## Italy : 0 1st Qu.:2011-08-19
## New Zealand : 0 Median :2013-03-12
## Puerto Rico : 0 Mean :2012-10-16
## United Kingdom : 0 3rd Qu.:2014-04-24
## United States of America: 0 Max. :2014-09-23
## NA's :1
## History.Smoking.PackYears History.Diagnosis.Date
## Min. : 0.75 Min. :2007-06-04
## 1st Qu.: 9.00 1st Qu.:2010-01-28
## Median :22.50 Median :2011-01-04
## Mean :26.89 Mean :2011-01-14
## 3rd Qu.:43.75 3rd Qu.:2012-02-15
## Max. :70.00 Max. :2012-10-17
## NA's :68
## History.Diagnosis.AgeAtYears History.Surgery.Date
## Min. :36.0 Min. :2007-05-29
## 1st Qu.:61.0 1st Qu.:2010-01-22
## Median :67.0 Median :2011-01-01
## Mean :66.4 Mean :2011-01-13
## 3rd Qu.:73.0 3rd Qu.:2012-02-13
## Max. :87.0 Max. :2012-10-17
##
## Treat.Surgery.Procedure
## Classic Whipple :79
## Splenectomy, Subtotal Panc/L sided Panc or distal Panc: 6
## Cholecystectomy, Classic Whipple : 5
## Subtotal Panc/L sided Panc or distal Panc : 4
## Classic Whipple, Exploratory laparotomy : 3
## PPPD : 3
## (Other) :10
## Treat.Surgery.ExcisionStatus Treat.Surgery.Margin.Pancreatic
## R0:69 <2 mm : 4
## R1:35 Clear :88
## R2: 6 Involved: 9
## NA's : 9
##
##
## Treat.Surgery.MarginSizeMm.Pancreatic Treat.Surgery.Margin.Periunc
## Min. : 0.0 <2 mm :20
## 1st Qu.: 5.0 Clear :52
## Median :10.0 Involved:15
## Mean :10.6 NA's :23
## 3rd Qu.:10.2
## Max. :40.0
## NA's :30
## Treat.Surgery.MarginSizeMm.Periunc Treat.Surgery.Margin.PVGroove
## Min. : 0.00 <2 mm :23
## 1st Qu.: 1.00 Clear :55
## Median : 3.00 Involved:12
## Mean : 6.21 NA's :20

```

```

## 3rd Qu.:10.00
## Max. :40.00
## NA's :43
## Treat.Surgery.MarginSizeMm.PVGroove Treat.Surgery.Margin.Retrop
## Min. : 0.00 <2 mm :21
## 1st Qu.: 1.00 Clear :68
## Median : 3.00 Involved: 9
## Mean : 4.08 NA's :12
## 3rd Qu.: 5.00
## Max. :30.00
## NA's :45
## Treat.Surgery.MarginSizeMm.Retrop Treat.Surgery.Margin.CBD
## Min. : 0.10 <2 mm : 1
## 1st Qu.: 1.75 Clear :83
## Median : 3.00 Involved: 0
## Mean : 5.62 NA's :26
## 3rd Qu.:10.00
## Max. :25.00
## NA's :31
## Treat.Surgery.MarginSizeMm.CBD Treat.Surgery.Margin.Duodenal
## Min. : 1.0 Clear :60
## 1st Qu.:11.8 Involved: 1
## Median :20.0 NA's :49
## Mean :23.6
## 3rd Qu.:32.5
## Max. :55.0
## NA's :47
## Treat.Surgery.MarginSizeMm.Duodenal Treat.Surgery.Margin.Gastric
## Min. : 10.0 Clear:59
## 1st Qu.: 40.0 NA's :51
## Median : 80.0
## Mean : 86.2
## 3rd Qu.:132.5
## Max. :190.0
## NA's :102
## Treat.Surgery.MarginSizeMm.Gastric Treat.Surgery.Margin.Comments
## Min. : 10.0 Length:110
## 1st Qu.: 50.0 Class :character
## Median : 70.0 Mode :character
## Mean : 67.9
## 3rd Qu.: 97.5
## Max. :100.0
## NA's :103
##
## Path.HistoType
## Pancreatic Ductal Adenocarcinoma:110
## Acinar Cell Carcinoma : 0
## Ampullary Adenocarcinoma : 0
## Carcinoid Tumour : 0
## Cholangiocarcinoma : 0
## Clear Cell Carcinoma : 0
## (Other) : 0
##
## Path.HistoType.Subtype Path.Grade
## Gastric : 0 1: 8
## Intestinal : 0 2:71

```

```

## Mixed : 0 3:30
## Not otherwise Specified (NOS):31 4: 1
## Pancreatobiliary :13
## Squamous : 0
## NA's :66
## Path.TumourLocation Path.TumourSizeMm Path.Invasion.PN
## Head :83 Min. :10.0 Absent :13
## Head (Uncinate):10 1st Qu.:28.0 Present:96
## Tail : 9 Median :35.0 NA's : 1
## Body : 7 Mean :37.6
## : 0 3rd Qu.:45.0
## (Other) : 0 Max. :90.0
## NA's : 1 NA's :1
## Path.Invasion.VS Path.Nodes.Regional.Total Path.Nodes.Regional.Involved
## Absent :34 Min. : 0.0 Min. : 0.00
## Present:72 1st Qu.:11.0 1st Qu.: 1.00
## NA's : 4 Median :16.0 Median : 2.00
## Mean :18.1 Mean : 3.18
## 3rd Qu.:24.0 3rd Qu.: 4.00
## Max. :46.0 Max. :18.00
##
## Path.Nodes.SepRec.Total Path.Nodes.SepRec.Involved
## Min. : 0.0 Min. : 0.00
## 1st Qu.:11.0 1st Qu.: 1.00
## Median :16.0 Median : 2.00
## Mean :18.1 Mean : 3.18
## 3rd Qu.:24.0 3rd Qu.: 4.00
## Max. :46.0 Max. :18.00
##
## Staging.Version Staging.pM Staging.pN
## pTNM AJCC 6th Ed 2002 :14 M0 : 2 N0 :25
## pTNM AJCC 7th Ed 2010 :96 M1 : 6 N1 :84
## pTNM AJCC 7th Ed 2010 (Ampulla) : 0 NA's:102 NA's: 1
## pTNM AJCC 7th Ed 2010 (Cholangiocarcinoma): 0
## pTNM AJCC 7th Ed 2010 (Neuroendocrine) : 0
##
## Staging.pT Staging.Stage History.Recurrence History.Recurrence.Date
## Tis : 0 IA : 0 Not observed:24 Min. :2007-10-14
## T1 : 0 IB : 3 Suspected : 4 1st Qu.:2010-12-11
## T2 : 6 IIA:20 Confirmed :78 Median :2012-02-22
## T3 :102 IIB:80 NA's : 4 Mean :2012-01-21
## T4 : 1 III: 1 3rd Qu.:2012-12-29
## NA's: 1 IV : 6 Max. :2014-08-27
## NA's :29
## History.Recurrence.Site.Stomach History.Recurrence.Site.Peritoneum
## Mode :logical Mode :logical
## FALSE:110 FALSE:94
## NA's :0 TRUE :16
## NA's :0
##
## History.Recurrence.Site.PancRemnant History.Recurrence.Site.PancBed

```

```

## Mode :logical                      Mode :logical
## FALSE:106                          FALSE:91
## TRUE :4                            TRUE :19
## NA's :0                            NA's :0
##
##
##
## History.Recurrence.Site.Other History.Recurrence.Site.Omentum
## Mode :logical                      Mode :logical
## FALSE:102                          FALSE:109
## TRUE :8                            TRUE :1
## NA's :0                            NA's :0
##
##
##
## History.Recurrence.Site.Mesentery History.Recurrence.Site.LymphNodes
## Mode :logical                      Mode :logical
## FALSE:108                          FALSE:88
## TRUE :2                            TRUE :22
## NA's :0                            NA's :0
##
##
##
## History.Recurrence.Site.Lung History.Recurrence.Site.Liver
## Mode :logical                      Mode :logical
## FALSE:88                           FALSE:72
## TRUE :22                           TRUE :38
## NA's :0                            NA's :0
##
##
##
## History.Recurrence.Site.Brain History.Recurrence.Site.Bone
## Mode :logical                      Mode :logical
## FALSE:109                          FALSE:104
## TRUE :1                            TRUE :6
## NA's :0                            NA's :0
##
##
##
##
## History.Status History.Death.Date
## Alive - With Disease :15 Min. :2007-11-21
## Alive - Without Disease :22 1st Qu.:2011-01-14
## Deceased - Of Disease :70 Median :2012-03-07
## Deceased - Of Other Cause : 3 Mean :2012-02-21
## Deceased - Of Unknown Cause: 0 3rd Qu.:2013-03-17
## Max. :2014-06-17
## NA's :37
##
## History.Death.Cause Surv.Event.Death
## Cancer Death (Pancreatic) :69 Min. :0.000
## Cancer Death (Other) - Lung ca : 1 1st Qu.:0.000
## Died of Treatment Complication : 1 Median :1.000
## Other (please specify) : 1 Mean :0.664
## Other (please specify) - Suicide: 1 3rd Qu.:1.000
## (Other) : 0 Max. :1.000

```

```

## NA's :37
## Surv.EventTimeFromDiag.Death Surv.EventTimeFromSurg.Death
## Min. : 36 Min. : 36
## 1st Qu.: 402 1st Qu.: 406
## Median : 632 Median : 634
## Mean : 674 Mean : 676
## 3rd Qu.: 912 3rd Qu.: 917
## Max. :1778 Max. :1779
##
## Surv.EventTimeFromRec.Death Surv.Event.DSDeath
## Min. : 7 Min. :0.000
## 1st Qu.: 68 1st Qu.:0.000
## Median : 183 Median :1.000
## Mean : 250 Mean :0.636
## 3rd Qu.: 338 3rd Qu.:1.000
## Max. :1333 Max. :1.000
## NA's :29
## Surv.EventTimeFromDiag.DSDeath Surv.EventTimeFromSurg.DSDeath
## Min. : 36 Min. : 36
## 1st Qu.: 402 1st Qu.: 406
## Median : 632 Median : 634
## Mean : 673 Mean : 675
## 3rd Qu.: 912 3rd Qu.: 917
## Max. :1778 Max. :1779
##
## Surv.EventTimeFromRec.DSDeath Surv.Event.Recurrence
## Min. : 7 Min. :0.000
## 1st Qu.: 68 1st Qu.:0.000
## Median : 183 Median :1.000
## Mean : 250 Mean :0.736
## 3rd Qu.: 338 3rd Qu.:1.000
## Max. :1333 Max. :1.000
## NA's :29 NA's :4
## Surv.EventTimeFromDiag.Recurrence Surv.EventTimeFromSurg.Recurrence
## Min. : 34 Min. : 34
## 1st Qu.: 240 1st Qu.: 240
## Median : 392 Median : 398
## Mean : 511 Mean : 512
## 3rd Qu.: 697 3rd Qu.: 699
## Max. :1778 Max. :1779
## NA's :6 NA's :6
## Path.Nodes.Regional.Involved.Fraction Treat.Surgery.ExcisionStatus.Coarse
## Min. :0.0000 Clear :69
## 1st Qu.:0.0435 Involved:41
## Median :0.1667
## Mean :0.2026
## 3rd Qu.:0.2727
## Max. :1.0000
## NA's :1
## Path.Grade.Coarse Path.TumourLocation.Coarse
## 1or2:79 Head :93
## 3or4:31 Other:17
##
##

```

```

##
##
##

sort(apply(is.na(cpvs.diag_dsd), 2, sum))

##          Patient.ID
##                0
##      Patient.Gender
##                0
##      Patient.Country
##                0
##      History.Diagnosis.Date
##                0
##      History.Diagnosis.AgeAtYears
##                0
##      History.Surgery.Date
##                0
##      Treat.Surgery.Procedure
##                0
##      Treat.Surgery.ExcisionStatus
##                0
##      Treat.Surgery.Margin.Comments
##                0
##      Path.HistoType
##                0
##      Path.Grade
##                0
##      Path.Nodes.Regional.Total
##                0
##      Path.Nodes.Regional.Involved
##                0
##      Path.Nodes.SepRec.Total
##                0
##      Path.Nodes.SepRec.Involved
##                0
##      Staging.Version
##                0
##      Staging.Stage
##                0
##      History.Recurrence.Site.Stomach
##                0
##      History.Recurrence.Site.Peritoneum
##                0
##      History.Recurrence.Site.PancRemnant
##                0
##      History.Recurrence.Site.PancBed
##                0
##      History.Recurrence.Site.Other
##                0
##      History.Recurrence.Site.Omentum
##                0
##      History.Recurrence.Site.Mesentery
##                0

```

```

## History.Recurrence.Site.LymphNodes
## 0
## History.Recurrence.Site.Lung
## 0
## History.Recurrence.Site.Liver
## 0
## History.Recurrence.Site.Brain
## 0
## History.Recurrence.Site.Bone
## 0
## History.Status
## 0
## Surv.Event.Death
## 0
## Surv.EventTimeFromDiag.Death
## 0
## Surv.EventTimeFromSurg.Death
## 0
## Surv.Event.DSDeath
## 0
## Surv.EventTimeFromDiag.DSDeath
## 0
## Surv.EventTimeFromSurg.DSDeath
## 0
## Treat.Surgery.ExcisionStatus.Coarse
## 0
## Path.Grade.Coarse
## 0
## Path.TumourLocation.Coarse
## 0
## Patient.Ethnicity
## 1
## History.LastFollowup.Date
## 1
## Path.TumourLocation
## 1
## Path.TumourSizeMm
## 1
## Path.Invasion.PN
## 1
## Staging.pN
## 1
## Staging.pT
## 1
## Path.Nodes.Regional.Involved.Fraction
## 1
## Path.Invasion.VS
## 4
## History.Recurrence
## 4
## Surv.Event.Recurrence
## 4
## Surv.EventTimeFromDiag.Recurrence
## 6

```



```

##      Surv.EventTimeFromSurg.Recurrence
##                                     6
##      Treat.Surgery.Margin.Pancreatic
##                                     9
##      Treat.Surgery.Margin.Retrop
##                                    12
##      Treat.Surgery.Margin.PVGroove
##                                    20
##      Treat.Surgery.Margin.Periunc
##                                    23
##      Treat.Surgery.Margin.CBD
##                                    26
##      History.Recurrence.Date
##                                    29
##      Surv.EventTimeFromRec.Death
##                                    29
##      Surv.EventTimeFromRec.DSDeath
##                                    29
## Treat.Surgery.MarginSizeMm.Pancreatic
##                                    30
##      Treat.Surgery.MarginSizeMm.Retrop
##                                    31
##      History.Death.Date
##                                    37
##      History.Death.Cause
##                                    37
##      Treat.Surgery.MarginSizeMm.Periunc
##                                    43
## Treat.Surgery.MarginSizeMm.PVGroove
##                                    45
##      Treat.Surgery.MarginSizeMm.CBD
##                                    47
##      Treat.Surgery.Margin.Duodenal
##                                    49
##      Treat.Surgery.Margin.Gastric
##                                    51
##      Path.HistoType.Subtype
##                                    66
##      History.Smoking.PackYears
##                                    68
## Treat.Surgery.MarginSizeMm.Duodenal
##                                    102
##      Staging.pM
##                                    102
##      Treat.Surgery.MarginSizeMm.Gastric
##                                    103

```

3 Probe selection

```

table(cpss.sis$sel)
##

```

```
## FALSE TRUE
## 12639 361

mean(cpss.sis$sel)

## [1] 0.02777

apply(cpss.sis.permuted, 2, sum)

## [1] 37 175 92 32 298 49 47 138 43 173 98 86 207 102 147 41 28
## [18] 160 75 273 154 124 415 109 41 141 50 63 107 63 64 237 84 52
## [35] 40 203 88 55 98 87 57 231 54 48 81 186 114 43 58 347

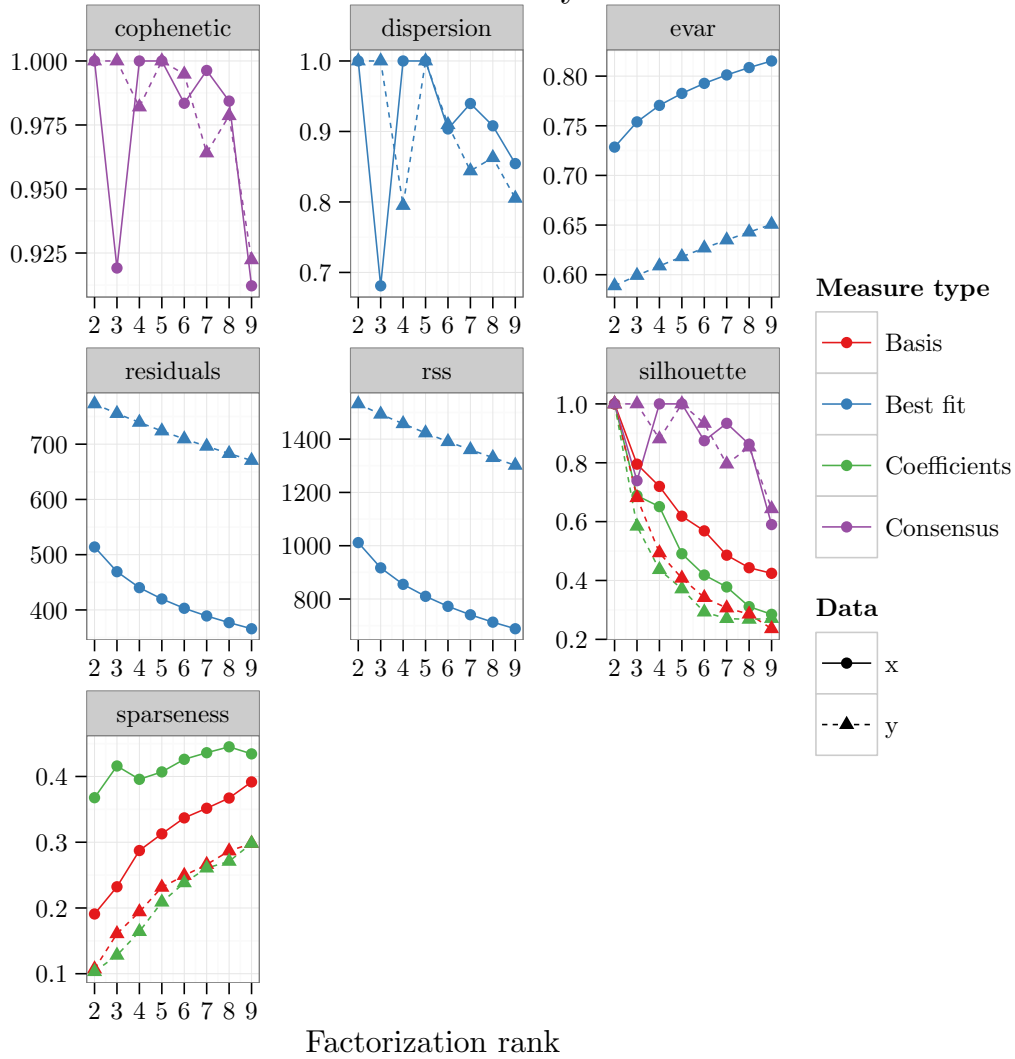
median(apply(cpss.sis.permuted, 2, sum))

## [1] 87.5
```

4 Factorization

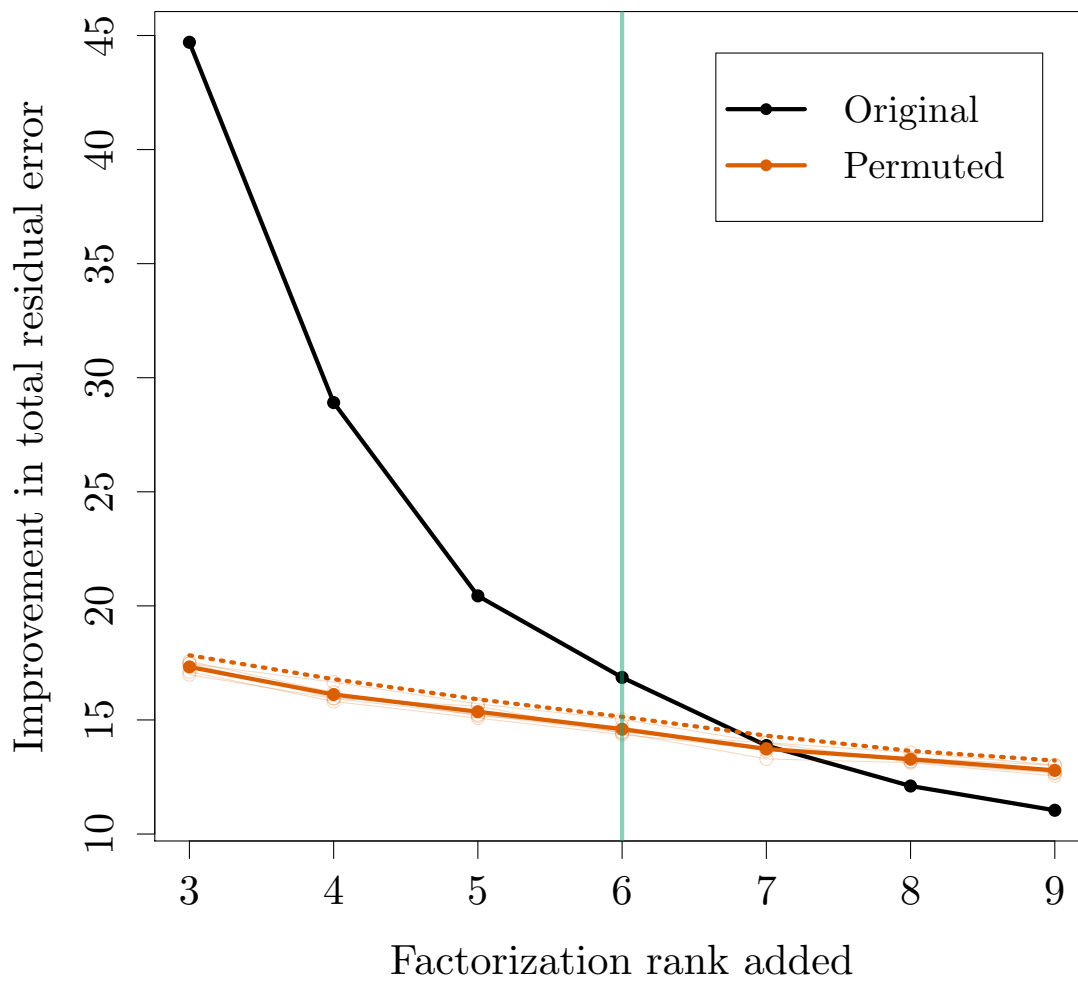
```
temp.pal = brewer.pal(3, "Dark2")
plot(nmf.runs.rank, nmf.runs.rank.random[[1]])
```

NMF rank survey



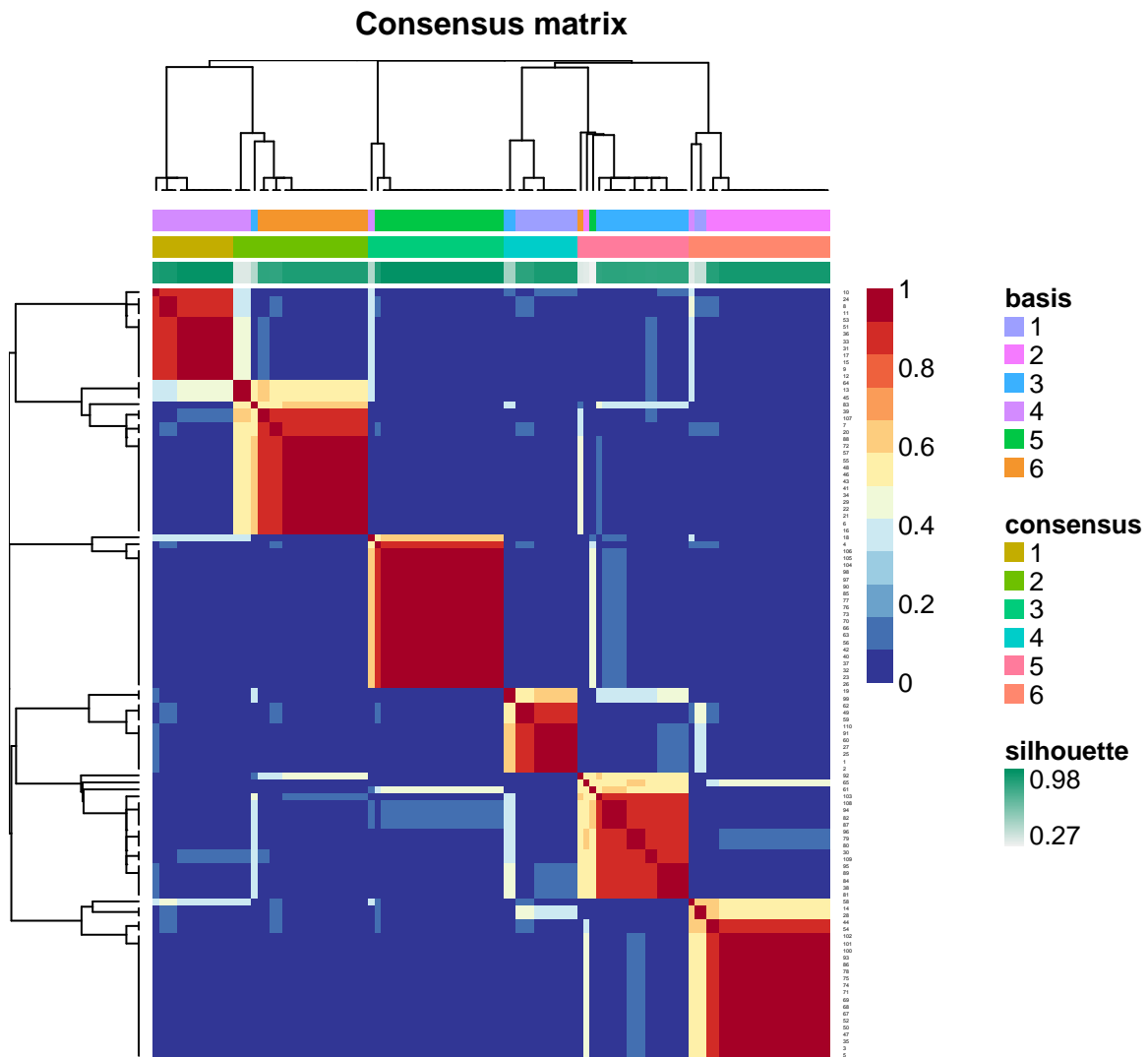
```
plot(nmf.rankrange[-1], -temp.orig_resids.delta,
     type = "o", col = "black", pch = 16, ylim = range(-c(temp.orig_resids.delta, temp.perm_resids.delta),
     xlab = "Factorization rank added", ylab = "Improvement in total residual error", lwd = 4)
lines(nmf.rankrange[-1], -temp.perm_resids.delta.mean, col = temp.pal[2], type = "o", pch = 16, lwd = 4)
for (i in 1:ncol(temp.perm_resids))
{
    lines(nmf.rankrange[-1], -temp.perm_resids.delta[,i], type = "o", col = do.call(rgb, as.list(c(
}
lines(nmf.rankrange[-1], -temp.perm_resids.delta.threshold, col = temp.pal[2], lty = "dotted", lwd = 4)
if (nmf.rank.wasauto == TRUE)
{
    temp.col = temp.pal[1]
} else {
    temp.col = temp.pal[3]
}
abline(v = nmf.rank, col = do.call(rgb, as.list(c(col2rgb(temp.col)[,1]/255, alpha = 0.5))), lwd = 4)
#legend("topright", legend = c("Original data", "Permuted data", sprintf("Selected rank (%s)", ifelse(nmf.rank.wasauto == TRUE, nmf.rank, "auto"))))
```

```
legend("topright", legend = c("Original", "Permuted"), col = c("black", temp.pal[2]), lty = "solid", p
```

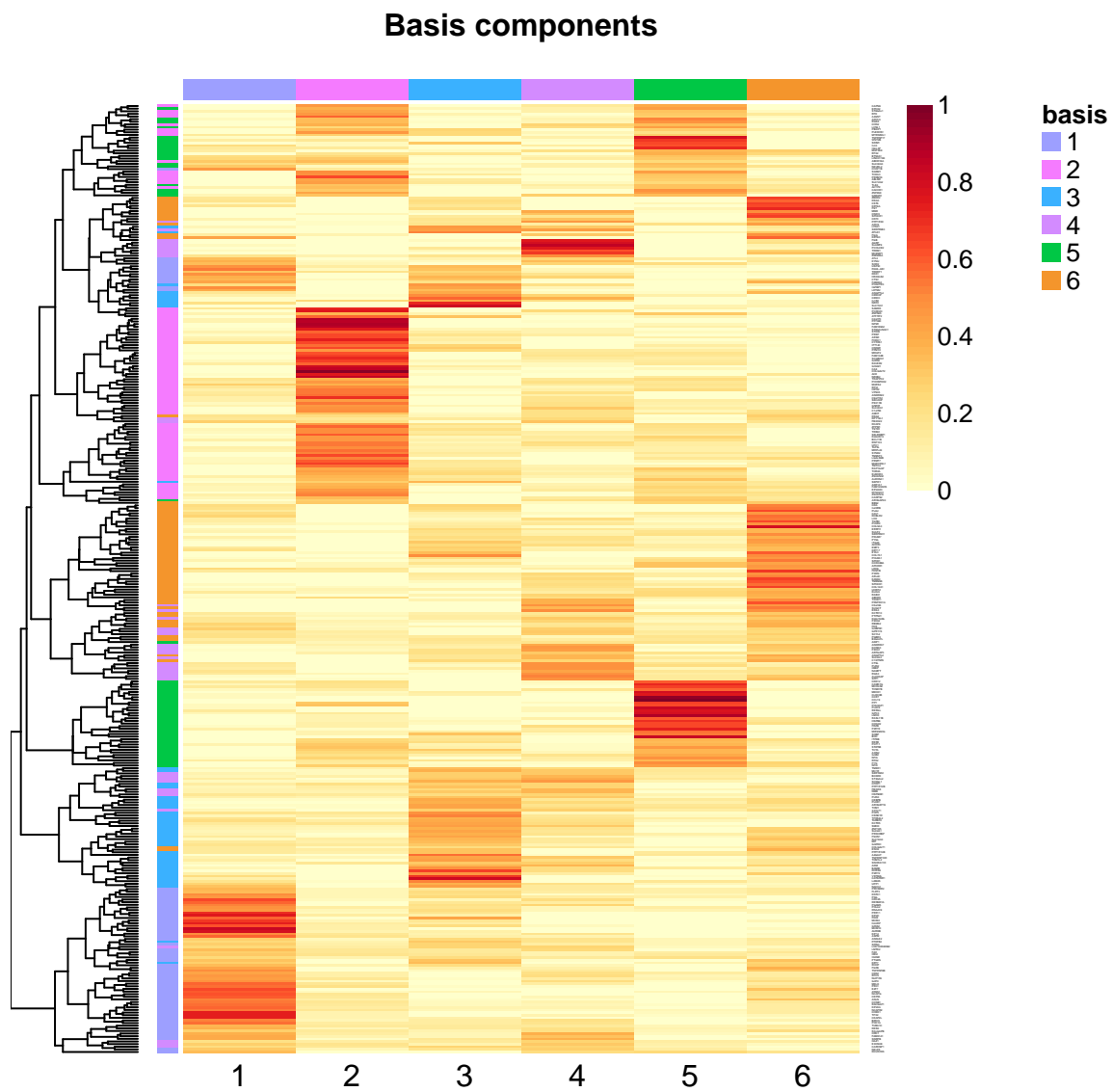


4.1 Fit

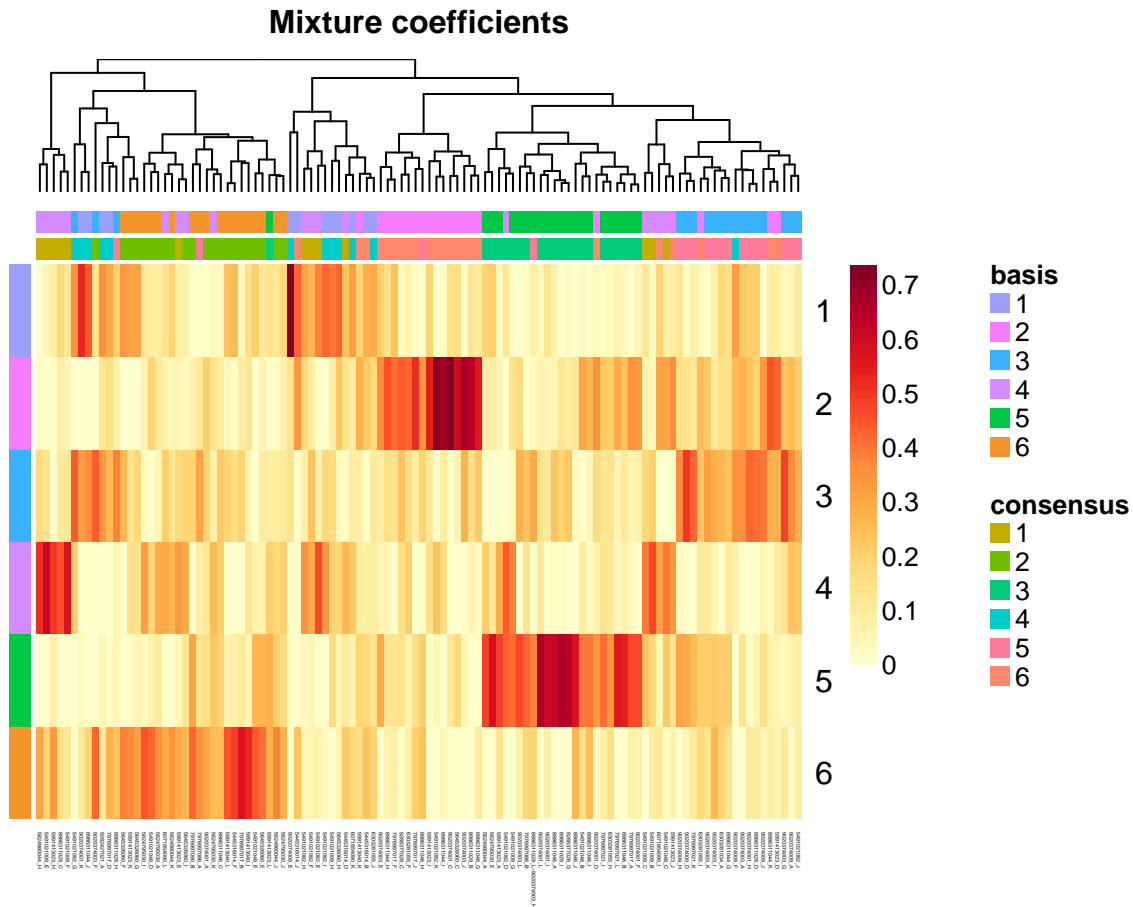
```
consensusmap(nmf.final)
```



```
basismap(nmf.final)
```



```
coefmap(nmf.final)
```



```

coefs.diag_dsd = apply(xlin.diag_dsd.sel, 2, function(xcol) nnls(basis(nmf.final), xcol)$x)
coefs.diag_rec = apply(xlin.diag_rec.sel, 2, function(xcol) nnls(basis(nmf.final), xcol)$x)
coefs.recr_dsd = apply(xlin.recr_dsd.sel, 2, function(xcol) nnls(basis(nmf.final), xcol)$x)
coefs.pdac_au = apply(xlin.pdac_au.sel, 2, function(xcol) nnls(basis(nmf.final), xcol)$x)
axis_coefs.diag_dsd = as.matrix(cbind(axis1 = coefs.diag_dsd[1,] - coefs.diag_dsd[5,], axis2 = coefs.diag_dsd[6,] - coefs.diag_dsd[2,]))

```

```

library(MASS)
W_plus = ginv(basis(nmf.final))

A1 = W_plus[1,] - W_plus[5,]
A2 = W_plus[6,] - W_plus[2,]
PARSE_approx = matrix(1.354*A1 + 1.548*A2, ncol = 1)

rownames(PARSE_approx) = rownames(basis(nmf.final))

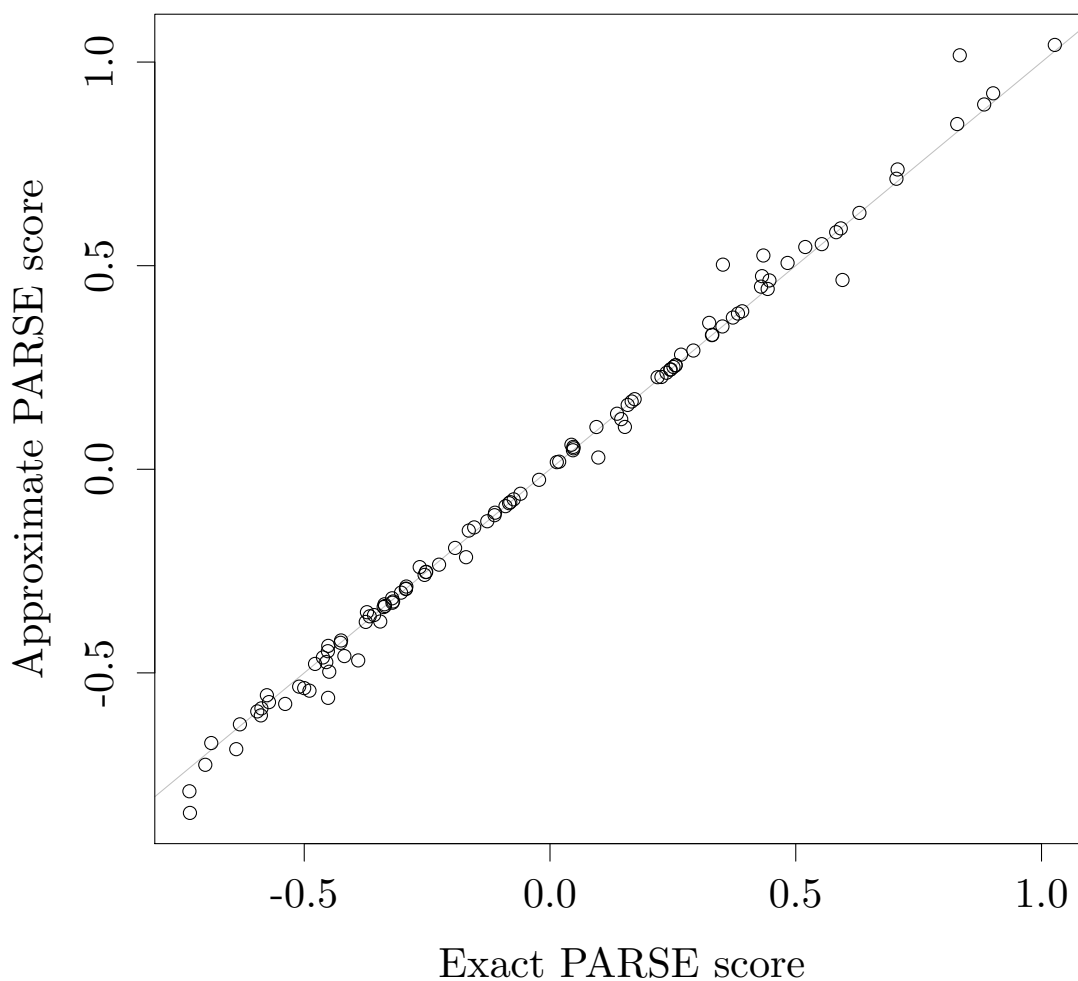
PARSE_approx_scores = t(xlin.diag_dsd.sel) %*% PARSE_approx

```

```

PARSE_exact_scores = 1.354*(coefs.diag_dsd[1,] - coefs.diag_dsd[5,]) + 1.548*(coefs.diag_dsd[6,] - coefs.diag_dsd[10,])
plot(PARSE_exact_scores, PARSE_approx_scores, xlab = "Exact PARSE score", ylab = "Approximate PARSE score",
     abline(0, 1, col = rgb(0, 0, 0, 0.25)))

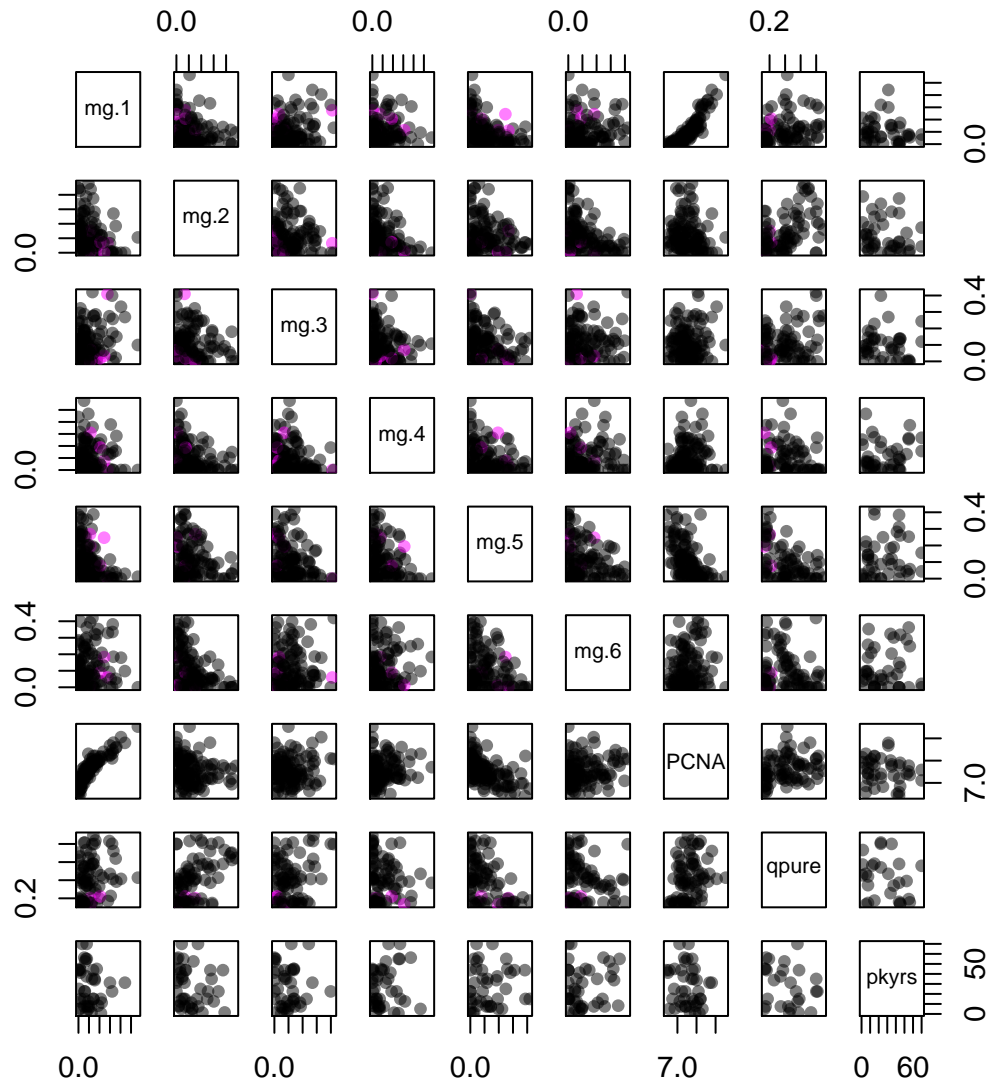
```



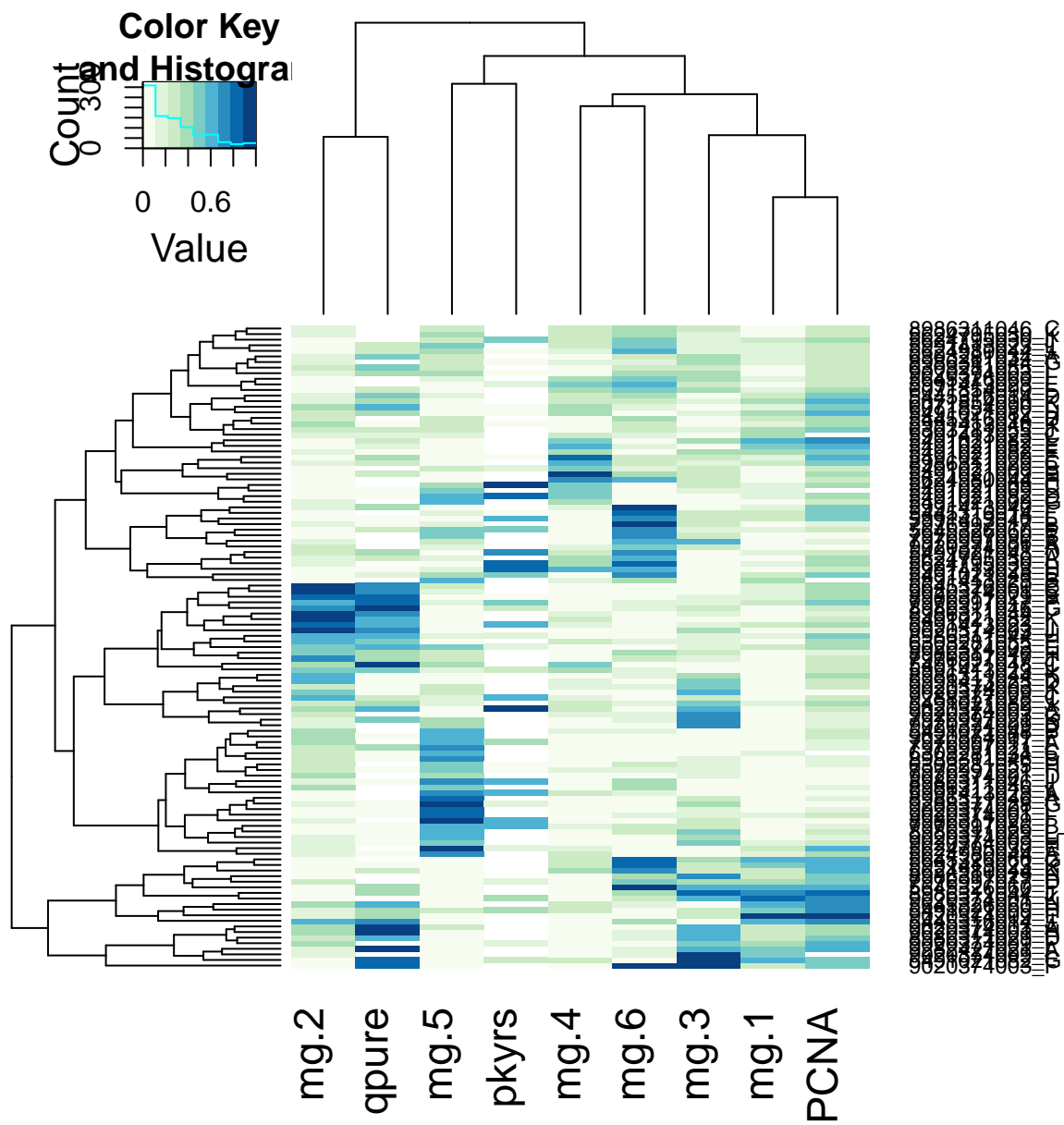
```

temp.pred.pairs = t(rbind(coefs.pdac_au, metapcna.scores[colnames(coefs.pdac_au)]))
colnames(temp.pred.pairs) = paste("mg", 1:ncol(temp.pred.pairs), sep = ".")
colnames(temp.pred.pairs)[ncol(temp.pred.pairs)] = "PCNA"
temp.pred.pairs = cbind(temp.pred.pairs, qpure = samp.pdac_au$purity_qpure, pkyrs = cpvs.pdac_au$Historical.pkyrs)
pairs(temp.pred.pairs, pch = 16, cex = 1, col = ifelse(rownames(temp.pred.pairs) %in% colnames(xlin.diag), "black", "red"))

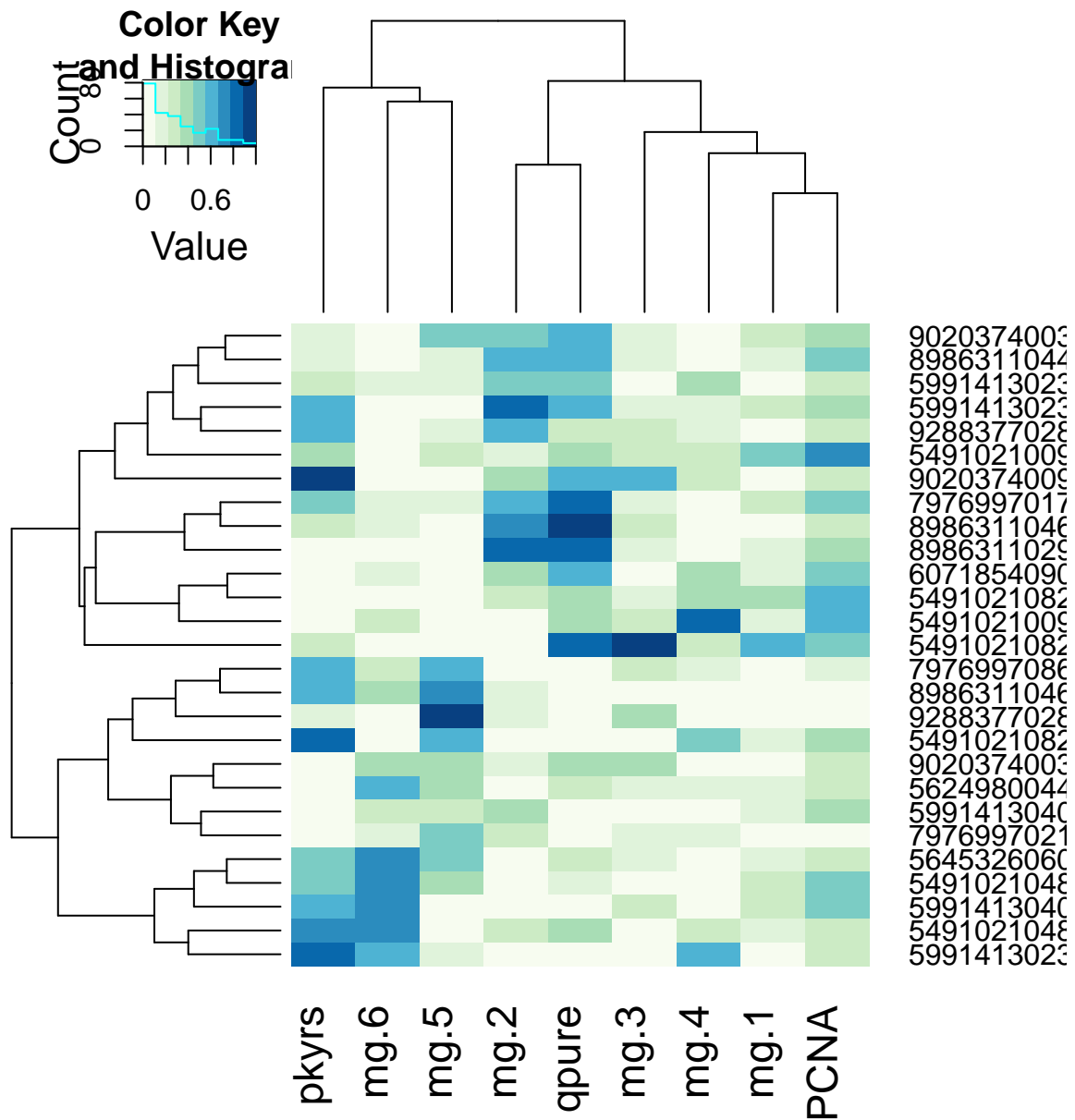
```

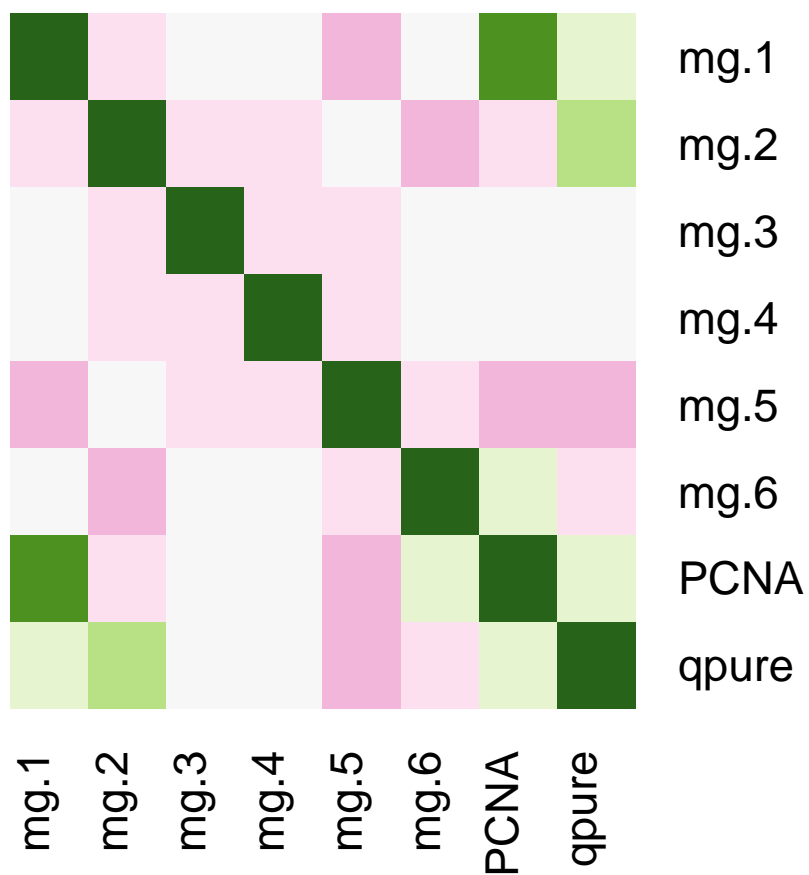
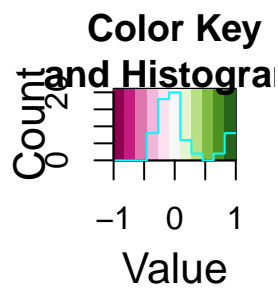
```
temp.pred.pairs.rescaled = t((t(temp.pred.pairs) - apply(temp.pred.pairs, 2, min, na.rm = TRUE)) / (apply(
heatmap.2(temp.pred.pairs.rescaled, trace = "none", scale = "none", col = brewer.pal(9, "GnBu"))
```



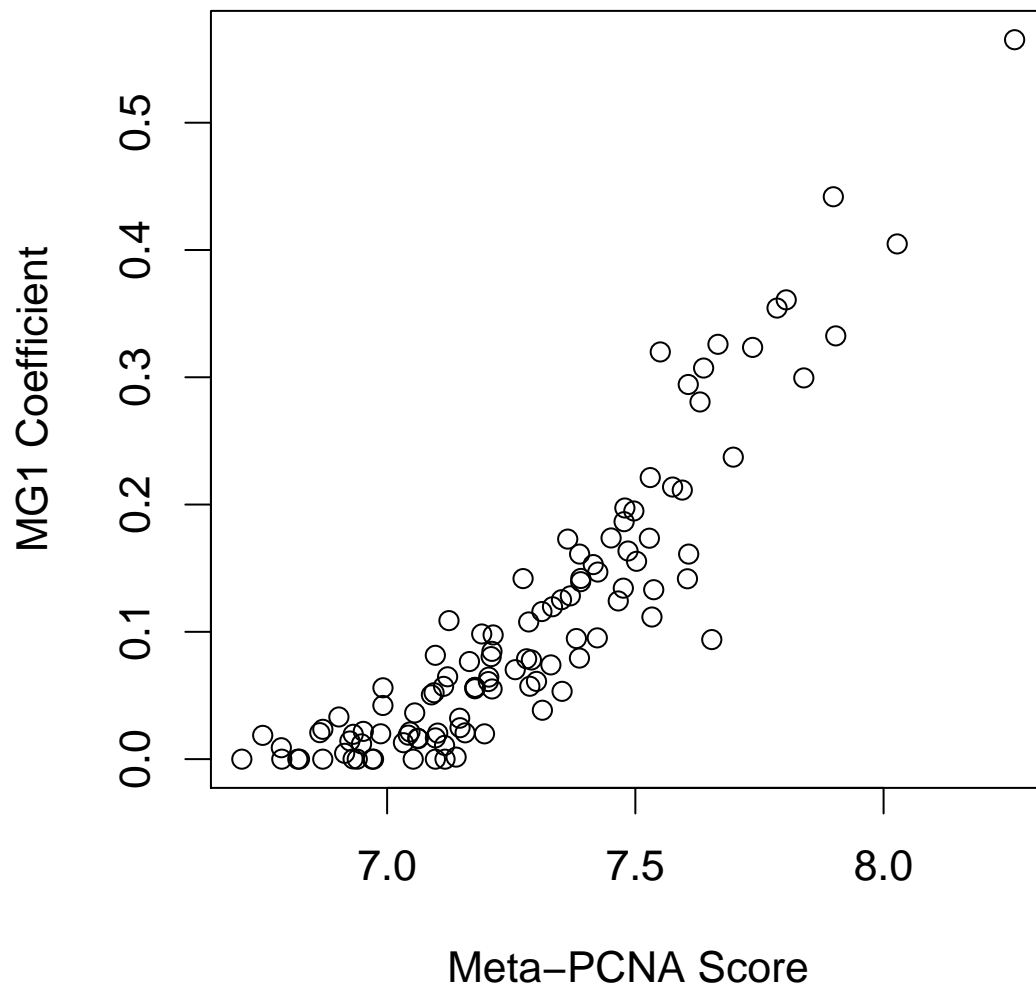
```
heatmap.2(temp.pred.pairs.rescaled[apply(!is.na(temp.pred.pairs.rescaled), 1, all)], trace = "none", s
```



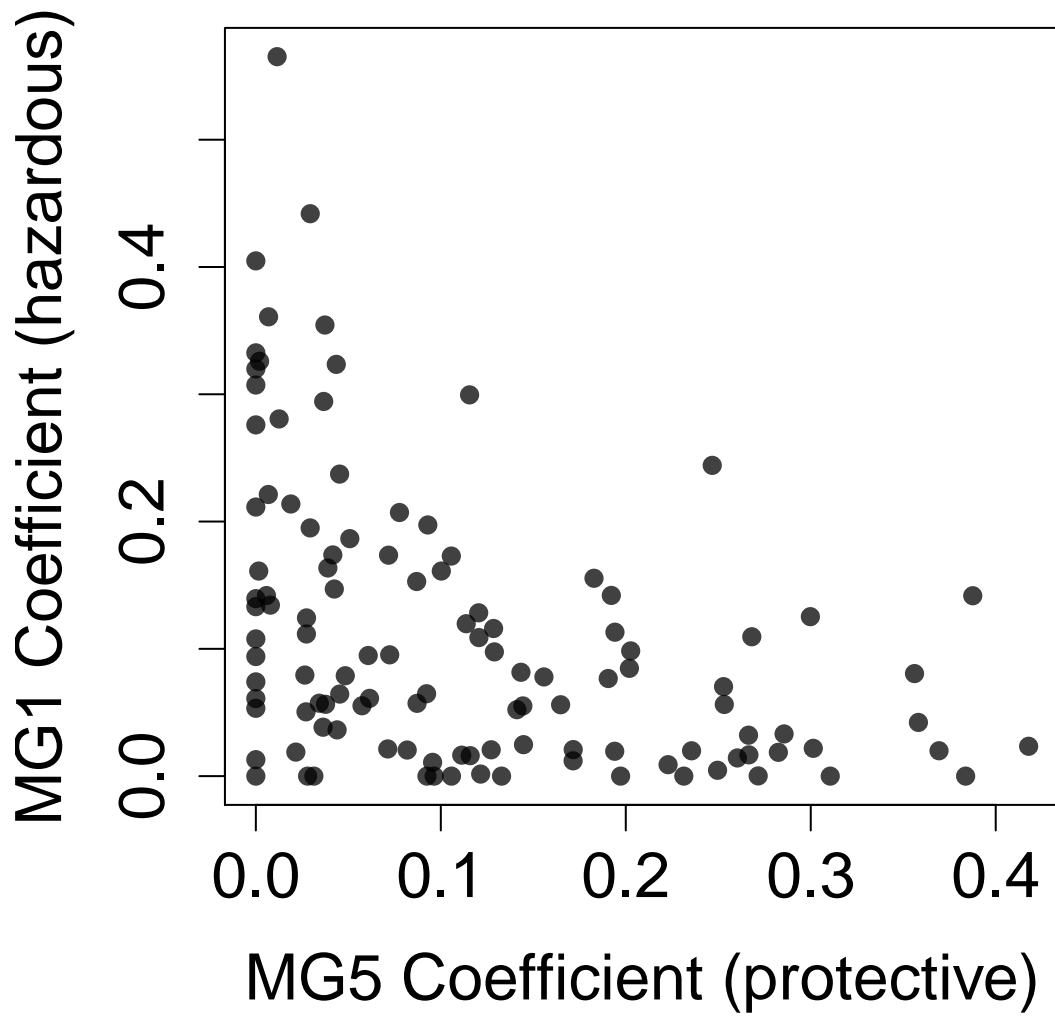
```
temp.pred.pairs.rescaled2 = temp.pred.pairs.rescaled[,colnames(temp.pred.pairs.rescaled) != "pkyrs"]
heatmap.2(temp.pred.pairs.rescaled2, trace = "none", scale = "none", col = brewer.pal(9, "GnBu"))
```

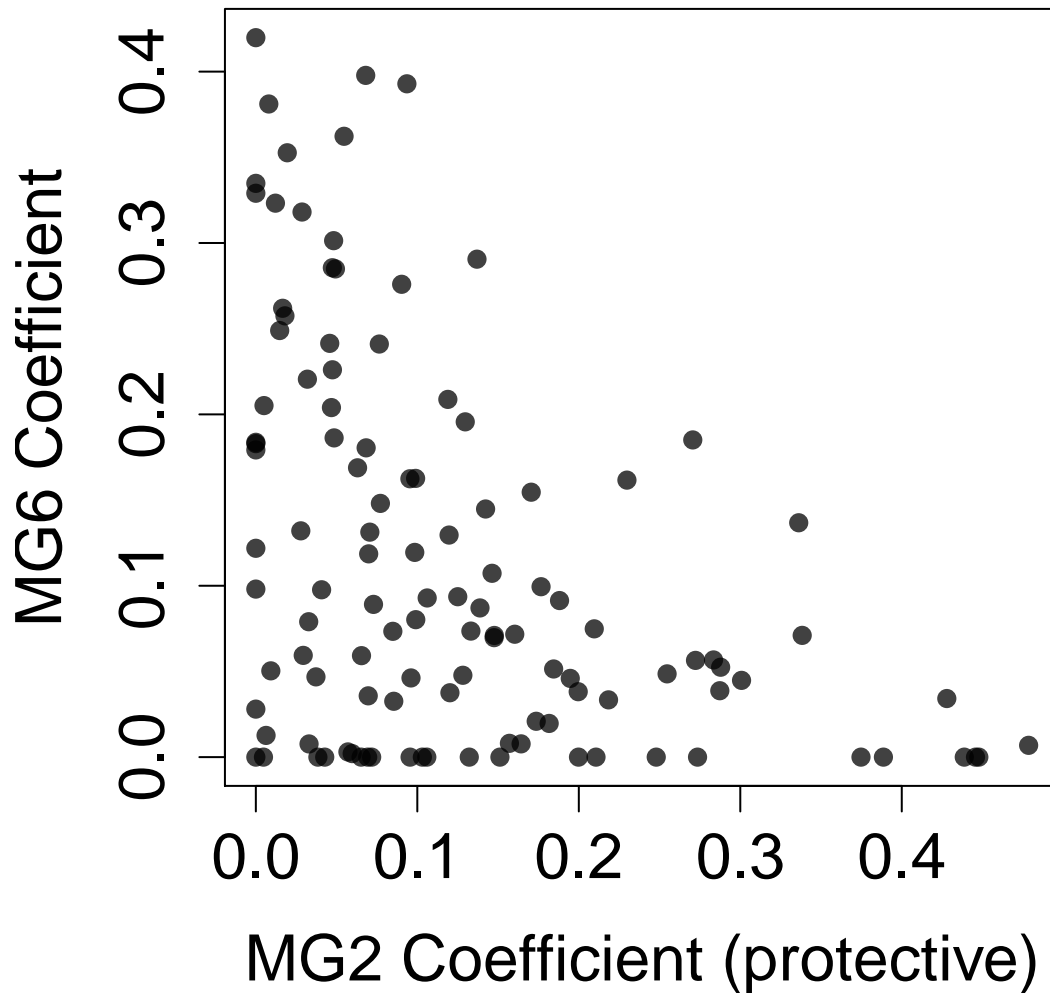
```
plot(temp.pred.pairs[, "mg.1"] ~ temp.pred.pairs[, "PCNA"], col = ifelse(rownames(temp.pred.pairs) %in% c("mg.1", "mg.2", "mg.3", "mg.4", "mg.5", "mg.6", "PCNA", "qpure"), "darkgreen", "darkred"))
```



```
plot(temp.pred.pairs[, "mg.5"], temp.pred.pairs[, "mg.1"], xlab = "MG5 Coefficient (protective)", ylab = "
```



```
plot(temp.pred.pairs[,"mg.2"], temp.pred.pairs[,"mg.6"], xlab = "MG2 Coefficient (protective)", ylab = "
```

```
#scatter.smooth(temp.pred.pairs[, "mg.5"], temp.pred.pairs[, "mg.1"], xlab = "MG5 Coefficient (protective)
#scatter.smooth(temp.pred.pairs[, "mg.2"], temp.pred.pairs[, "mg.6"], xlab = "MG2 Coefficient (protective)
#smoothScatter(temp.pred.pairs[, "mg.5"], temp.pred.pairs[, "mg.1"], xlab = "MG5 Coefficient (protective)
#smoothScatter(temp.pred.pairs[, "mg.2"], temp.pred.pairs[, "mg.6"], xlab = "MG2 Coefficient (protective)

temp.coefs.pdcor = apply(coefs.diag_dsd, 1, function(x1) apply(coefs.diag_dsd, 1, function(x2) dcov.test
temp.coefs.pfisher = apply(coefs.diag_dsd, 1, function(x1) apply(coefs.diag_dsd, 1, function(x2) fisher
diag(temp.coefs.pdcor) = NA
temp.coefs.pdcor[lower.tri(temp.coefs.pdcor)] = NA
diag(temp.coefs.pfisher) = NA
temp.coefs.pfisher[lower.tri(temp.coefs.pfisher)] = NA
temp.coefs.pdcor.holm = matrix(p.adjust(temp.coefs.pdcor, "holm"), nrow = nrow(temp.coefs.pdcor))
temp.coefs.pfisher.holm = matrix(p.adjust(temp.coefs.pfisher, "holm"), nrow = nrow(temp.coefs.pfisher))
temp.coefs.pdcor.holm
```

```

##      [,1] [,2] [,3] [,4] [,5] [,6]
## [1,] NA 0.2016 0.4500 1.0000 0.0015 1.0000
## [2,] NA      NA 0.3066 0.0130 0.1800 0.0015
## [3,] NA      NA      NA 0.0336 0.0451 1.0000
## [4,] NA      NA      NA      NA 0.0480 1.0000
## [5,] NA      NA      NA      NA      NA 0.0480
## [6,] NA      NA      NA      NA      NA      NA

temp.coefs.pfisher.holm

##      [,1] [,2] [,3] [,4] [,5] [,6]
## [1,] NA      1 1.0000      1 0.03203 1.00000
## [2,] NA      NA 0.7286      1 1.00000 0.03203
## [3,] NA      NA      NA      1 1.00000 1.00000
## [4,] NA      NA      NA      NA 0.72858 1.00000
## [5,] NA      NA      NA      NA      NA 1.00000
## [6,] NA      NA      NA      NA      NA      NA

dcov.test(coefs.diag_dsd[5,], coefs.diag_dsd[1,], R = 19999)

##
## dCov test of independence
##
## data: index 1, replicates 19999
## nV^2 = 0.1291, p-value = 5e-05
## sample estimates:
##      dCov
## 0.03426

dcov.test(coefs.diag_dsd[2,], coefs.diag_dsd[6,], R = 19999)

##
## dCov test of independence
##
## data: index 1, replicates 19999
## nV^2 = 0.1396, p-value = 5e-05
## sample estimates:
##      dCov
## 0.03562

cor.test(coefs.diag_dsd[5,], coefs.diag_dsd[1,], method = "kendall")

##
## Kendall's rank correlation tau
##
## data: coefs.diag_dsd[5, ] and coefs.diag_dsd[1, ]
## z = -4.97, p-value = 6.694e-07
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##      tau
## -0.3243

cor.test(coefs.diag_dsd[2,], coefs.diag_dsd[6,], method = "kendall")

```

```

##
## Kendall's rank correlation tau
##
## data:  coefs.diag_dsd[2, ] and coefs.diag_dsd[6, ]
## z = -4.931, p-value = 8.195e-07
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##      tau
## -0.3236

temp.axis1 = coefs.diag_dsd[1,] - coefs.diag_dsd[5,]
temp.axis2 = coefs.diag_dsd[6,] - coefs.diag_dsd[2,]
dcov.test(temp.axis1, temp.axis2, R = 19999)

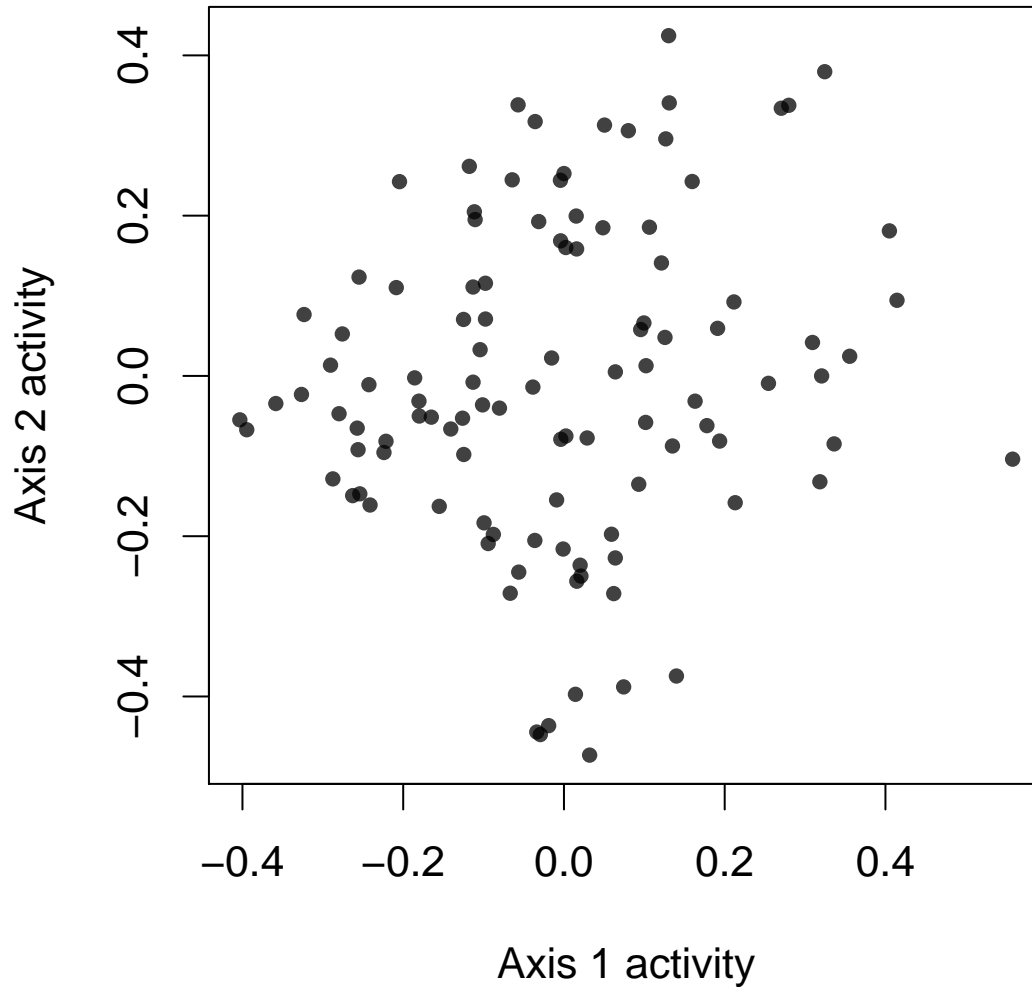
##
## dCov test of independence
##
## data:  index 1, replicates 19999
## nV^2 = 0.1074, p-value = 0.0197
## sample estimates:
##      dCov
## 0.03124

cor.test(temp.axis1, temp.axis2, method = "kendall")

##
## Kendall's rank correlation tau
##
## data:  temp.axis1 and temp.axis2
## z = 1.253, p-value = 0.2103
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##      tau
## 0.0809

plot(temp.axis2 ~ temp.axis1, xlab = "Axis 1 activity", ylab = "Axis 2 activity", pch = 16, col = rgb(0,

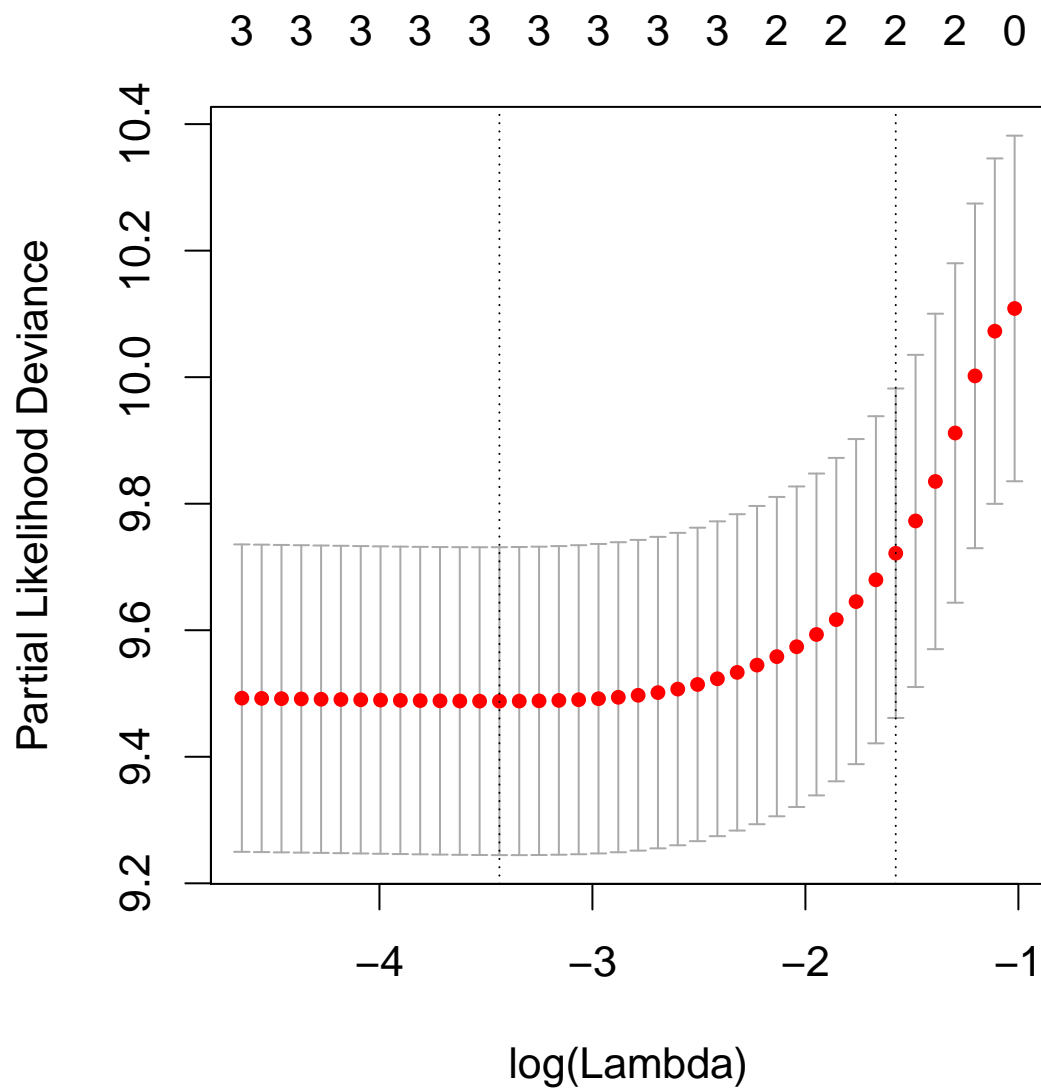
```



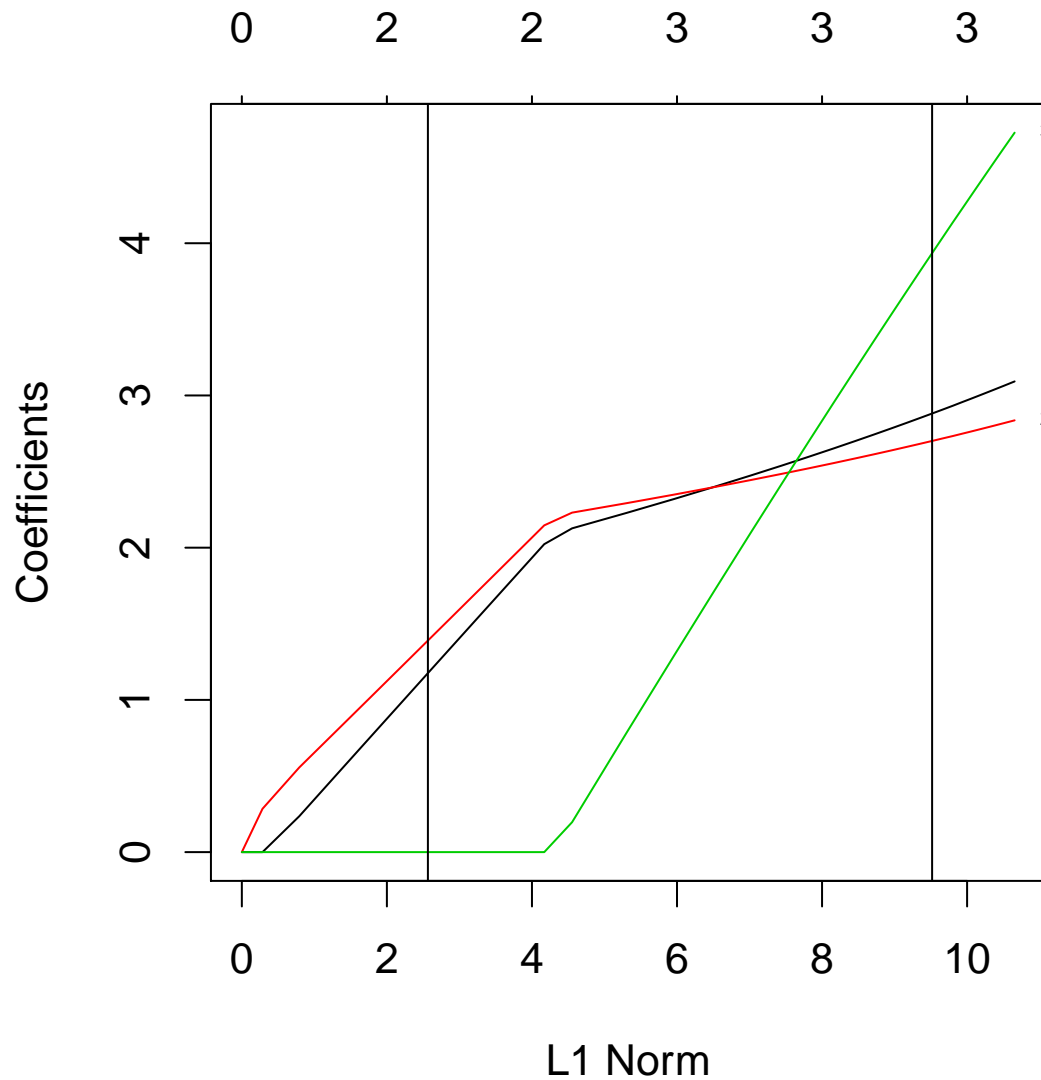
```
coxph(y.diag_dsd ~ temp.axis1 * temp.axis2)

## Call:
## coxph(formula = y.diag_dsd ~ temp.axis1 * temp.axis2)
##
##
##              coef exp(coef) se(coef)      z      p
## temp.axis1      3.19      24.2    0.676  4.72 2.4e-06
## temp.axis2      2.89      18.0    0.657  4.40 1.1e-05
## temp.axis1:temp.axis2 5.03     153.1    4.189  1.20 2.3e-01
##
## Likelihood ratio test=48  on 3 df, p=2.12e-10  n= 110, number of events= 70

temp = cv.glmnet(cbind(temp.axis1, temp.axis2, temp.axis1*temp.axis2), y.diag_dsd, family = "cox", nfolds
plot(temp)
```



```
plot(temp$glmnet.fit, label = TRUE)
abline(v = sum(abs(coef(temp$glmnet.fit, s = temp$lambda.1se))))
abline(v = sum(abs(coef(temp$glmnet.fit, s = temp$lambda.min))))
```



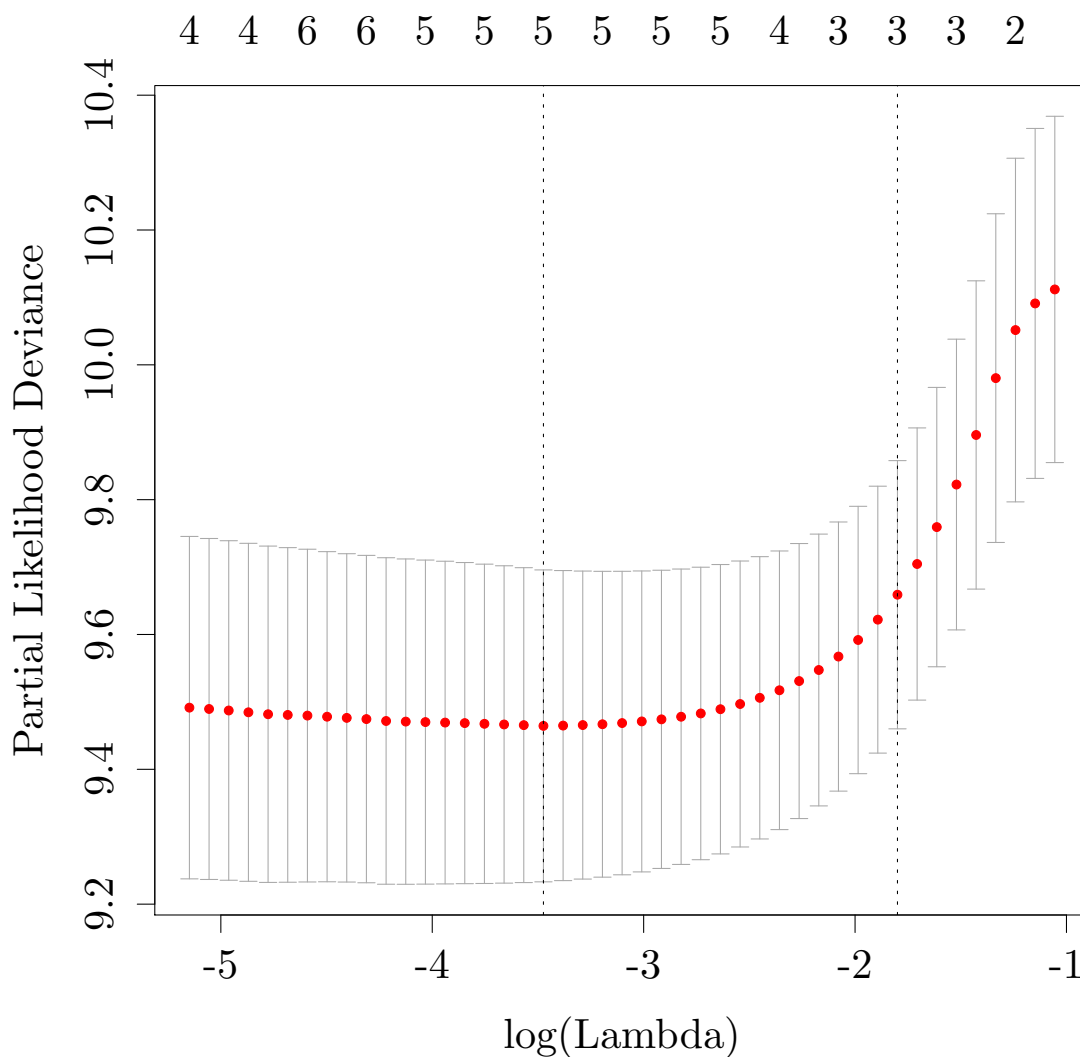
```
coef(temp$glmnet.fit, s = temp$lambda.1se)

## 3 x 1 sparse Matrix of class "dgCMatrix"
##           1
## temp.axis1 1.176
## temp.axis2 1.390
##           .
```

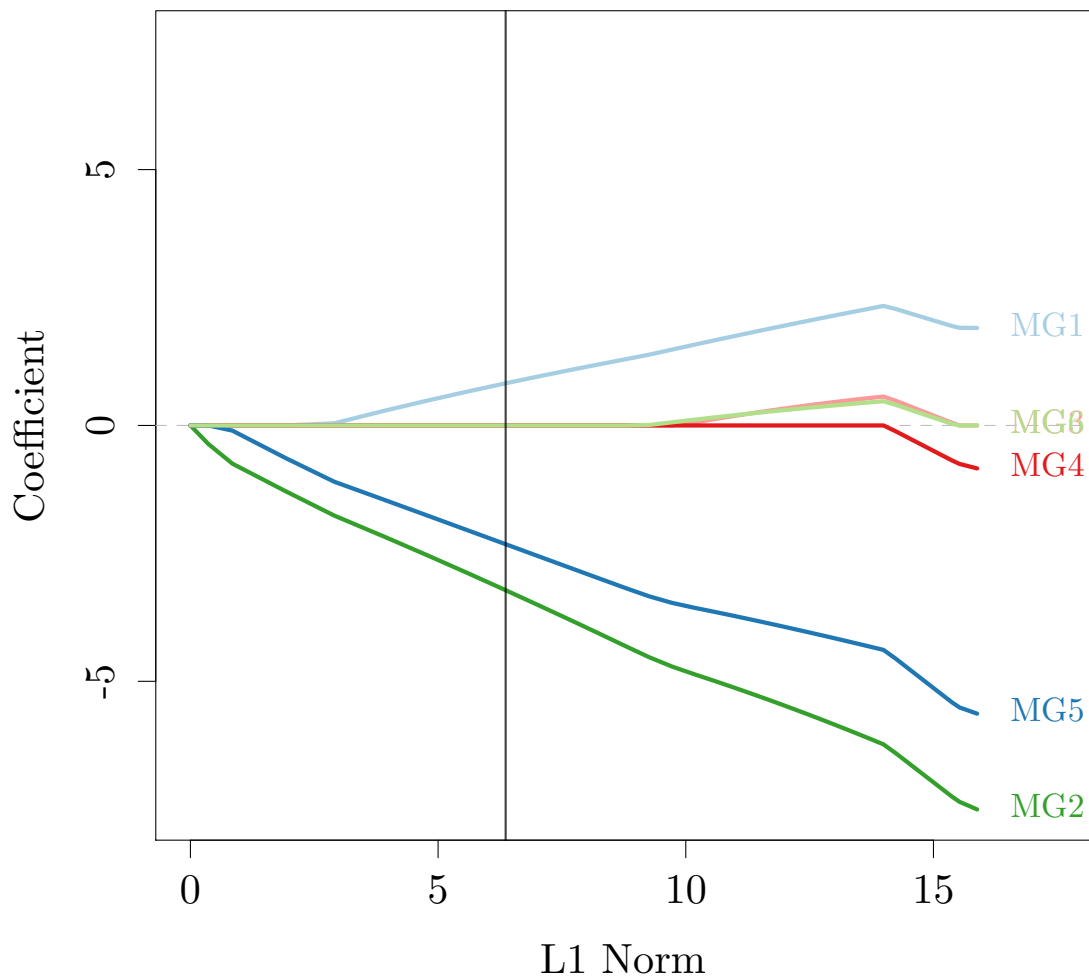
4.2 LASSO on training set

```
glmnet.fit.cv.diag_dsd = cv.glmnet(t(coefs.diag_dsd), y.diag_dsd, family = "cox", nfolds = 10)
glmnet.fit.cv.diag_rec = cv.glmnet(t(coefs.diag_rec), y.diag_rec, family = "cox", nfolds = 10)
glmnet.fit.cv.recr_dsd = cv.glmnet(t(coefs.recr_dsd), y.recr_dsd, family = "cox", nfolds = 10)
```

```
plot(glmnet.fit.cv.diag_dsd)
```



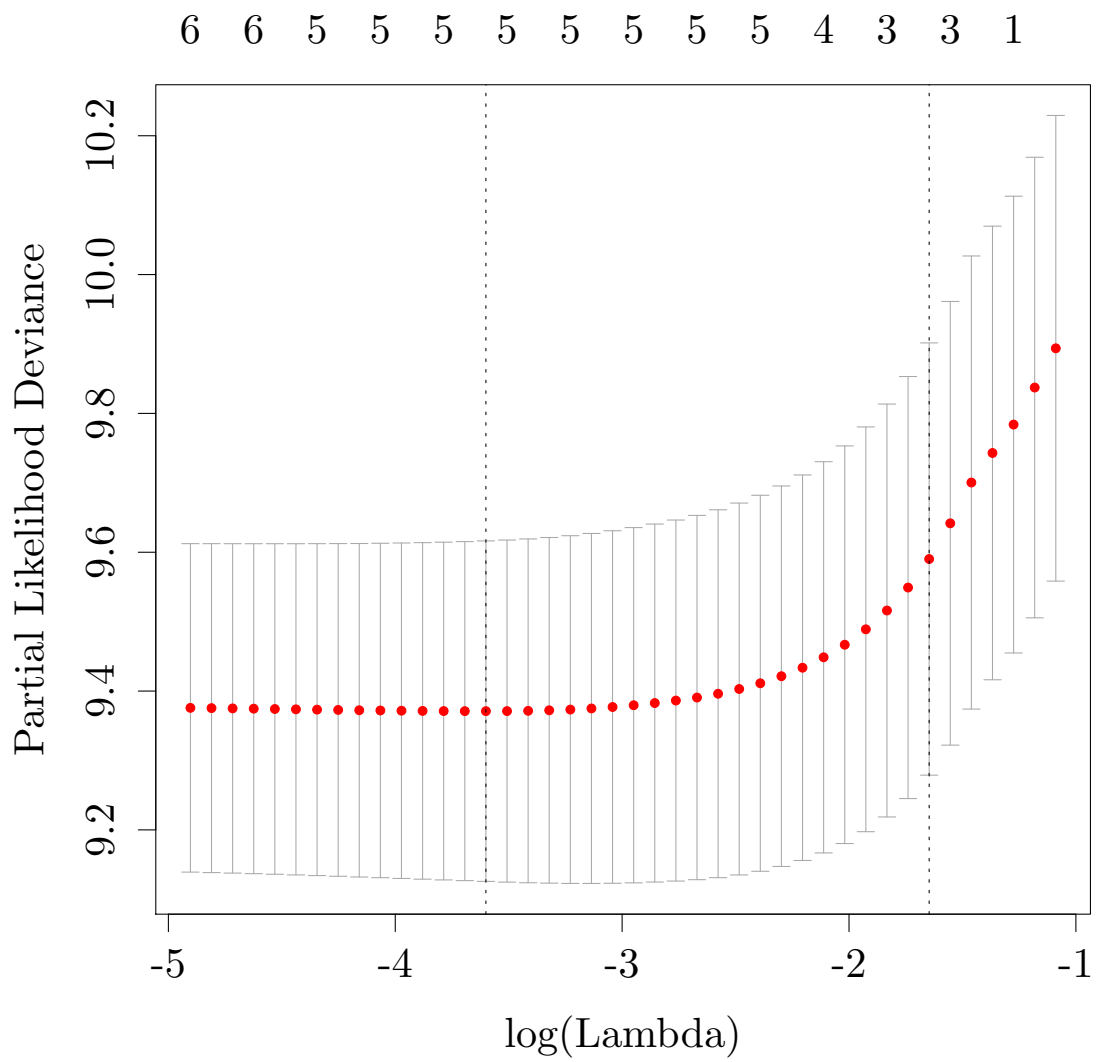
```
#plot(glmnet.fit.cv.diag_dsd$glmnet.fit, label = TRUE)
temp = glmnet.fit.cv.diag_dsd$glmnet.fit
temp.betamax = max(abs(temp$beta))
temp.l1 = colSums(abs(temp$beta))
plot(0 ~ 0, xlim = c(0, max(temp.l1) * 1.1), ylim = c(-temp.betamax, temp.betamax), type = "n", xlab = "log(Lambda)")
abline(h = 0, lty = "dashed", col = "grey")
temp.pal = brewer.pal(nrow(temp$beta), "Paired")[c(1,4,5,6,2,3)]
for (i in 1:nrow(temp$beta))
{
  lines(temp$beta[i,] ~ temp.l1, col = temp.pal[i], lwd = 4)
  text(max(temp.l1) * 1.02, temp$beta[i,length(temp.l1)], paste("MG", i, sep = ""), col = temp.pal[i])
}
abline(v = sum(abs(coef(glmnet.fit.cv.diag_dsd$glmnet.fit, s = glmnet.fit.cv.diag_dsd$lambda.1se))), col = "green")
```



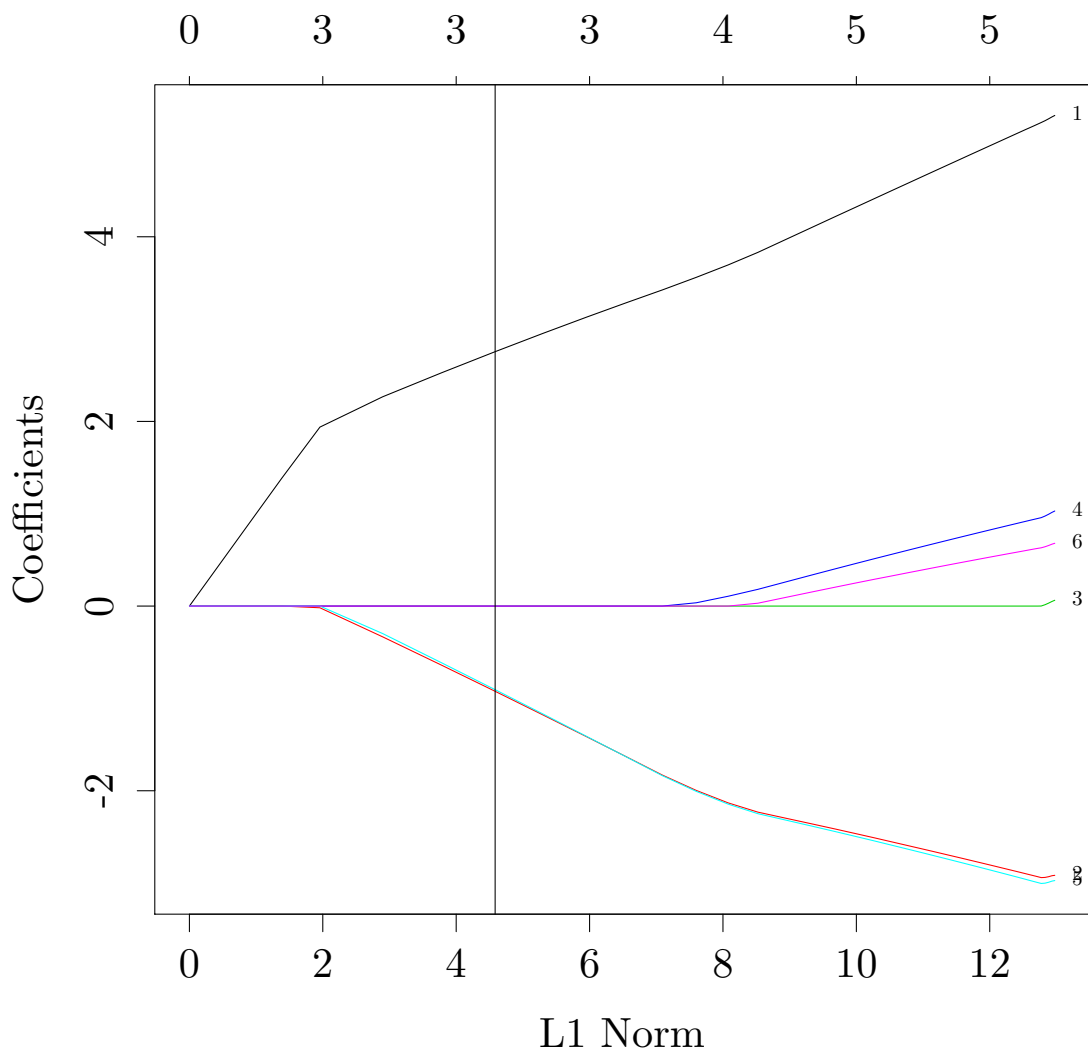
```
#abline(v = sum(abs(coef(glmnet.fit.cv.diag_dsd$glmnet.fit, s = glmnet.fit.cv.diag_dsd$lambda.min))))
coef(glmnet.fit.cv.diag_dsd$glmnet.fit, s = glmnet.fit.cv.diag_dsd$lambda.1se)

## 6 x 1 sparse Matrix of class "dgCMatrix"
##      1
## V1  0.8238
## V2 -3.2195
## V3   .
## V4   .
## V5 -2.3208
## V6   .

plot(glmnet.fit.cv.diag_rec)
```

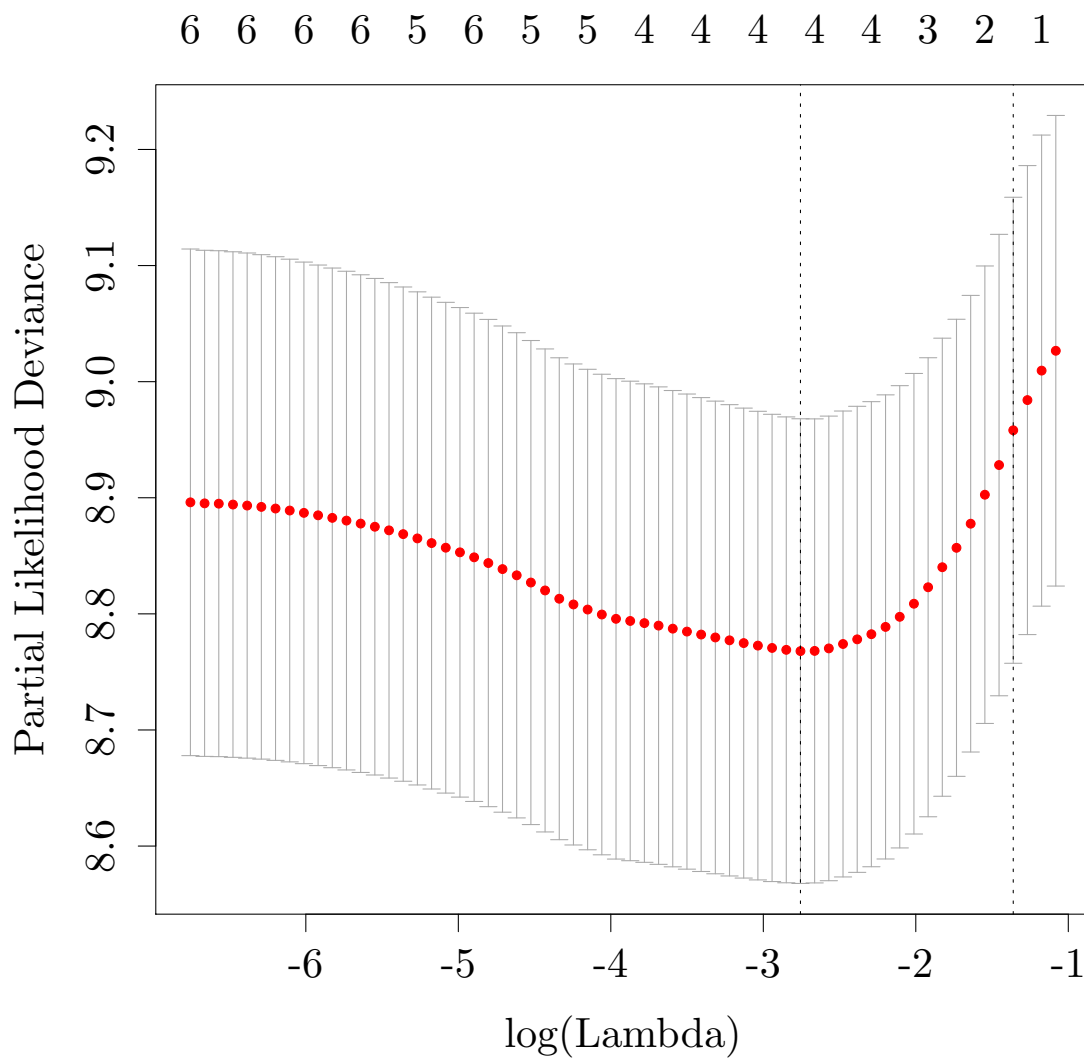
```
plot(glmnet.fit.cv.diag_rec$glmnet.fit, label = TRUE)
abline(v = sum(abs(coef(glmnet.fit.cv.diag_rec$glmnet.fit, s = glmnet.fit.cv.diag_rec$lambda.1se))))
```



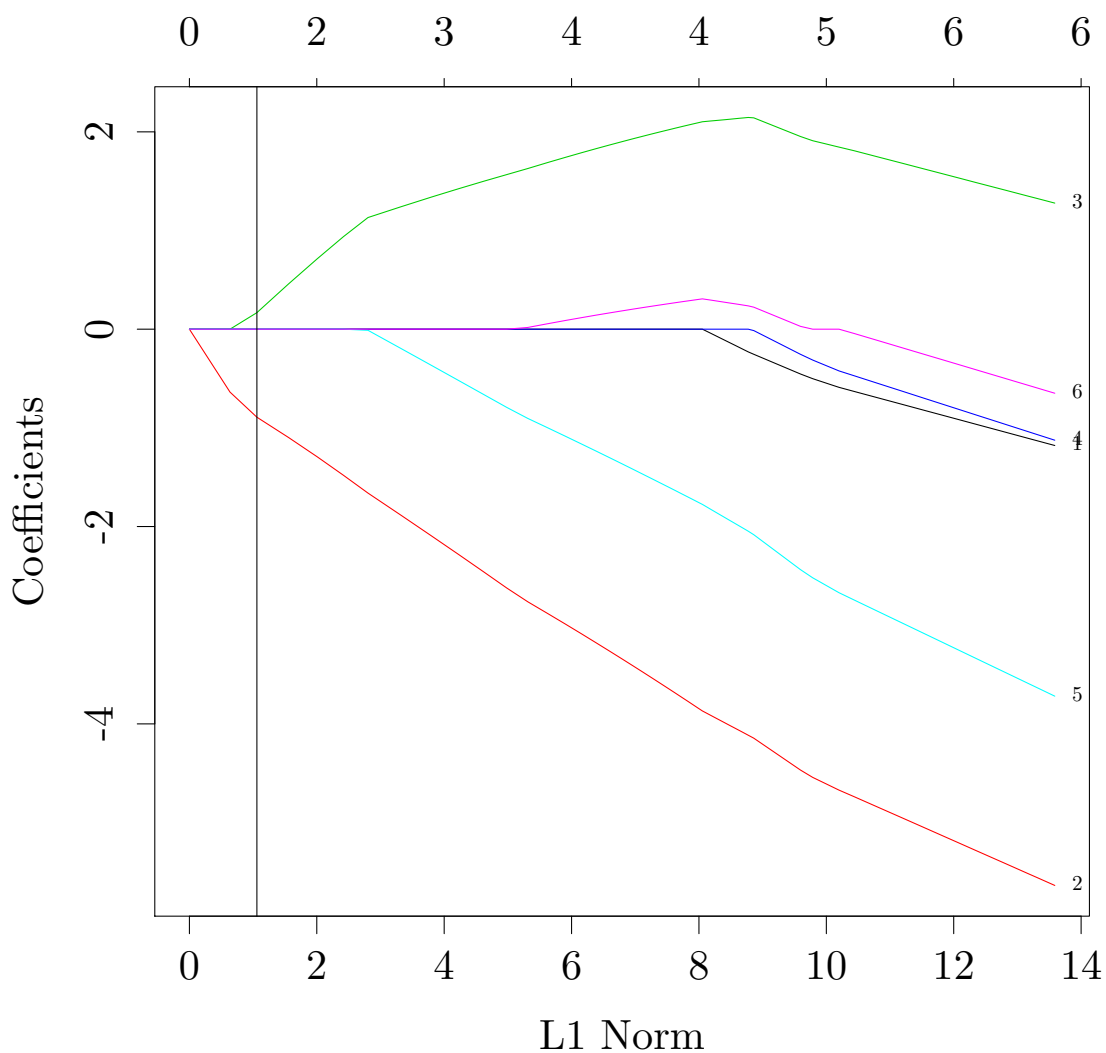
```
#abline(v = sum(abs(coef(glmnet.fit.cv.diag_rec$glmnet.fit, s = glmnet.fit.cv.diag_rec$lambda.min))))
coef(glmnet.fit.cv.diag_rec$glmnet.fit, s = glmnet.fit.cv.diag_rec$lambda.1se)

## 6 x 1 sparse Matrix of class "dgCMatrix"
##      1
## V1  2.7555
## V2 -0.9230
## V3   .
## V4   .
## V5 -0.9055
## V6   .

plot(glmnet.fit.cv.recr_dsd)
```



```
plot(glmnet.fit.cv.recr_dsd$glmnet.fit, label = TRUE)
abline(v = sum(abs(coef(glmnet.fit.cv.recr_dsd$glmnet.fit, s = glmnet.fit.cv.recr_dsd$lambda.1se))))
```



```
#abline(v = sum(abs(coef(glmnet.fit.cv.recr_dsd$glmnet.fit, s = glmnet.fit.cv.recr_dsd$lambda.min))))
coef(glmnet.fit.cv.recr_dsd$glmnet.fit, s = glmnet.fit.cv.recr_dsd$lambda.1se)

## 6 x 1 sparse Matrix of class "dgCMatrix"
##      1
## V1  .
## V2 -0.8920
## V3  0.1676
## V4  .
## V5  .
## V6  .
```

4.3 Prediction on validation sets

```
load("../data/15_validation.rda")
```

```
val.basis = basis(nmf.final)
rownames(GSE21501.lingex) = GSE21501.feats$Gene.symbol
rownames(GSE28735.lingex) = GSE28735.feats$Gene.symbol
GSE21501.lingex.for_basis = GSE21501.lingex[match(rownames(val.basis), rownames(GSE21501.lingex)),]
GSE28735.lingex.for_basis = GSE28735.lingex[match(rownames(val.basis), rownames(GSE28735.lingex)),]
GSE21501.lingex.for_basis[is.na(GSE21501.lingex.for_basis)] = 0
GSE28735.lingex.for_basis[is.na(GSE28735.lingex.for_basis)] = 0

GSE21501.coefs = apply(GSE21501.lingex.for_basis, 2, function(xcol) nnls(val.basis, xcol)$x)
GSE28735.coefs = apply(GSE28735.lingex.for_basis, 2, function(xcol) nnls(val.basis, xcol)$x)

GSE21501.axis1 = GSE21501.coefs[1,] - GSE21501.coefs[5,]
GSE21501.axis2 = GSE21501.coefs[6,] - GSE21501.coefs[2,]
GSE28735.axis1 = GSE28735.coefs[1,] - GSE28735.coefs[5,]
GSE28735.axis2 = GSE28735.coefs[6,] - GSE28735.coefs[2,]

GSE21501.score = 1.354*GSE21501.axis1 + 1.548*GSE21501.axis2
GSE28735.score = 1.354*GSE28735.axis1 + 1.548*GSE28735.axis2

GSE21501.pcna = apply(GSE21501.gex[match(metapcna.sig, GSE21501.feats$Gene.symbol),], 2, median, na.rm =
GSE28735.pcna = apply(GSE28735.gex[match(metapcna.sig, GSE28735.feats$Gene.symbol),], 2, median, na.rm =
```

```
temp = coxph(Surv(GSE21501.samp$time, GSE21501.samp$event) ~ GSE21501.score)
summary(temp)
```

```
## Call:
## coxph(formula = Surv(GSE21501.samp$time, GSE21501.samp$event) ~
##      GSE21501.score)
##
##      n= 102, number of events= 66
##
##              coef exp(coef) se(coef)      z Pr(>|z|)
## GSE21501.score 1.81      6.13      1.14 1.59      0.11
##
##              exp(coef) exp(-coef) lower .95 upper .95
## GSE21501.score      6.13      0.163      0.655      57.3
##
## Concordance= 0.577 (se = 0.042 )
## Rsquare= 0.024 (max possible= 0.993 )
## Likelihood ratio test= 2.49 on 1 df,  p=0.115
## Wald test              = 2.52 on 1 df,  p=0.112
## Score (logrank) test = 2.54 on 1 df,  p=0.111
```

```
temp = coxph(Surv(GSE28735.samp$time, GSE28735.samp$event) ~ GSE28735.score)
summary(temp)
```

```
## Call:
## coxph(formula = Surv(GSE28735.samp$time, GSE28735.samp$event) ~
##      GSE28735.score)
##
```

```
## n= 42, number of events= 29
##
##          coef exp(coef) se(coef)      z Pr(>|z|)
## GSE28735.score 1.867      6.471    0.752 2.48    0.013
##
##          exp(coef) exp(-coef) lower .95 upper .95
## GSE28735.score      6.47      0.155      1.48      28.2
##
## Concordance= 0.655 (se = 0.064 )
## Rsquare= 0.132 (max possible= 0.981 )
## Likelihood ratio test= 5.92 on 1 df, p=0.0149
## Wald test = 6.17 on 1 df, p=0.013
## Score (logrank) test = 6.46 on 1 df, p=0.011

anova(coxph(Surv(GSE21501.samp$time, GSE21501.samp$event) ~ GSE21501.axis1 + GSE21501.axis2))

## Analysis of Deviance Table
## Cox model: response is Surv(GSE21501.samp$time, GSE21501.samp$event)
## Terms added sequentially (first to last)
##
##          loglik Chisq Df Pr(>|Chi|)
## NULL          -255
## GSE21501.axis1 -254  1.44  1      0.23
## GSE21501.axis2 -254  1.09  1      0.30

anova(coxph(Surv(GSE28735.samp$time, GSE28735.samp$event) ~ GSE28735.axis1 + GSE28735.axis2))

## Analysis of Deviance Table
## Cox model: response is Surv(GSE28735.samp$time, GSE28735.samp$event)
## Terms added sequentially (first to last)
##
##          loglik Chisq Df Pr(>|Chi|)
## NULL          -83.1
## GSE28735.axis1 -81.4  3.43  1      0.064
## GSE28735.axis2 -80.2  2.51  1      0.113
```

```
load("../data/validation/tcga-clin-gex.20141118.rda")
```

```
doValForSingleCancer = function(cancer_id)
{
  # nevents, ntotal, score_p, anova_pcna, anova_score, anova_axis1, anova_axis2
  message(cancer_id)
  cancer_data = data.merged[[cancer_id]]
  if (!"illumina_hiseq_rnaseqv2" %in% names(cancer_data$gex)) { return(c(0, 0, NA, NA, NA, NA, NA)) }

  gex = cancer_data$gex$illumina_hiseq_rnaseqv2
  clin = cancer_data$clin

  days_to_death = clin$days_to_death
  days_to_death[days_to_death == "[Not Applicable]"] = NA
  days_to_death = as.numeric(as.character(days_to_death))

  days_to_initial_pathologic_diagnosis = clin$days_to_initial_pathologic_diagnosis
```

}

```

val_pvals = sapply(names(data.merged), doValForSingleCancer)

## acc
## blca
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## brca
## cesc
## coad
## dlbc
## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Loglik converged
before variable 1,2 ; beta may be infinite.
## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Loglik converged
before variable 1,2 ; beta may be infinite.
## gbm
## hnsc
## kich
## kirc
## kirp
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## lgg
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## lihc
## luad
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## lusc
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## meso
## ov
## paad
## prad
## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Ran out of
iterations and did not converge
## Warning in fitter(X, Y, strats, offset, init, control, weights = weights, : Ran out of
iterations and did not converge
## read
## sarc
## skcm
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion
## thca
## ucec
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hnsc", : NAs introduced
by coercion

```



```
## Warning in FUN(c("acc", "blca", "brca", "cesc", "coad", "dlbc", "gbm", "hns", : NAs introduced
by coercion
## ucs

rownames(val_pvals) = c("nevents", "ntotal", "p.score", "p.anova.pcna", "p.anova.pcna_score", "p.anova.a
val_pvals = as.data.frame(t(val_pvals))

val_pvals[val_pvals$nevents >= 50 | rownames(val_pvals) == "paad",]

##      nevents ntotal   p.score p.anova.pcna p.anova.pcna_score
## gbm         54    143 2.287e-01    8.185e-01          0.1587102
## hns         124    367 8.075e-03    4.719e-01          0.0107907
## kirc         153    497 2.034e-12    9.569e-11          0.0028892
## lgg          53    272 1.493e-05    6.316e-04          0.0078542
## luad         106    431 8.336e-06    7.205e-03          0.0001042
## lusc         117    395 9.624e-01    7.035e-02          0.4109578
## ov          115    251 2.380e-02    5.903e-01          0.0178108
## paad         17     58 4.952e-03    8.549e-02          0.0239990
##      p.anova.axis1 p.anova.axis1_axis2
## gbm      9.252e-01          6.877e-02
## hns      4.367e-02          8.341e-02
## kirc      2.673e-08          1.639e-05
## lgg      1.593e-04          3.350e-02
## luad      1.238e-03          1.543e-03
## lusc      1.597e-01          2.559e-01
## ov       3.655e-01          3.298e-02
## paad      1.562e-02          1.249e-01
```

```
plot_km_axes = function(axis1, axis2, y, mc = FALSE, ...)
{
  t1 = t2 = 0
  if (mc == TRUE)
  {
    t1 = median(axis1, na.rm = TRUE)
    t2 = median(axis2, na.rm = TRUE)
  }

  class = paste(c("L", "H")[I(axis1 >= t1)+1], c("L", "H")[I(axis2 >= t2)+1], sep = "")
  class = ordered(class, levels = c("LL", "LH", "HL", "HH"))
  fit = survfit(y ~ class)
  print(fit)
  print(survdiff(y ~ class))
  pval = pchisq(survdiff(y ~ class)$chisq, 3, lower.tail = FALSE)
  pal = brewer.pal(4, "Set2")
  names(pal) = c("LL", "LH", "HL", "HH")
  plot(axis2 ~ axis1, xlab = "A1 activity", ylab = "A2 activity", col = pal[class], pch = 16, ...)
  abline(h = t2)
  abline(v = t1)
  #plot(fit, col = pal, lwd = 2, xlab = "Time from diagnosis (days)", ylab = "Fraction surviving")
  plot(fit$surv ~ fit$time, type = "n", ylim = c(0, 1), xlab = "Time from diagnosis (days)", ylab = "Fraction surviving")
  for (i in 1:length(fit$strata))
  {
    stratum_start = sum(fit$strata[1:i]) - fit$strata[i] + 1
```

```

        stratum_end = stratum_start + fit$strata[i] - 1
        stratum_surv = c(1, fit$urv[stratum_start:stratum_end])
        stratum_time = c(0, fit$time[stratum_start:stratum_end])
        lines(stratum_surv ~ stratum_time, col = pal[i], type = "s", ...)
    }
}

plot_km_axes_tcga = function(code, mc, ...)
{
    if ("illuminahisec_rnaseqv2" %in% names(data.merged[[code]]$gex))
    {
        temp.gex = data.merged[[code]]$gex$illuminahisec_rnaseqv2
        temp.gex = temp.gex[!grepl("^\\|?\\|\\|", rownames(temp.gex)),]
        rownames(temp.gex) = gsub("\\|\\|\\.?", "", rownames(temp.gex))
        temp.gex.axes = temp.gex[match(rownames(val.basis), rownames(temp.gex)),]
        temp.gex.axes[apply(is.na(temp.gex.axes), 1, all),] = 0
        temp.gex.axes = temp.gex.axes - apply(temp.gex.axes, 1, min, na.rm = TRUE)
        temp.gex.axes = temp.gex.axes / apply(temp.gex.axes, 1, max, na.rm = TRUE)
        temp.gex.axes[is.na(temp.gex.axes)] = 0
        temp.coefs = apply(temp.gex.axes, 2, function(xcol) nnls(val.basis, xcol)$x)
        temp.axis1 = temp.coefs[1,] - temp.coefs[5,]
        temp.axis2 = temp.coefs[6,] - temp.coefs[2,]

        temp.clin = data.merged[[code]]$clin
        temp.days_to_death = temp.clin$days_to_death
        temp.days_to_death[temp.days_to_death == "[Not Applicable]"] = NA
        temp.days_to_death = as.numeric(as.character(temp.days_to_death))
        temp.days_to_initial_pathologic_diagnosis = temp.clin$days_to_initial_pathologic_diagnosis
        temp.days_to_initial_pathologic_diagnosis[temp.days_to_initial_pathologic_diagnosis == "[Not Applicable]"] = NA
        temp.days_to_initial_pathologic_diagnosis = as.numeric(as.character(temp.days_to_initial_pathologic_diagnosis))
        temp.days_to_last_followup = temp.clin$days_to_last_followup
        temp.days_to_last_followup[temp.days_to_last_followup == "[Not Applicable]"] = NA
        temp.days_to_last_followup = as.numeric(as.character(temp.days_to_last_followup))
        temp.time_event = temp.days_to_death - temp.days_to_initial_pathologic_diagnosis
        temp.time_lfu = temp.days_to_last_followup - temp.days_to_initial_pathologic_diagnosis
        temp.time_obs = temp.time_event
        temp.time_obs[is.na(temp.time_obs)] = temp.time_lfu[is.na(temp.time_obs)]
        temp.time_obs[!is.na(temp.time_obs) & !is.na(temp.time_lfu)] = pmin(temp.time_obs[!is.na(temp.time_obs)], temp.time_lfu[!is.na(temp.time_lfu)])
        temp.event = (temp.time_event <= temp.time_lfu & !is.na(temp.time_event) & !is.na(temp.time_lfu))
        temp.y = Surv(temp.time_obs, temp.event)

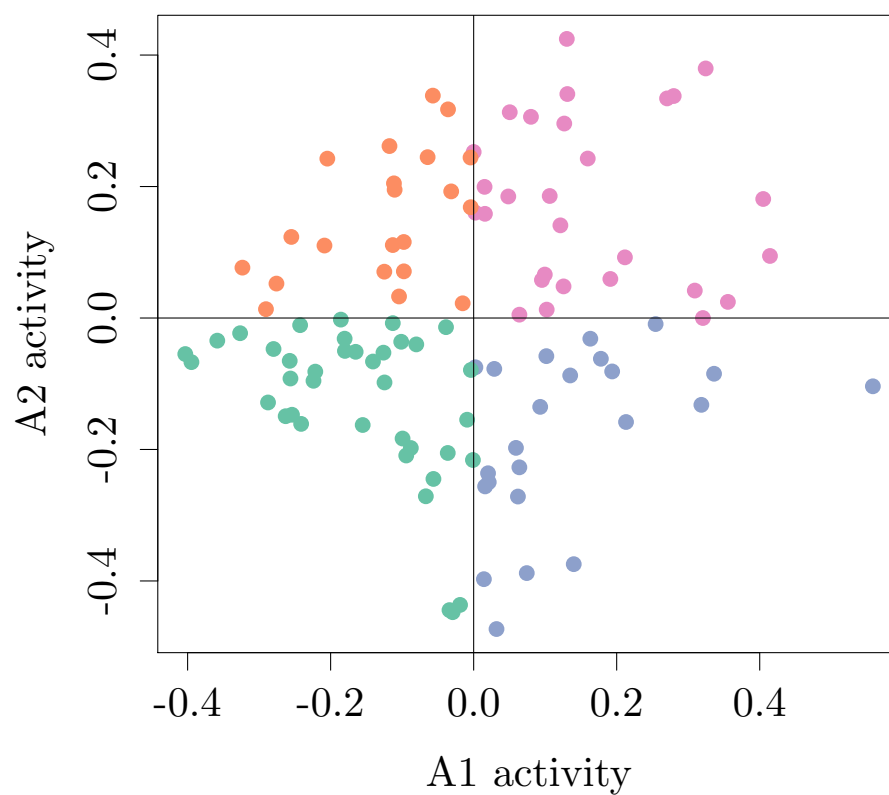
        plot_km_axes(temp.axis1, temp.axis2, temp.y, mc = FALSE, main = "", ...)
    }
}

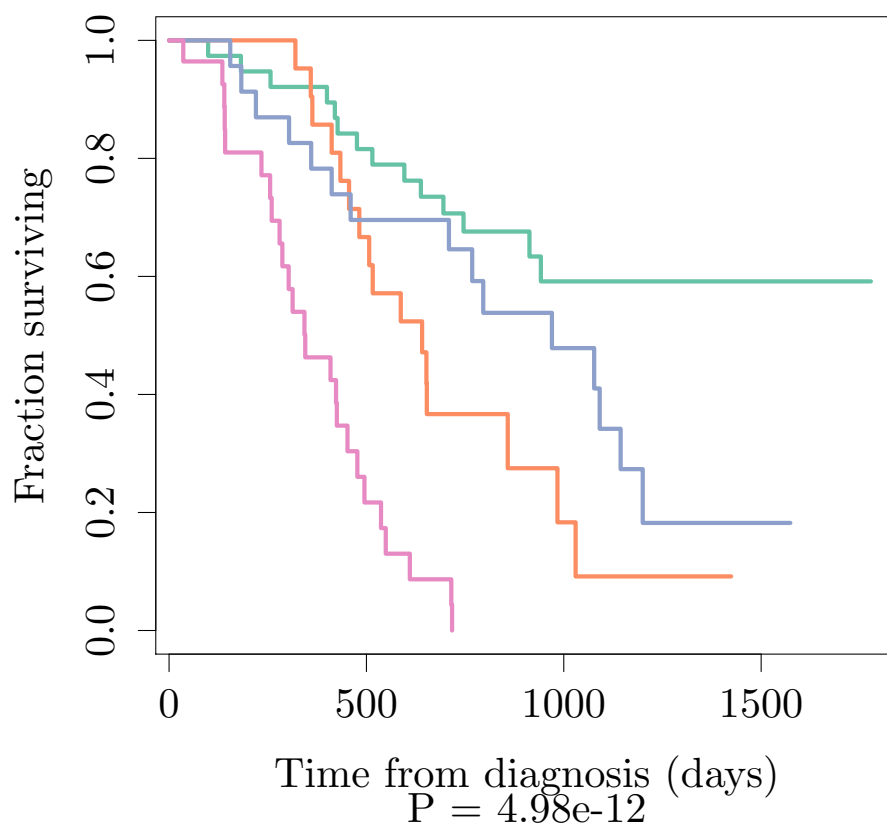
plot_km_axes(axis_coefs.diag_dsd[,1], axis_coefs.diag_dsd[,2], y.diag_dsd, mc = FALSE, main = "", lwd = 2)

## Call: survfit(formula = y ~ class)
##
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL       38   38     38     14     NA     913     NA
## class=LH       21   21     21     16    641     482     NA
## class=HL       23   23     23     15    970     709     NA
## class=HH       28   28     28     25    345     280     495

```

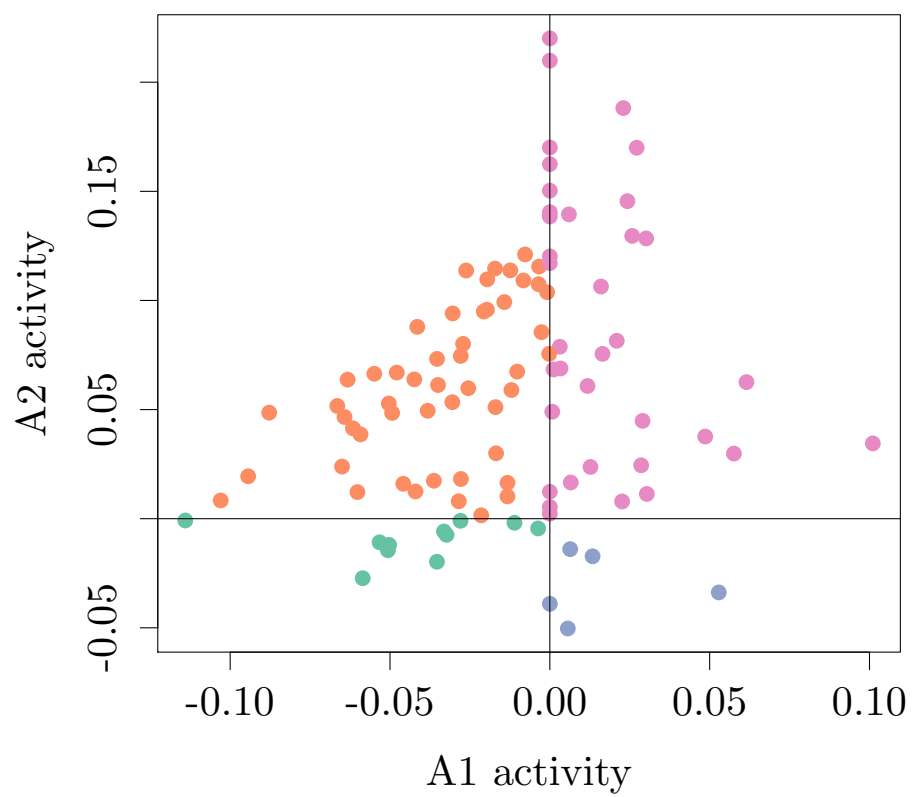
```
## Call:
## survdiff(formula = y ~ class)
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL 38      14   31.77    9.942   18.645
## class=LH 21      16   13.02    0.683    0.852
## class=HL 23      15   17.66    0.401    0.543
## class=HH 28      25    7.55   40.376   48.292
##
## Chisq= 55.7  on 3 degrees of freedom, p= 4.98e-12
```

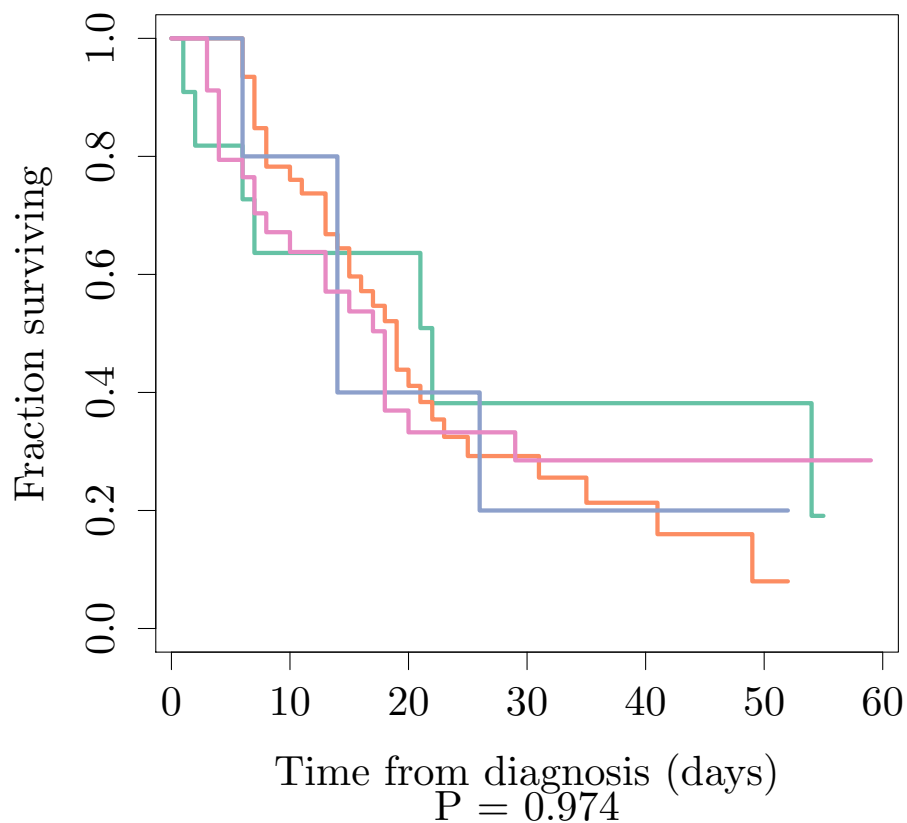




```
plot_km_axes(GSE21501.axis1, GSE21501.axis2, Surv(GSE21501.samp$time, GSE21501.samp$event), mc = FALSE,

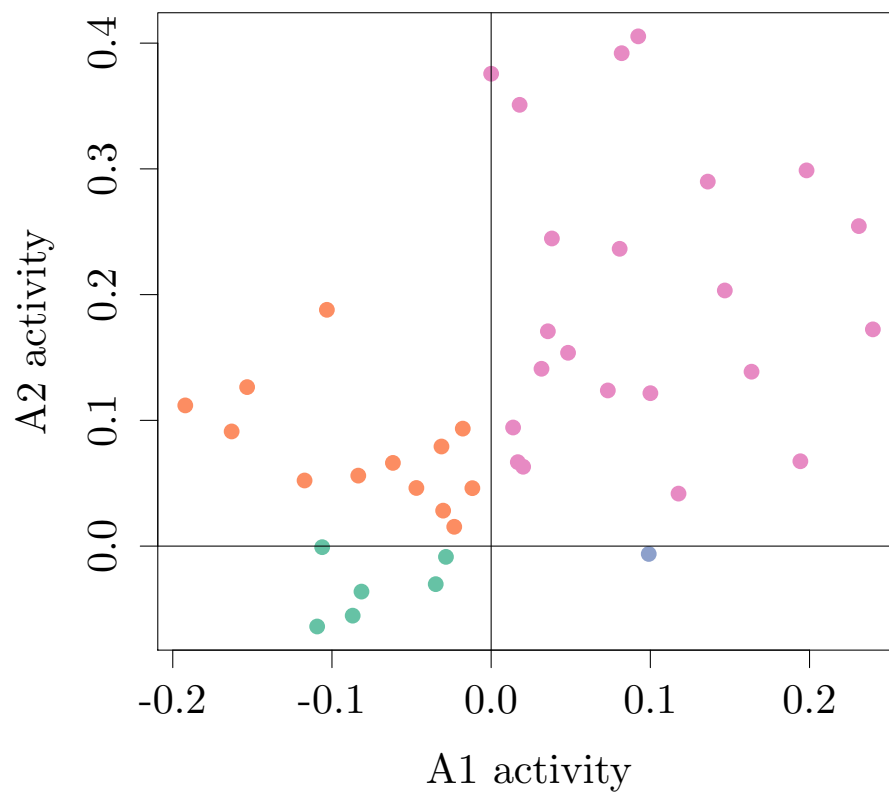
## Call: survfit(formula = y ~ class)
##
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL         11    11      11      7      22      7      NA
## class=LH         50    50      50     33      19     15     25
## class=HL          5     5        5      4      14     14     NA
## class=HH         36    36      36     22      18     10     NA
## Call:
## survdiff(formula = y ~ class)
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL 11         7      8.12  1.56e-01  1.95e-01
## class=LH 50        33     32.96  3.96e-05  8.43e-05
## class=HL  5         4      3.91  2.27e-03  2.53e-03
## class=HH 36        22     21.01  4.71e-02  7.23e-02
##
## Chisq= 0.2  on 3 degrees of freedom, p= 0.974
```

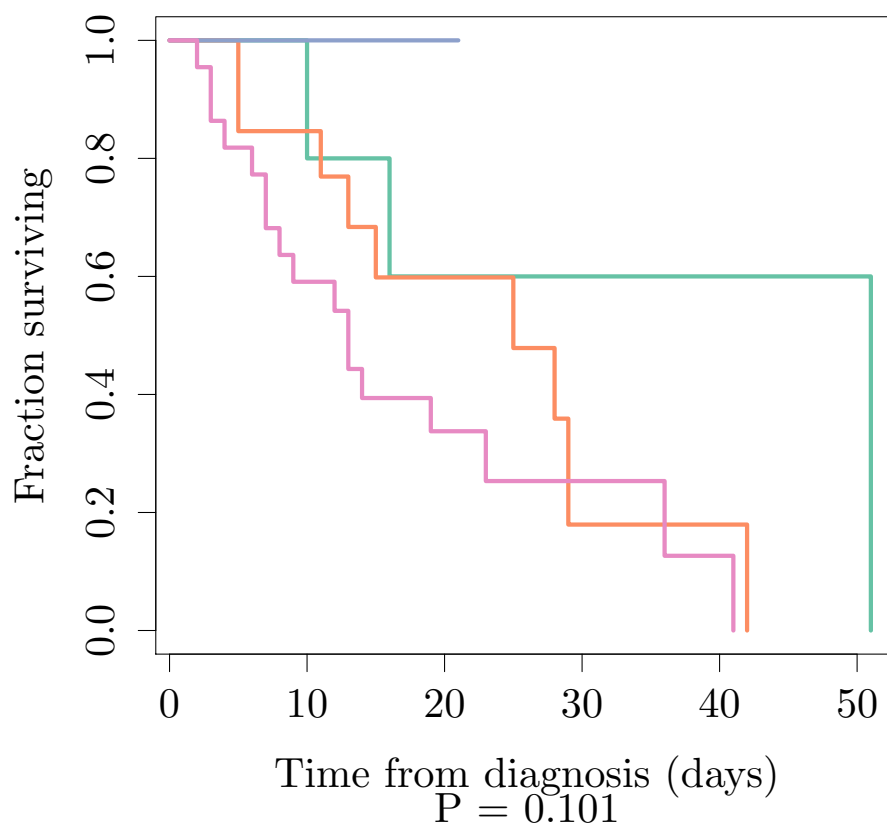




```
plot_km_axes(GSE28735.axis1, GSE28735.axis2, Surv(GSE28735.samp$time, GSE28735.samp$event), mc = FALSE,

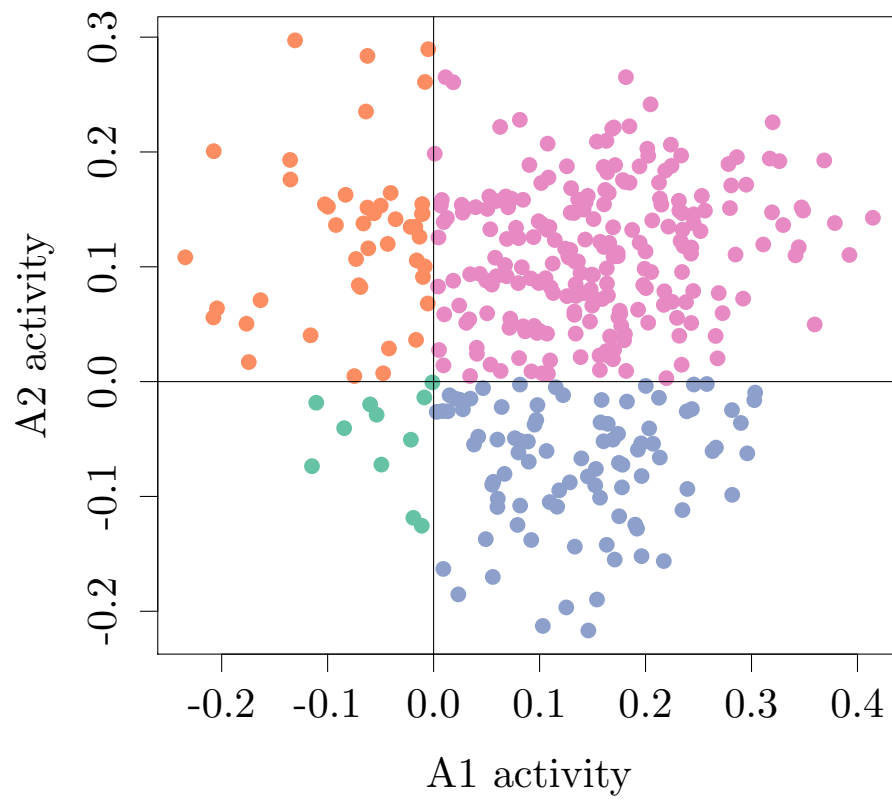
## Call: survfit(formula = y ~ class)
##
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL         6     6       6      3     51      16     NA
## class=LH        13    13      13      9     25      13     NA
## class=HL         1     1       1      0     NA      NA     NA
## class=HH        22    22      22     17     13       8     NA
## Call:
## survdiff(formula = y ~ class)
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL   6         3   6.651   2.004   3.168
## class=LH  13         9  10.078   0.115   0.186
## class=HL   1         0   0.735   0.735   0.779
## class=HH  22        17  11.536   2.588   4.733
##
## Chisq= 6.2  on 3 degrees of freedom, p= 0.101
```

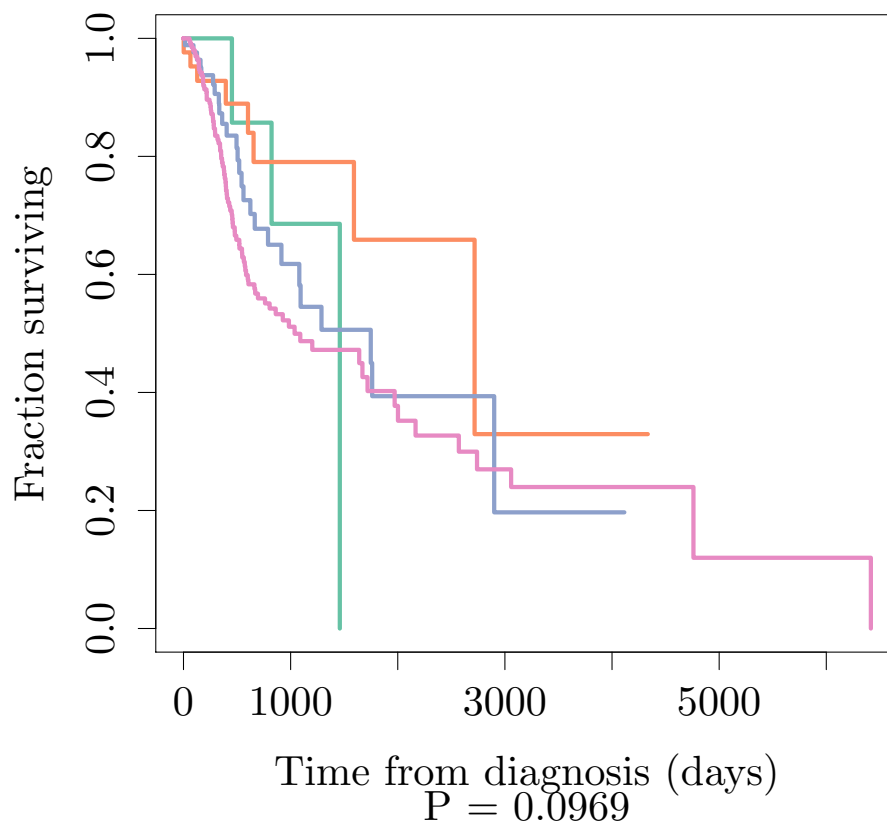




```
plot_km_axes_tcga("hnscc", mc = FALSE, lwd = 4, cex = 1.2)

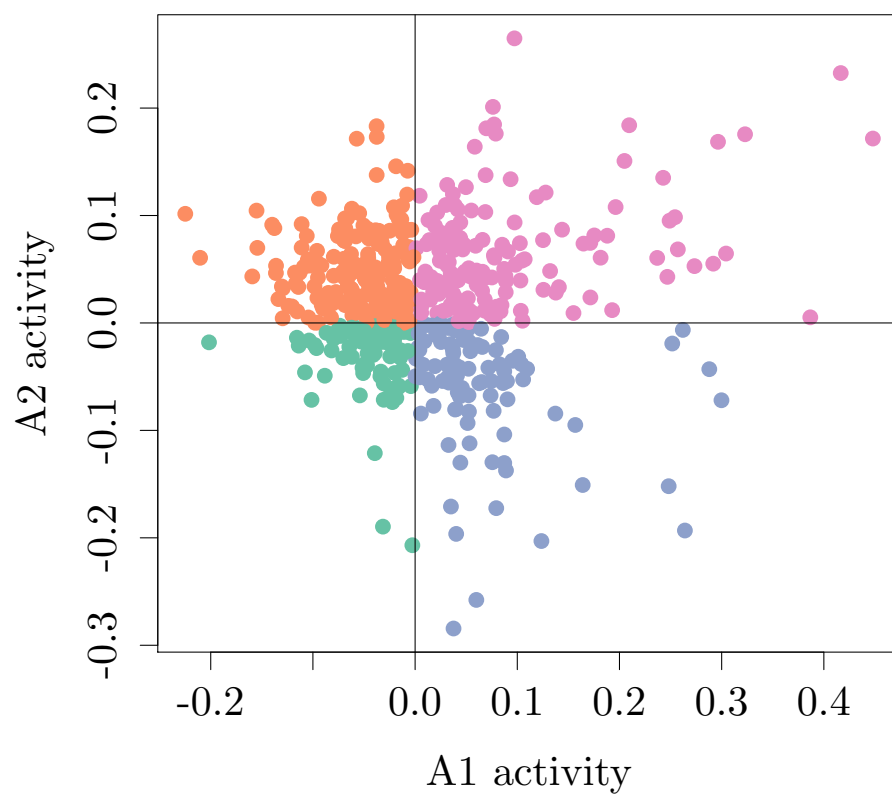
## Call: survfit(formula = y ~ class)
##
##      1 observation deleted due to missingness
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL      11      11       11      3  1459      822      NA
## class=LH      43      43       43      8  2717     1591      NA
## class=HL      90      90       90     26  1748      914      NA
## class=HH     223     223      223     87  1037      669     2002
## Call:
## survdiff(formula = y ~ class)
##
## n=367, 1 observation deleted due to missingness.
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL  11         3      3.77    0.156    0.162
## class=LH  43         8     15.60    3.700    4.249
## class=HL  90        26     29.68    0.457    0.606
## class=HH 223        87     74.95    1.936    4.969
##
## Chisq= 6.3  on 3 degrees of freedom, p= 0.0969
```

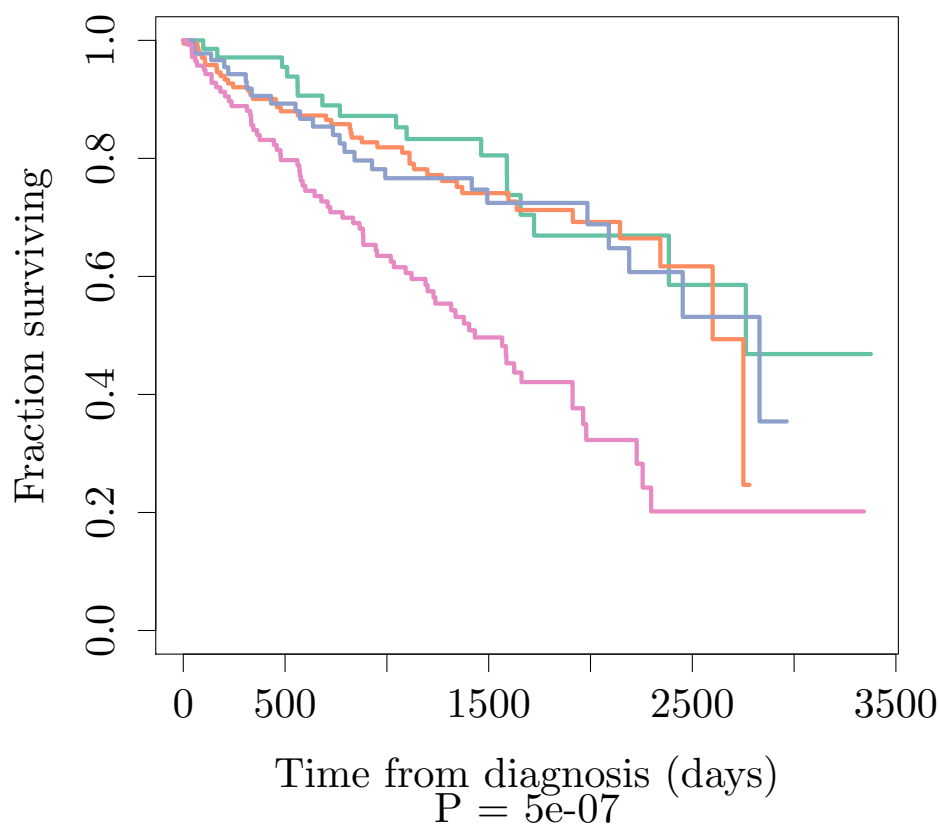





```
plot_km_axes_tcga("kirc", mc = FALSE, lwd = 4, cex = 1.2)

## Call: survfit(formula = y ~ class)
##
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL         77    77      77     17  2763    2385     NA
## class=LH        179   179     179     42  2600    2343     NA
## class=HL         96    96      96     25  2830    2190     NA
## class=HH        146   146     146     69  1432    1200    1964
## Call:
## survdiff(formula = y ~ class)
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL  77      17    26.8      3.59      4.39
## class=LH 179      42    55.3      3.21      5.08
## class=HL  96      25    32.0      1.54      1.96
## class=HH 146      69    38.8     23.44     31.71
##
## Chisq= 32.1 on 3 degrees of freedom, p= 5e-07
```

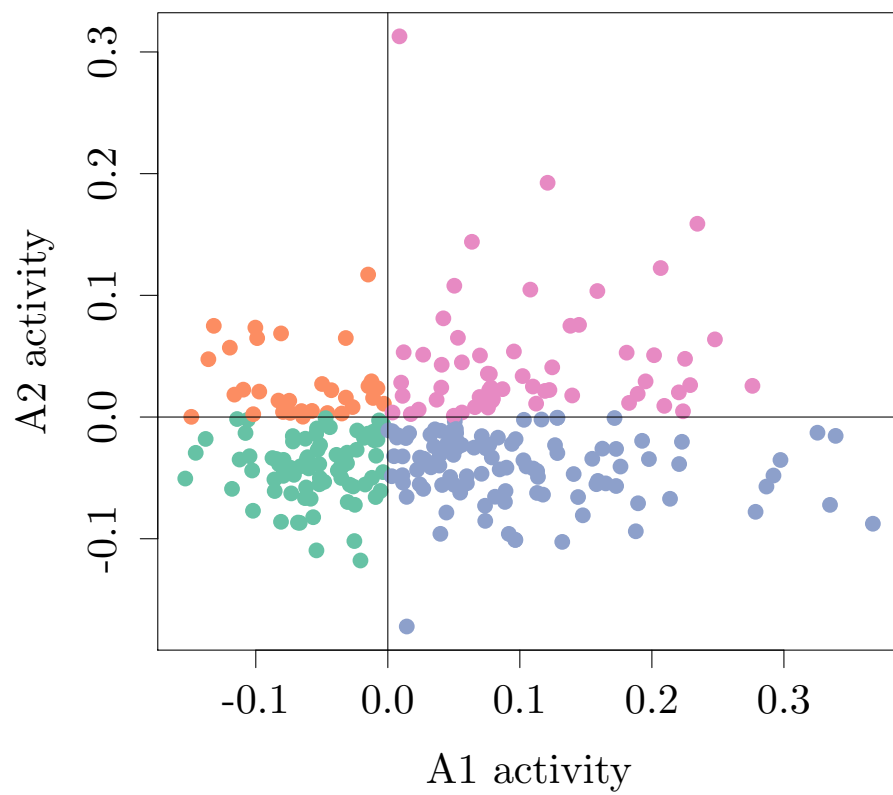


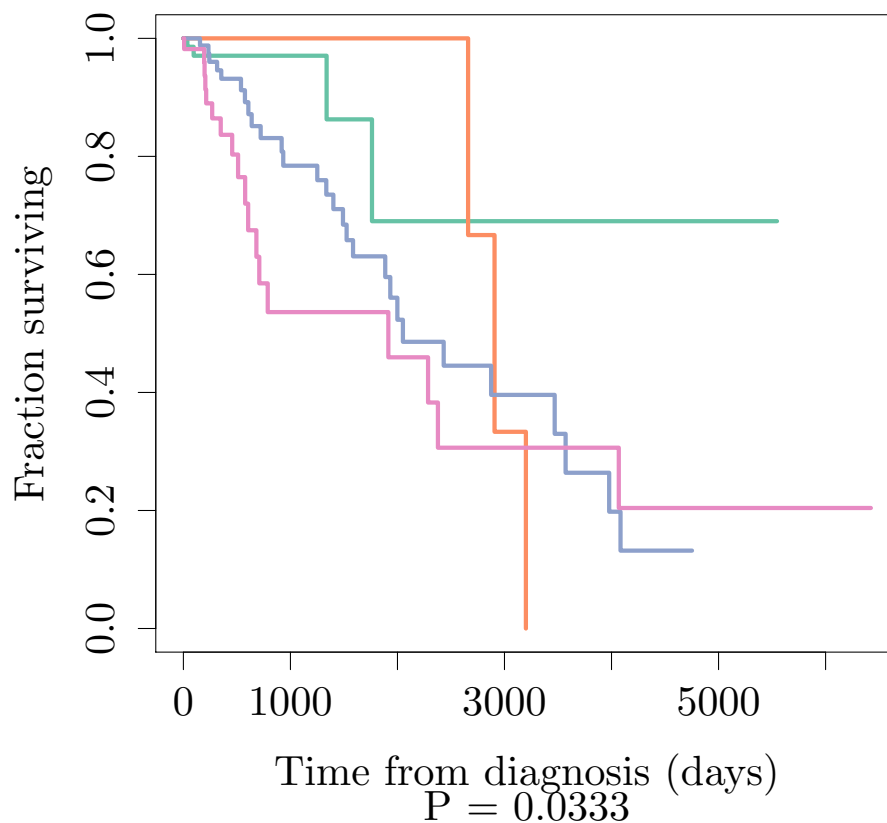


```
plot_km_axes_tcga("lgg", mc = FALSE, lwd = 4, cex = 1.2)

## Warning in plot_km_axes_tcga("lgg", mc = FALSE, lwd = 4, cex = 1.2): NAs introduced by coercion

## Call: survfit(formula = y ~ class)
##
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL         77    77      77      4      NA    1762      NA
## class=LH         32    32      32      3    2907    2660      NA
## class=HL        106   106     106     28    2051    1886    3978
## class=HH         57    57      57     18    1915     682      NA
## Call:
## survdiff(formula = y ~ class)
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL  77         4      9.86      3.479      4.389
## class=LH  32         3      5.38      1.055      1.191
## class=HL 106        28     26.36      0.102      0.207
## class=HH  57        18     11.40      3.815      4.950
##
## Chisq= 8.7  on 3 degrees of freedom, p= 0.0333
```



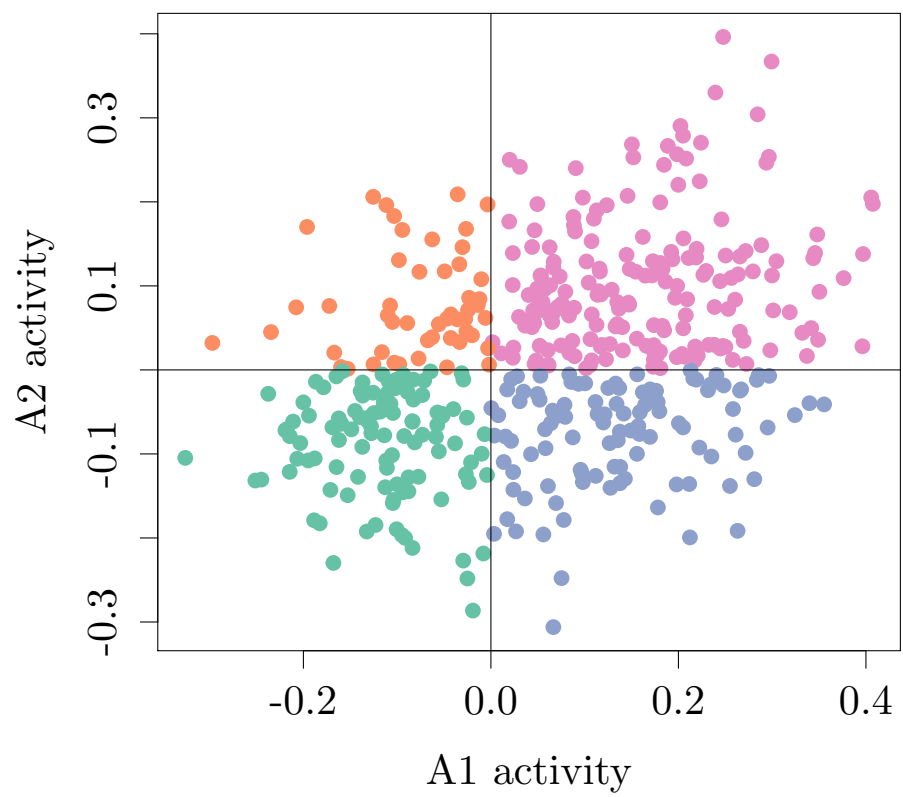


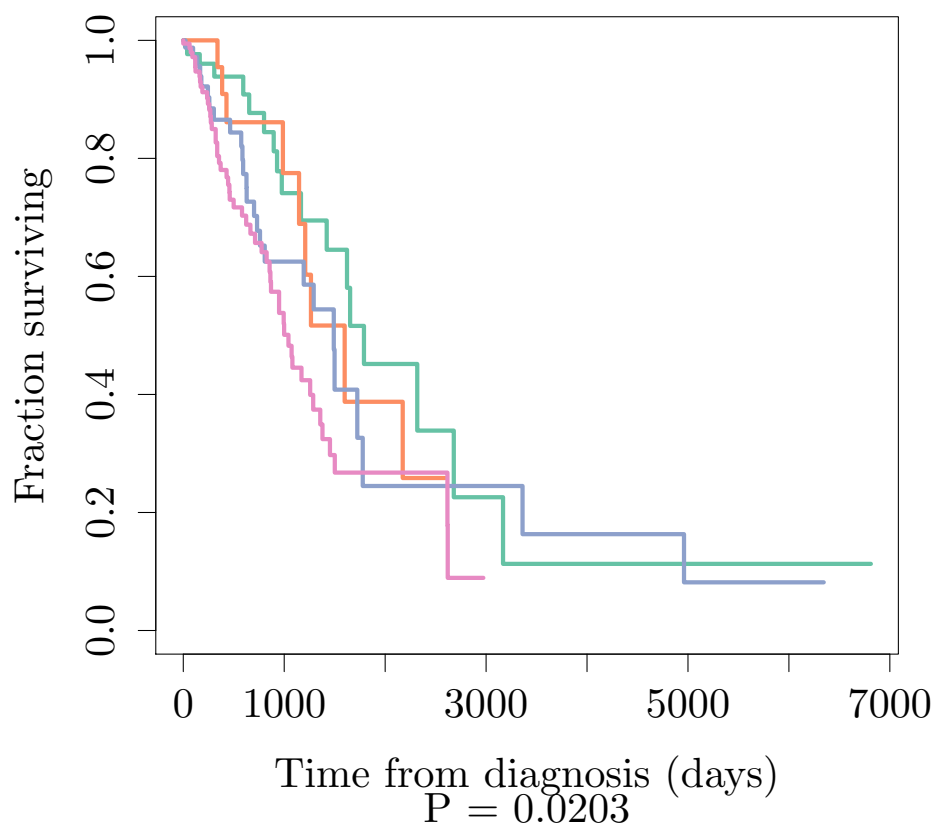
```
plot_km_axes_tcga("luad", mc = FALSE, lwd = 4, cex = 1.2)

## Warning in plot_km_axes_tcga("luad", mc = FALSE, lwd = 4, cex = 1.2): NAs introduced by coercion

## Call: survfit(formula = y ~ class)
##
##      19 observations deleted due to missingness
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL      102   102    102     18   1790    1421     NA
## class=LH       49    49     49      9   1599    1147     NA
## class=HL       98    98     98     26   1491     807     NA
## class=HH      182   182    182     53   1042     863    1379
## Call:
## survdiff(formula = y ~ class)
##
## n=431, 19 observations deleted due to missingness.
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL 102      18    28.0   3.5523    4.875
## class=LH  49       9    11.9   0.6911    0.786
## class=HL  98      26    27.5   0.0801    0.112
## class=HH 182     53    38.7   5.2967    8.567
##
```

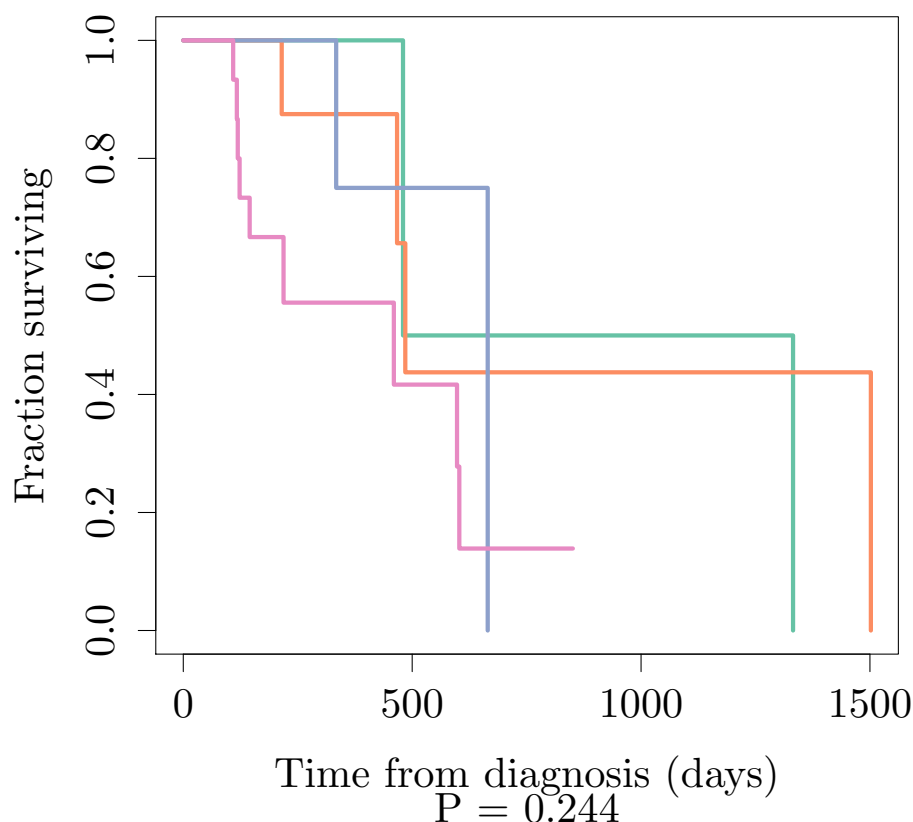
Chisq= 9.8 on 3 degrees of freedom, p= 0.0203





```
plot_km_axes_tcga("paad", mc = FALSE, lwd = 4, cex = 1.2)

## Call: survfit(formula = y ~ class)
##
##           records n.max n.start events median 0.95LCL 0.95UCL
## class=LL         9     9       9      2   906     480     NA
## class=LH        19    19      19      4   485     467     NA
## class=HL         9     9       9      2   665     334     NA
## class=HH        21    21      21      9   460     145     NA
## Call:
## survdiff(formula = y ~ class)
##
##           N Observed Expected (O-E)^2/E (O-E)^2/V
## class=LL   9         2    3.13    0.408    0.536
## class=LH  19         4    5.86    0.592    1.052
## class=HL   9         2    2.71    0.187    0.233
## class=HH  21         9    5.29    2.593    4.105
##
## Chisq= 4.2  on 3 degrees of freedom, p= 0.244
```

```
sig.emt_groger_pos = c("ADAM12", "COL1A1", "COL3A1", "COL5A1", "COL6A1", "COL6A3", "CTGF", "CYP1B1", "DI
sig.emt_groger_neg = c("CD24", "CXCL16", "DSG3", "ELF3", "EPCAM", "EPHA1", "JUP", "MPZL2", "OVOL2", "PLXNB1", "S10
x.medcent = x - apply(x, 1, median)
emt.scores.pos = apply(x.medcent[rownames(x.medcent) %in% sig.emt_groger_pos,], 2, median)
emt.scores.neg = apply(x.medcent[rownames(x.medcent) %in% sig.emt_groger_neg,], 2, median)
emt.scores = emt.scores.pos - emt.scores.neg
```

4.4 MSigDB score correlation thresholding

```
axis_coefs.msigdb.corr = cor(axis_coefs.diag_dsd, t(sigs), method = "kendall")

temp.sel_cols = apply(abs(axis_coefs.msigdb.corr) >= sig.corr.threshold, 2, any)
#heatmap.2(axis_coefs.msigdb.corr[, temp.sel_cols], trace = "none", scale = "none", useRaster = TRUE, co
#heatmap.2(axis_coefs.msigdb.corr[, temp.sel_cols], trace = "none", scale = "none", useRaster = TRUE, co

cpv.pvals = apply(axis_coefs.diag_dsd, 2, function(mg) sapply(cbind(cpv.diag_dsd, purity = samp.diag_co
  s = !is.na(mg) & !is.na(x)
  x = x[s]
  mg = mg[s]
  if (any(c("numeric", "integer") %in% class(x)))
  {
```

```

        return(cor.test(x, mg, method = "pearson")$p.value)
    }
    else if (any(c("factor", "ordered", "logical") %in% class(x)) && length(unique(x)) > 1)
    {
        return(anova(lm(mg ~ x))[, "Pr(>F)"][1])
    }
    NA
}))
cpv.pvals = cpv.pvals[!apply(is.na(cpv.pvals), 1, all),]
cpv.pvals = cpv.pvals[!grepl("^Surv\\.", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^Treat\\.", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^Path\\.Nodes", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^Staging\\.Version", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^History\\.Recurrence$", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^History\\.Status$", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^History\\.Death\\.Cause$", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^Path\\.Grade$", rownames(cpv.pvals)),]
cpv.pvals = cpv.pvals[!grepl("^Path\\.TumourLocation$", rownames(cpv.pvals)),]

temp = as.vector(cpv.pvals)
temp = p.adjust(temp, "holm")
cpv.qvals = matrix(temp, nrow = nrow(cpv.pvals))
rownames(cpv.qvals) = rownames(cpv.pvals)
colnames(cpv.qvals) = colnames(cpv.pvals)

cpv.pvals

##
## Patient.Gender
## Patient.Ethnicity
## History.Smoking.PackYears
## History.Diagnosis.AgeAtYears
## Path.HistoType.Subtype
## Path.TumourSizeMm
## Path.Invasion.PN
## Path.Invasion.VS
## Staging.pM
## Staging.pN
## Staging.pT
## Staging.Stage
## History.Recurrence.Site.Peritoneum
## History.Recurrence.Site.PancRemnant
## History.Recurrence.Site.PancBed
## History.Recurrence.Site.Other
## History.Recurrence.Site.Omentum
## History.Recurrence.Site.Mesentery
## History.Recurrence.Site.LymphNodes
## History.Recurrence.Site.Lung
## History.Recurrence.Site.Liver
## History.Recurrence.Site.Brain
## History.Recurrence.Site.Bone
## Path.Grade.Coarse
## Path.TumourLocation.Coarse
## purity

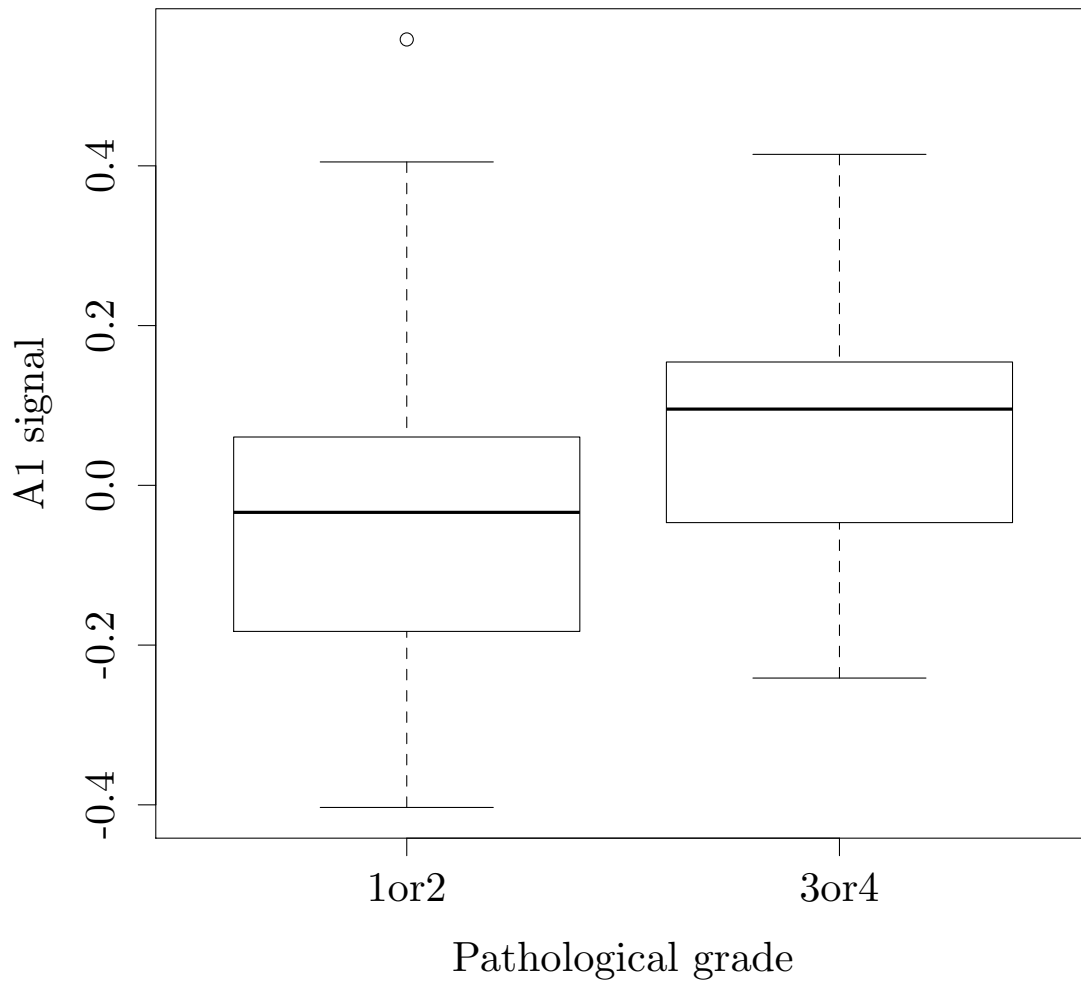
```

| | axis1 | axis2 |
|--|-----------|-----------|
| ## Patient.Gender | 0.1581541 | 0.0098535 |
| ## Patient.Ethnicity | 0.7711156 | 0.1130046 |
| ## History.Smoking.PackYears | 0.3562152 | 0.2753851 |
| ## History.Diagnosis.AgeAtYears | 0.9250804 | 0.6658699 |
| ## Path.HistoType.Subtype | 0.6966533 | 0.1569139 |
| ## Path.TumourSizeMm | 0.8438715 | 0.1709600 |
| ## Path.Invasion.PN | 0.0951996 | 0.2251091 |
| ## Path.Invasion.VS | 0.6500594 | 0.0707968 |
| ## Staging.pM | 0.4414498 | 0.4245233 |
| ## Staging.pN | 0.2524195 | 0.2629997 |
| ## Staging.pT | 0.2640385 | 0.4273685 |
| ## Staging.Stage | 0.0605854 | 0.2355348 |
| ## History.Recurrence.Site.Peritoneum | 0.9162045 | 0.0149891 |
| ## History.Recurrence.Site.PancRemnant | 0.5341395 | 0.1839586 |
| ## History.Recurrence.Site.PancBed | 0.8869735 | 0.5303110 |
| ## History.Recurrence.Site.Other | 0.1930828 | 0.1614602 |
| ## History.Recurrence.Site.Omentum | 0.1388378 | 0.0820434 |
| ## History.Recurrence.Site.Mesentery | 0.9326763 | 0.1206991 |
| ## History.Recurrence.Site.LymphNodes | 0.9332622 | 0.8703023 |
| ## History.Recurrence.Site.Lung | 0.3900712 | 0.7130517 |
| ## History.Recurrence.Site.Liver | 0.1596616 | 0.1046158 |
| ## History.Recurrence.Site.Brain | 0.4296978 | 0.0621650 |
| ## History.Recurrence.Site.Bone | 0.7889803 | 0.4128670 |
| ## Path.Grade.Coarse | 0.0023854 | 0.0001297 |
| ## Path.TumourLocation.Coarse | 0.1767526 | 0.1392750 |
| ## purity | 0.0002129 | 0.0004113 |

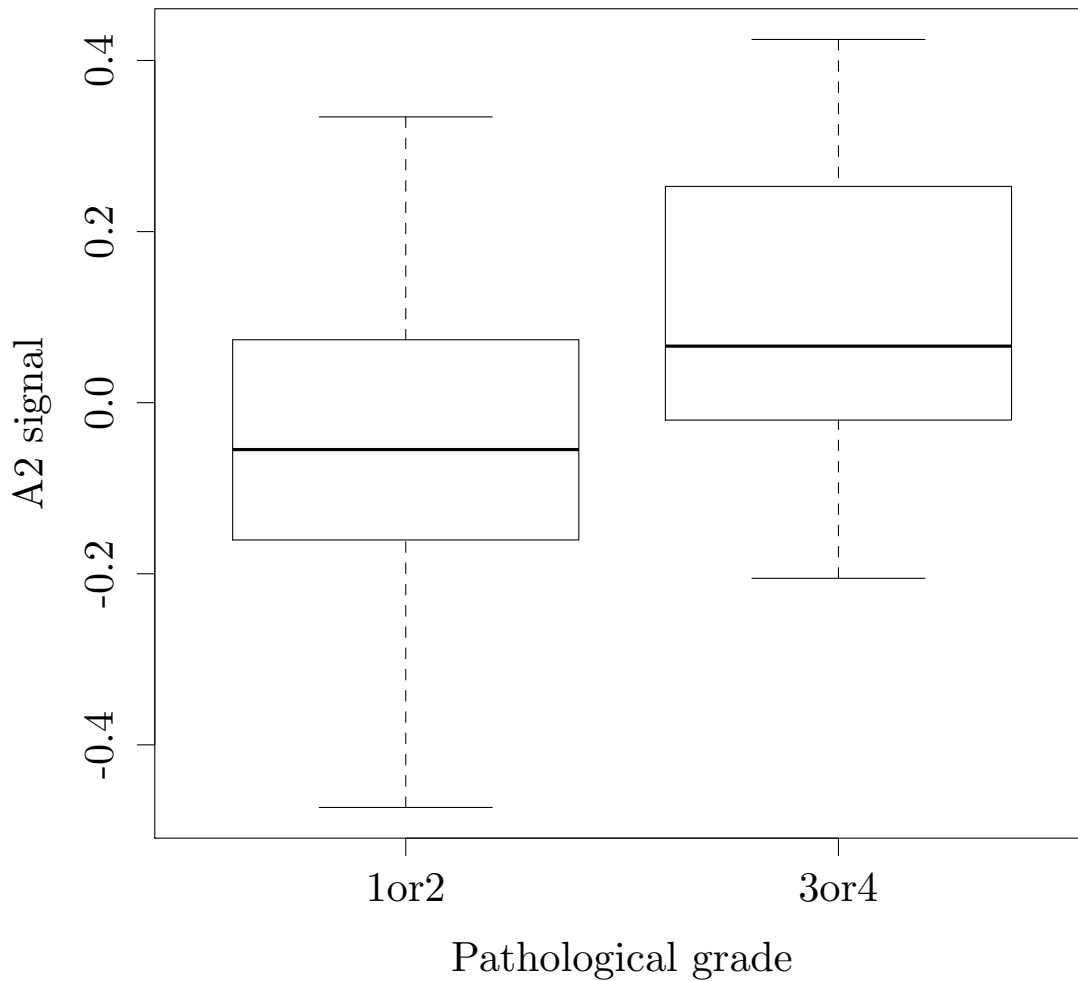
```
cpv.qvals
```

```
##                axis1    axis2
## Patient.Gender    1.00000 0.472968
## Patient.Ethnicity  1.00000 1.000000
## History.Smoking.PackYears 1.00000 1.000000
## History.Diagnosis.AgeAtYears 1.00000 1.000000
## Path.HistoType.Subtype 1.00000 1.000000
## Path.TumourSizeMm 1.00000 1.000000
## Path.Invasion.PN 1.00000 1.000000
## Path.Invasion.VS 1.00000 1.000000
## Staging.pM 1.00000 1.000000
## Staging.pN 1.00000 1.000000
## Staging.pT 1.00000 1.000000
## Staging.Stage 1.00000 1.000000
## History.Recurrence.Site.Peritoneum 1.00000 0.704486
## History.Recurrence.Site.PancRemnant 1.00000 1.000000
## History.Recurrence.Site.PancBed 1.00000 1.000000
## History.Recurrence.Site.Other 1.00000 1.000000
## History.Recurrence.Site.Omentum 1.00000 1.000000
## History.Recurrence.Site.Mesentery 1.00000 1.000000
## History.Recurrence.Site.LymphNodes 1.00000 1.000000
## History.Recurrence.Site.Lung 1.00000 1.000000
## History.Recurrence.Site.Liver 1.00000 1.000000
## History.Recurrence.Site.Brain 1.00000 1.000000
## History.Recurrence.Site.Bone 1.00000 1.000000
## Path.Grade.Coarse 0.11688 0.006743
## Path.TumourLocation.Coarse 1.00000 1.000000
## purity 0.01086 0.020564
```

```
boxplot(axis_coefs.diag_dsd[,1] ~ cpvs.diag_dsd$Path.Grade.Coarse, xlab = "Pathological grade", ylab = "Purity")
```



```
boxplot(axis_coefs.diag_dsd[,2] ~ cpvs.diag_dsd$Path.Grade.Coarse, xlab = "Pathological grade", ylab = 'A1 signal')
```



```
lm(axis_coefs.diag_dsd[,2] ~ cpvs.diag_dsd$Path.Grade.Coarse)

##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 2] ~ cpvs.diag_dsd$Path.Grade.Coarse)
##
## Coefficients:
##              (Intercept)  cpvs.diag_dsd$Path.Grade.Coarse.L
##                   0.0261                      0.1103

summary(lm(axis_coefs.diag_dsd[,2] ~ cpvs.diag_dsd$Path.Grade.Coarse))

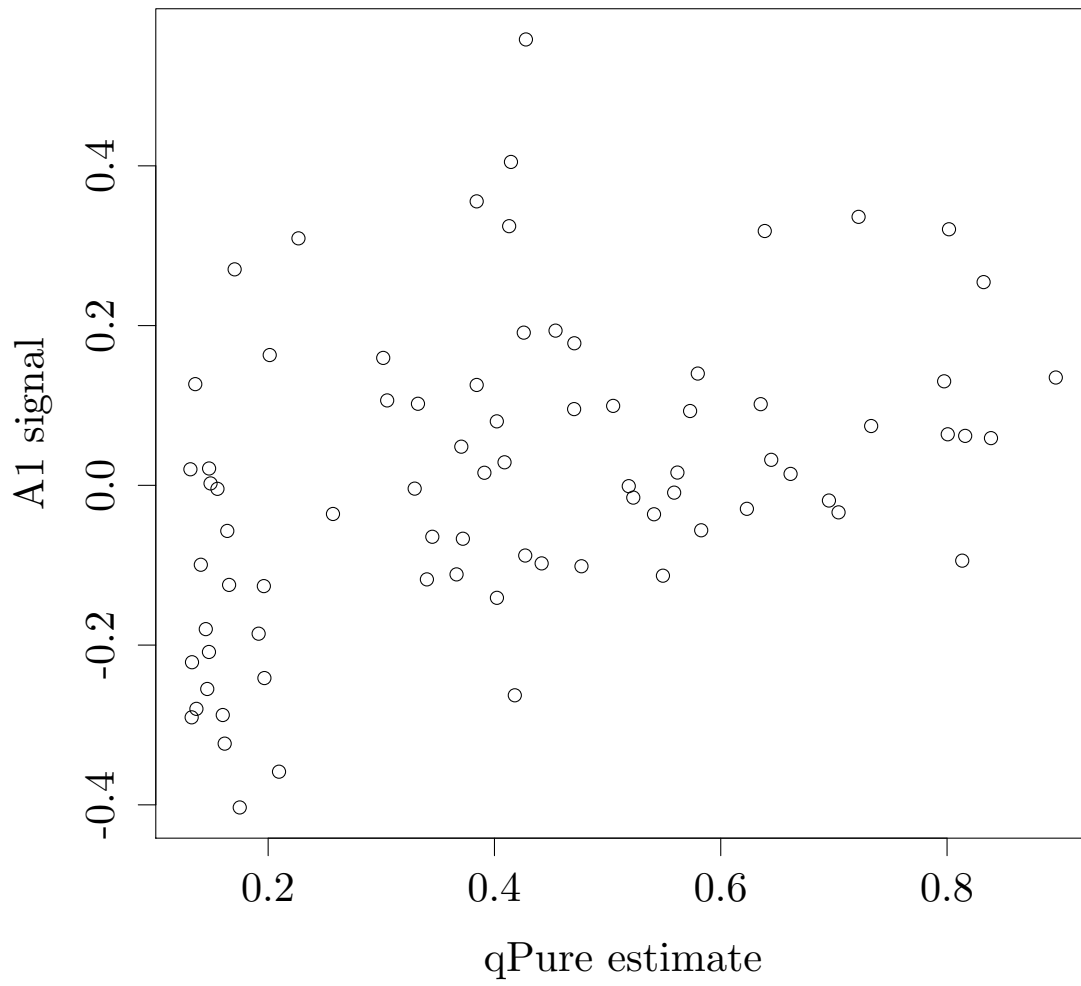
##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 2] ~ cpvs.diag_dsd$Path.Grade.Coarse)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -0.4212 -0.1130 -0.0137  0.1372  0.3860
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)          0.0261     0.0197    1.33  0.18771
## cpvs.diag_dsd$Path.Grade.Coarse.L  0.1103     0.0278    3.97  0.00013
##
## Residual standard error: 0.185 on 108 degrees of freedom
## Multiple R-squared:  0.127, Adjusted R-squared:  0.119
## F-statistic: 15.8 on 1 and 108 DF,  p-value: 0.00013

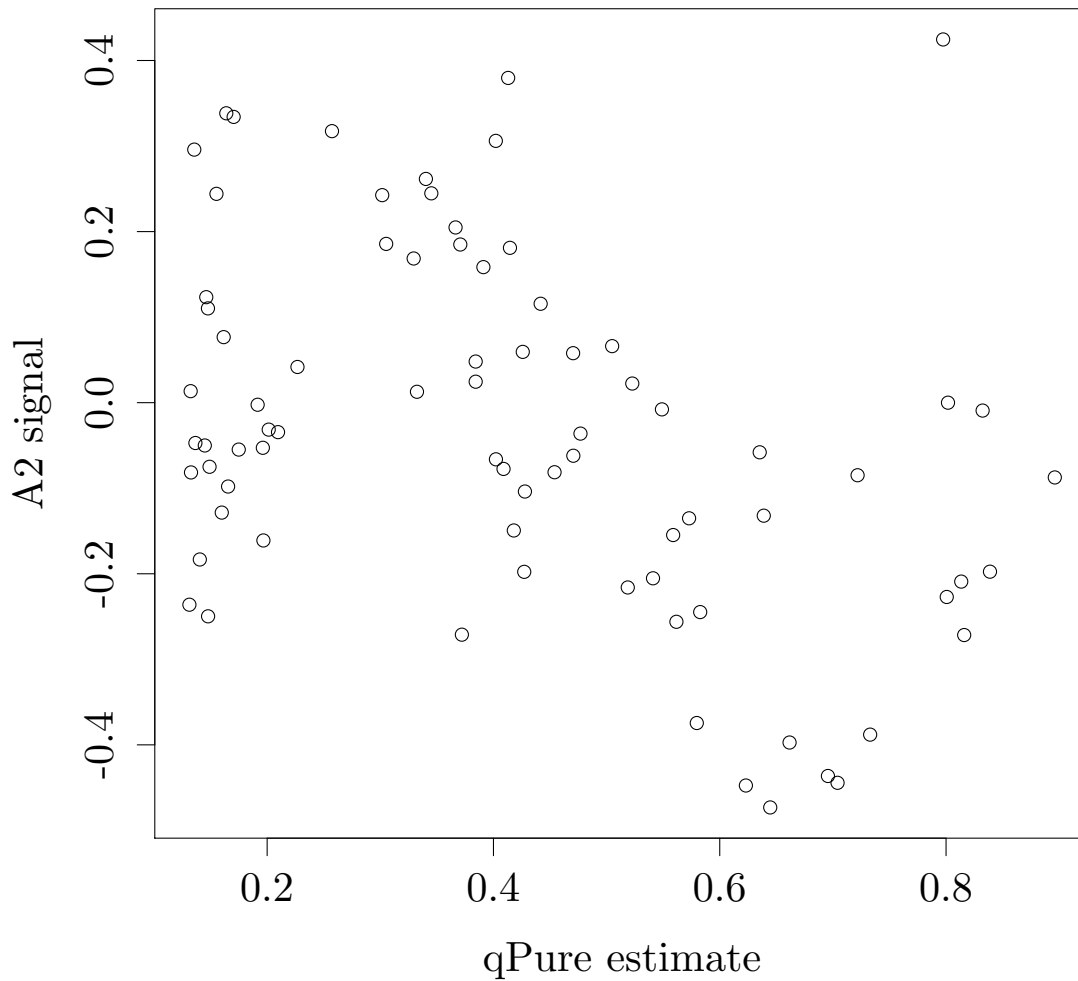
anova(lm(axis_coefs.diag_dsd[,2] ~ cpvs.diag_dsd$Path.Grade.Coarse))

## Analysis of Variance Table
##
## Response: axis_coefs.diag_dsd[, 2]
##                      Df Sum Sq Mean Sq F value  Pr(>F)
## cpvs.diag_dsd$Path.Grade.Coarse    1    0.54    0.542    15.8 0.00013
## Residuals                      108    3.71    0.034

plot(axis_coefs.diag_dsd[,1] ~ samps$purity_qpure, xlab = "qPure estimate", ylab = "A1 signal")
```



```
plot(axis_coefs.diag_dsd[,2] ~ sampsWithpurity_qpure, xlab = "qPure estimate", ylab = "A2 signal")
```

```
cor.test(axis_coefs.diag_dsd[,1], samps$purity_qpure, method = "kendall")

##
## Kendall's rank correlation tau
##
## data: axis_coefs.diag_dsd[, 1] and samps$purity_qpure
## z = 3.676, p-value = 0.0002369
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
## tau
## 0.2838

cor.test(axis_coefs.diag_dsd[,2], samps$purity_qpure, method = "kendall")

##
## Kendall's rank correlation tau
##
## data: axis_coefs.diag_dsd[, 2] and samps$purity_qpure
```

```

## z = -3.598, p-value = 0.0003203
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##      tau
## -0.2778

summary(lm(axis_coefs.diag_dsd[,1] ~ samps$purity_qpure))

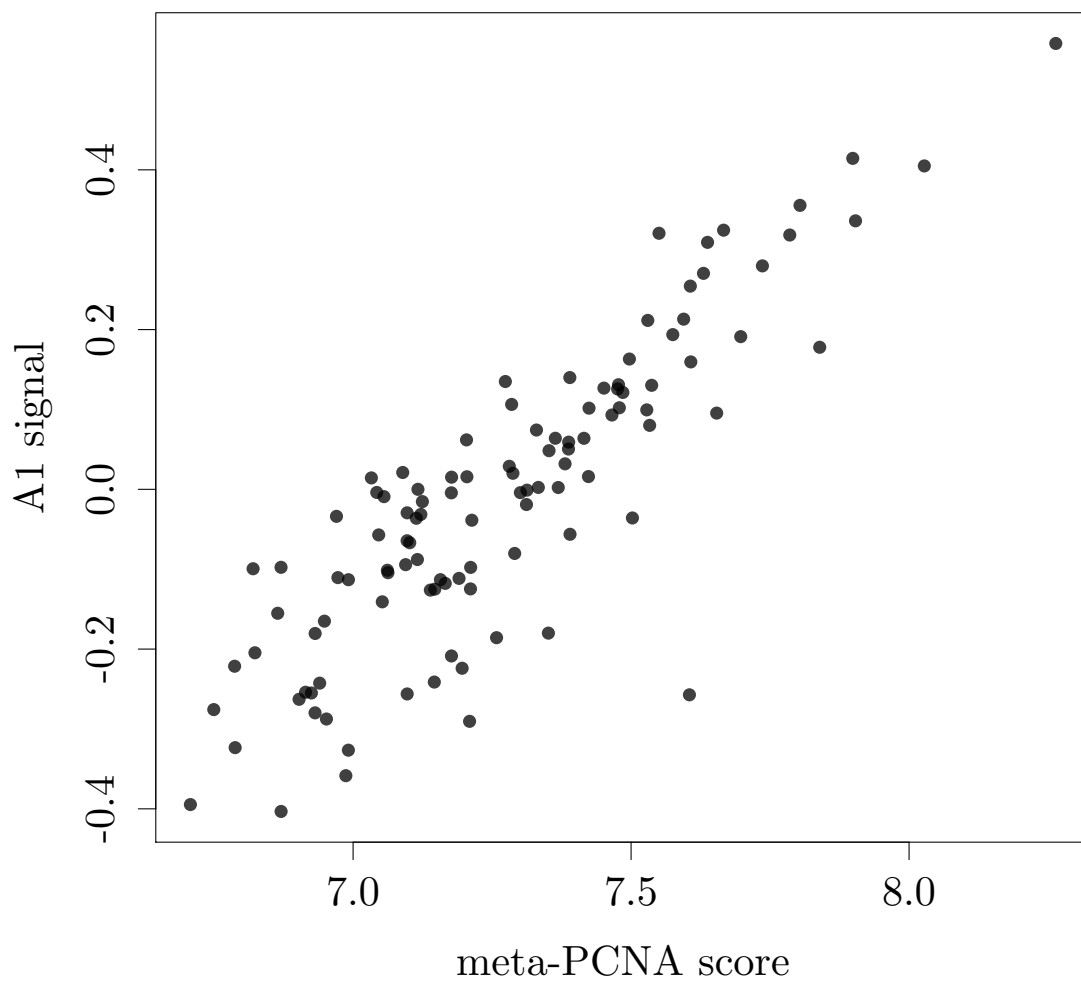
##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 1] ~ samps$purity_qpure)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.3318 -0.1172 -0.0469  0.1011  0.5422
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      -0.132      0.042   -3.14  0.00240
## samps$purity_qpure  0.346      0.089    3.89  0.00021
##
## Residual standard error: 0.173 on 76 degrees of freedom
## (32 observations deleted due to missingness)
## Multiple R-squared:  0.166, Adjusted R-squared:  0.155
## F-statistic: 15.1 on 1 and 76 DF,  p-value: 0.000213

summary(lm(axis_coefs.diag_dsd[,2] ~ samps$purity_qpure))

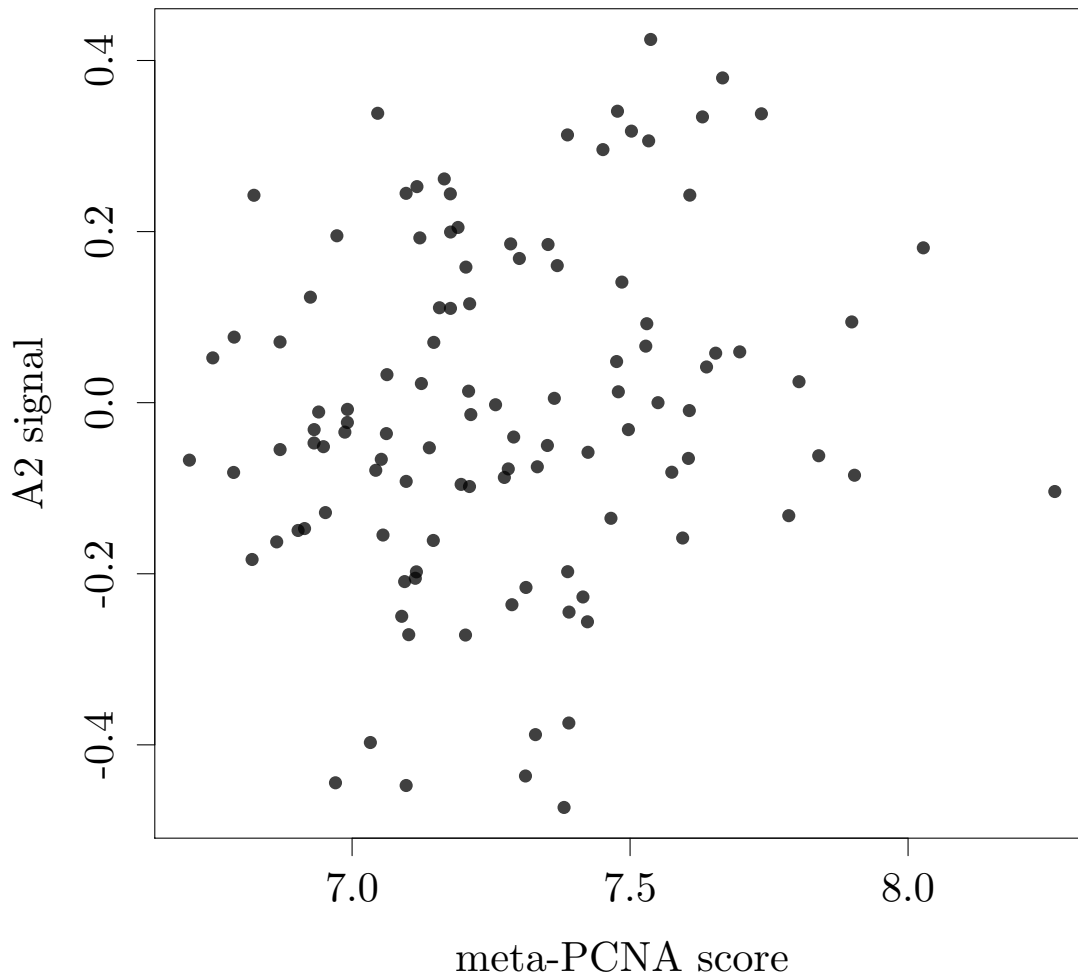
##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 2] ~ samps$purity_qpure)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.3541 -0.1356 -0.0213  0.1531  0.6002
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      0.1195      0.0473   2.53  0.01363
## samps$purity_qpure -0.3701      0.1001  -3.70  0.00041
##
## Residual standard error: 0.195 on 76 degrees of freedom
## (32 observations deleted due to missingness)
## Multiple R-squared:  0.152, Adjusted R-squared:  0.141
## F-statistic: 13.7 on 1 and 76 DF,  p-value: 0.000411

plot(axis_coefs.diag_dsd[,1] ~ metapcna.scores, xlab = "meta-PCNA score", ylab = "A1 signal", pch = 16,

```



```
plot(axis_coefs.diag_dsd[,2] ~ metapcna.scores, xlab = "meta-PCNA score", ylab = "A2 signal", pch = 16,
```



```
cor.test(axis_coefs.diag_dsd[,1], metapcna.scores, method = "kendall")

##
## Kendall's rank correlation tau
##
## data: axis_coefs.diag_dsd[, 1] and metapcna.scores
## z = 10.27, p-value < 2.2e-16
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
## tau
## 0.6634

cor.test(axis_coefs.diag_dsd[,2], metapcna.scores, method = "kendall")

##
## Kendall's rank correlation tau
##
## data: axis_coefs.diag_dsd[, 2] and metapcna.scores
```

```
## z = 1.899, p-value = 0.05762
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##      tau
## 0.1226

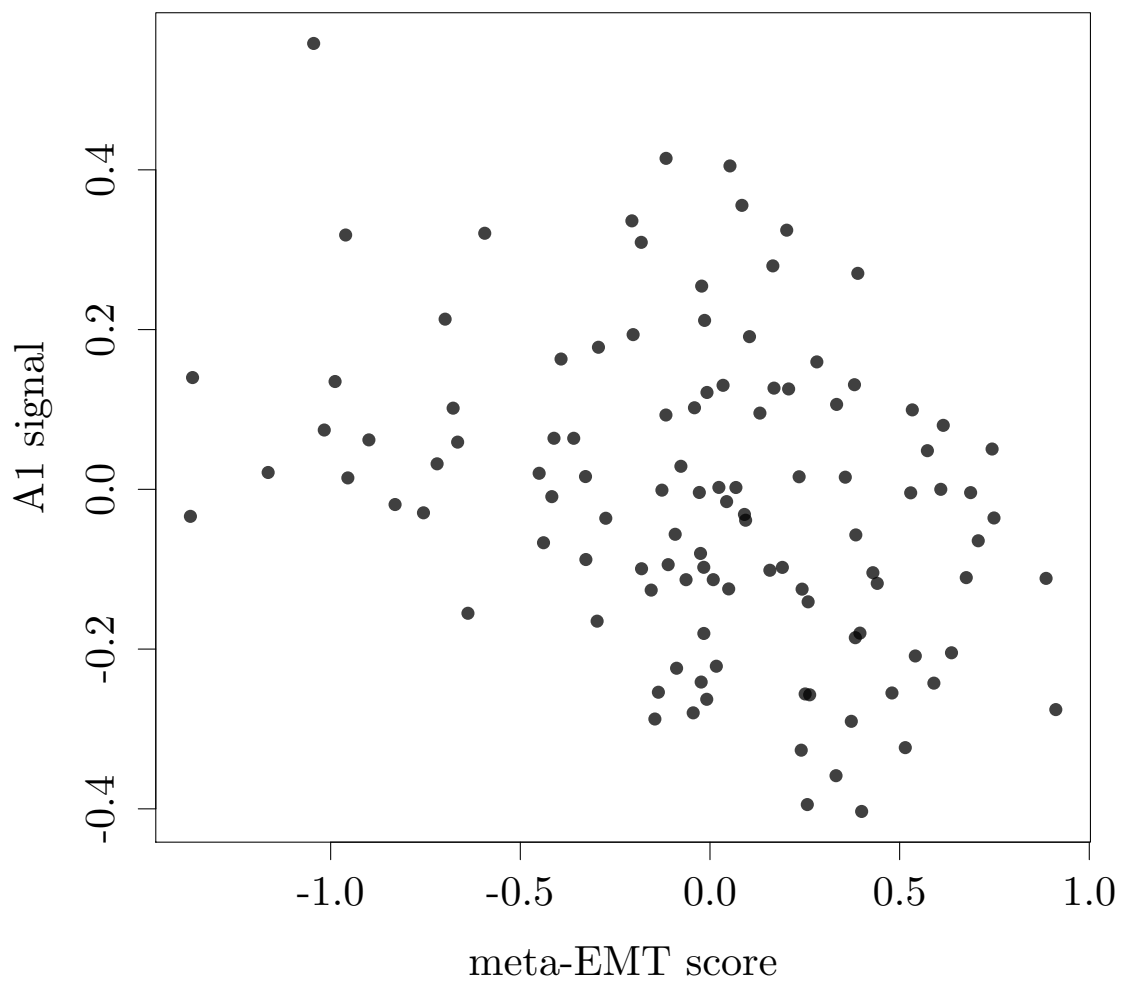
summary(lm(axis_coefs.diag_dsd[,1] ~ metapcna.scores))

##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 1] ~ metapcna.scores)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.4295 -0.0477  0.0151  0.0622  0.1785
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -4.0135     0.2274   -17.6   <2e-16
## metapcna.scores  0.5504     0.0312    17.6   <2e-16
##
## Residual standard error: 0.0971 on 108 degrees of freedom
## Multiple R-squared:  0.742, Adjusted R-squared:  0.74
## F-statistic: 311 on 1 and 108 DF,  p-value: <2e-16

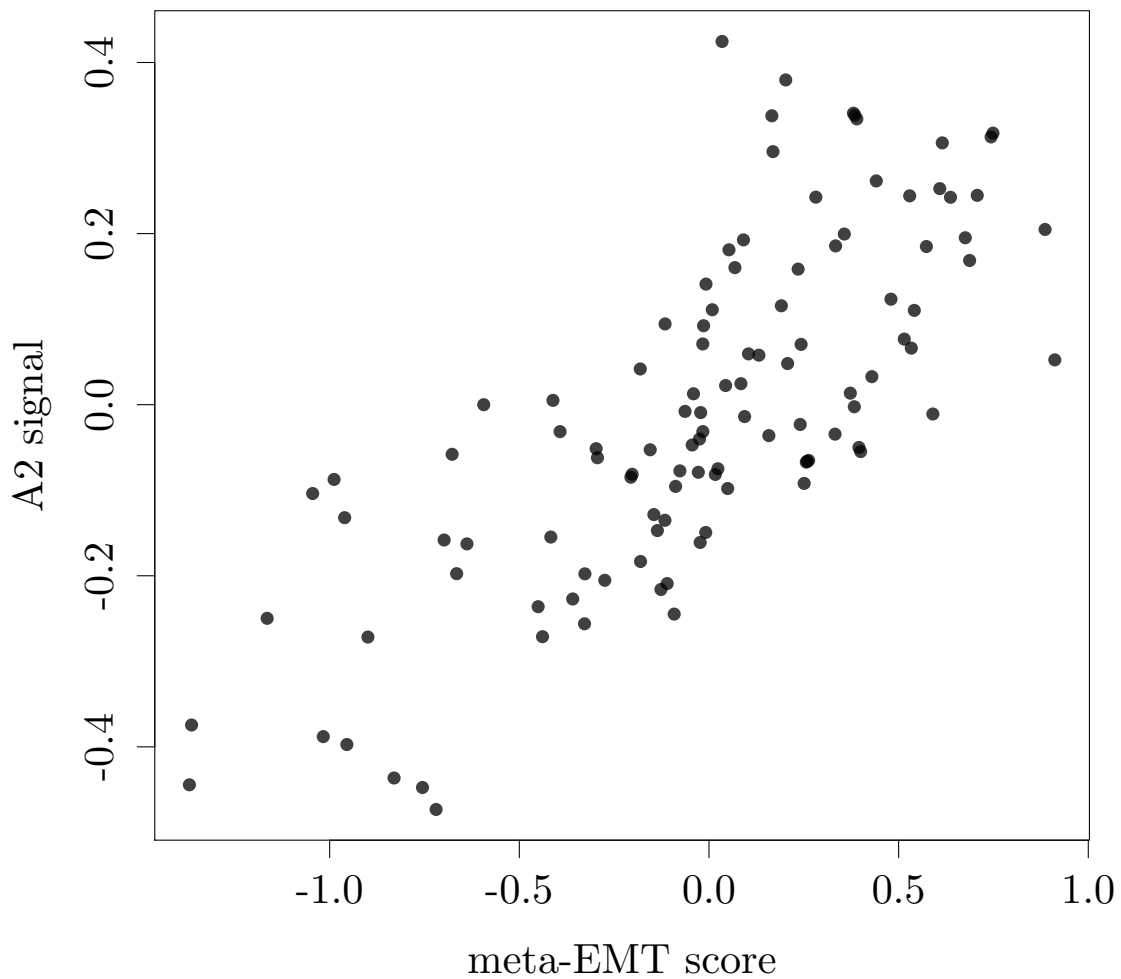
summary(lm(axis_coefs.diag_dsd[,2] ~ metapcna.scores))

##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 2] ~ metapcna.scores)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.478 -0.117  0.000  0.132  0.402
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    -0.8487     0.4577   -1.85   0.066
## metapcna.scores  0.1156     0.0629    1.84   0.069
##
## Residual standard error: 0.195 on 108 degrees of freedom
## Multiple R-squared:  0.0303, Adjusted R-squared:  0.0214
## F-statistic: 3.38 on 1 and 108 DF,  p-value: 0.0688

plot(axis_coefs.diag_dsd[,1] ~ emt.scores, xlab = "meta-EMT score", ylab = "A1 signal", pch = 16, col =
```



```
plot(axis_coefs.diag_dsd[,2] ~ emt.scores, xlab = "meta-EMT score", ylab = "A2 signal", pch = 16, col =
```



```
cor.test(axis_coefs.diag_dsd[,1], emt.scores, method = "kendall")

##
## Kendall's rank correlation tau
##
## data: axis_coefs.diag_dsd[, 1] and emt.scores
## z = -3.371, p-value = 0.0007492
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
## tau
## -0.2177

cor.test(axis_coefs.diag_dsd[,2], emt.scores, method = "kendall")

##
## Kendall's rank correlation tau
##
## data: axis_coefs.diag_dsd[, 2] and emt.scores
```

```
## z = 8.795, p-value < 2.2e-16
## alternative hypothesis: true tau is not equal to 0
## sample estimates:
##   tau
## 0.568

summary(lm(axis_coefs.diag_dsd[,1] ~ emt.scores))

##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 1] ~ emt.scores)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.3487 -0.1156 -0.0137  0.1312  0.4365
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -0.0129     0.0172   -0.75  0.45511
## emt.scores   -0.1289     0.0351   -3.68  0.00037
##
## Residual standard error: 0.18 on 108 degrees of freedom
## Multiple R-squared:  0.111, Adjusted R-squared:  0.103
## F-statistic: 13.5 on 1 and 108 DF,  p-value: 0.000372

summary(lm(axis_coefs.diag_dsd[,2] ~ emt.scores))

##
## Call:
## lm(formula = axis_coefs.diag_dsd[, 2] ~ emt.scores)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.2545 -0.0977 -0.0088  0.0914  0.4166
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.00235     0.01255   -0.19   0.85
## emt.scores   0.30063     0.02560   11.74 <2e-16
##
## Residual standard error: 0.132 on 108 degrees of freedom
## Multiple R-squared:  0.561, Adjusted R-squared:  0.557
## F-statistic: 138 on 1 and 108 DF,  p-value: <2e-16

anova(lm(axis_coefs.diag_dsd[,1] ~ samp$s_purity_qpure + emt.scores))

## Analysis of Variance Table
##
## Response: axis_coefs.diag_dsd[, 1]
##              Df Sum Sq Mean Sq F value  Pr(>F)
## samp$s_purity_qpure  1  0.453   0.453   15.20 0.00021
## emt.scores          1  0.039   0.039    1.32 0.25381
## Residuals          75  2.236   0.030

anova(lm(axis_coefs.diag_dsd[,2] ~ samp$s_purity_qpure + emt.scores))
```



```
## Analysis of Variance Table
##
## Response: axis_coefs.diag_dsd[, 2]
##           Df Sum Sq Mean Sq F value    Pr(>F)
## sampspurity_qpure  1  0.518    0.518    28.4 1.0e-06
## emt.scores        1  1.513    1.513    82.9 9.4e-14
## Residuals        75  1.369    0.018

temp.sig_id = colnames(axis_coefs.msigdb.corr)
temp.sig_class = gsub("\\\\.\\.", "", temp.sig_id)
temp.nsigs = length(temp.sig_id)
temp.nmeta = nrow(axis_coefs.msigdb.corr)
tables = lapply(1:temp.nmeta, function(metagene_i) {
  tapply(1:temp.nsigs, temp.sig_class, function(sig_class_is) {
    all_cors = axis_coefs.msigdb.corr[, sig_class_is]
    this_cors = all_cors[metagene_i, ]
    this_ids = temp.sig_id[sig_class_is]

    all_sig_cors = abs(all_cors) >= sig.corr.threshold
    this_sig_cors = all_sig_cors[metagene_i, ]

    sigs_to_report = which(this_sig_cors)

    if (length(sigs_to_report) == 0)
    {
      table = data.frame(GeneSet = c(), Correlation = c(), Metagenes = c())
    }
    else
    {
      table = data.frame(
        GeneSet = this_ids[sigs_to_report],
        Correlation = this_cors[sigs_to_report],
        Metagenes = apply(all_cors[,sigs_to_report,drop=FALSE], 2, function(cors)
          sel = abs(cors) >= sig.corr.threshold
          # A positive number implies that positive GSVA signal is associated
          paste(which(sel) * sign(cors[which(sel)]), collapse = ",")
        )))
      table = table[order(-(table$Correlation)),]
      rownames(table) <- NULL
    }
    table
  }, simplify = FALSE)
})
tables

## [[1]]
## [[1]]$c1
## data frame with 0 columns and 0 rows
##
## [[1]]$c2
##
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c2.AMUNDSON_GAMMA_RADIATION_RESPONSE/c4.GNF2_CDC2

c2.EGUCHI_CELL_CYCLE_RB1_TARGETS/c2.ROSTY_CERVIC

```
## 57 c2.REACTOME_ACTIVATION_OF_THE_PRE_F
## 58
## 59
## 60
## 61
## 62
## 63
## 64
## 65
## 66
## 67
## 68
## 69 c2.REACTOME_CELL_CYCLE_CHECKPOINTS/c2.REACTOME_G1_S_TRANSITION/c2.REACTOME_SYNTHESIS_OF_DNA/c2.R
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## 174
## 175
##      Correlation Metagenes
## 1      0.7141      1
## 2      0.6991      1
## 3      0.6981      1
## 4      0.6981      1
## 5      0.6964      1
## 6      0.6911      1
## 7      0.6894      1
## 8      0.6767      1
## 9      0.6767      1
## 10     0.6737      1
## 11     0.6711      1
## 12     0.6694      1
## 13     0.6617      1
## 14     0.6601      1
## 15     0.6584      1
## 16     0.6474      1
## 17     0.6470      1
## 18     0.6464      1
## 19     0.6460      1
## 20     0.6444      1
## 21     0.6440      1
## 22     0.6434      1
## 23     0.6404      1
## 24     0.6400      1
## 25     0.6344      1
## 26     0.6317      1
## 27     0.6294      1
## 28     0.6290      1
## 29     0.6287      1
## 30     0.6264      1
## 31     0.6257      1
## 32     0.6254      1
## 33     0.6230      1
## 34     0.6224      1
## 35     0.6180      1
## 36     0.6153      1
## 37     0.6143      1
## 38     0.6140      1
## 39     0.6123      1
## 40     0.6117      1
## 41     0.6073      1

```

| | | |
|-------|--------|---|
| ## 42 | 0.6060 | 1 |
| ## 43 | 0.6053 | 1 |
| ## 44 | 0.6050 | 1 |
| ## 45 | 0.6047 | 1 |
| ## 46 | 0.6037 | 1 |
| ## 47 | 0.5993 | 1 |
| ## 48 | 0.5990 | 1 |
| ## 49 | 0.5963 | 1 |
| ## 50 | 0.5960 | 1 |
| ## 51 | 0.5950 | 1 |
| ## 52 | 0.5883 | 1 |
| ## 53 | 0.5870 | 1 |
| ## 54 | 0.5857 | 1 |
| ## 55 | 0.5853 | 1 |
| ## 56 | 0.5837 | 1 |
| ## 57 | 0.5833 | 1 |
| ## 58 | 0.5807 | 1 |
| ## 59 | 0.5807 | 1 |
| ## 60 | 0.5770 | 1 |
| ## 61 | 0.5756 | 1 |
| ## 62 | 0.5753 | 1 |
| ## 63 | 0.5750 | 1 |
| ## 64 | 0.5733 | 1 |
| ## 65 | 0.5730 | 1 |
| ## 66 | 0.5713 | 1 |
| ## 67 | 0.5683 | 1 |
| ## 68 | 0.5680 | 1 |
| ## 69 | 0.5660 | 1 |
| ## 70 | 0.5653 | 1 |
| ## 71 | 0.5650 | 1 |
| ## 72 | 0.5640 | 1 |
| ## 73 | 0.5620 | 1 |
| ## 74 | 0.5586 | 1 |
| ## 75 | 0.5586 | 1 |
| ## 76 | 0.5560 | 1 |
| ## 77 | 0.5536 | 1 |
| ## 78 | 0.5513 | 1 |
| ## 79 | 0.5500 | 1 |
| ## 80 | 0.5473 | 1 |
| ## 81 | 0.5466 | 1 |
| ## 82 | 0.5466 | 1 |
| ## 83 | 0.5463 | 1 |
| ## 84 | 0.5463 | 1 |
| ## 85 | 0.5456 | 1 |
| ## 86 | 0.5453 | 1 |
| ## 87 | 0.5336 | 1 |
| ## 88 | 0.5319 | 1 |
| ## 89 | 0.5313 | 1 |
| ## 90 | 0.5309 | 1 |
| ## 91 | 0.5306 | 1 |
| ## 92 | 0.5296 | 1 |
| ## 93 | 0.5279 | 1 |
| ## 94 | 0.5276 | 1 |
| ## 95 | 0.5273 | 1 |

| | | |
|--------|---------|----|
| ## 96 | 0.5273 | 1 |
| ## 97 | 0.5246 | 1 |
| ## 98 | 0.5243 | 1 |
| ## 99 | 0.5239 | 1 |
| ## 100 | 0.5233 | 1 |
| ## 101 | 0.5226 | 1 |
| ## 102 | 0.5223 | 1 |
| ## 103 | 0.5199 | 1 |
| ## 104 | 0.5199 | 1 |
| ## 105 | 0.5196 | 1 |
| ## 106 | 0.5179 | 1 |
| ## 107 | 0.5179 | 1 |
| ## 108 | 0.5173 | 1 |
| ## 109 | 0.5173 | 1 |
| ## 110 | 0.5159 | 1 |
| ## 111 | 0.5146 | 1 |
| ## 112 | 0.5129 | 1 |
| ## 113 | 0.5103 | 1 |
| ## 114 | 0.5103 | 1 |
| ## 115 | 0.5099 | 1 |
| ## 116 | 0.5086 | 1 |
| ## 117 | 0.5073 | 1 |
| ## 118 | 0.5063 | 1 |
| ## 119 | 0.5059 | 1 |
| ## 120 | 0.5056 | 1 |
| ## 121 | 0.5056 | 1 |
| ## 122 | 0.5043 | 1 |
| ## 123 | 0.5029 | 1 |
| ## 124 | 0.5019 | 1 |
| ## 125 | 0.5019 | 1 |
| ## 126 | 0.5016 | 1 |
| ## 127 | 0.5013 | 1 |
| ## 128 | 0.5009 | 1 |
| ## 129 | 0.5003 | 1 |
| ## 130 | 0.5003 | 1 |
| ## 131 | -0.5009 | -1 |
| ## 132 | -0.5033 | -1 |
| ## 133 | -0.5043 | -1 |
| ## 134 | -0.5056 | -1 |
| ## 135 | -0.5083 | -1 |
| ## 136 | -0.5089 | -1 |
| ## 137 | -0.5096 | -1 |
| ## 138 | -0.5243 | -1 |
| ## 139 | -0.5289 | -1 |
| ## 140 | -0.5316 | -1 |
| ## 141 | -0.5319 | -1 |
| ## 142 | -0.5393 | -1 |
| ## 143 | -0.5399 | -1 |
| ## 144 | -0.5416 | -1 |
| ## 145 | -0.5433 | -1 |
| ## 146 | -0.5516 | -1 |
| ## 147 | -0.5520 | -1 |
| ## 148 | -0.5570 | -1 |
| ## 149 | -0.5580 | -1 |

```

## 150      -0.5583      -1
## 151      -0.5640      -1
## 152      -0.5646      -1
## 153      -0.5730      -1
## 154      -0.5733      -1
## 155      -0.5750      -1
## 156      -0.5893      -1
## 157      -0.5900      -1
## 158      -0.5913      -1
## 159      -0.5940      -1
## 160      -0.6047      -1
## 161      -0.6063      -1
## 162      -0.6147      -1
## 163      -0.6153      -1
## 164      -0.6217      -1
## 165      -0.6247      -1
## 166      -0.6260      -1
## 167      -0.6310      -1
## 168      -0.6347      -1
## 169      -0.6357      -1
## 170      -0.6370      -1
## 171      -0.6387      -1
## 172      -0.6454      -1
## 173      -0.6791      -1
## 174      -0.6894      -1
## 175      -0.6951      -1
##
## [[1]]$c3
##           GeneSet Correlation Metagenes
## 1          c3.V$ELK1_02      0.5740      1
## 2 c3.SCGGAAGY_V$ELK1_02      0.5580      1
## 3          c3.CTGCAGY_UNKNOWN -0.5046     -1
## 4          c3.V$OCT1_01      -0.5089     -1
## 5          c3.V$GATA_Q6       -0.5153     -1
## 6          c3.V$OCT1_04       -0.5313     -1
## 7          c3.V$OCT_C        -0.5436     -1
##
## [[1]]$c4
##
##                                     GeneSet
## 1 c4.GNF2_RFC3/c4.GNF2_RFC4/c4.GNF2_SMC2L1/c4.GNF2_CKS1B/c4.GNF2_CKS2/c4.GNF2_TTK
## 2                                     c4.MODULE_17
## 3                                     c4.MODULE_315
## 4                                     c4.MORF_BUB1B
## 5                                     c4.MODULE_244
## 6                                     c4.MODULE_337
## 7                                     c4.MORF_FEN1
## 8                                     c4.MODULE_126
## 9                                     c4.MODULE_124
## 10                                    c4.MORF_ESPL1
## 11                                    c4.MORF_BUB1
## 12                                    c4.MODULE_403
## 13                                    c4.MORF_BUB3/c4.MORF_RAD23A
## 14                                    c4.MORF_RFC4/c4.MORF_RRM1
## 15                                    c4.MODULE_98/c4.MODULE_198/c4.MODULE_252

```


| | | |
|-------|-----------------------|---|
| ## 16 | | c4.MODULE_125/c4.MODULE_158 |
| ## 17 | | c4.MORF_UNG |
| ## 18 | | c4.MODULE_278 |
| ## 19 | | c4.MORF_GSPT1 |
| ## 20 | | c4.MODULE_320 |
| ## 21 | | c4.MODULE_8 |
| ## 22 | | c4.MORF_CCNF |
| ## 23 | | c4.MORF_EI24 |
| ## 24 | | c4.GNF2_PA2G4/c4.GNF2_RAN |
| ## 25 | | c4.MORF_PRKDC |
| ## 26 | | c4.MORF_GMPS |
| ## 27 | | c4.MODULE_219 |
| ## 28 | | c4.GNF2_MCM5 |
| ## 29 | | c4.MORF_DNMT1 |
| ## 30 | | c4.GNF2_MSH2 |
| ## 31 | | c4.MORF_CSNK2B |
| ## 32 | | c4.MORF_PTPN11 |
| ## 33 | | c4.MORF_PPP1CC |
| ## 34 | | c4.MORF_XRCC5/c4.MORF_GNB1 |
| ## 35 | | c4.MODULE_451 |
| ## 36 | | c4.MORF_SOD1 |
| ## 37 | | c4.MORF_HDAC1 |
| ## 38 | | c4.MODULE_51 |
| ## 39 | | c4.GNF2_MAPT |
| ## 40 | | c4.MODULE_19 |
| ## 41 | | c4.MODULE_11/c4.MODULE_66/c4.MODULE_100/c4.MODULE_137 |
| ## | Correlation Metagenes | |
| ## 1 | 0.6637 | 1 |
| ## 2 | 0.6510 | 1 |
| ## 3 | 0.6324 | 1 |
| ## 4 | 0.6307 | 1 |
| ## 5 | 0.6294 | 1 |
| ## 6 | 0.6244 | 1 |
| ## 7 | 0.5860 | 1 |
| ## 8 | 0.5817 | 1 |
| ## 9 | 0.5813 | 1 |
| ## 10 | 0.5656 | 1 |
| ## 11 | 0.5650 | 1 |
| ## 12 | 0.5640 | 1 |
| ## 13 | 0.5633 | 1 |
| ## 14 | 0.5606 | 1 |
| ## 15 | 0.5586 | 1 |
| ## 16 | 0.5586 | 1 |
| ## 17 | 0.5536 | 1 |
| ## 18 | 0.5536 | 1 |
| ## 19 | 0.5503 | 1 |
| ## 20 | 0.5490 | 1 |
| ## 21 | 0.5480 | 1 |
| ## 22 | 0.5436 | 1 |
| ## 23 | 0.5379 | 1 |
| ## 24 | 0.5313 | 1 |
| ## 25 | 0.5279 | 1 |
| ## 26 | 0.5279 | 1 |

```

## 27      0.5266      1
## 28      0.5249      1
## 29      0.5243      1
## 30      0.5206      1
## 31      0.5203      1
## 32      0.5163      1
## 33      0.5089      1
## 34      0.5039      1
## 35      0.5026      1
## 36      0.5019      1
## 37      0.5009      1
## 38     -0.5066     -1
## 39     -0.5259     -1
## 40     -0.5656     -1
## 41     -0.5967     -1
##
## [[1]]$c5
##
##                                     GeneSet
## 1                                c5.M_PHASE/c5.MITOSIS/c5.M_PHASE_OF_MITOTIC_CELL_CYCLE
## 2                                c5.REGULATION_OF_MITOSIS
## 3                   c5.CELL_CYCLE_PROCESS/c5.MITOTIC_CELL_CYCLE/c5.CELL_CYCLE_PHASE
## 4                                c5.SPINDLE
## 5                                c5.SPINDLE_POLE
## 6                   c5.ORGANELLE_PART/c5.INTRACELLULAR_ORGANELLE_PART
## 7                                c5.CHROMOSOME_SEGREGATION
## 8                                c5.CELL_CYCLE_GO_0007049
## 9                                c5.SPINDLE_MICROTUBULE
## 10                   c5.MITOTIC_CELL_CYCLE_CHECKPOINT
## 11                   c5.CONDENSED_CHROMOSOME
## 12                   c5.MITOTIC_SISTER_CHROMATID_SEGREGATION/c5.SISTER_CHROMATID_SEGREGATION
## 13                   c5.CELL_CYCLE_CHECKPOINT_GO_0000075
## 14 c5.MITOTIC_SPINDLE_ORGANIZATION_AND_BIOGENESIS/c5.SPINDLE_ORGANIZATION_AND_BIOGENESIS
## 15                                c5.DOUBLE_STRAND_BREAK_REPAIR
## 16                                c5.DNA_METABOLIC_PROCESS
## 17                   c5.REGULATION_OF_MITOTIC_CELL_CYCLE
## 18                   c5.RESPONSE_TO_ENDOGENOUS_STIMULUS/c5.RESPONSE_TO_DNA_DAMAGE_STIMULUS
## 19                   c5.CHROMOSOMEPERICENTRIC_REGION/c5.KINETOCHORE
## 20                                c5.PORE_COMPLEX/c5.NUCLEAR_PORE
## 21                                c5.DNA_REPAIR
## 22                   c5.MACROMOLECULAR_COMPLEX/c5.PROTEIN_COMPLEX
## 23                   c5.INTERPHASE/c5.INTERPHASE_OF_MITOTIC_CELL_CYCLE
## 24                   c5.NON_MEMBRANE_BOUND_ORGANELLE/c5.INTRACELLULAR_NON_MEMBRANE_BOUND_ORGANELLE
## 25                   c5.NUCLEAR_MEMBRANE/c5.NUCLEAR_MEMBRANE_PART
## 26                   c5.CHROMOSOMAL_PART/c5.CHROMOSOME
## 27                   c5.PHOSPHORIC_DIESTER_HYDROLASE_ACTIVITY
## 28                   c5.CELL_SURFACE_RECEPTOR_LINKED_SIGNAL_TRANSDUCTION_GO_0007166
##
## Correlation Metagenes
## 1      0.6894      1
## 2      0.6821      1
## 3      0.6527      1
## 4      0.6437      1
## 5      0.6280      1
## 6      0.6244      1
## 7      0.5883      1

```

```

## 8      0.5760      1
## 9      0.5726      1
## 10     0.5690      1
## 11     0.5620      1
## 12     0.5546      1
## 13     0.5426      1
## 14     0.5420      1
## 15     0.5369      1
## 16     0.5166      1
## 17     0.5156      1
## 18     0.5146      1
## 19     0.5136      1
## 20     0.5083      1
## 21     0.5063      1
## 22     0.5059      1
## 23     0.5033      1
## 24     0.5029      1
## 25     0.5013      1
## 26     0.5003      1
## 27     -0.5023     -1
## 28     -0.5176     -1
##
## [[1]]$c6
##               GeneSet Correlation Metagenes
## 1      c6.CSR_LATE_UP.V1_SIGNED      0.6297      1
## 2      c6.MTOR_UP.V1_SIGNED      0.5123      1
## 3 c6.GCNP_SHH_UP_EARLY.V1_SIGNED      0.5026      1
##
## [[1]]$c7
##
## 1
## 2
## 3
## 4
## 5
## 6
## 7
## 8
## 9
## 10
## 11
## 12
## 13
## 14
## 15
## 16
## 17
## 18
## 19
## 20
## 21
## 22
## 23
## 24

```

c7.GSE15750_DAY6_VS_I

c7.GSE24634_TEFF_VS_TCONV.

```

## 25
## 26
## 27
## 28
## 29
## 30
## 31
## 32
## 33
## 34
## 35
## 36
## 37
## 38
## 39
## 40
## 41
## 42
## 43
## 44
## 45
## 46
## 47
## 48
## 49
## 50
## 51
## 52
## 53
## 54 c7.GSE15930_NAIVE_VS_24H_IN_VITRO_STIM_CD8_TCELL_SIGNED/c7.GSE15930_NAIVE_VS_24H_IN_VITRO_STIM_IL
## 55
## 56
## 57
## 58
## 59
## 60
## 61
## 62
## 63
## 64
## 65
## 66
## 67 c7.GSE36476_CTRL_VS_TSST_ACT_40H_MEMORY_C
## 68
## 69
## 70
## 71 c7.GSE36476_CTRL_VS_TSST_ACT_40H_MEMORY_CD4_T
##
## Correlation Metagenes
## 1 0.6187 1
## 2 0.6160 1
## 3 0.6143 1
## 4 0.5880 1
## 5 0.5857 1
## 6 0.5756 1

```

| | | |
|-------|---------|----|
| ## 7 | 0.5696 | 1 |
| ## 8 | 0.5653 | 1 |
| ## 9 | 0.5630 | 1 |
| ## 10 | 0.5623 | 1 |
| ## 11 | 0.5580 | 1 |
| ## 12 | 0.5553 | 1 |
| ## 13 | 0.5546 | 1 |
| ## 14 | 0.5476 | 1 |
| ## 15 | 0.5466 | 1 |
| ## 16 | 0.5423 | 1 |
| ## 17 | 0.5349 | 1 |
| ## 18 | 0.5336 | 1 |
| ## 19 | 0.5276 | 1 |
| ## 20 | 0.5186 | 1 |
| ## 21 | 0.5186 | 1 |
| ## 22 | 0.5036 | 1 |
| ## 23 | -0.5039 | -1 |
| ## 24 | -0.5086 | -1 |
| ## 25 | -0.5109 | -1 |
| ## 26 | -0.5119 | -1 |
| ## 27 | -0.5119 | -1 |
| ## 28 | -0.5149 | -1 |
| ## 29 | -0.5179 | -1 |
| ## 30 | -0.5183 | -1 |
| ## 31 | -0.5223 | -1 |
| ## 32 | -0.5239 | -1 |
| ## 33 | -0.5269 | -1 |
| ## 34 | -0.5303 | -1 |
| ## 35 | -0.5316 | -1 |
| ## 36 | -0.5336 | -1 |
| ## 37 | -0.5343 | -1 |
| ## 38 | -0.5343 | -1 |
| ## 39 | -0.5426 | -1 |
| ## 40 | -0.5516 | -1 |
| ## 41 | -0.5520 | -1 |
| ## 42 | -0.5543 | -1 |
| ## 43 | -0.5560 | -1 |
| ## 44 | -0.5603 | -1 |
| ## 45 | -0.5603 | -1 |
| ## 46 | -0.5613 | -1 |
| ## 47 | -0.5630 | -1 |
| ## 48 | -0.5636 | -1 |
| ## 49 | -0.5650 | -1 |
| ## 50 | -0.5716 | -1 |
| ## 51 | -0.5743 | -1 |
| ## 52 | -0.5786 | -1 |
| ## 53 | -0.5830 | -1 |
| ## 54 | -0.5853 | -1 |
| ## 55 | -0.5860 | -1 |
| ## 56 | -0.5867 | -1 |
| ## 57 | -0.5920 | -1 |
| ## 58 | -0.5950 | -1 |
| ## 59 | -0.5953 | -1 |
| ## 60 | -0.6007 | -1 |

```

## 61      -0.6010      -1
## 62      -0.6090      -1
## 63      -0.6190      -1
## 64      -0.6193      -1
## 65      -0.6254      -1
## 66      -0.6417      -1
## 67      -0.6500      -1
## 68      -0.6530      -1
## 69      -0.6637      -1
## 70      -0.6654      -1
## 71      -0.6667      -1
##
##
## [[2]]
## [[2]]$c1
## data frame with 0 columns and 0 rows
##
## [[2]]$c2
##
## 1
## 2
## 3
## 4
## 5
## 6
## 7
## 8
## 9
## 10
## 11
## 12
## 13
## 14
## 15
## 16 c2.FARMER_BREAST_CANCER_CLUSTER_5/c2.ANASTASSIOU_CANCER_MESENCHYMAL_TRANSITION_SIGNATURE/c4.GNF2_
## 17
## 18 c2.REACTOME_EXTRACELLULAR_MATRIX_ORGANIZATION/c2.REACTOME_COLLAGEN_FORMA
## 19
## 20
## 21
## 22
## 23
## 24
## 25
## 26
## 27
## 28
## 29
## 30
## 31
## 32
## 33
## 34
## 35

```

Gen

c2.PID_INTEGRIN1_PAT

c2.VECCHI_GASTRIC_CANCER_ADVANCED_VS_EARLY_SI

c2.LIEN_BREAST_CARCINOMA_METAPLASTIC_VS_DUCTAL_SI

c2.PID_INTEGRIN3_PAT

c2.SUZUKI_RESPONSE_TO_TSA_AND_DECITABIN

c2.HUANG_DASATINIB_RESISTANCE_SI

c2.WIEDERSCHAIN_TARGETS_OF_BMI1_AND_F

c2.BURTON_ADIPOGENES

c2.POTTI_TOPOTECAN_SENSITI

c2.KARAKAS_TGFB1_SIGNA

c2.PID_UPA_UPAR_PAT

c2.CROMER_TUMORIGENESIS_SI

c2.ROZANOV_MMP14_TARGETS_SU

c2.WOO_LIVER_CANCER_RECURRENCE_SI

c2.KEGG_ECM_RECEPTOR_INTERAC

c2.FARMER_BREAST_CANCER_CLUSTER_5/c2.ANASTASSIOU_CANCER_MESENCHYMAL_TRANSITION_SIGNATURE/c4.GNF2_

c2.PID_INTEGRIN5_PAT

c2.REACTOME_EXTRACELLULAR_MATRIX_ORGANIZATION/c2.REACTOME_COLLAGEN_FORMA

c2.ROY_WOUND_BLOOD_VESSEL_SI

c2.KEGG_FOCAL_ADHE

c2.CHICAS_RB1_TARGETS_CONFI

c2.YIH_RESPONSE_TO_ARSENIT

c2.PHONG_TNF_RESPONSE_VIA_P38_PAF

c2.SERVITJA_ISLET_HNF1A_TARGETS_SI

c2.LI_PROSTATE_CANCER_EPIGEN

c2.PID_SYNDECAN_1_PAT

c2.AGARWAL_AKT_PATHWAY_TAF

c2.REACTOME_CELL_EXTRACELLULAR_MATRIX_INTERACT

c2.PID_INTEGRIN_CS_PAT

c2.HELLEBREKERS_SILENCED_DURING_TUMOR_ANGIOGEN

c2.MATTHEWS_AP1_TAF

c2.RODWELL_AGING_KIDNEY_NO_BLOOD_SI

c2.YAO_TEMPORAL_RESPONSE_TO_PROGESTERONE_CLUSTER

c2.WESTON_VEGFA_TAF

c2.WU_CELL_MIGRA

| | | |
|-------|-------------|--|
| ## 36 | | c2.SCHUETZ_BREAST_CANCER_DUCTAL_INVASIVE_S1 |
| ## 37 | | c2.KAN_RESPONSE_TO_ARSENIC_TRI |
| ## 38 | | c2.VERHAAK_GLIOMASTOMA_NE |
| ## 39 | | c2.REACTOME_INTEGRIN_CELL_SURFACE_INTERACT |
| ## 40 | | c2.GILDEA_METAST |
| ## 41 | | c2.TURASHVILI_BREAST_LOBULAR_CARCINOMA_VS_DUCTAL_NORMAL_S1 |
| ## 42 | | c2.HARRIS_HYPOXIA/c2.WINTER_HYPOXIA_MET |
| ## 43 | | c2.BIOCARTA_PLATELETAPP_PAT |
| ## 44 | | c2.WANG_METHYLATED_IN_BREAST_CA |
| ## 45 | | c2.RICKMAN_TUMOR_DIFFERENTIATED_WELL_VS_POORLY_S1 |
| ## 46 | | c2.CHARAFE_BREAST_CANCER_LUMINAL_VS_BASAL_S1 |
| ## 47 | | c2.WALLACE_PROSTATE_CANCER_S1 |
| ## 48 | | c2.WANG_BARRETTS_ESOPHAGUS_AND_ESOPHAGUS_CANCER_S1 |
| ## 49 | | c2.SMID_BREAST_CANCER_RELAPSE_IN_BONE_S1 |
| ## 50 | | c2.MIYAGAWA_TARGETS_OF_EWSR1_ETS_FUSIONS_S1 |
| ## 51 | | c2.LIU_PROSTATE_CANCER_S1 |
| ## 52 | | c2.PASINI_SUZ12_TARGETS_S1 |
| ## 53 | | c2.NAKAMURA_ADIPOGENESIS_LATE_S1 |
| ## 54 | | c2.DOANE_BREAST_CANCER_CLASSES_S1 |
| ## 55 | | c2.CHARAFE_BREAST_CANCER_LUMINAL_VS_MESENCHYMAL_S1 |
| ## | Correlation | Metagenes |
| ## 1 | 0.6544 | 2 |
| ## 2 | 0.6514 | 2 |
| ## 3 | 0.6454 | 2 |
| ## 4 | 0.6374 | 2 |
| ## 5 | 0.6370 | 2 |
| ## 6 | 0.6350 | 2 |
| ## 7 | 0.6250 | 2 |
| ## 8 | 0.6103 | 2 |
| ## 9 | 0.6017 | 2 |
| ## 10 | 0.5997 | 2 |
| ## 11 | 0.5970 | 2 |
| ## 12 | 0.5910 | 2 |
| ## 13 | 0.5907 | 2 |
| ## 14 | 0.5883 | 2 |
| ## 15 | 0.5817 | 2 |
| ## 16 | 0.5783 | 2 |
| ## 17 | 0.5766 | 2 |
| ## 18 | 0.5723 | 2 |
| ## 19 | 0.5676 | 2 |
| ## 20 | 0.5666 | 2 |
| ## 21 | 0.5643 | 2 |
| ## 22 | 0.5623 | 2 |
| ## 23 | 0.5590 | 2 |
| ## 24 | 0.5586 | 2 |
| ## 25 | 0.5543 | 2 |
| ## 26 | 0.5516 | 2 |
| ## 27 | 0.5486 | 2 |
| ## 28 | 0.5379 | 2 |
| ## 29 | 0.5363 | 2 |
| ## 30 | 0.5289 | 2 |
| ## 31 | 0.5279 | 2 |
| ## 32 | 0.5256 | 2 |
| ## 33 | 0.5239 | 2 |

```

## 34      0.5229      2
## 35      0.5209      2
## 36      0.5206      2
## 37      0.5206      2
## 38      0.5203      2
## 39      0.5179      2
## 40      0.5179      2
## 41      0.5146      2
## 42      0.5119      2
## 43      0.5056      2
## 44      0.5009      2
## 45     -0.5043     -2
## 46     -0.5209     -2
## 47     -0.5209     -2
## 48     -0.5443     -2
## 49     -0.5536     -2
## 50     -0.5563     -2
## 51     -0.5643     -2
## 52     -0.5663     -2
## 53     -0.5680     -2
## 54     -0.6010     -2
## 55     -0.6097     -2
##
## [[2]]$c3
## data frame with 0 columns and 0 rows
##
## [[2]]$c4
##      GeneSet Correlation Metagenes
## 1  c4.GNF2_PTX3      0.5933      2
## 2  c4.GNF2_MMP1      0.5750      2
## 3  c4.MODULE_412      0.5670      2
## 4  c4.MODULE_122      0.5600      2
## 5  c4.MODULE_47       0.5463      2
## 6  c4.MODULE_153      0.5426      2
## 7  c4.MODULE_321      0.5309      2
## 8  c4.MODULE_275      0.5253      2
## 9  c4.MODULE_562      0.5066      2
##
## [[2]]$c5
##
##      GeneSet
## 1      c5.AXON_GUIDANCE
## 2      c5.TISSUE_DEVELOPMENT
## 3      c5.COLLAGEN
## 4  c5.AXONOGENESIS/c5.CELLULAR_MORPHOGENESIS_DURING_DIFFERENTIATION
##      Correlation Metagenes
## 1      0.5710      2
## 2      0.5363      2
## 3      0.5313      2
## 4      0.5146      2
##
## [[2]]$c6
##
##      GeneSet Correlation Metagenes
## 1  c6.CORDENONSI_YAP_CONSERVED_SIGNATURE      0.5256      2
## 2      c6.LEF1_UP.V1_SIGNED      0.5193      2

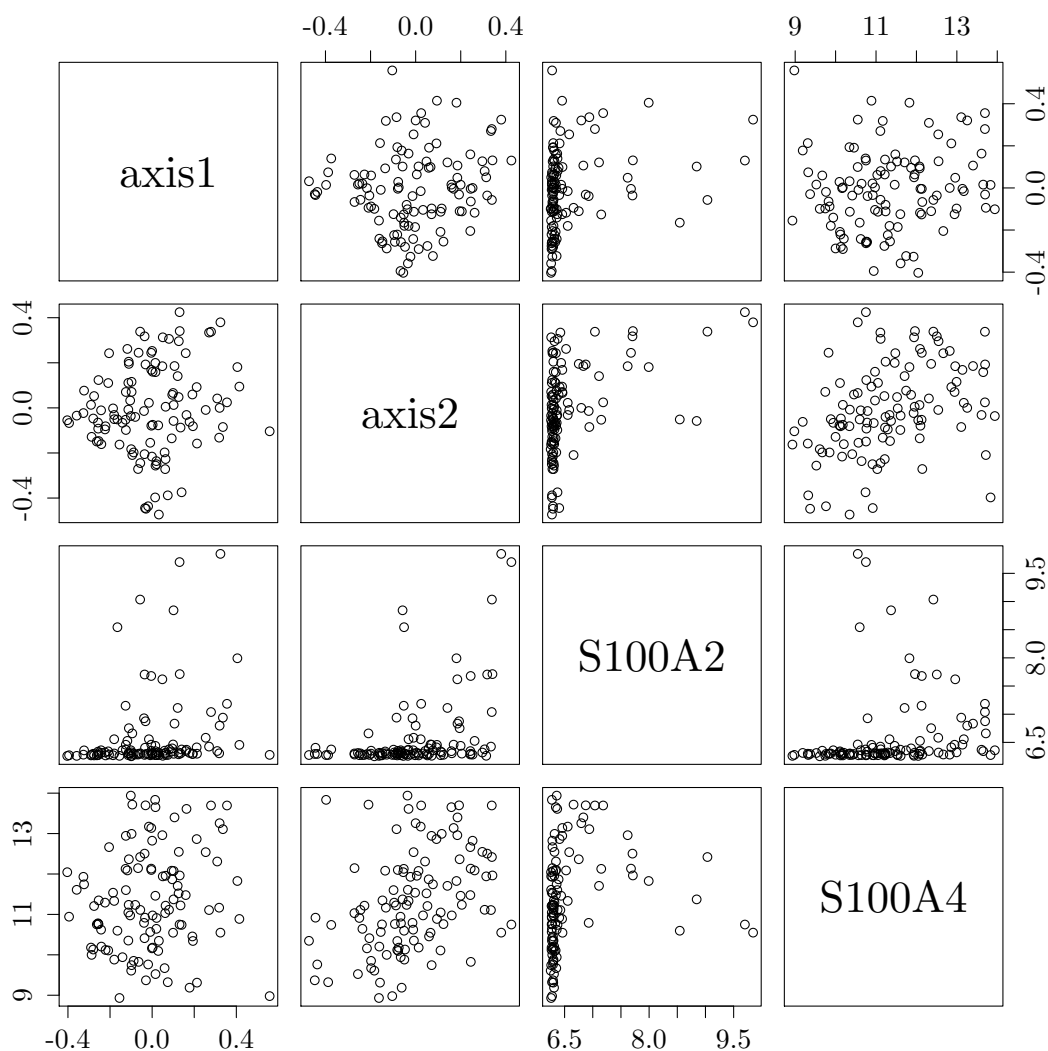
```



```
## 3          c6.STK33_NOMO_SIGNED      0.5073      2
##
## [[2]]$c7
##
##                                     GeneSet
## 1          c7.GSE17721_CTRL_VS_CPG_12H_BMDM_SIGNED
## 2 c7.GSE1460_INTRATHYMIC_T_PROGENITOR_VS_THYMIC_STROMAL_CELL_SIGNED
## Correlation Metagenes
## 1      -0.5076      -2
## 2      -0.5079      -2

for (subtable_index in 1:length(tables))
{
  write.csv(do.call(rbind, tables[[subtable_index]]), file = sprintf("A%d_corrs.csv", subtable_index))
}
```

```
pairs(cbind(axis_coefs.diag_dsd, t(x.diag_dsd[c("S100A2", "S100A4"),])))
```



Underwhelming, but the poor detection rate of A2 and A4 probes is a likely culprit. When I get APGI scores from DC, I can directly compare the staining patterns to A1 and A2 signals – this would be a better comparison to the work of chapter 2 anyway.

5 Session information

```
session_info

## R version 3.1.1 (2014-07-10)
## Platform: x86_64-unknown-linux-gnu (64-bit)
##
## locale:
##  [1] LC_CTYPE=en_AU.UTF-8      LC_NUMERIC=C
##  [3] LC_TIME=en_AU.UTF-8      LC_COLLATE=en_AU.UTF-8
##  [5] LC_MONETARY=en_AU.UTF-8  LC_MESSAGES=en_AU.UTF-8
##  [7] LC_PAPER=en_AU.UTF-8     LC_NAME=en_AU.UTF-8
##  [9] LC_ADDRESS=en_AU.UTF-8   LC_TELEPHONE=en_AU.UTF-8
## [11] LC_MEASUREMENT=en_AU.UTF-8 LC_IDENTIFICATION=en_AU.UTF-8
##
## attached base packages:
## [1] splines    parallel  methods    stats      graphics  grDevices  utils
## [8] datasets  base
##
## other attached packages:
##  [1] doParallel_1.0.8    iterators_1.0.7    foreach_1.4.2
##  [4] ahaz_1.14           survival_2.37-7    NMF_0.20.5
##  [7] Biobase_2.26.0      BiocGenerics_0.12.1 cluster_1.15.3
## [10] rngtools_1.2.4      pkgmaker_0.22      registry_0.2
## [13] energy_1.6.2        glmnet_1.9-8       Matrix_1.1-4
## [16] glmulti_1.0.7       rJava_0.9-6
##
## loaded via a namespace (and not attached):
##  [1] boot_1.3-13         codetools_0.2-9    colorspace_1.2-4
##  [4] compiler_3.1.1      digest_0.6.4       ggplot2_1.0.0
##  [7] grid_3.1.1          gridBase_0.4-7     gtable_0.1.2
## [10] lattice_0.20-29     MASS_7.3-35        munsell_0.4.2
## [13] plyr_1.8.1          proto_0.3-10       RColorBrewer_1.0-5
## [16] Rcpp_0.11.3         reshape2_1.4       scales_0.2.4
## [19] stringr_0.6.2       tools_3.1.1        xtable_1.7-4

sessionInfo()

## R version 3.1.1 (2014-07-10)
## Platform: x86_64-unknown-linux-gnu (64-bit)
##
## locale:
##  [1] LC_CTYPE=en_US.UTF-8      LC_NUMERIC=C
##  [3] LC_TIME=en_US.UTF-8      LC_COLLATE=en_US.UTF-8
##  [5] LC_MONETARY=en_US.UTF-8  LC_MESSAGES=en_US.UTF-8
##  [7] LC_PAPER=en_US.UTF-8     LC_NAME=en_US.UTF-8
##  [9] LC_ADDRESS=en_US.UTF-8   LC_TELEPHONE=en_US.UTF-8
## [11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=en_US.UTF-8
##
```

```
## attached base packages:
## [1] parallel  methods  splines  stats      graphics  grDevices  utils
## [8] datasets  base
##
## other attached packages:
## [1] MASS_7.3-39      stargazer_5.1      xtable_1.7-4
## [4] gplots_2.16.0    RColorBrewer_1.1-2 glmnet_1.9-8
## [7] Matrix_1.1-5     glmulti_1.0.7      rJava_0.9-6
## [10] bnlearn_3.7.1    nnls_1.4           NMF_0.20.5
## [13] synchronicity_1.1.4 bigmemory_4.4.6    BH_1.55.0-3
## [16] bigmemory.sri_0.1.3 Biobase_2.26.0     BiocGenerics_0.12.1
## [19] cluster_2.0.1    rngtools_1.2.4     pkgmaker_0.22
## [22] registry_0.2     energy_1.6.2       survival_2.37-7
## [25] tikzDevice_0.8.1 knitr_1.9
##
## loaded via a namespace (and not attached):
## [1] bitops_1.0-6      boot_1.3-15        caTools_1.17.1
## [4] codetools_0.2-10  colorspace_1.2-4   digest_0.6.8
## [7] doParallel_1.0.8  evaluate_0.5.5     filehash_2.2-2
## [10] foreach_1.4.2     formatR_1.0        gdata_2.13.3
## [13] ggplot2_1.0.0     grid_3.1.1         gridBase_0.4-7
## [16] gtable_0.1.2      gtools_3.4.1       highr_0.4
## [19] iterators_1.0.7   KernSmooth_2.23-14 labeling_0.3
## [22] lattice_0.20-30   munsell_0.4.2      plyr_1.8.1
## [25] proto_0.3-10      Rcpp_0.11.4        reshape2_1.4.1
## [28] scales_0.2.4      stringr_0.6.2      tools_3.1.1
```