

Supplementary data for the manuscript on the Pyrenodesmia Syngameon. Part I

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1 Introduction

This document contains the supplemenatary material necessary for the interpretation of the main manuscript regarding the taxonomically complex genus Pyrenodesmia. The supplement is organized in three parts.

The first part deals with population genetics and phylogenetic methods and aims at discussing the extent to which different methodological approaches can be used to identify species in this genus.

The second part uses sequences of the Mating type idiomorphs found in dykariotic samples to identify the extent to which there is a missmatch between postzygotic and prezygotic reproductive isolation.

Finally the third part surveys genomic signatures of hybridization encountered in the genome of Pyrenodesmia erodens.

The R code used for data processing, as untidy as it may be is shown together with the results. Some parts of the code have been commented out and substituted by importing a final environment to avoid repeating costly computations while compiling the supplement.

2 Part I. Population and phylogenetic structure

2.1 I.I Estimation of evolutionary populations in BAPS

```
knitr:::opts_chunk$set(echo = TRUE)
load("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v15.Rdata")
#load("/Users/Fernando/Desktop/01_Sanger_paper/14_bGMYC_All_loci/03_Processed/workspace_step3.Rdata")

library(ggplot2)
library(reshape2)
library(fpc)
library(vcd)
```

```

## Loading required package: grid
library(ape)
library(phangorn)
library(bipartite)

## Loading required package: vegan
## Loading required package: permute
## Loading required package: lattice
## This is vegan 2.6-2
##
## Attaching package: 'vegan'
## The following objects are masked from 'package:phangorn':
## 
##      diversity, treedist

## Loading required package: sna
## Loading required package: statnet.common
##
## Attaching package: 'statnet.common'
## The following objects are masked from 'package:base':
## 
##      attr, order

## Loading required package: network
##
## 'network' 1.17.1 (2021-06-12), part of the Statnet Project
## * 'news(package="network")' for changes since last version
## * 'citation("network")' for citation information
## * 'https://statnet.org' for help, support, and other information

## sna: Tools for Social Network Analysis
## Version 2.6 created on 2020-10-5.
## copyright (c) 2005, Carter T. Butts, University of California-Irvine
## For citation information, type citation("sna").
## Type help(package="sna") to get started.

##
## Attaching package: 'sna'
## The following objects are masked from 'package:ape':
## 
##      consensus, degree

## This is bipartite 2.17.
## For latest changes see versionlog in ?"bipartite-package". For citation see: citation("bipartite").
## Have a nice time plotting and analysing two-mode networks.

##
## Attaching package: 'bipartite'
## The following object is masked from 'package:vegan':
## 
##      nullmodel

```

```

library(knitr)
library(dplyr)

## 
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
## 
##     filter, lag
## The following objects are masked from 'package:base':
## 
##     intersect, setdiff, setequal, union

colorinos.bipolar<-c("#CAB2D6",
                      "#A6CEE3",
                      "#999999",
                      "#6A3D9A",
                      "#339933",
                      "#E31A1C",
                      "#FF7F00",
                      "#1F78B4",
                      "#B2DF8A",
                      "#FB9A99",
                      "#720DOE")

#
#
# Take out samples 810,811 Americanas and correct 281 and 357
#
#baps.adm["281",c(3,4,5,6)]<-baps.adm["1111",c(3,4,5,6)]
#baps.adm["357",c(3,4,5,6)]<-baps.adm["355",c(3,4,5,6)]
#baps.adm["194",c(3,4,5,6)]<-baps.adm["192",c(3,4,5,6)]
#baps.adm["261",c(3,4,5,6)]<-baps.adm["259",c(3,4,5,6)]
#baps.adm["262",c(3,4,5,6)]<-baps.adm["259",c(3,4,5,6)]
#baps.adm["318",c(3,4,5,6)]<-baps.adm["317",c(3,4,5,6)]
#baps.adm["318",2]<-baps.adm["17",2]
#baps.adm["283",2]<-baps.adm["17",2]
#baps.adm["178",2]<-baps.adm["17",2]
#baps.adm["1181",2]<-baps.adm["17",2]
#baps.adm["5",c(3,4,5,6)]<-baps.adm["3",c(3,4,5,6)]
#baps.adm["5.1",c(3,4,5,6)]<-baps.adm["3",c(3,4,5,6)]
#baps.adm["439",c(3,4,5,6)]<-baps.adm["438",c(3,4,5,6)]
#baps.adm["753",c(3,4,5,6)]<-baps.adm["751",c(3,4,5,6)]
#baps.adm["753.1",c(3,4,5,6)]<-baps.adm["751",c(3,4,5,6)]
#baps.adm["792",c(3,4,5,6)]<-baps.adm["794",c(3,4,5,6)]
#baps.adm["792.1",c(3,4,5,6)]<-baps.adm["794",c(3,4,5,6)]
#baps.adm["364",c(3,4,5,6)]<-baps.adm["854",c(3,4,5,6)]
#save.image("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v12.Rdata")
#
# Did not trim
#
#baps.adm<-baps.adm[rownames(baps.adm)!="810",]
#baps.adm<-baps.adm[rownames(baps.adm)!="811",]
#
# Last edit, ID correction

```

```

#  

#a<-read.table("/Users/Fernando/Desktop/01_paper_sanger_drive/reidentify.txt",header=FALSE,sep="\t")  

#rownames(a)<-a[,1]  

#baps.adm$Species<-a[as.character(sapply(strsplit(rownames(baps.adm), "\\."), `[,1]),2])  

#baps.adm["1049",3:6]<-c(439,6.465392,45.991996,1755)  

#save.image("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v13.Rdata")  

#  

sample_names<-sapply(strsplit(rownames(baps.adm), "\\."), `[,1)  

condensed_baps_adm<-baps.adm[!duplicated(sample_names),]  

foo<-aggregate(x=baps.adm[,13:22],by=list(sample_names),FUN=mean)  

rownames(foo)<-foo$Group.1  

condensed_baps_adm[,13:22]<-foo[rownames(condensed_baps_adm),-1]  

condensed_baps_adm<-cbind(sample=rownames(condensed_baps_adm),condensed_baps_adm)  

condensed_baps_adm$name<-apply(condensed_baps_adm[,14:23],1,FUN=which.max)  

orden.foo<-rownames(condensed_baps_adm)[order(condensed_baps_adm$name,-condensed_baps_adm$X1,-condensed_baps_adm$X2)]  

orden<-condensed_baps_adm[orden.foo,]  

foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo)  

foo<-melt(foo[,c(1,15:24)])  

## Using orden as id variables  

#### Rarefaction curves  

draw_haplo<-function(x)
{
require(future.apply)
plan(multicore,workers=100)
foo<-x
foo<-foo[row.names(foo)!="Xanpa",]
foo.list<-seq(from=5,to=dim(foo)[1],by=50)
salida<-future_lapply(foo.list,FUN=function(z){
  sapply(c(1:100),FUN=function(y){
    mean(
      dist(
        foo[sample(1:dim(foo)[1],size=z),]
      )
    )
  })
})
return(melt(salida))
}

#fer<-draw_haplo(seq.dataset[[1]])

```

2.1.1 Supplementary Figure 0. Species distribution in the dataset

```

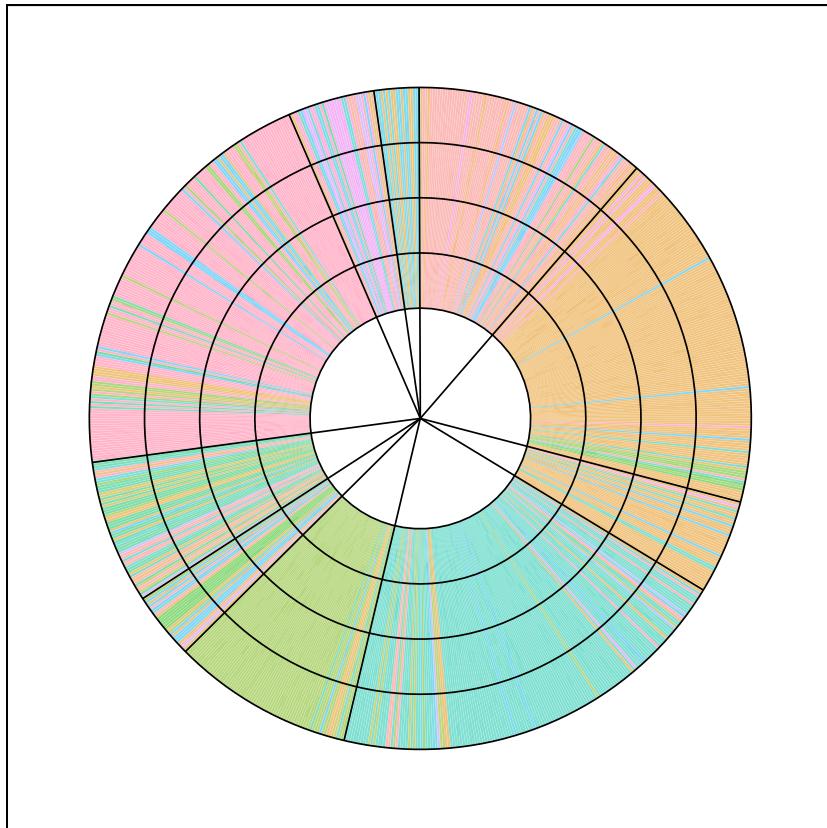
species_foo<-condensed_baps_adm[orden.foo,]
species_foo<-cbind(orden=factor(c(1:dim(species_foo)[1])),species_foo)
species_foo<-melt(species_foo[,c(1,3)])

```

```

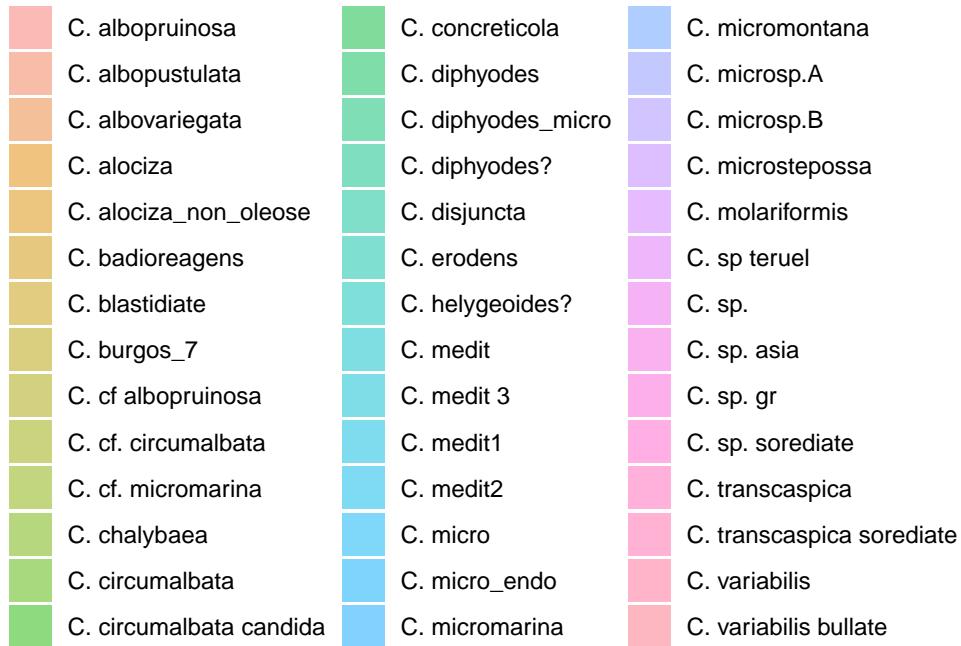
## Using orden, Species as id variables
p<-ggplot(species_foo) +
  geom_bar(aes(x=orden, y=1, fill=Species),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar) +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 0.25, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 0.5, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 0.75, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(), axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p+theme(legend.position = "none"))

```

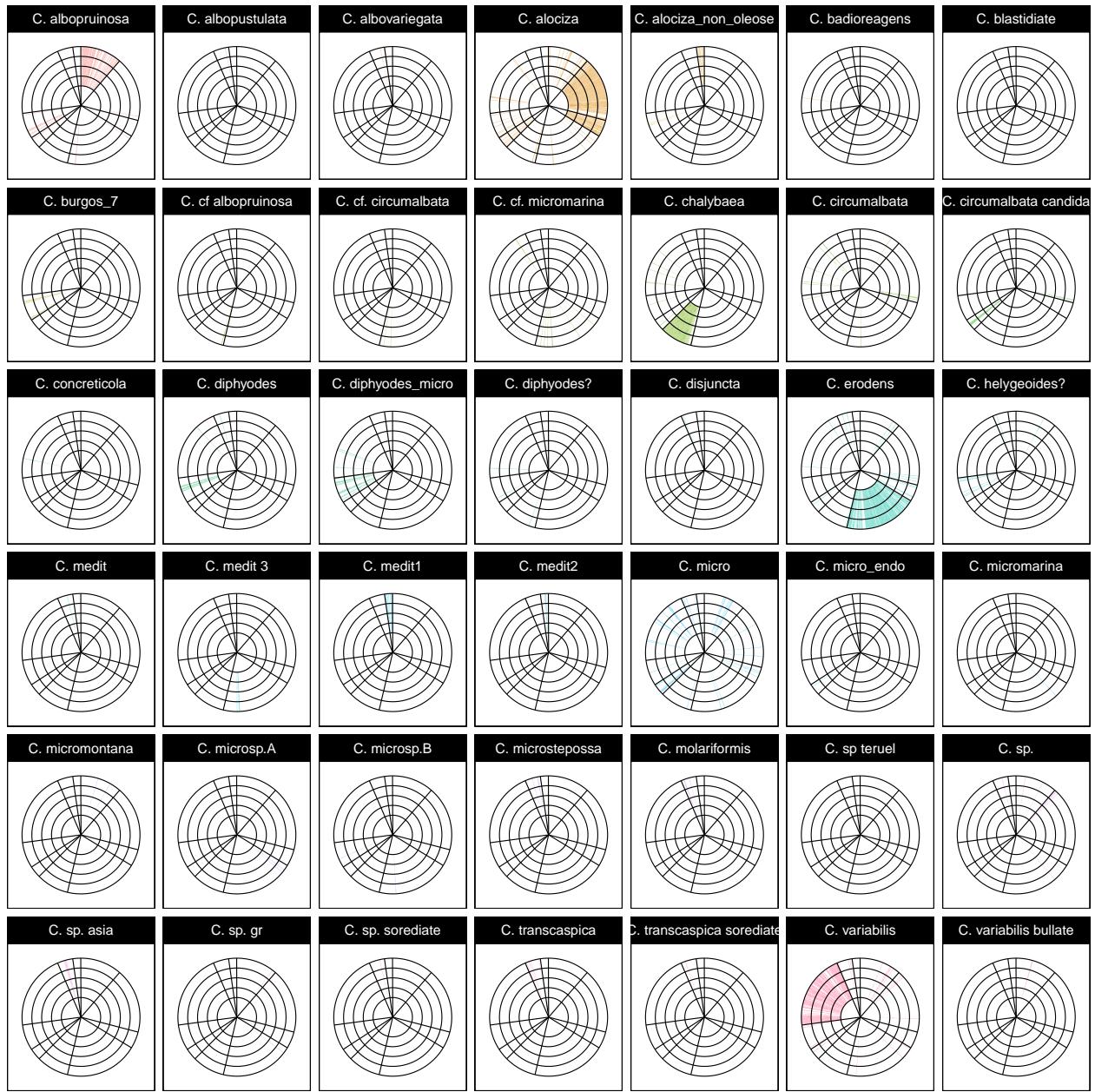


```
legend <- cowplot::get_legend(p)
grid.newpage()
grid.draw(legend)
```

#CAB2D6



```
print(p+theme(legend.position = "none")+facet_wrap(vars(Species)))
```



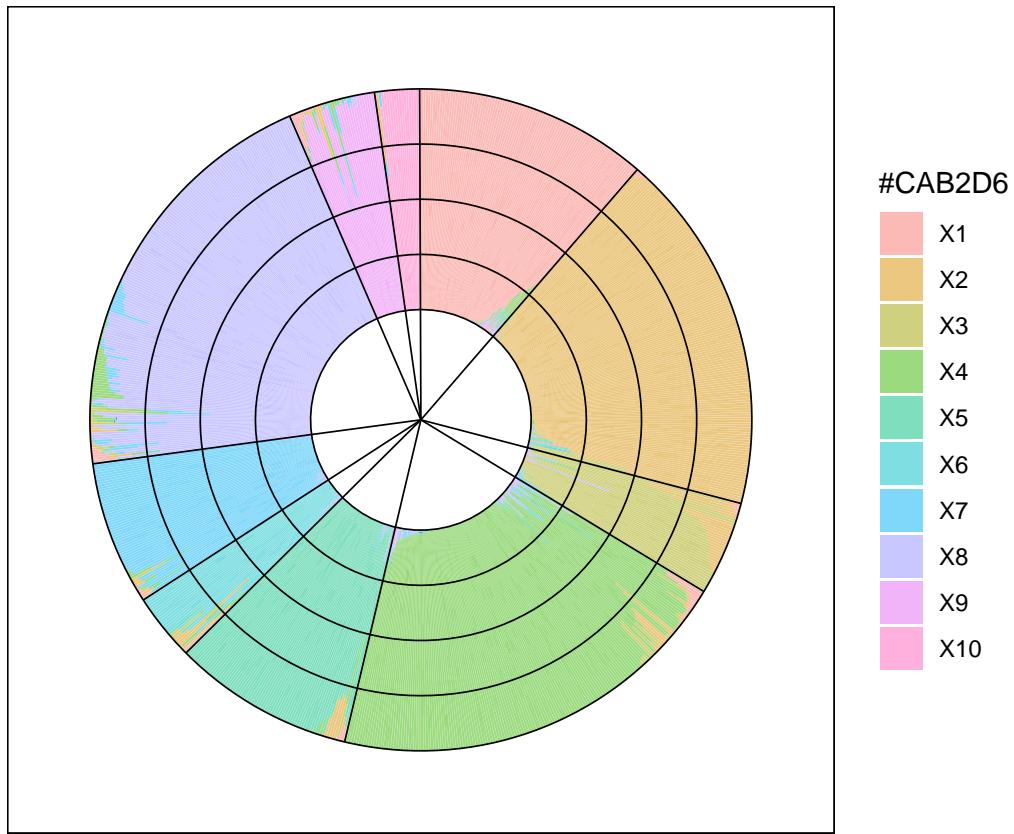
2.1.2 Supplementary Figure 1. Differential contribution to admixture of each gene-pool.

```
p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=value,fill=variable),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar) +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 0.25, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 0.5, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 0.75, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
```

```

geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
ylim(c(-0.5,1)) +
theme_linedraw() + theme(panel.grid.major.x = element_blank(),panel.grid.major.y = element_blank(),
axis.text.x=element_blank(),
axis.ticks.x=element_blank(),axis.title.y=element_blank(),
axis.text.y=element_blank(),
axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



2.1.3 Supplementary Figure 2. Contribution of each genepool to the minoritary admixed fractions.

```

library(dplyr)
min_fract<-melt(condensed_baps_adm[,c(1,14:23)])

## Using sample as id variables
foo<-sum(min_fract$value)
min_fract %>% group_by(variable) %>% arrange(value,.by_group = TRUE) %>% summarize(Sum = sum(value, na.rm=TRUE))

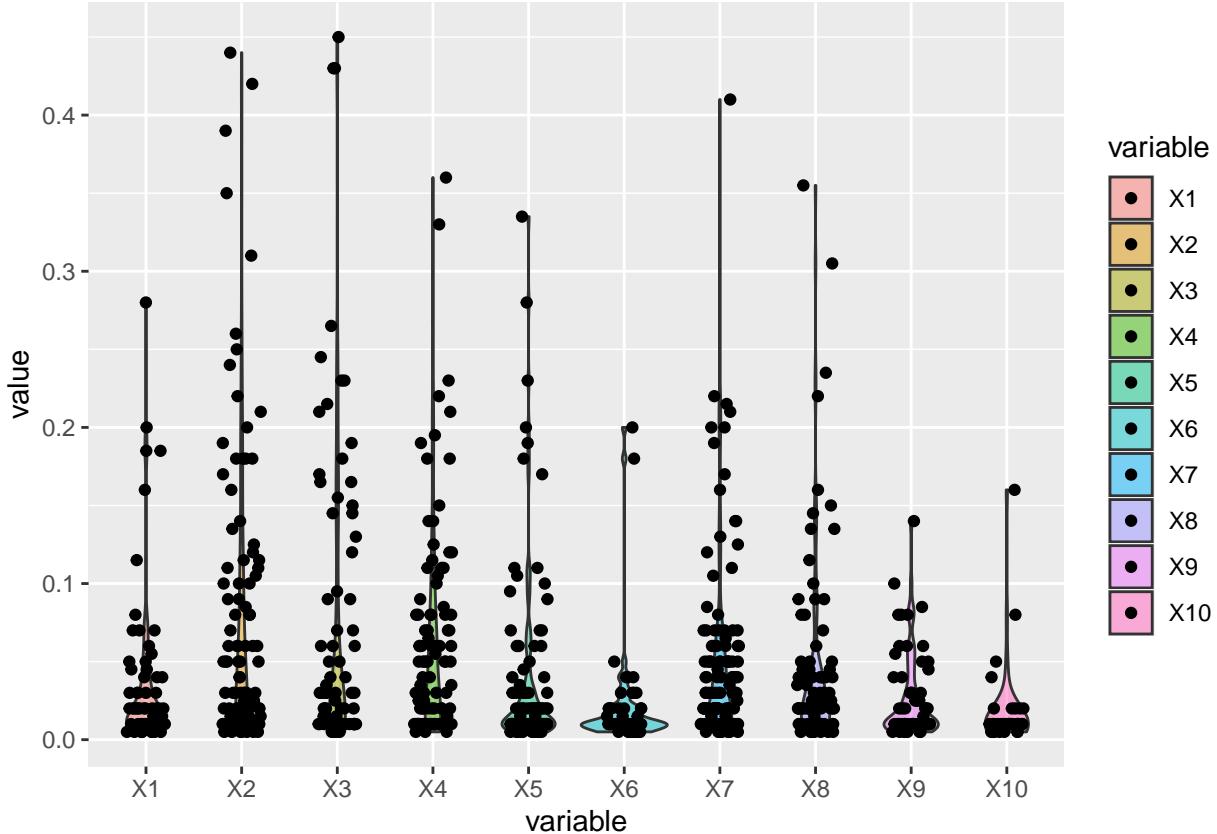
```

```

min_fract %>% group_by(sample) %>% slice_max(., order_by = value) -> max_fract
min_fract<-min_fract[min_fract$value!=0&min_fract$value!=1,]
#min_fract %>% group_by(sample) %>% arrange(value,.by_group = TRUE)

min_fract %>% group_by(sample) %>% arrange(value,.by_group = TRUE) %>% dplyr::slice(1:n()-1) %>% ggplot

```



```

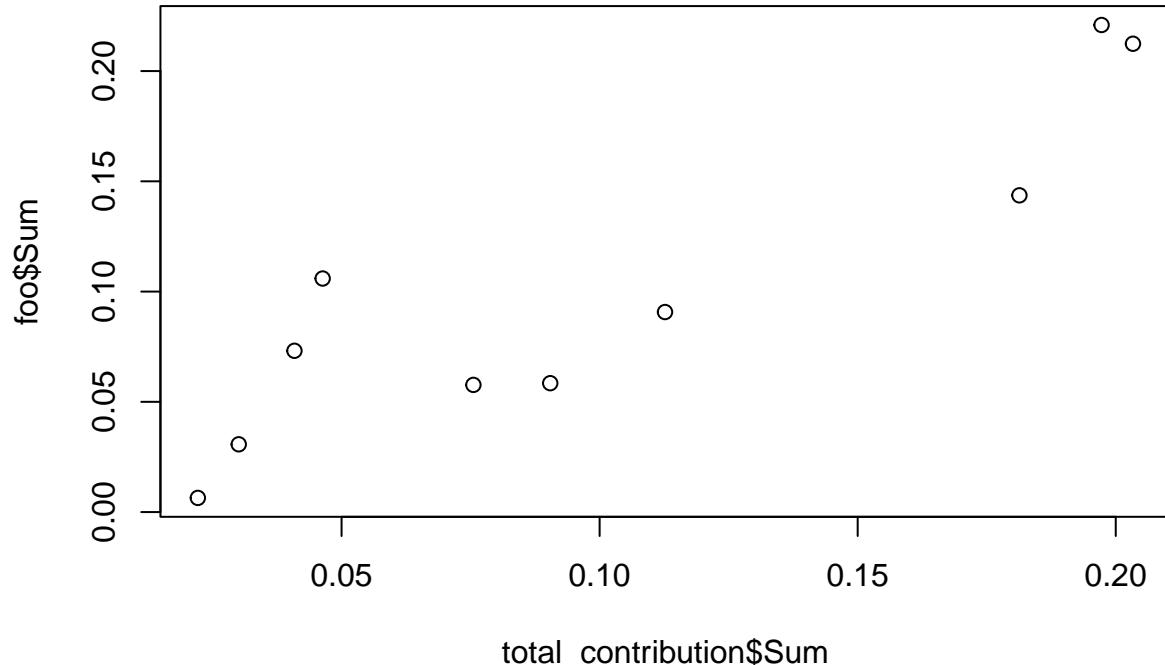
foo<-sum(min_fract$value)
min_fract %>% group_by(variable) %>% arrange(value,.by_group = TRUE) %>% summarize(Sum = sum(value, na.rm = TRUE))
table_admixture_anovas<-cbind(total=total_contribution,admix=foo$Sum)
kable(table_admixture_anovas)

```

total.variable	total.Sum	admix
X1	0.1126699	0.0907123
X2	0.1813350	0.1436467
X3	0.0463350	0.1059259
X4	0.1972512	0.2208974
X5	0.0904308	0.0584473
X6	0.0300789	0.0307265
X7	0.0755400	0.0576781
X8	0.2033374	0.2123932
X9	0.0408677	0.0731481
X10	0.0221541	0.0064245

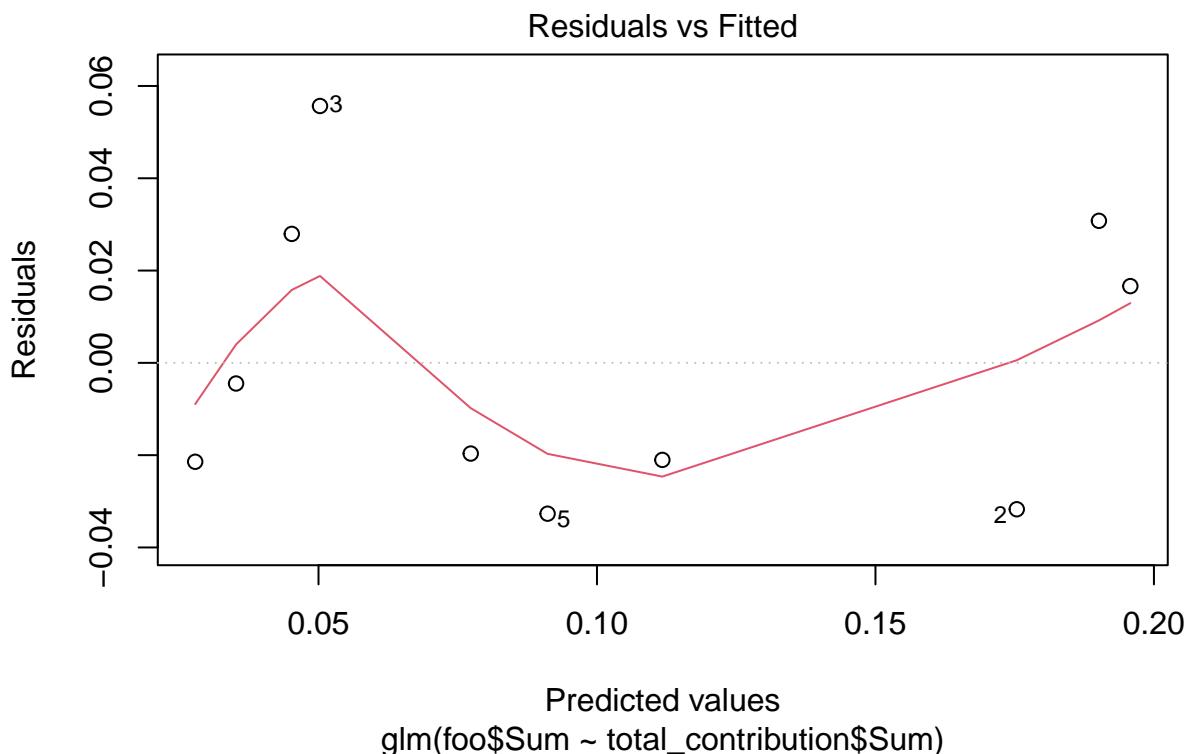
2.1.5 Supplementary Figure 3 (A-E). Contribution of each genepool to the minoritary admixed fractions. Added contribution of each component to the minor component vs fraction of the total contribution to ancestry of the whole dataset.

```
plot(foo$Sum~total_contribution$Sum)
```



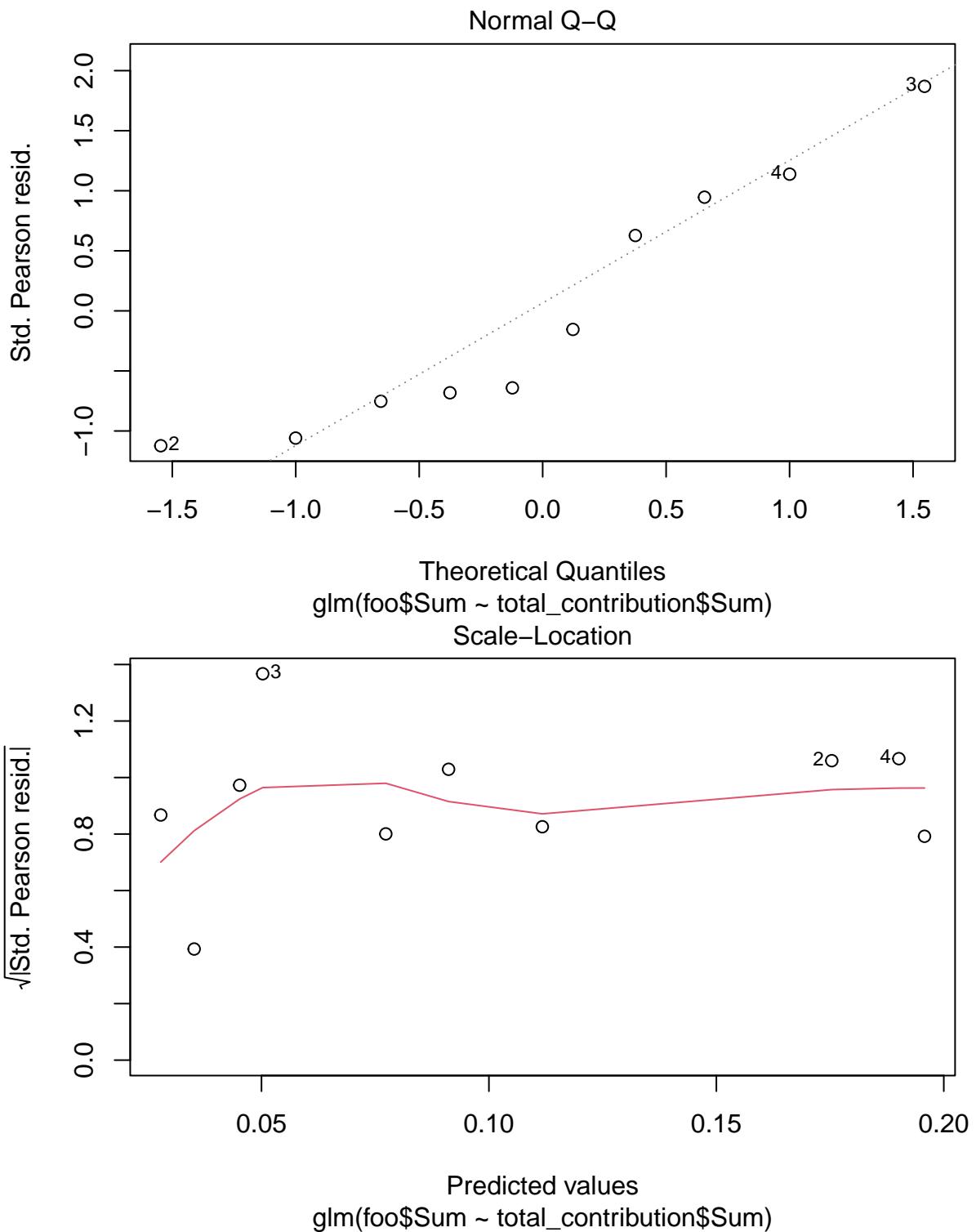
total_contribution\$Sum

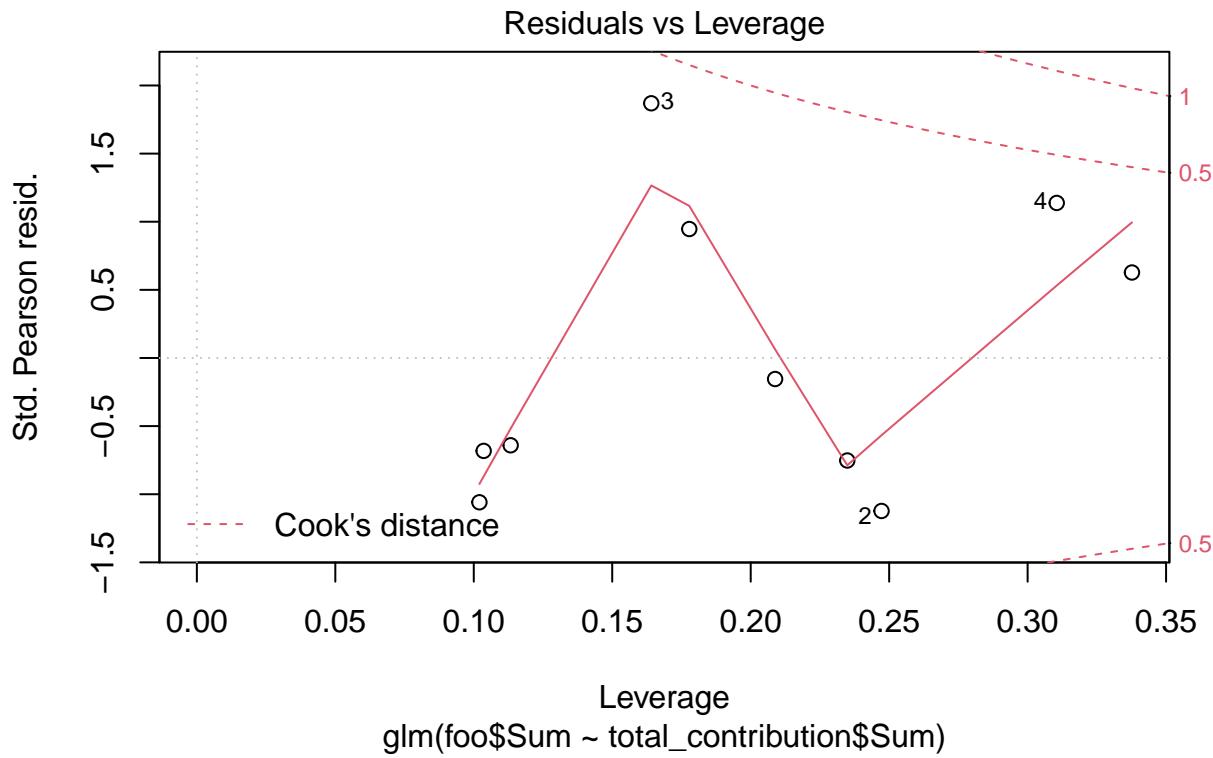
```
linear_model<-glm(foo$Sum~total_contribution$Sum)
plot(linear_model)
```



Predicted values

`glm(foo$Sum ~ total_contribution$Sum)`





2.1.6 Supplementary table 2. Contribution of each genepool to the minority admixed fractions.

```
kable(anova(linear_model))
```

	Df	Deviance	Resid. Df	Resid. Dev
NULL	NA	NA	9	0.0470688
total_contribution\$Sum	1	0.0385835	8	0.0084853

2.1.7 Supplementary Figure 4. Contribution of each genepool to the minority admixed fractions.

```
min_fract<-melt(condensed_baps_adm[,c(1,14:23)])

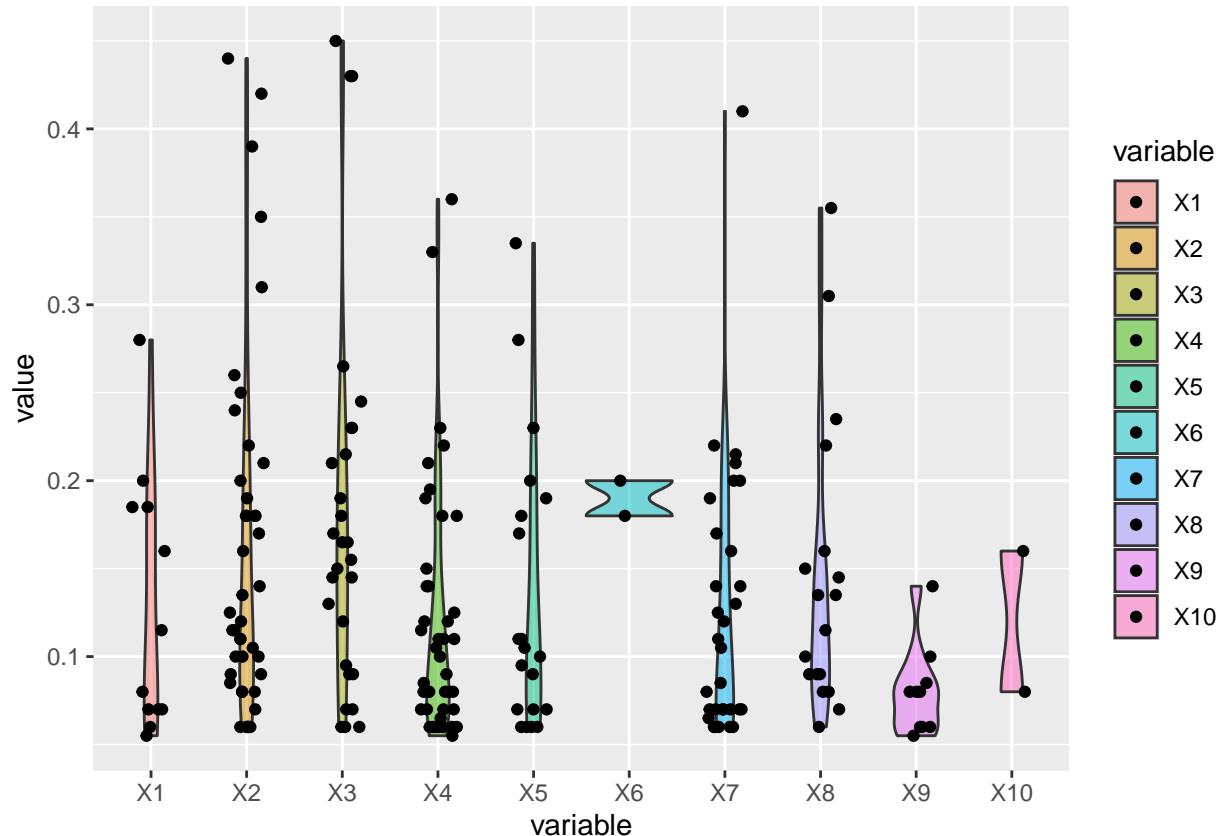
## Using sample as id variables
min_fract<-min_fract[min_fract$value>0.05&min_fract$value<0.95,]
min_fract %>% group_by(sample) %>% arrange(value, .by_group = TRUE)

## # A tibble: 396 x 3
## # Groups:   sample [187]
##   sample variable value
##   <chr>   <fct>   <dbl>
## 1 1005    X5      0.105
## 2 1005    X3      0.15
## 3 1005    X7      0.675
## 4 1008    X7      0.9
## 5 1016    X4      0.065
## 6 1016    X8      0.235
```

```

## 7 1016 X1      0.28
## 8 1016 X6      0.335
## 9 1022 X8      0.135
## 10 1022 X1     0.86
## # ... with 386 more rows
min_fract %>% group_by(sample) %>% arrange(value, .by_group = TRUE) %>% dplyr::slice(1:n()-1) %>% ggplot

```



2.1.8 Supplementary table 3. Contribution of each genepool to the minority admixed fractions.

```

min_fract %>% group_by(variable) %>% summarize(Mean = mean(value, na.rm=TRUE), Sum = sum(value, na.rm=TRUE)
foo %>% glm(Mean~Max,data=.) %>% anova %>% kable()

```

	Df	Deviance	Resid. Df	Resid. Dev
NULL	NA	NA	9	0.1022319
Max	1	0.0007222	8	0.1015098

```
table_admixture_anovas<-cbind(table_admixture_anovas,Mean05=foo$Mean,Sum05=foo$Sum,Max05=foo$Max)
```

2.1.9 Supplementary table 4. Analisis of variance.

```
foo %>% lm(Sum~Max,data=.) %>% anova %>% kable()
```

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Max	1	791.2860	791.28595	11.49888	0.0094859
Residuals	8	550.5135	68.81418	NA	NA

2.1.10 Supplementary Figure 5. Contribution of each genepool to the minoritary admixed fractions considering at least 0.1 as a significant fraction.

```

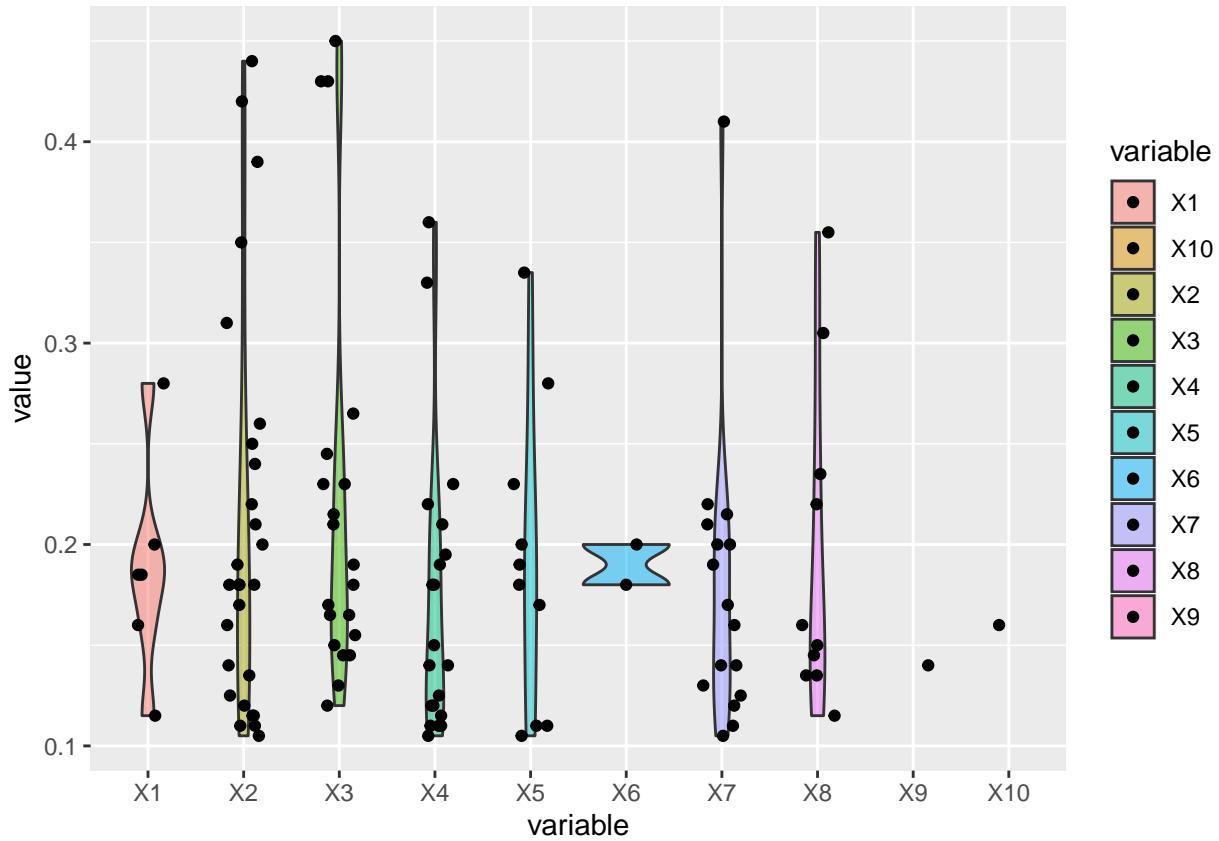
min_fract<-melt(condensed_baps_adm[,c(1,14:23)])

## Using sample as id variables
min_fract<-min_fract[min_fract$value>0.10&min_fract$value<0.90,]
min_fract %>% group_by(sample) %>% arrange(value,.by_group = TRUE)

## # A tibble: 242 x 3
## # Groups:   sample [129]
##   sample variable value
##   <chr>   <fct>   <dbl>
## 1 1005    X5      0.105
## 2 1005    X3      0.15 
## 3 1005    X7      0.675
## 4 1016    X8      0.235
## 5 1016    X1      0.28 
## 6 1016    X6      0.335
## 7 1022    X8      0.135
## 8 1022    X1      0.86 
## 9 1031    X1      0.895
## 10 1033   X2      0.105
## # ... with 232 more rows
min_fract %>% group_by(sample) %>% arrange(value,.by_group = TRUE) %>% dplyr::slice(1:n()-1) %>% ggplot

## Warning: Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.

```



2.1.11 Supplementary table 5. Analysis of variance using average assignments

```
min_fract %>% group_by(variable) %>% summarize(Mean = mean(value, na.rm=TRUE), Sum = sum(value, na.rm=TRUE))
foo %>% lm(Mean~Max,data=.) %>% anova

## Analysis of Variance Table
##
## Response: Mean
##             Df   Sum Sq   Mean Sq F value Pr(>F)
## Max          1 0.000626 0.0006264  0.0519 0.8254
## Residuals    8 0.096479 0.0120599
```

2.1.12 Supplementary table 6. Analysis of variance using summed assignments.

```
foo %>% lm(Sum~Max,data=.) %>% anova

## Analysis of Variance Table
##
## Response: Sum
##             Df   Sum Sq   Mean Sq F value    Pr(>F)
## Max          1 277.94 277.945   18.15 0.00276 ***
## Residuals    8 122.51  15.314
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

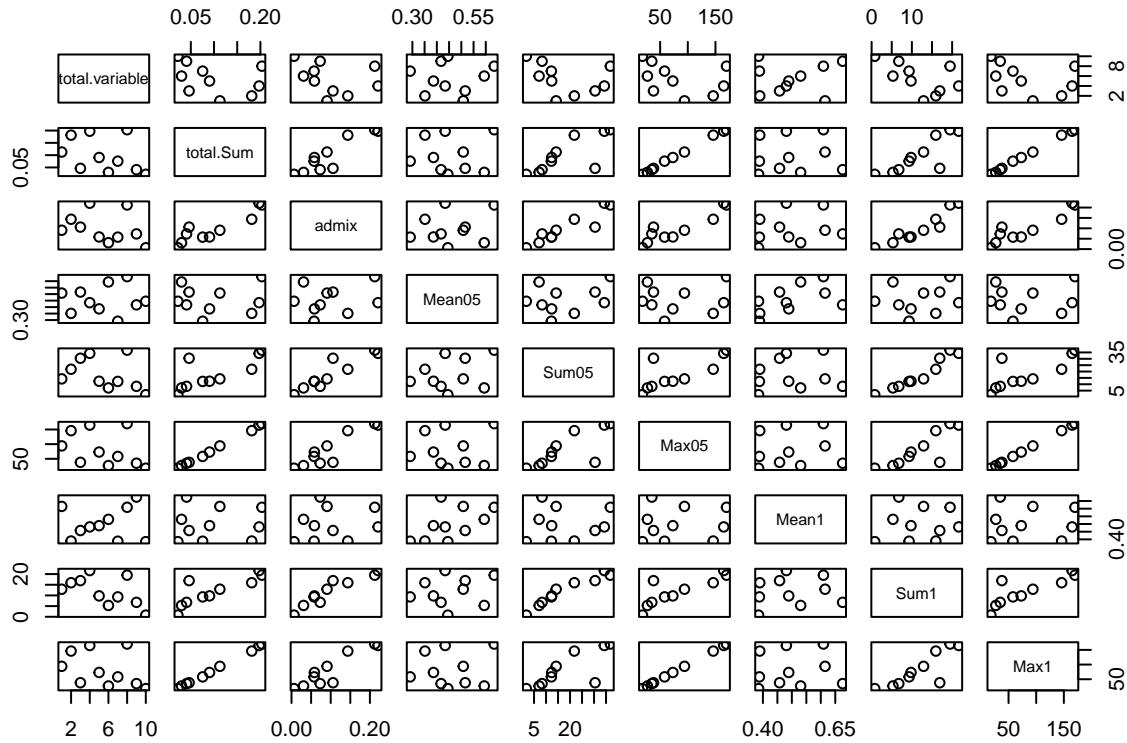
2.1.13 Supplementary table 7. Contribution of each gene-pool to the minor admixed component across the dataset.

```
table_admixture_anovas<-cbind(table_admixture_anovas,Mean1=foo$Mean,Sum1=foo$Sum,Max1=foo$Max)
kable(table_admixture_anovas)
```

total.variable	total.Sum	admix	Mean05	Sum05	Max05	Mean1	Sum1	Max1
X1	0.1126699	0.0907123	0.5080357	14.225	94	0.6147619	12.910	94
X2	0.1813350	0.1436467	0.3514516	21.790	146	0.3891463	15.955	146
X3	0.0463350	0.1059259	0.5158475	30.435	38	0.4575676	16.930	38
X4	0.1972512	0.2208974	0.4340506	34.290	165	0.4811111	21.650	165
X5	0.0904308	0.0584473	0.3862500	12.360	73	0.4892500	9.785	73
X6	0.0300789	0.0307265	0.5937500	7.125	27	0.5305000	5.305	27
X7	0.0755400	0.0576781	0.2909524	12.220	58	0.3879167	9.310	58
X8	0.2033374	0.2123932	0.6344828	36.800	170	0.6090625	19.490	170
X9	0.0408677	0.0731481	0.4172500	8.345	35	0.6755000	6.755	35
X10	0.0221541	0.0064245	0.4450000	1.780	18	0.3850000	0.770	18

2.1.14 Supplementary Figure 6.

```
plot(table_admixture_anovas)
```



2.1.15 Supplementary table 8.

```
table_admixture_anovas %>% glm(Max05~total.Sum,data=.) %>% anova %>% kable ()
```

	Df	Deviance	Resid. Df	Resid. Dev
NULL	NA	NA	9	30794.40000

	Df	Deviance	Resid.	Df	Resid.	Dev
total.Sum	1	30742.67		8		51.73341

2.1.16 Supplementary table 9.

```
table_admixture_anovas %>% glm(Max1~total.Sum,data=.) %>% anova %>% kable ()
```

	Df	Deviance	Resid.	Df	Resid.	Dev
NULL	NA	NA		9	30794.40000	
total.Sum	1	30742.67		8		51.73341

2.1.17 Supplementary table 10.

```
table_admixture_anovas %>% glm(Mean05~total.Sum,data=.) %>% anova %>% kable ()
```

	Df	Deviance	Resid.	Df	Resid.	Dev
NULL	NA	NA		9	0.1022319	
total.Sum	1	0.0002686		8		0.1019633

```
table_admixture_anovas %>% glm(Mean1~total.Sum,data=.) %>% anova %>% kable ()
```

	Df	Deviance	Resid.	Df	Resid.	Dev
NULL	NA	NA		9	0.0971052	
total.Sum	1	0.0002626		8		0.0968427

```
table_admixture_anovas %>% glm(Sum05~total.Sum,data=.) %>% anova %>% kable ()
```

	Df	Deviance	Resid.	Df	Resid.	Dev
NULL	NA	NA		9	1341.7994	
total.Sum	1	777.27		8		564.5295

```
table_admixture_anovas %>% glm(Sum1~total.Sum,data=.) %>% anova %>% kable ()
```

	Df	Deviance	Resid.	Df	Resid.	Dev
NULL	NA	NA		9	400.4559	
total.Sum	1	275.8771		8		124.5789

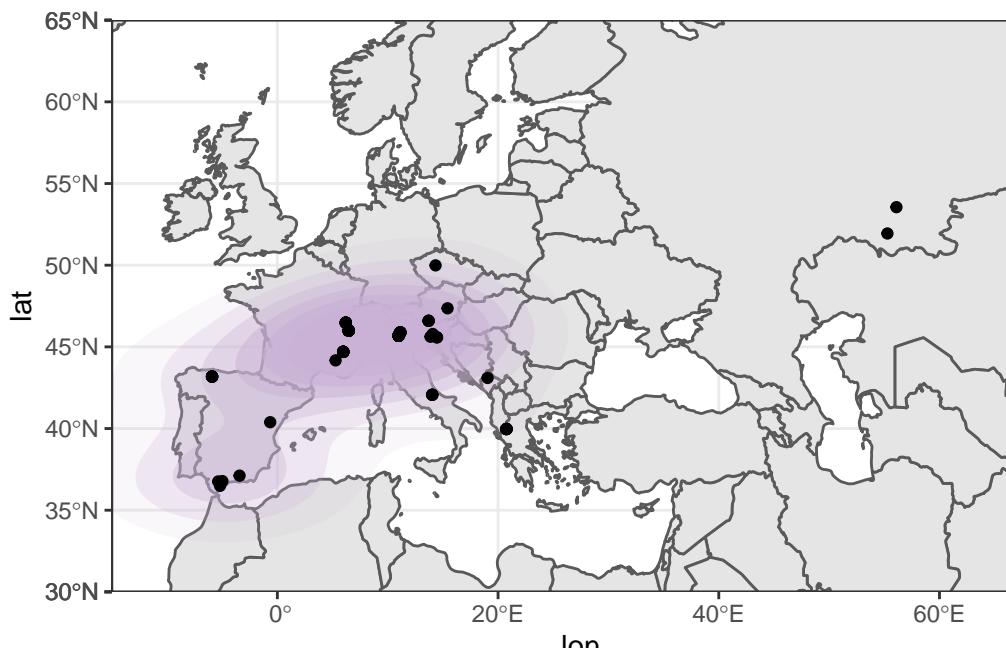
```
kable(anova(linear_model))
```

	Df	Deviance	Resid.	Df	Resid.	Dev
NULL	NA	NA		9	0.0470688	
total_contribution\$Sum	1	0.0385835		8		0.0084853

2.1.18 Geographic distribution of BAPS gene-pools

```
library("rnaturalearth")
library("rnaturalearthdata")

world <- ne_countries(scale = "medium", returnclass = "sf")
foo<-condensed_baps_adm[condensed_baps_adm$X1>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                  data=foo[!duplicated(foo$Locality),],
                  mapping = aes(x=lon,y=lat,alpha = ..level..),
                  fill = colorinos.bipolar[1]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))
```



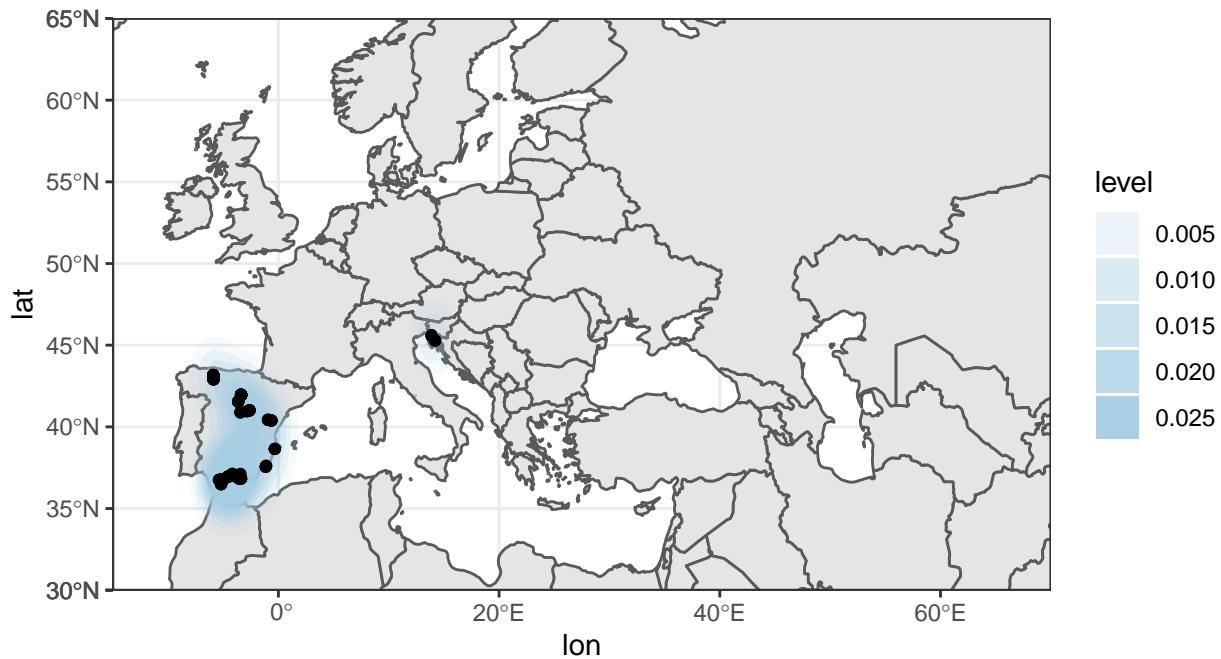
2.1.18.1 Supplementary figure

```
foo<-condensed_baps_adm[condensed_baps_adm$X2>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                  data=foo[!duplicated(foo$Locality),],
                  mapping = aes(x=lon,y=lat,alpha = ..level..),
                  fill = colorinos.bipolar[2]) +
```

```

expand_limits(x= c(-30, 70),
              y = c(30, 65)) +
geom_point(data=foo,
           aes(x=lon,y=lat))

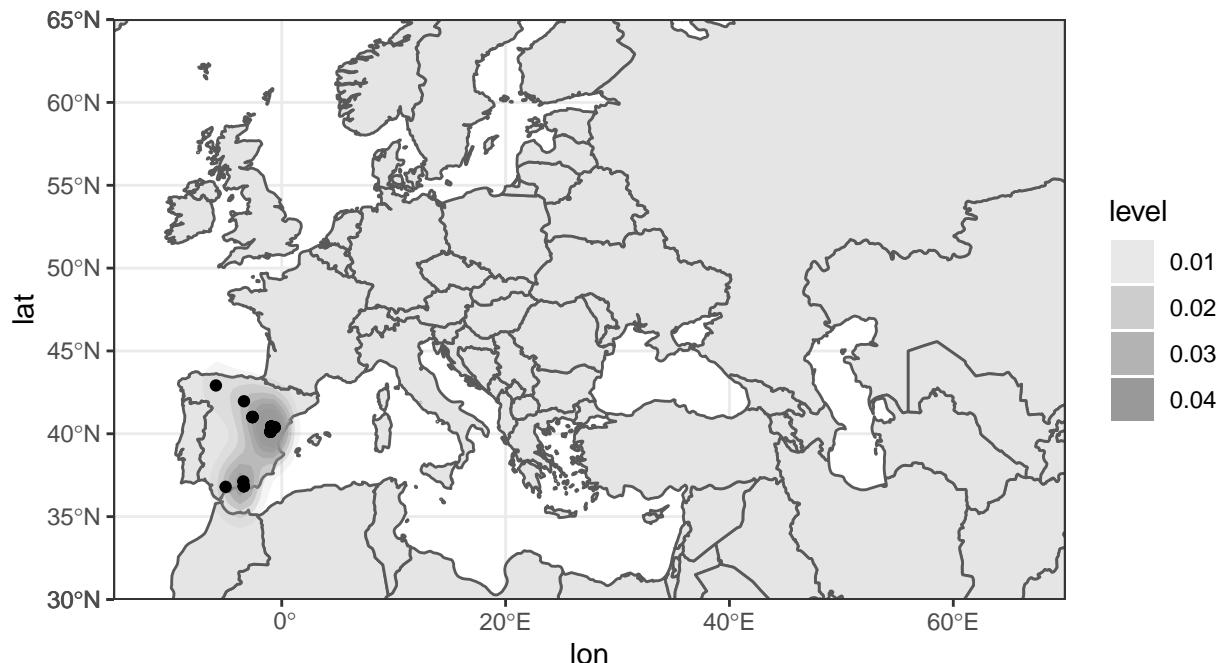
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X3>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[3]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

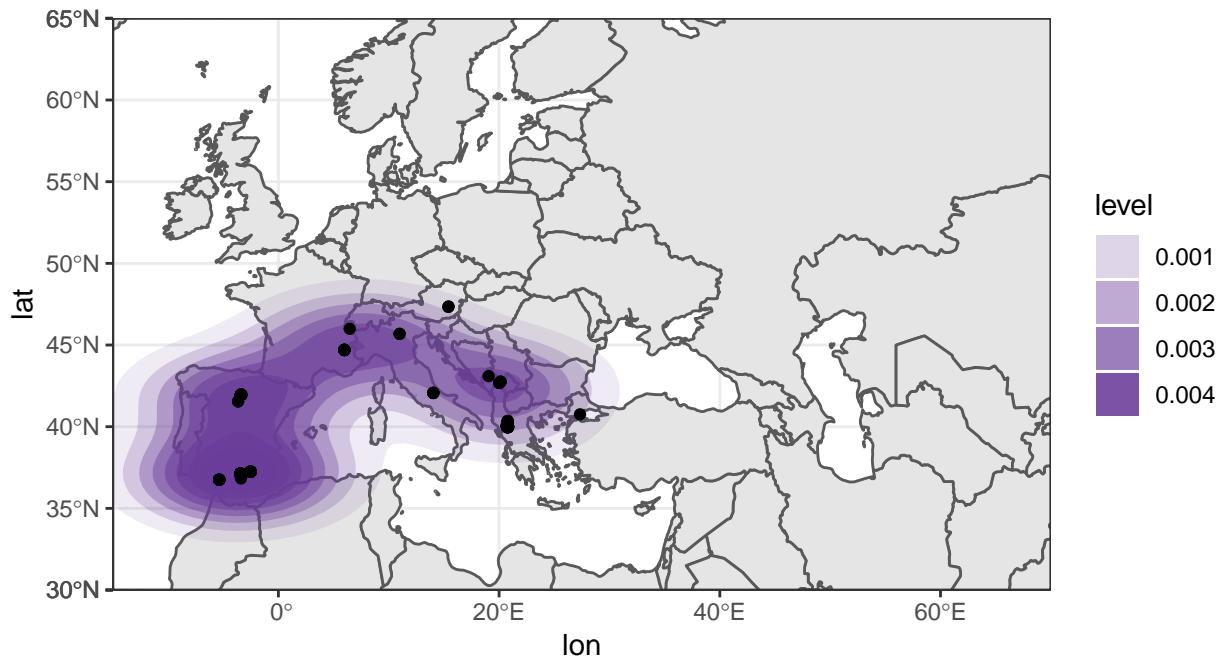
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X4>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[4]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

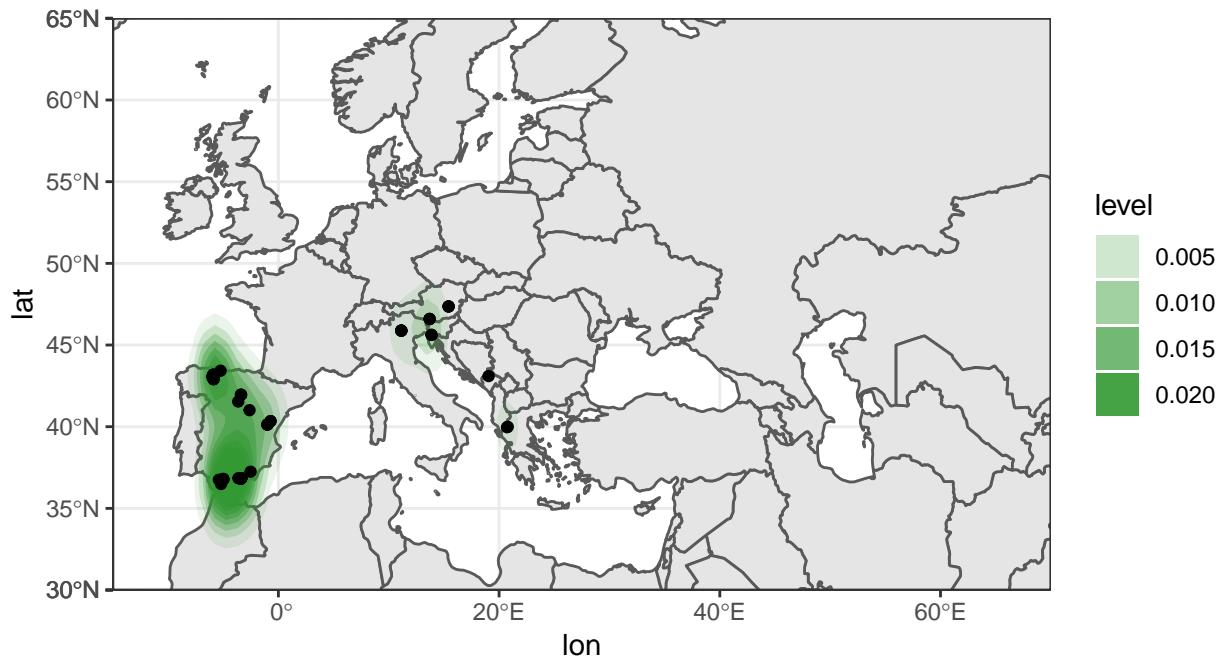
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X5>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[5]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

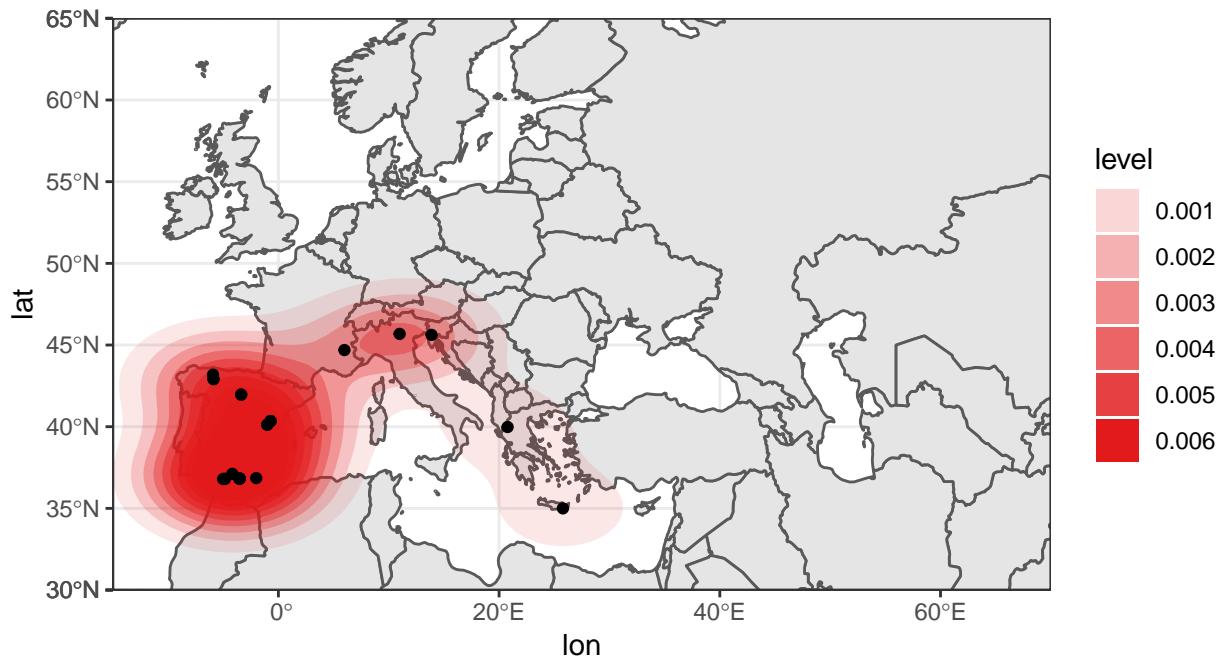
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X6>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[6]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

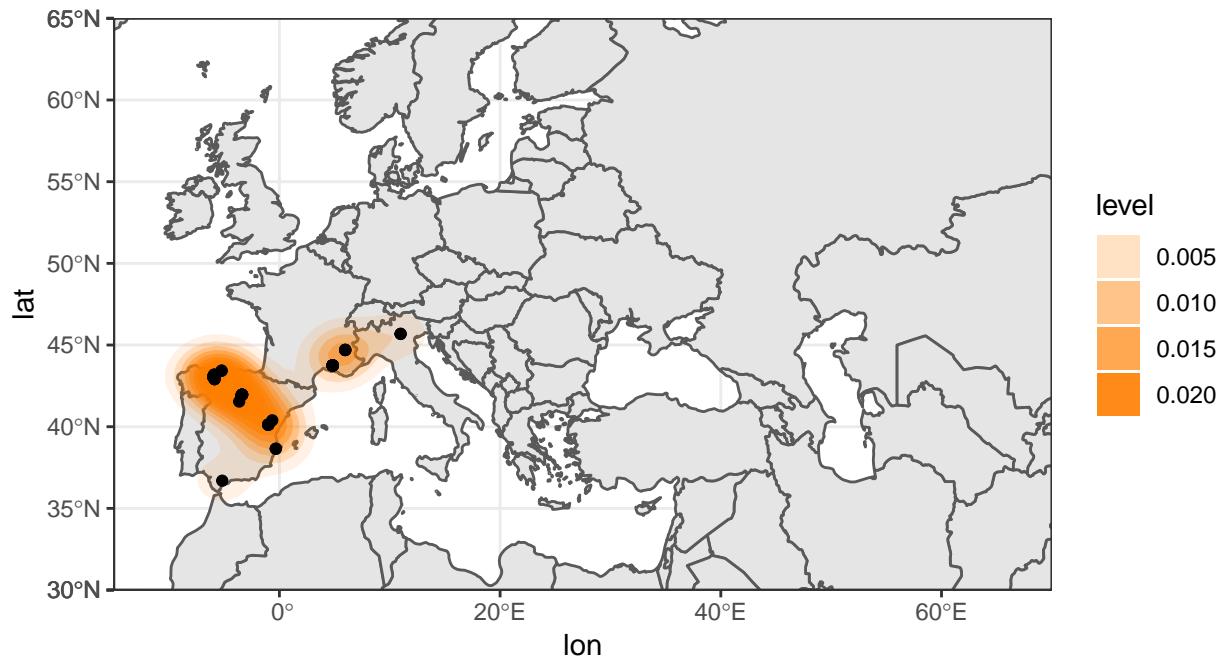
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X7>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[7]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

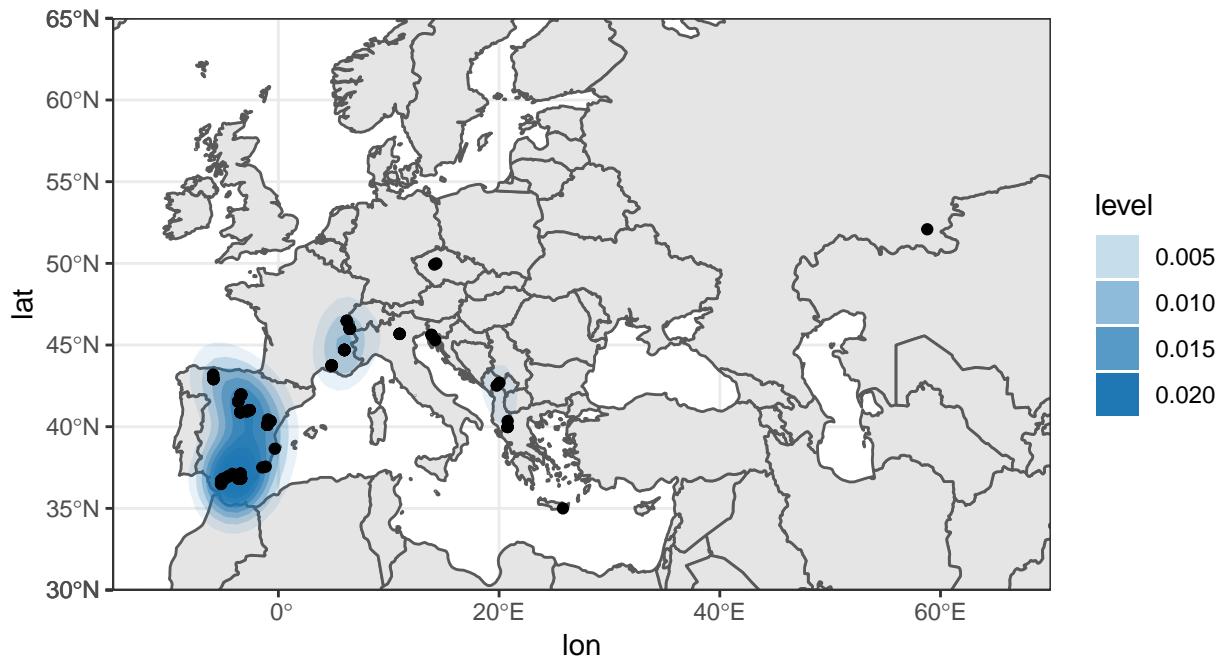
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X8>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[8]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

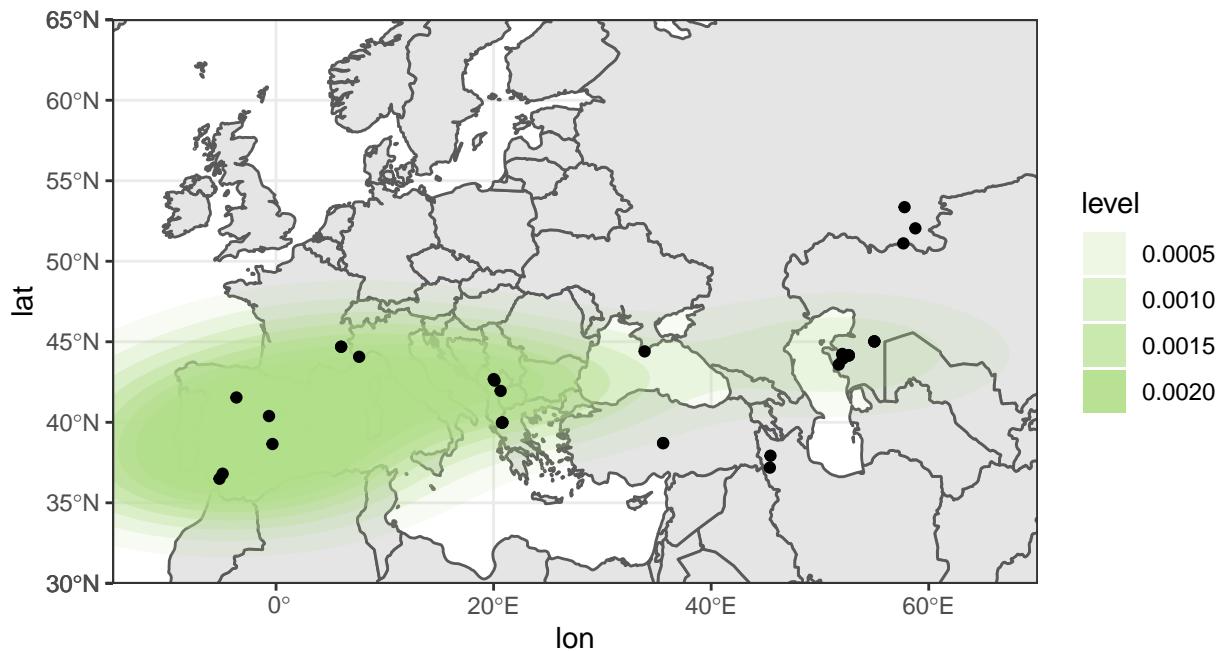
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X9>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[9]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

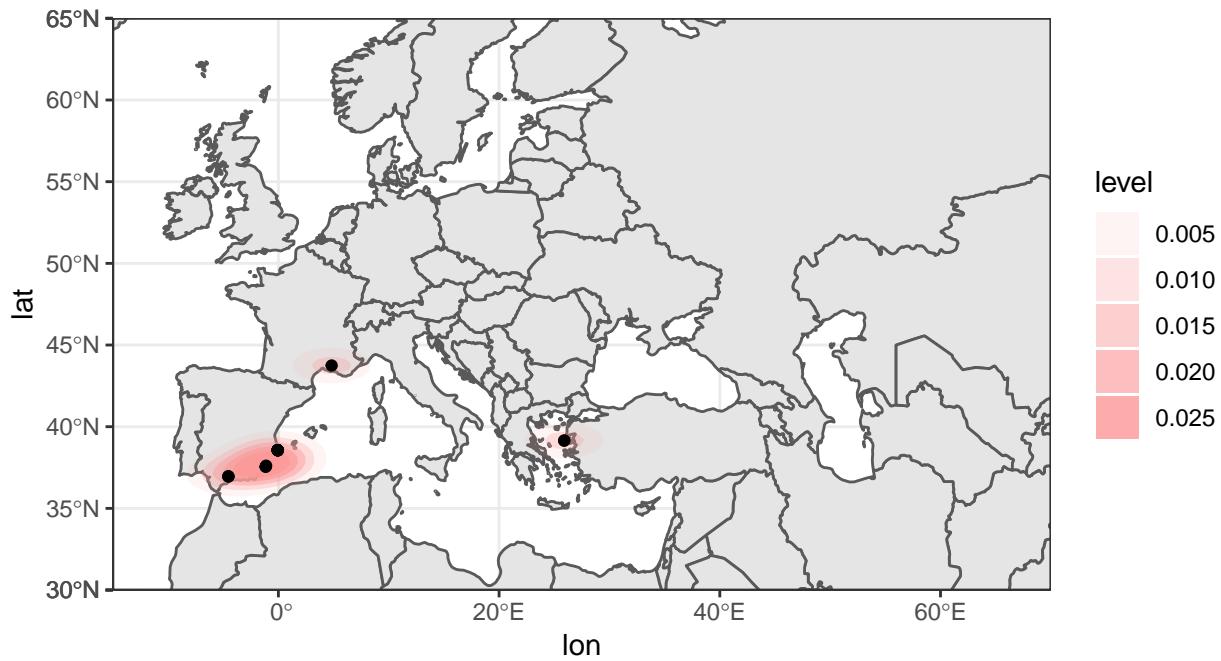
```



```

foo<-condensed_baps_adm[condensed_baps_adm$X10>0.5,]
ggplot(data = world) +
  geom_sf() +
  theme_bw() +
  coord_sf(xlim = c(-15, 70),
            ylim = c(30, 65),
            expand = FALSE) +
  stat_density_2d(geom = "polygon",
                 data=foo[!duplicated(foo$Locality),],
                 mapping = aes(x=lon,y=lat,alpha = ..level..),
                 fill = colorinos.bipolar[10]) +
  expand_limits(x= c(-30, 70),
                y = c(30, 65)) +
  geom_point(data=foo,
             aes(x=lon,y=lat))

```



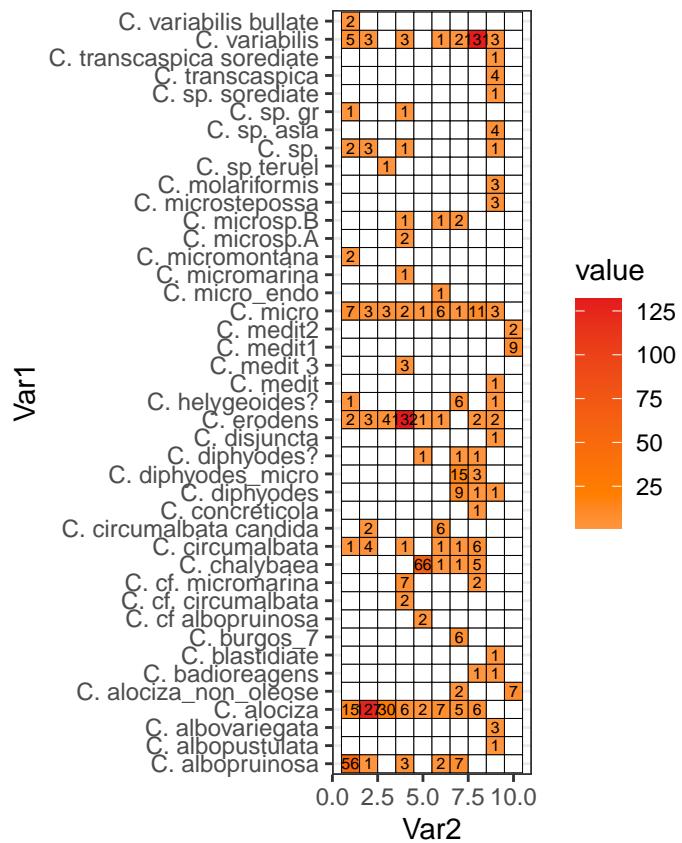
2.1.19 Association between gene-pools and morphospecies

```
# Heatmap 1 Species vs BAPS

foo_tabla<-melt(table(condensed_baps_adm$Species,condensed_baps_adm$name))
foo_tabla$value[foo_tabla$value==0]<-NA

ggplot(foo_tabla,aes(x=Var2,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label =
  scale_fill_gradient2(low = "#FFFFFF",
  mid = colorinos.bipolar[7],
  high = colorinos.bipolar[6],
  midpoint = 20,
  space = "Lab",
  na.value = "#FFFFFF",
  guide = "colourbar",
  aesthetics = "fill"
) +
  coord_fixed() + theme_bw()

## Warning: Removed 321 rows containing missing values (geom_text).
```



```
print(assoc(table(condensed_baps_adm$Species,condensed_baps_adm$name),shade=TRUE))
```



	B	1	2	3	4	5	6	7	8	9	10
## A											
## C. albopruinosa		56	1	0	3	0	2	7	0	0	0
## C. albopustulata		0	0	0	0	0	0	0	0	1	0
## C. albovariegata		0	0	0	0	0	0	0	0	3	0
## C. alociza		15	127	30	6	2	7	5	6	0	0
## C. alociza_non_oleose		0	0	0	0	0	0	2	0	0	7
## C. badioreagens		0	0	0	0	0	0	0	1	1	0
## C. blastidiata		0	0	0	0	0	0	0	0	1	0
## C. burgos_7		0	0	0	0	0	0	6	0	0	0
## C. cf albopruinosa		0	0	0	0	2	0	0	0	0	0
## C. cf. circumalbata		0	0	0	2	0	0	0	0	0	0
## C. cf. micromarina		0	0	0	7	0	0	0	2	0	0
## C. chalybaea		0	0	0	0	66	1	1	5	0	0

```

## C. circumalbata      1  4  0  1  0  1  1  6  0  0
## C. circumalbata candida  0  2  0  0  0  6  0  0  0  0
## C. concreticola     0  0  0  0  0  0  0  1  0  0
## C. diphyodes        0  0  0  0  0  0  9  1  1  0
## C. diphyodes_micro   0  0  0  0  0  0  0  15 3  0
## C. diphyodes?       0  0  0  0  1  0  1  1  0  0
## C. disjuncta         0  0  0  0  0  0  0  0  0  1
## C. erodens          2  3  4 132 1  1  0  2  2  0
## C. helygeoides?     1  0  0  0  0  0  6  0  1  0
## C. medit            0  0  0  0  0  0  0  0  0  1
## C. medit 3          0  0  0  3  0  0  0  0  0  0
## C. medit1           0  0  0  0  0  0  0  0  0  9
## C. medit2           0  0  0  0  0  0  0  0  0  2
## C. micro             7  3  3  2  1  6  1 11 3  0
## C. micro_endo       0  0  0  0  0  1  0  0  0  0
## C. micromarina      0  0  0  1  0  0  0  0  0  0
## C. micromontana     2  0  0  0  0  0  0  0  0  0
## C. microsp.A        0  0  0  2  0  0  0  0  0  0
## C. microsp.B        0  0  0  1  0  1  2  0  0  0
## C. microstepossa    0  0  0  0  0  0  0  0  0  3
## C. molariformis     0  0  0  0  0  0  0  0  0  0
## C. sp teruel        0  0  1  0  0  0  0  0  0  0
## C. sp.              2  3  0  1  0  0  0  0  0  1
## C. sp. asia          0  0  0  0  0  0  0  0  0  4
## C. sp. gr            1  0  0  1  0  0  0  0  0  0
## C. sp. sorediate    0  0  0  0  0  0  0  0  0  1
## C. transcaspica     0  0  0  0  0  0  0  0  0  4
## C. transcaspica sorediate  0  0  0  0  0  0  0  0  0  1
## C. variabilis        5  3  0  3  0  1  2 131 3  0
## C. variabilis bullate  2  0  0  0  0  0  0  0  0  0

assocstats(table(condensed_baps_adm$Species,condensed_baps_adm$name))

##          X^2  df P(> X^2)
## Likelihood Ratio 2168.8 369      0
## Pearson        4234.2 369      0
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.915
## Cramer's V      : 0.756

#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm$Species,condensed_baps_adm$name))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm$Species, condensed_baps_adm$name)
## f(x) = 23.41, p-value < 2.2e-16

```

2.1.20 How much of the species splitting is explained by the assignment to gene-pools?

```
library(mda)
```

```

## Loading required package: class
## Loaded mda 0.5-3
##
## Attaching package: 'mda'
## The following object is masked from 'package:fpc':
##      confusion
foo_fdas<-condensed_baps_adm[,c("Species","X1","X2","X3","X4","X5","X6","X7","X8","X9","X10")]
disc_clusters<-mda::fda(Species~X1+X2+X3+X4+X5+X6+X7+X8+X9+X10, foo_fdas)
print(disc_clusters)

## Call:
## mda::fda(formula = Species ~ X1 + X2 + X3 + X4 + X5 + X6 + X7 +
##           X8 + X9 + X10, data = foo_fdas)
##
## Dimension: 26
##
## Percent Between-Group Variance Explained:
##      v1      v2      v3      v4      v5      v6      v7      v8      v9      v10     v11
## 36.82 61.53 73.39 82.90 90.00 94.98 98.32 99.96 100.00 100.00 100.00
##      v12     v13     v14     v15     v16     v17     v18     v19     v20     v21     v22
## 100.00 100.00 100.00 100.00 100.00 100.00 100.00 100.00 100.00 100.00 100.00
##      v23     v24     v25     v26
## 100.00 100.00 100.00 100.00
##
## Degrees of Freedom (per dimension): 10
##
## Training Misclassification Error: 0.33374 ( N = 824 )
kable(coef(disc_clusters,foo_fdas))

```

Intercept	21.89455	-	-	0.0750303662867391465e+00	2e-1	1e-1	0e+00	-	-	0e+00	1e-1	-	0e+00	0e+00			
	0.999120380627737			0.02125307	07	07	07	07	2e-1	1e-1	07	07	1e-1	07			
									07	07			07	07			
X1	-	2.043324463853373	-	2.376558106324270	-	-	-	-	2e-1	1e-1	0e+00	0e+00	1e-1	-	0e+00		
	22.17266		0.71373296006		07	1e-1	2e-1	3e-1	1e-1	2e-1	07	07	3e-1	07	07	2e-1	
					07	07	07	07	07	07			07		07	07	
X2	-	2.23010209258064009	0.43700820.410216879670	-	-	-	-	-	0e+00	1e-1	1e-1	-	-	0e+00	0e+00	0e+00	
	22.42849		1.39645201.3844321		1e-1	1e-1	1e-1		2e-1	07	07	1e-1	3e-1	07	07	07	2e-1
					07	07	07	07	07	07			07	07	07	07	
X3	-	2.4484392205393380.3905420.5511548e-1	e-1	-	0e+00	-	0e+00	1e-1	2e-1	-	-	0e+00	+00	0e+00	0e+00		
	22.51756		1.37378471.33193924.897088707	5e-1		2e-1	2e-1		07	07	07	2e-1	2e-1				
					07	07	07	07	07	07			07	07	07	07	
X4	-	2.846118	-	0.3110352	-	-	0.18400600	-	-	0e+00	1e-1	0e+00	+00	-	2e-1	0e+00	+00
	22.748172.638946031532.413278000280410		1e-1	2e-1	1e-1		2e-1	07		4e-1	1e-1	07		07	1e-1		
					07	07	07	07	07	07			07	07	07	07	
X5	-	-	-	0.4037786	-	-	0.074902766380	-	-	0e+00	1e-1	1e-1	0e+00	-	2e-1	1e-1	-
	23.12207280237500.835199315077679				2e-1	3e-1	1e-1		2e-1	07	07	3e-1	1e-1	07	07	1e-1	2e-1
					07	07	07	07	07	07			07	07	07	07	
X6	-	1.582809989081880	-	0.2296065	-	0e+00	-	-	-	0e+00	+00	1e-1	0e+00	1e-1	-	1e-1	-
	22.42707		0.54495850297.15699992882e-2	3e-1		3e-1				07	07	3e-1	07	1e-1	07	1e-1	3e-1
					07	07	07	07	07	07			07	07	07	07	

X7	-	1.265292101634239	-	-	0.02667900	-	-	-	-	4e-	2e-	1e-	-	0e+00	1e-	-	0e+00	
20.60123		0.4654848209782989660		2e-	2e-	5e-	1e-	2e-	4e-	07	07	07	3e-	07	07	3e-	3e-	
				07	07	07	07	07	07				07		07	07	07	
X8	-	0.802420578542.8237446	-	0.146707370800	-	0e+00	0e+00	1e-	2e-	-	-	-	1e-	0e+00	1e-	-	-	
22.41035		0.7161290034986007845			1e-	2e-		1e-		07	07	1e-	4e-	2e-	07	1e-	07	2e-
				07	07	07	07	07	07			07	07	07	07	07	07	
X9	-	1.88319852298	-	0.14404570.12700959430e+00	0e+00+00+00	1e-	0e+00	0e+00	1e-	0e+00	0e+00+00	1e-	0e+00	-	-	-	-	
22.51708		7.46173601360.2172969			1e-		1e-			07	07	07	07	07	07	07	07	07
X10	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	

2.2 I.II Phylogenetic signal in BAPS clusters and species IDs

2.2.1 Phylogenetic signal in BAPS clusters

```

library(picante)

## Loading required package: nlme

##
## Attaching package: 'nlme'

## The following object is masked from 'package:dplyr':
##
##      collapse

## The following object is masked from 'package:sna':
##
##      gapply

library(ape)
library(adephylo)

## Loading required package: ade4

library(ade4)
library(phylobase)

##
## Attaching package: 'phylobase'

## The following object is masked from 'package:ape':
##
##      edges

library(geiger)
library(phytools)

## Loading required package: maps

##
## Attaching package: 'phytools'

## The following object is masked from 'package:phylobase':
##
##      readNexus

## The following object is masked from 'package:vegan':

```

```

## scores
library(future.apply)

## Loading required package: future
foo_adm<-baps.adm
rownames(foo_adm)<-paste("X",gsub("\\\\.", "B", rownames(foo_adm)), sep="")
foo_adm<-rbind(foo_adm, XXanpa=0)

## Warning in `<-factor`(`*tmp*`, ri, value = 0): invalid factor level, NA
## generated
plan(multicore,workers=10)

## Warning in supportsMulticoreAndRStudio(...): [ONE-TIME WARNING] Forked
## processing ('multicore') is not supported when running R from RStudio
## because it is considered unstable. For more details, how to control forked
## processing or not, and how to silence this warning in future R sessions,
## see ?parallelly::supportsMulticore

#phylosig_final<-future_lapply(
#  c("X1", "X2", "X3", "X4", "X5", "X6", "X7", "X8", "X9", "X10"),
#  FUN=function(GRUPO)
#  {
#    phylo_signal<-lapply(tree.dataset,
#      FUN=function(x){
#        groups_mix<-as.numeric(foo_adm[x$tip.label,GRUPO])
#        names(groups_mix)<-x$tip.label
#        foo_out<-phytools::phylosig(
#          root(
#            compute.brlen(x),
#            outgroup = "XXanpa",
#            node=NULL,
#            resolve.root = TRUE),
#            groups_mix, method="lambda", test=TRUE, nsim=999)
#        return(foo_out)
#      })
#    return(phylo_signal)
#  })
load("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v15.Rdata")
print(phylosig_final)

## [[1]]
## [[1]]$its
##
## Phylogenetic signal lambda : 0.985151
## logL(lambda) : 972.292
## LR(lambda=0) : 2371.59
## P-value (based on LR test) : 0
##
## 
## [[1]]$bt
##
## Phylogenetic signal lambda : 0.976185
## logL(lambda) : 1306.81

```

```

## LR(lambda=0) : 3028.15
## P-value (based on LR test) : 0
##
## 
## [[1]]$efa
##
## Phylogenetic signal lambda : 0.991727
## logL(lambda) : 1046.69
## LR(lambda=0) : 2524.15
## P-value (based on LR test) : 0
##
## 
## [[1]]$mcm7
##
## Phylogenetic signal lambda : 0.949642
## logL(lambda) : 978.181
## LR(lambda=0) : 2384.65
## P-value (based on LR test) : 0
##
## 
## [[1]]$rpb1
##
## Phylogenetic signal lambda : 0.980254
## logL(lambda) : 1242.56
## LR(lambda=0) : 2918.21
## P-value (based on LR test) : 0
##
## 
## [[2]]
## [[2]]$its
##
## Phylogenetic signal lambda : 0.946358
## logL(lambda) : 306.393
## LR(lambda=0) : 1338.18
## P-value (based on LR test) : 5.71696e-293
##
## 
## [[2]]$bt
##
## Phylogenetic signal lambda : 0.987747
## logL(lambda) : 632.235
## LR(lambda=0) : 1990.26
## P-value (based on LR test) : 0
##
## 
## [[2]]$efa
##
## Phylogenetic signal lambda : 0.976179
## logL(lambda) : 479.532
## LR(lambda=0) : 1685.05
## P-value (based on LR test) : 0
##
## 

```

```

## [[2]]$mcm7
##
## Phylogenetic signal lambda : 0.955581
## logL(lambda) : 340.943
## LR(lambda=0) : 1407.18
## P-value (based on LR test) : 5.78936e-308
##
##
## [[2]]$rpb1
##
## Phylogenetic signal lambda : 0.982278
## logL(lambda) : 1218.48
## LR(lambda=0) : 3158.82
## P-value (based on LR test) : 0
##
##
## [[3]]
## [[3]]$its
##
## Phylogenetic signal lambda : 0.980867
## logL(lambda) : 592.101
## LR(lambda=0) : 876.511
## P-value (based on LR test) : 1.25351e-192
##
##
## [[3]]$bt
##
## Phylogenetic signal lambda : 0.981899
## logL(lambda) : 471.122
## LR(lambda=0) : 614.289
## P-value (based on LR test) : 1.30562e-135
##
##
## [[3]]$efa
##
## Phylogenetic signal lambda : 0.995713
## logL(lambda) : 512.649
## LR(lambda=0) : 685.575
## P-value (based on LR test) : 4.09705e-151
##
##
## [[3]]$mcm7
##
## Phylogenetic signal lambda : 0.977399
## logL(lambda) : 424.968
## LR(lambda=0) : 556.075
## P-value (based on LR test) : 6.00321e-123
##
##
## [[3]]$rpb1
##
## Phylogenetic signal lambda : 0.976345
## logL(lambda) : 1145.33

```

```

## LR(lambda=0) : 1457.88
## P-value (based on LR test) : 5.55685513190567e-319
##
## 
## [[4]]
## [[4]]$its
##
## Phylogenetic signal lambda : 0.998203
## logL(lambda) : 612.232
## LR(lambda=0) : 2032.77
## P-value (based on LR test) : 0
##
## 
## [[4]]$bt
##
## Phylogenetic signal lambda : 0.985362
## logL(lambda) : 523.791
## LR(lambda=0) : 1843.61
## P-value (based on LR test) : 0
##
## 
## [[4]]$efa
##
## Phylogenetic signal lambda : 0.99734
## logL(lambda) : 480.262
## LR(lambda=0) : 1761.6
## P-value (based on LR test) : 0
##
## 
## [[4]]$mcm7
##
## Phylogenetic signal lambda : 0.982317
## logL(lambda) : 406.019
## LR(lambda=0) : 1606.21
## P-value (based on LR test) : 0
##
## 
## [[4]]$rpb1
##
## Phylogenetic signal lambda : 0.987243
## logL(lambda) : 1315.6
## LR(lambda=0) : 3411.64
## P-value (based on LR test) : 0
##
## 
## [[5]]
## [[5]]$its
##
## Phylogenetic signal lambda : 0.968204
## logL(lambda) : 863.889
## LR(lambda=0) : 1896.33
## P-value (based on LR test) : 0

```

```

##
## 
## [[5]]$bt
##
## Phylogenetic signal lambda : 0.960392
## logL(lambda) : 1078.17
## LR(lambda=0) : 2329.35
## P-value (based on LR test) : 0
##
## 
## [[5]]$efa
##
## Phylogenetic signal lambda : 0.983874
## logL(lambda) : 672.117
## LR(lambda=0) : 1519.24
## P-value (based on LR test) : 0
##
## 
## [[5]]$mcm7
##
## Phylogenetic signal lambda : 0.967411
## logL(lambda) : 1160.41
## LR(lambda=0) : 2497.33
## P-value (based on LR test) : 0
##
## 
## [[5]]$rpb1
##
## Phylogenetic signal lambda : 0.98799
## logL(lambda) : 1343.86
## LR(lambda=0) : 2906.63
## P-value (based on LR test) : 0
##
## 
## 
## [[6]]
## [[6]]$its
##
## Phylogenetic signal lambda : 0.929256
## logL(lambda) : 855.021
## LR(lambda=0) : 945.439
## P-value (based on LR test) : 1.30087e-207
##
## 
## [[6]]$bt
##
## Phylogenetic signal lambda : 0.956926
## logL(lambda) : 1311.12
## LR(lambda=0) : 1873.37
## P-value (based on LR test) : 0
##
## 
## [[6]]$efa
##

```

```

## Phylogenetic signal lambda : 0.996587
## logL(lambda) : 1207.97
## LR(lambda=0) : 1642.34
## P-value (based on LR test) : 0
##
##
## [[6]]$mcm7
##
## Phylogenetic signal lambda : 0.964438
## logL(lambda) : 976.087
## LR(lambda=0) : 1207.38
## P-value (based on LR test) : 1.51889e-264
##
##
## [[6]]$rpb1
##
## Phylogenetic signal lambda : 0.999718
## logL(lambda) : 1561.92
## LR(lambda=0) : 2385.7
## P-value (based on LR test) : 0
##
##
## [[7]]
## [[7]]$its
##
## Phylogenetic signal lambda : 0.978565
## logL(lambda) : 1334.59
## LR(lambda=0) : 2664.09
## P-value (based on LR test) : 0
##
##
## [[7]]$bt
##
## Phylogenetic signal lambda : 0.983128
## logL(lambda) : 679.032
## LR(lambda=0) : 1378.91
## P-value (based on LR test) : 8.0287e-302
##
##
## [[7]]$efa
##
## Phylogenetic signal lambda : 0.974724
## logL(lambda) : 688.562
## LR(lambda=0) : 1380.25
## P-value (based on LR test) : 4.11762e-302
##
##
## [[7]]$mcm7
##
## Phylogenetic signal lambda : 0.967518
## logL(lambda) : 970.301
## LR(lambda=0) : 1933.27
## P-value (based on LR test) : 0

```

```

##
##
## [[7]]$rpb1
##
## Phylogenetic signal lambda : 0.973388
## logL(lambda) : 1549.33
## LR(lambda=0) : 3097.74
## P-value (based on LR test) : 0
##
##
##
## [[8]]
## [[8]]$its
##
## Phylogenetic signal lambda : 0.996282
## logL(lambda) : 668.806
## LR(lambda=0) : 2153.55
## P-value (based on LR test) : 0
##
##
## [[8]]$bt
##
## Phylogenetic signal lambda : 0.990548
## logL(lambda) : 612.644
## LR(lambda=0) : 2035.68
## P-value (based on LR test) : 0
##
##
## [[8]]$efa
##
## Phylogenetic signal lambda : 0.996121
## logL(lambda) : 891.413
## LR(lambda=0) : 2595.75
## P-value (based on LR test) : 0
##
##
## [[8]]$mcm7
##
## Phylogenetic signal lambda : 0.975594
## logL(lambda) : 670.7
## LR(lambda=0) : 2146.01
## P-value (based on LR test) : 0
##
##
## [[8]]$rpb1
##
## Phylogenetic signal lambda : 0.967816
## logL(lambda) : 1064.16
## LR(lambda=0) : 2927.27
## P-value (based on LR test) : 0
##
##
##
## [[9]]

```

```

## [[9]]$its
##
## Phylogenetic signal lambda : 1.00089
## logL(lambda) : 1176.47
## LR(lambda=0) : 2018.47
## P-value (based on LR test) : 0
##
## 
## [[9]]$bt
##
## Phylogenetic signal lambda : 1.00064
## logL(lambda) : 1227.75
## LR(lambda=0) : 2153.56
## P-value (based on LR test) : 0
##
## 
## [[9]]$efa
##
## Phylogenetic signal lambda : 0.978528
## logL(lambda) : 1027.2
## LR(lambda=0) : 1731.78
## P-value (based on LR test) : 0
##
## 
## [[9]]$mcm7
##
## Phylogenetic signal lambda : 0.942054
## logL(lambda) : 921.095
## LR(lambda=0) : 1499.77
## P-value (based on LR test) : 0
##
## 
## [[9]]$rpb1
##
## Phylogenetic signal lambda : 0.998093
## logL(lambda) : 1411.81
## LR(lambda=0) : 2583.45
## P-value (based on LR test) : 0
##
## 
## 
## [[10]]
## [[10]]$its
##
## Phylogenetic signal lambda : 1.00103
## logL(lambda) : 2128.67
## LR(lambda=0) : 3254.84
## P-value (based on LR test) : 0
##
## 
## [[10]]$bt
##
## Phylogenetic signal lambda : 0.986982
## logL(lambda) : 1342.61

```

```

## LR(lambda=0) : 1740.57
## P-value (based on LR test) : 0
##
## 
## [[10]]$efa
##
## Phylogenetic signal lambda : 0.989386
## logL(lambda) : 2132.8
## LR(lambda=0) : 3281.78
## P-value (based on LR test) : 0
##
## 
## [[10]]$mcm7
##
## Phylogenetic signal lambda : 1.00105
## logL(lambda) : 2050.02
## LR(lambda=0) : 3102.6
## P-value (based on LR test) : 0
##
## 
## [[10]]$rpb1
##
## Phylogenetic signal lambda : 0.99608
## logL(lambda) : 1637.05
## LR(lambda=0) : 2428.47
## P-value (based on LR test) : 0
#save.image("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v14.Rdata")

```

2.2.2 Migrate-n migration network between BAPS gene clusters

```

library(igraph)

##
## Attaching package: 'igraph'
## The following objects are masked from 'package:future':
##     %>%, %<%
## The following object is masked from 'package:phylobase':
##     edges
## The following object is masked from 'package:class':
##     knn
## The following objects are masked from 'package:dplyr':
##     as_data_frame, groups, union
## The following object is masked from 'package:bipartite':
##     strength
## The following objects are masked from 'package:sna':

```

```

## betweenness, bonpow, closeness, components, degree, dyad.census,
## evcent, hierarchy, is.connected, neighborhood, triad.census

## The following objects are masked from 'package:network':
## %c%, %s%, add.edges, add.vertices, delete.edges, delete.vertices,
## get.edge.attribute, get.edges, get.vertex.attribute, is.bipartite,
## is.directed, list.edge.attributes, list.vertex.attributes,
## set.edge.attribute, set.vertex.attribute

## The following object is masked from 'package:vegan':
## diversity

## The following object is masked from 'package:permute':
## permute

## The following object is masked from 'package:phangorn':
## diversity

## The following objects are masked from 'package:ape':
## degree, edges, mst, ring

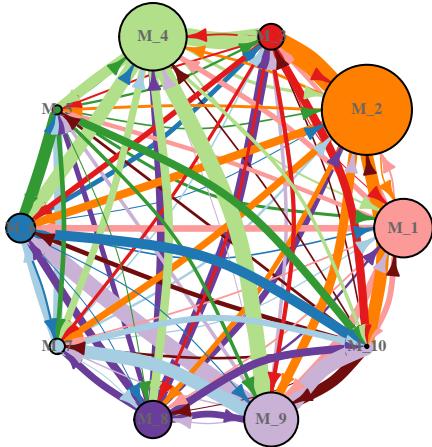
## The following objects are masked from 'package:stats':
## decompose, spectrum

## The following object is masked from 'package:base':
## union

connectors<-read.delim2("/Users/Fernando/Desktop/01_Sanger_paper/19_migrate-n/for_network.txt",header =
nodes<-read.delim2("/Users/Fernando/Desktop/01_Sanger_paper/19_migrate-n/for_network2.txt",header = FALSE)
nodes<-data.frame(nodes=as.character(nodes[,1]),theta=as.numeric(nodes[,2]))
connectors<-data.frame(from = as.character(connectors[,1]),to = as.character(connectors[,2]),weight = as.numeric(connectors[,3]))
foo_col<-colorinos.bipolar[c(10,7,6,9,5,8,2,4,1,11)]
names(foo_col)<-nodes$nodes
rownames(nodes)<-nodes$nodes
migrate_M<-graph_from_data_frame(connectors, directed = TRUE, vertices = nodes)

coords<-layout_(migrate_M,
                 in_circle())
plot(migrate_M,
      vertex.size = 500*vertex_attr(migrate_M,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight/20,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_M)],
      edge.curved=seq(-0.3, 0.3, length = ecoun(migrate_M)),
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
)

```



```

connectors$weight<-connectors$weight*nodes[connectors$to, "theta"]
connectors_backup<-connectors
connectors<-connectors[connectors$weight>=2,]

#foo_col[connectors$to]
migrate_2Ne<-graph_from_data_frame(connectors, directed = TRUE, vertices = nodes)

#set_vertex_attr(migrate, "theta", index = V(migrate), value = 100*as.numeric(nodes[,2]))

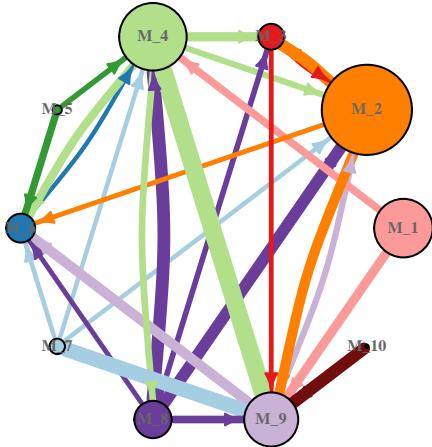
coords<-layout_(migrate_2Ne,
                 in_circle())
curves<-mat.or.vec(ccount(migrate_2Ne),1)

paste(connectors[,1],connectors[,2],sep="")%in%paste(connectors[,2],connectors[,1],sep="")

## [1] TRUE FALSE FALSE FALSE TRUE TRUE FALSE FALSE FALSE TRUE FALSE
## [13] TRUE FALSE TRUE FALSE FALSE FALSE TRUE FALSE TRUE FALSE FALSE
## [25] FALSE FALSE FALSE

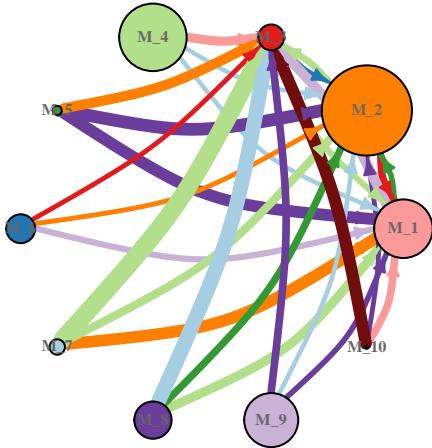
curves[gsub("M_","",connectors[,1])!=gsub("M_","",connectors[,2])]<-0.1
curves[!(paste(connectors[,1],connectors[,2],sep=""))%in%paste(connectors[,2],connectors[,1],sep=""))]<-
plot(migrate_2Ne,
      vertex.size = 500*vertex_attr(migrate_2Ne,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_2Ne)],
      edge.curved=curves,
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
)

```



```

coords<-layout_(migrate_M,
                 in_circle())
plot(migrate_M,
      vertex.size = 500*vertex_attr(migrate_M,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_M)],
      edge.curved=seq(-0.3, 0.3, length = ecount(migrate_M)),
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
    )
  
```



```

foo.table<-cbind(nodes,from=sapply(nodes[,1],FUN=function(x){sum(connectors_backup$weight[connectors_backup$to==x])},balance=foo.table$to-foo.table$from))
  
```

	theta	from	to	balance
M_1	0.06120	14.903528	9.821988	-5.081540
M_2	0.09422	19.967251	23.771706	3.804455
M_3	0.02697	11.789365	18.226326	6.436961
M_4	0.07056	27.713918	22.219344	-5.494574
M_5	0.00956	13.920574	4.584307	-9.336267
M_6	0.03020	7.791225	25.014660	17.223435

	theta	from	to	balance
M_7	0.01612	16.856821	5.958758	-10.898062
M_8	0.03898	24.803882	9.014125	-15.789757
M_9	0.05651	12.572468	41.022869	28.450401
M_10	0.00346	12.025443	2.710391	-9.315052

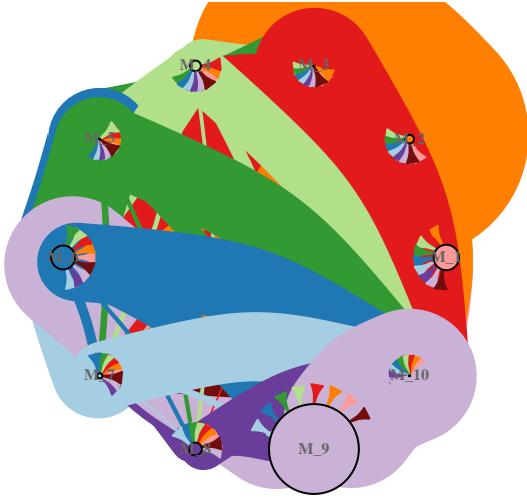
```
#kable(
#  rbind(
#    c("M_2",
#      sum(connectors_backup$weight[connectors_backup$from=="M_2" & connectors_backup$to!="M_3"]),
#      sum(connectors_backup$weight[connectors_backup$to=="M_2" & connectors_backup$from!="M_3"])
#    ),
#    c("M_3",
#      sum(connectors_backup$weight[connectors_backup$from=="M_3" & connectors_backup$to!="M_2"]),
#      sum(connectors_backup$weight[connectors_backup$to=="M_3" & connectors_backup$from!="M_2"])
#    )
#  )
#)
```

2.2.3 Migrate-n migration network between BAPS gene clusters using mat genes

```
library(igraph)
connectors<-read.delim2("/Users/Fernando/Desktop/01_Sanger_paper/19_migrate-n/for_network_hmg2",header = FALSE)
nodes<-read.delim2("/Users/Fernando/Desktop/01_Sanger_paper/19_migrate-n/for_network_hmg",header = FALSE)
nodes<-data.frame(nodes=as.character(nodes[,1]),theta=as.numeric(nodes[,2]))
connectors<-data.frame(from = as.character(connectors[,1]),to = as.character(connectors[,2]),weight = as.numeric(connectors[,3]))
foo_col<-colorinos.bipolar[c(10,7,6,9,5,8,2,4,1,11)]
names(foo_col)<-nodes$nodes
rownames(nodes)<-nodes$nodes
migrate_M<-graph_from_data_frame(connectors, directed = TRUE, vertices = nodes)
```

2.2.3.1 HMG

```
coords<-layout_(migrate_M,
                 in_circle())
plot(migrate_M,
      vertex.size = 100*vertex_attr(migrate_M,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight/10,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_M)],
      edge.curved=seq(-0.3, 0.3, length = ecoun(migrate_M)),
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
    )
```



2.2.3.2 Complete network edges proportional to M

```

connectors$weight<-connectors$weight*nodes[connectors$to,"theta"]
connectors_backup<-connectors
connectors<-connectors[connectors$weight>=2,]

#foo_col[connectors$to]
migrate_2Ne<-graph_from_data_frame(connectors, directed = TRUE, vertices = nodes)

#set_vertex_attr(migrate, "theta", index = V(migrate), value = 100*as.numeric(nodes[,2]))

```

```

coords<-layout_(migrate_2Ne,
                 in_circle())
curves<-mat.or.vec(ecount(migrate_2Ne),1)

paste(connectors[,1],connectors[,2],sep="")%in%paste(connectors[,2],connectors[,1],sep="")

```

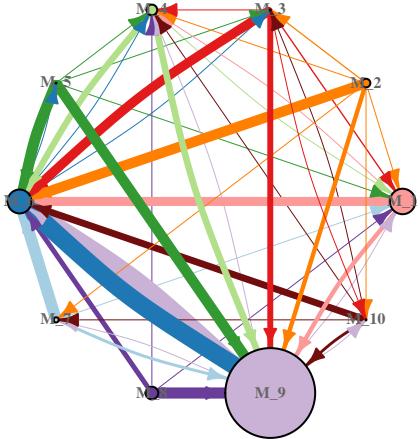
2.2.3.3 Reduced netwrok edges are 2Neu only connections above 2 migrants per generation are shown.

```

## [1] FALSE FALSE TRUE FALSE FALSE FALSE TRUE FALSE FALSE TRUE TRUE TRUE
## [13] FALSE FALSE FALSE TRUE FALSE TRUE FALSE TRUE FALSE FALSE TRUE TRUE
## [25] TRUE FALSE FALSE TRUE FALSE FALSE TRUE FALSE TRUE FALSE FALSE TRUE
## [37] FALSE TRUE TRUE FALSE TRUE FALSE TRUE TRUE

curves[gsub("M_","",connectors[,1])!=gsub("M_","",connectors[,2])]<-0.1
curves[!(paste(connectors[,1],connectors[,2],sep="")%in%paste(connectors[,2],connectors[,1],sep=""))]<-
plot(migrate_2Ne,
     vertex.size = 100*vertex_attr(migrate_2Ne,"theta"),
     edge.arrow.size = 0.5,
     edge.width = connectors$weight/10,
     edge.color = foo_col[connectors$from],
     vertex.color = foo_col[V(migrate_2Ne)],
     edge.curved=curves,
     layout = coords,
     vertex.label.font=2,
     vertex.label.color="gray40",
     vertex.label.cex=.5
)

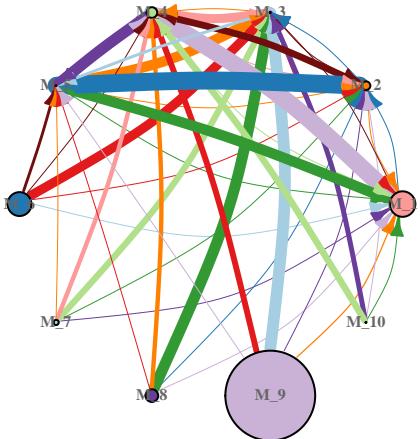
```



```

coords<-layout_(migrate_M,
                 in_circle())
plot(migrate_M,
      vertex.size = 100*vertex_attr(migrate_M,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight/10,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_M)],
      edge.curved=seq(-0.3, 0.3, length = ecount(migrate_M)),
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
)

```



```

foo.table<-cbind(nodes,from=sapply(nodes[,1],FUN=function(x){sum(connectors_backup$weight[connectors_back
kable(cbind(foo.table[,-1],balance=foo.table$to-foo.table$from))

```

	theta	from	to	balance
M_1	0.13309	78.26837	29.448824	-48.81954
M_2	0.04521	96.42590	9.127899	-87.29800
M_3	0.00504	95.30452	19.258798	-76.04572
M_4	0.05593	74.11253	28.008066	-46.10446
M_5	0.00474	120.81621	11.834168	-108.98205
M_6	0.12475	104.67702	433.836838	329.15982

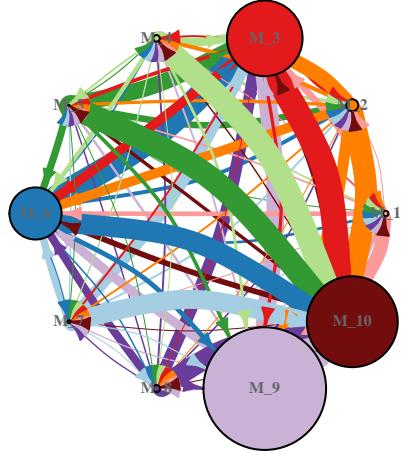
	theta	from	to	balance
M_7	0.02732	82.93010	15.611468	-67.31864
M_8	0.06655	91.77378	9.941904	-81.83187
M_9	0.46894	104.88441	334.077545	229.19313
M_10	0.00505	60.43188	18.479212	-41.95267

```
#kable(
#  rbind(
#    c("M_2",
#      sum(connectors_backup$weight[connectors_backup$from=="M_2" & connectors_backup$to!="M_3"]),
#      sum(connectors_backup$weight[connectors_backup$to=="M_2" & connectors_backup$from!="M_3"])
#    ),
#    c("M_3",
#      sum(connectors_backup$weight[connectors_backup$from=="M_3" & connectors_backup$to!="M_2"]),
#      sum(connectors_backup$weight[connectors_backup$to=="M_3" & connectors_backup$from!="M_2"])
#    )
#  )
#)
```

```
library(igraph)
connectors<-read.delim2("/Users/Fernando/Desktop/01_Sanger_paper/19_migrate-n/for_network_a2", header = TRUE)
nodes<-read.delim2("/Users/Fernando/Desktop/01_Sanger_paper/19_migrate-n/for_network_a", header = FALSE)
nodes<-data.frame(nodes=as.character(nodes[,1]), theta=as.numeric(nodes[,2]))
connectors<-data.frame(from = as.character(connectors[,1]), to = as.character(connectors[,2]), weight = as.numeric(connectors[,3]))
foo_col<-colorinos.bipolar[c(10,7,6,9,5,8,2,4,1,11)]
names(foo_col)<-nodes$nodes
rownames(nodes)<-nodes$nodes
migrate_M<-graph_from_data_frame(connectors, directed = TRUE, vertices = nodes)
```

2.2.3.4 Alpha

```
coords<-layout_(migrate_M,
                 in_circle())
plot(migrate_M,
      vertex.size = 50*vertex_attr(migrate_M,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight/50,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_M)],
      edge.curved=seq(-0.3, 0.3, length = ecoun(migrate_M)),
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
    )
```



2.2.3.5 Complete network edges proportional to M

```

connectors$weight<-connectors$weight*nodes[connectors$to,"theta"]
connectors_backup<-connectors
connectors<-connectors[connectors$weight>=2,]

#foo_col[connectors$to]
migrate_2Ne<-graph_from_data_frame(connectors, directed = TRUE, vertices = nodes)

#set_vertex_attr(migrate, "theta", index = V(migrate), value = 100*as.numeric(nodes[,2]))

coords<-layout_(migrate_2Ne,
                 in_circle())
curves<-mat.or.vec(ecount(migrate_2Ne),1)

paste(connectors[,1],connectors[,2],sep="")%in%paste(connectors[,2],connectors[,1],sep="")

```

2.2.3.6 Reduced netwrok edges are 2Neu only connections above 2 migrants per generation are shown.

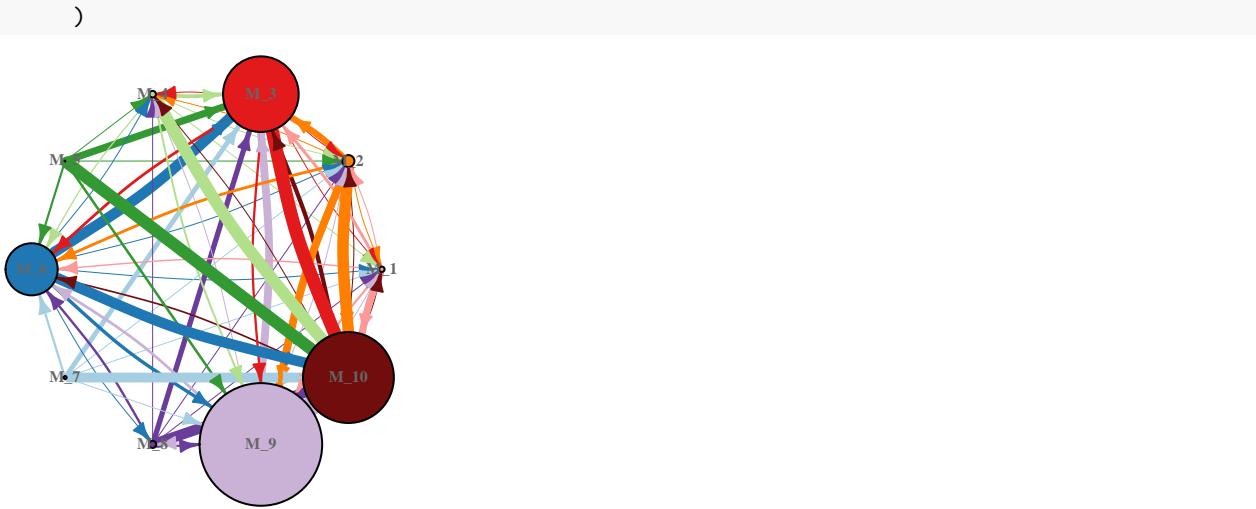
```

## [1] TRUE TRUE FALSE TRUE FALSE FALSE TRUE TRUE TRUE TRUE TRUE FALSE
## [13] TRUE FALSE FALSE TRUE TRUE TRUE TRUE FALSE TRUE FALSE FALSE
## [25] TRUE TRUE TRUE TRUE FALSE TRUE FALSE TRUE TRUE TRUE TRUE TRUE
## [37] TRUE FALSE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## [49] FALSE TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE FALSE TRUE FALSE
## [61] FALSE TRUE

curves[gsub("M_","",connectors[,1])!=gsub("M_","",connectors[,2])]<-0.1
curves[!(paste(connectors[,1],connectors[,2],sep="")%in%paste(connectors[,2],connectors[,1],sep=""))]<-

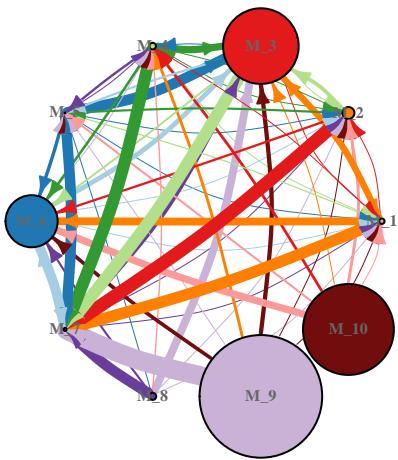
plot(migrate_2Ne,
      vertex.size = 50*vertex_attr(migrate_2Ne,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight/100,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_2Ne)],
      edge.curved=curves,
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5

```



```

coords<-layout_(migrate_M,
                 in_circle())
plot(migrate_M,
      vertex.size = 50*vertex_attr(migrate_M,"theta"),
      edge.arrow.size = 0.5,
      edge.width = connectors$weight/100,
      edge.color = foo_col[connectors$from],
      vertex.color = foo_col[V(migrate_M)],
      edge.curved=seq(-0.3, 0.3, length = ecount(migrate_M)),
      layout = coords,
      vertex.label.font=2,
      vertex.label.color="gray40",
      vertex.label.cex=.5
      )
  
```



```

foo.table<-cbind(nodes,from=sapply(nodes[,1],FUN=function(x){sum(connectors_backup$weight[connectors_
kable(cbind(foo.table[,-1],balance=foo.table$to-foo.table$from))
```

	theta	from	to	balance
M_1	0.06155	686.1425	25.343828	-660.7986
M_2	0.13727	1446.1728	101.846104	-1344.3267
M_3	0.86359	934.7295	2660.168092	1725.4386

	theta	from	to	balance
M_4	0.07551	975.4596	28.823677	-946.6359
M_5	0.00995	1233.2686	5.462251	-1227.8064
M_6	0.59535	1254.0096	978.814935	-275.1947
M_7	0.03581	899.5700	10.061894	-889.5081
M_8	0.08169	1031.2539	16.370676	-1014.8832
M_9	1.40057	1528.0789	1339.056966	-189.0219
M_10	1.03815	494.2520	5316.989040	4822.7370

```
#kable(
#  rbind(
#    c("M_2",
#      sum(connectors_backup$weight[connectors_backup$from=="M_2"&connectors_backup$to!="M_3"]),
#      sum(connectors_backup$weight[connectors_backup$to=="M_2"&connectors_backup$from!="M_3"]),
#      ),
#    ##      c("M_3",
#    #      sum(connectors_backup$weight[connectors_backup$from=="M_3"&connectors_backup$to!="M_2"]),
#    #      sum(connectors_backup$weight[connectors_backup$to=="M_3"&connectors_backup$from!="M_2"])
#    #      )
#    )
#)
```

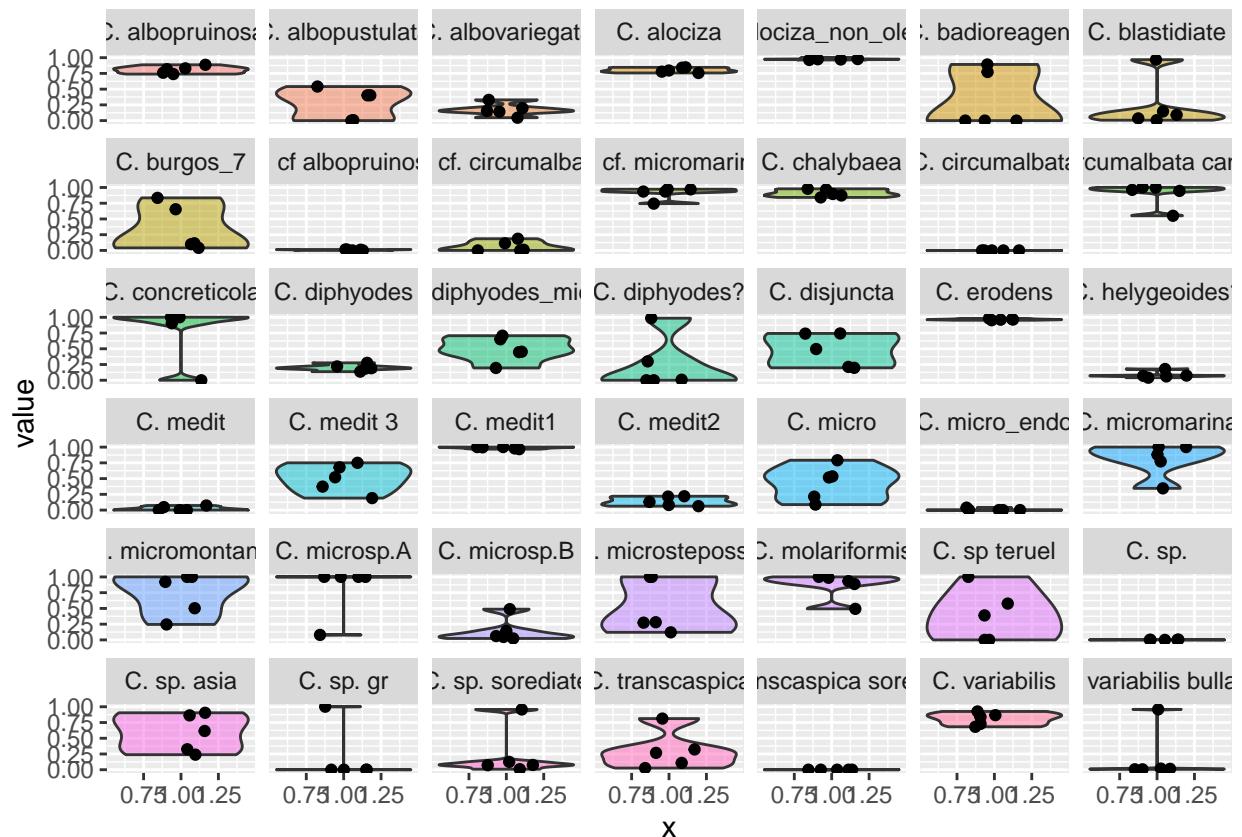
2.2.4 Phylogenetic signal in Species IDs

```
#load("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v14.Rdata")
#c(levels(factor(foo_adm$Species))[-1])
#plan(multicore,workers=12)
#phylosig_final2<-future_lapply(
#  levels(factor(foo_adm$Species))[-1],
#  FUN=function(GRUPO)
#  {
#    phylo_signal<-lapply(tree.dataset,
#      FUN=function(ARBOL)
#      {
#        foo_tree<-root(
#          ARBOL,
#          outgroup = "XXanpa",
#          node=NULL,
#          resolve.root = TRUE)
#        groups_mix<-as.numeric(factor(foo_adm[foo_tree$tip.label,"Species"])==GRUPO)
#        names(groups_mix)<-foo_tree$tip.label
#        # foo.out<-phytools::phylosig(
#        #   compute.brlen(multi2di(foo_tree)),
#        #   groups_mix, method="lambda", test=TRUE, nsim=100)
#        return(foo.out)
#      })
#    return(phylo_signal)
#  })
#names(phylosig_final2)<-levels(factor(foo_adm$Species))[-1]
#print(phylosig_final2)
#save.image("/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v15.Rdata")
```

```

fooeraseme<-melt(sapply(phylosig_final2,FUN=function(x){unlist(unlist(x)[c(1,6,11,16,21])]}))
colnames(fooeraseme)<-c("gene","sp","value")
ggplot(fooeraseme,aes(x=1,y=value,fill=sp))+geom_violin(alpha=0.5)+geom_point(position = position_jitte

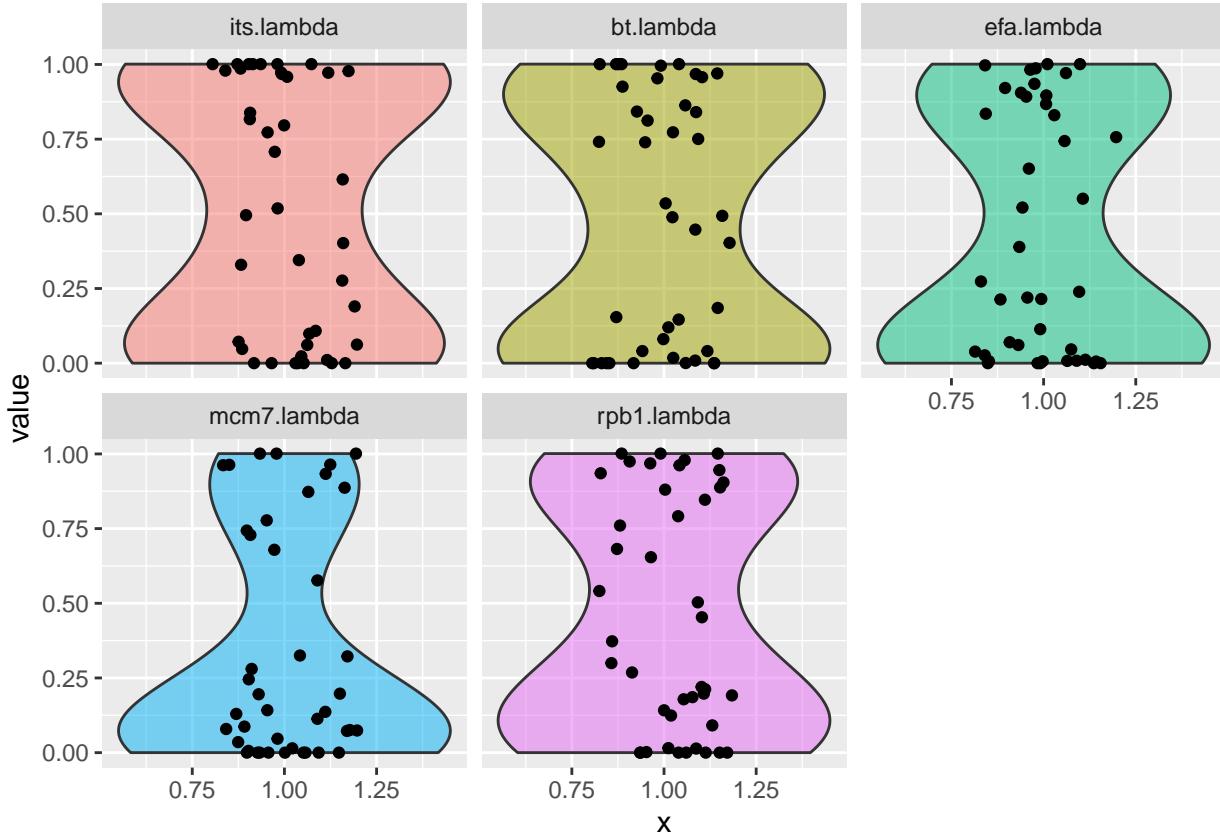
```



```

ggplot(fooeraseme,aes(x=1,y=value,fill=gen)) + geom_violin(alpha=0.5) + geom_point(position = position_jitte

```



2.3 I.III Concordance between gene phylogenies

2.3.1 ML

The concordance between gene phylogenies was measured using Nye's similarity measurement (Nye 2000) implemented in r-package treedist. The trees were trimmed using function drop.tip to be made comparable and the number of shared The maximum concordance value was obtained as standarizing factor across loci, and trees with randomized tip assignments were used as random expectation.

```
tree_similarity_fer<-function(x,y,reps=100)
{
  require(TreeDist)
  require(ape)
  foo.x<-keep.tip(x,x$tip.label[x$tip.label%in%y$tip.label])
  foo.y<-keep.tip(y,y$tip.label[y$tip.label%in%x$tip.label])
  foo.max<-NyeSimilarity(foo.x,foo.x)
  foo.obs<-NyeSimilarity(foo.x,foo.y)
  foo.ran<-c(1:reps)
  foo.ran<-sapply(foo.ran,FUN=function(z){
    foo.y$tip.label<-sample(foo.y$tip.label)
    return(NyeSimilarity(foo.x,foo.y))
  })
  return(c(foo.max,foo.obs/foo.max,mean(foo.ran)/foo.max))
}

results_foo<-NULL
for (i in c(1:length(tree.dataset)))
{
```

```

    for (j in c(1:length(tree.dataset)))
{
  print(paste (i,j))
  if (i!=j)
  {
    results_foo<-rbind(results_foo,tree_similarity_fer(tree.dataset[[i]],tree.dataset[[j]],10))
  }
}
}

## [1] "1 1"
## [1] "1 2"

## Loading required package: TreeDist

## [1] "1 3"
## [1] "1 4"
## [1] "1 5"
## [1] "2 1"
## [1] "2 2"
## [1] "2 3"
## [1] "2 4"
## [1] "2 5"
## [1] "3 1"
## [1] "3 2"
## [1] "3 3"
## [1] "3 4"
## [1] "3 5"
## [1] "4 1"
## [1] "4 2"
## [1] "4 3"
## [1] "4 4"
## [1] "4 5"
## [1] "5 1"
## [1] "5 2"
## [1] "5 3"
## [1] "5 4"
## [1] "5 5"

print(t.test(results_foo[,2],results_foo[,3],paired = TRUE,alternative = "greater"))

## 
## Paired t-test
##
## data: results_foo[, 2] and results_foo[, 3]
## t = 35.01, df = 19, p-value < 2.2e-16
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
## 0.2061996      Inf
## sample estimates:
## mean of the differences
##                      0.216913

print(t.test(results_foo[,2],results_foo[,3],alternative = "greater"))

##

```

```

## Welch Two Sample t-test
##
## data: results_foo[, 2] and results_foo[, 3]
## t = 38.264, df = 20.015, p-value < 2.2e-16
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.2071361      Inf
## sample estimates:
## mean of x mean of y
## 0.3767541 0.1598411

```

2.3.2 Bayesian. Concordance within loci

```

results_foo<-NULL
control_foo<-cbind(
  sample(c(1:length(all.trees)),1500,replace=TRUE),
  sample(c(1:length(all.trees)),1500,replace=TRUE),
  sample(c(1:50),1500,replace=TRUE),
  sample(c(1:50),1500,replace=TRUE)
)

control_foo<-control_foo[paste(control_foo[,1],control_foo[,3])!=paste(control_foo[,2],control_foo[,4])]

control_foo<-control_foo[!(paste(control_foo[,1],control_foo[,3],control_foo[,2],control_foo[,4])%in%pa]

control_foo<-control_foo[sample(c(1:dim(control_foo)[1]),1000),]

results_foo<-future_apply(control_foo,1,FUN=function(x){
  return(c(x[1],x[2],x[3],x[4],results_foo,tree_similarity_fer(all.trees[[x[1]]]][[x[3]]],all.trees[[x[2]]])
})

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-1') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-2') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-3') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations

```

```

## ('future_apply-4') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-5') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-6') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-7') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

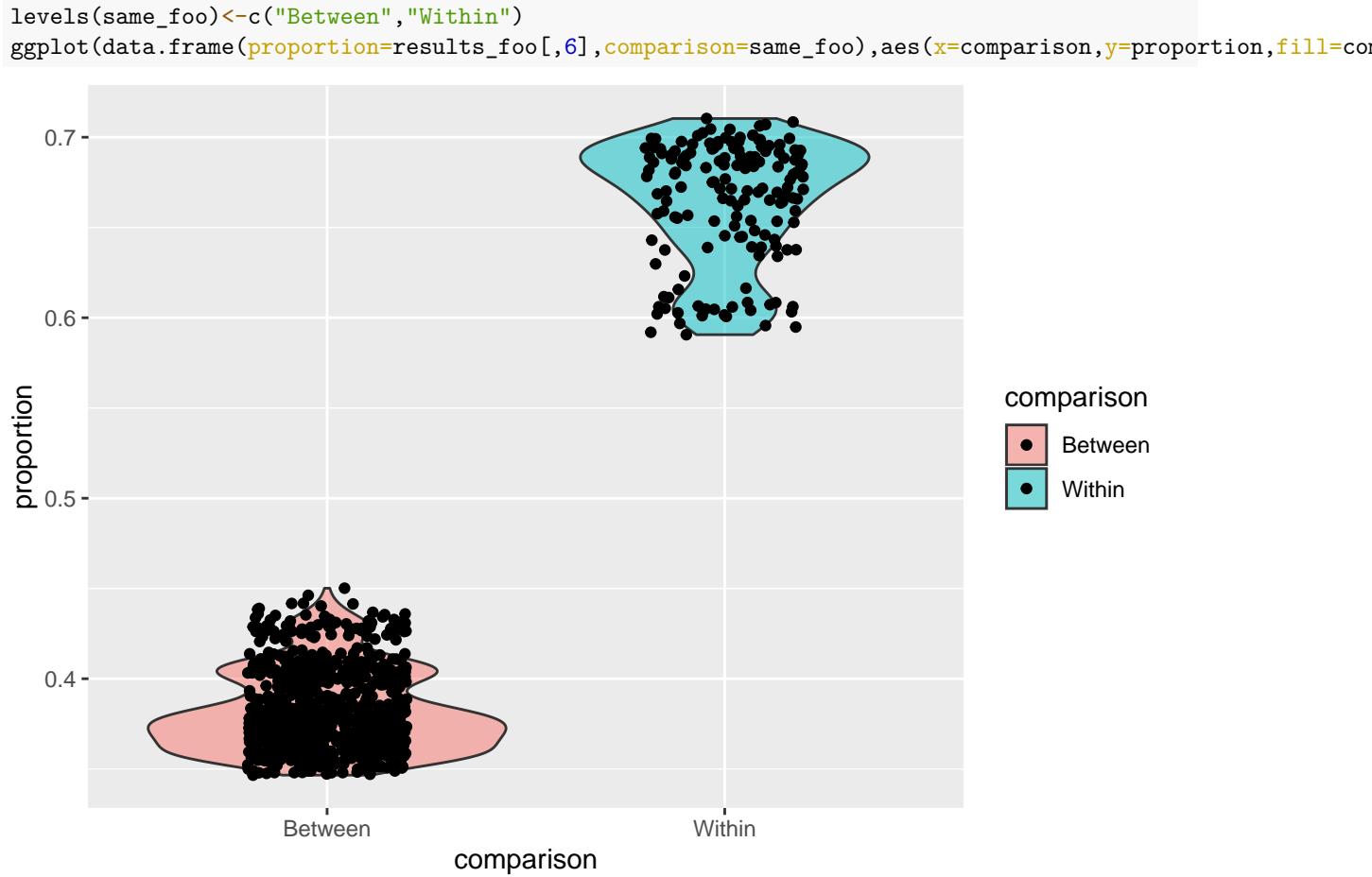
## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-8') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-9') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

## Warning: UNRELIABLE VALUE: One of the 'future.apply' iterations
## ('future_apply-10') unexpectedly generated random numbers without declaring
## so. There is a risk that those random numbers are not statistically sound and
## the overall results might be invalid. To fix this, specify 'future.seed=TRUE'.
## This ensures that proper, parallel-safe random numbers are produced via the
## L'Ecuyer-CMRG method. To disable this check, use 'future.seed = NULL', or set
## option 'future.rng.onMisuse' to "ignore".

results_foo<-t(results_foo)
same_foo<-factor(results_foo[,1]==results_foo[,2])

```



2.3.3 Within and between loci

```

print(t.test(results_foo[same_foo=="Between", 6], results_foo[same_foo=="Within", 6], alternative = "less"))

##
## Welch Two Sample t-test
##
## data: results_foo[same_foo == "Between", 6] and results_foo[same_foo == "Within", 6]
## t = -101.38, df = 181.44, p-value < 2.2e-16
## alternative hypothesis: true difference in means is less than 0
## 95 percent confidence interval:
##       -Inf -0.2772493
## sample estimates:
## mean of x mean of y
## 0.3826056 0.6644514
  
```

2.3.4 Between loci, random vs observed

```

print(t.test(results_foo[same_foo=="Between", 6], results_foo[same_foo=="Between", 7], alternative = "greater"))

##
## Welch Two Sample t-test
## 
```

```

## data: results_foo[same_foo == "Between", 6] and results_foo[same_foo == "Between", 7]
## t = 242.4, df = 869.18, p-value < 2.2e-16
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval:
##  0.1899233      Inf
## sample estimates:
## mean of x mean of y
## 0.3826056 0.1913833

```

2.4 I.IV Multilocus summary of bGMYC delimitations

2.4.1 Averaging coassignment matrices

```

names.bGMYC<-c("its","bt","efa","mcm7","rpb1","alpha","hmg")
#
#
#
#
#
#
recast_probmat <- function (x)
{
  class(x)<-NULL
  x<-x [rownames(x) != "Xanpa", colnames(x) != "Xanpa"]
  x<-melt(x)
  x$Var1<-gsub("[A-Z]", "", x$Var1, perl=TRUE)
  x$Var2<-gsub("[A-Z]", "", x$Var2, perl=TRUE)
  #x<-aggregate(value~Var1+Var2, data_bgmyc_all, FUN = combined_probability)
  return(acast(x, Var1~Var2, fun.aggregate = mean))
}

x1<-recast_probmat(output.bgmyc.1[[3]])
x2<-recast_probmat(output.bgmyc.2[[3]])
x3<-recast_probmat(output.bgmyc.3[[3]])
x4<-recast_probmat(output.bgmyc.4[[3]])
x5<-recast_probmat(output.bgmyc.5[[3]])

nombres_tabla<-c(rownames(x1), rownames(x2), rownames(x3), rownames(x4), rownames(x5))
nombres_tabla<-nombres_tabla[!duplicated(nombres_tabla)]
nombres_tabla<-nombres_tabla[order(as.numeric(nombres_tabla))]

data_bgmyc_all<-rbind(melt(x1), melt(x2), melt(x3), melt(x4), melt(x5))
data_bgmyc_all<-acast(data_bgmyc_all, Var1~Var2, fun.aggregate = mean)

```

2.4.2 Extended range of K for kmedoids K=1:200

```

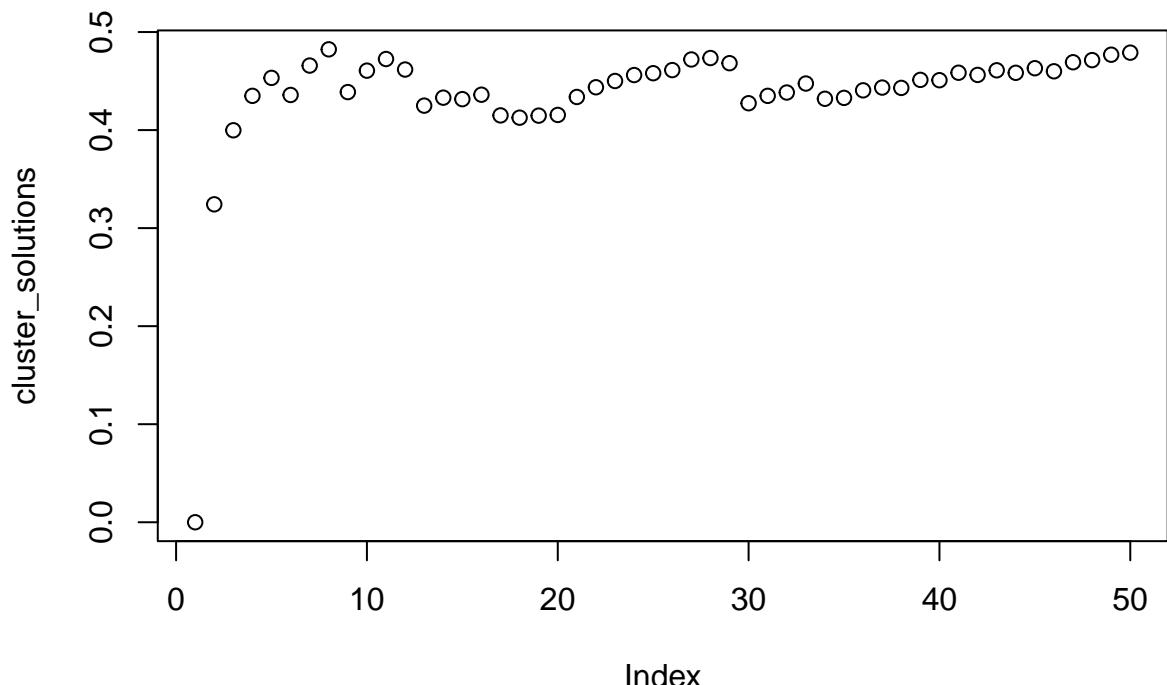
#coco<-pamk(1-data_bgmyc_all,1:200,diss=TRUE)
#cluster_solutions<-coco$crit
#plot(cluster_solutions)

```

```

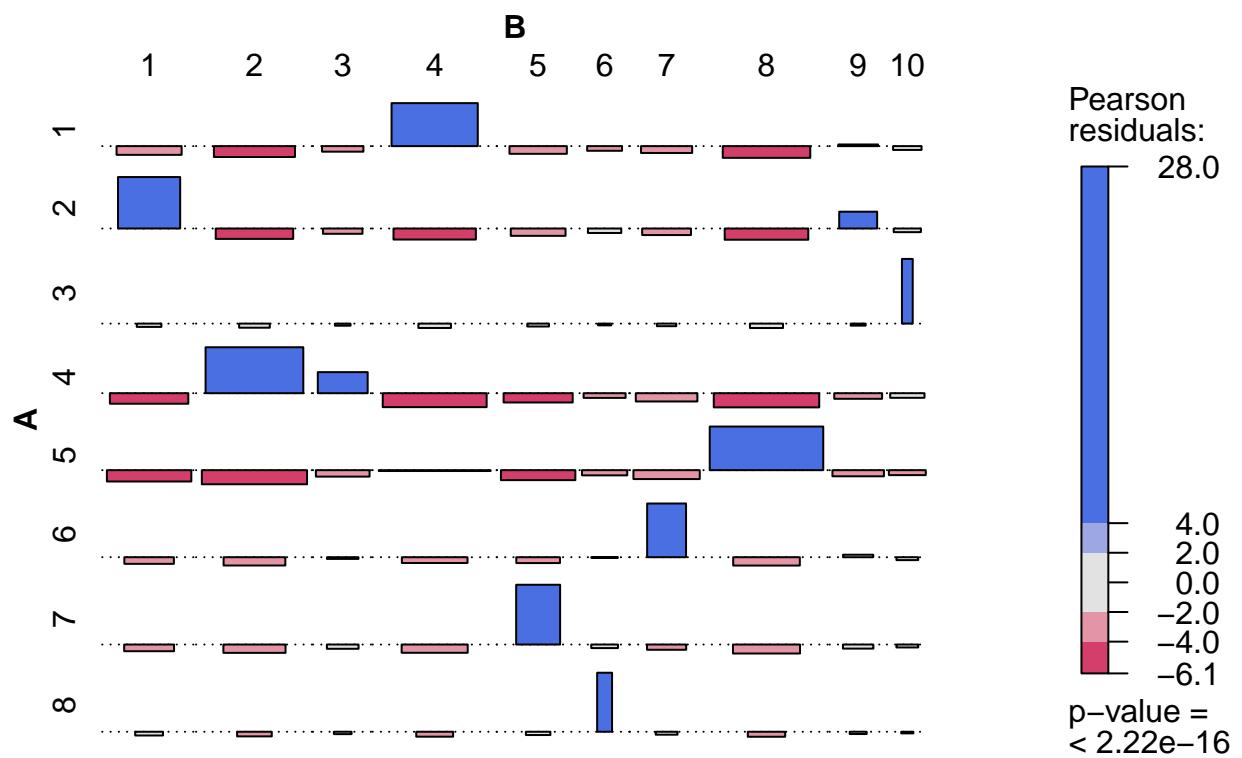
coco<-pamk(1-data_bgmyc_all,1:50,diss=TRUE)
cluster_solutions<-coco$crit
plot(cluster_solutions)

```



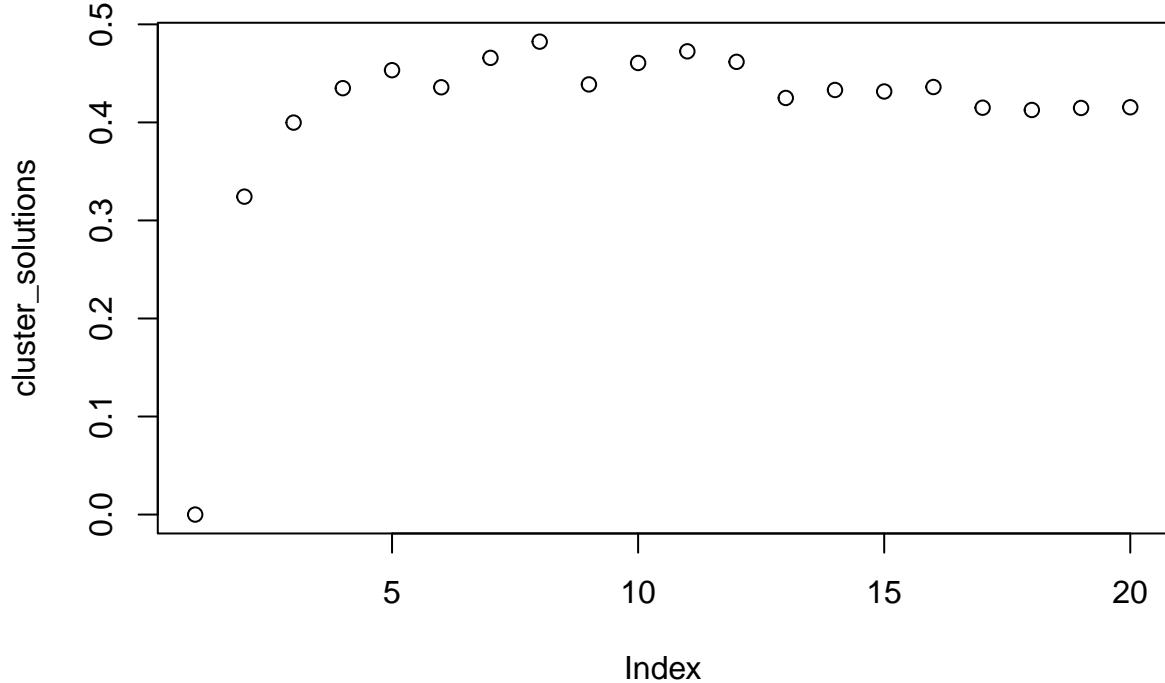
```
# Manually reorder
foo_bgmyc_clusters<-coco$pamobject$clustering

assoc(table(as.numeric(foo_bgmyc_clusters),condensed_baps_adm[names(foo_bgmyc_clusters),"name"]), shade
```



2.4.3 Reduced range of K values K=1:20

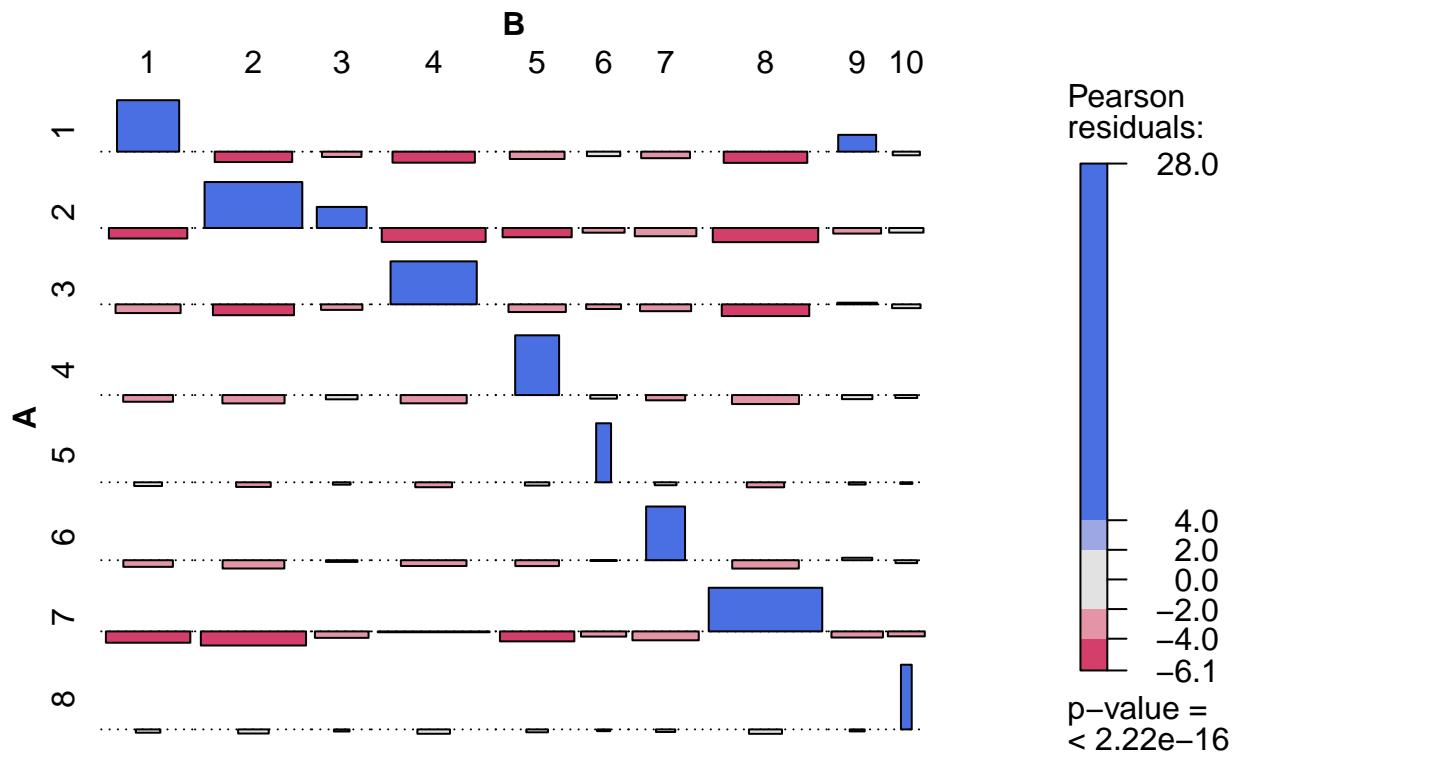
```
coco<-pamk(1-data_bgmyc_all,1:20,diss=TRUE)
cluster_solutions<-coco$crit
plot(cluster_solutions)
```



```
#save.image("/Users/Fernando/Desktop/01_Sanger_paper/14_bGMYC_All_loci/03_Processed/workspace_step5.Rda"

# Manually reorder
foo_bgmyc_clusters<-coco$pamobject$clustering
foo_bgmyc_clusters<-factor(foo_bgmyc_clusters,levels = c(2,4,1,7,8,6,5,3))

assoc(table(as.numeric(foo_bgmyc_clusters),condensed_baps_adm[names(foo_bgmyc_clusters),"name"]), shade
```



```

assocstats(table(as.numeric(foo_bgmyc_clusters),condensed_baps_adm[names(foo_bgmyc_clusters),"name"]))

##          X^2 df P(> X^2)
## Likelihood Ratio 2683.3 63      0
## Pearson         5010.4 63      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.927
## Cramer's V        : 0.932
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(as.numeric(foo_bgmyc_clusters),condensed_baps_adm[names(foo_bgmyc_clusters),"name"]))

##
## Permutation test for conditional independence
##
## data: table(as.numeric(foo_bgmyc_clusters), condensed_baps_adm[names(foo_bgmyc_clusters), "name"])
## f(x) = 28.078, p-value < 2.2e-16

foo_tabla<-melt(table(as.numeric(foo_bgmyc_clusters),condensed_baps_adm[names(foo_bgmyc_clusters),"name"]),
foo_tabla$value[foo_tabla$value==0]<-NA

ggplot(foo_tabla,aes(x=Var1,y=Var2,fill=value)) + geom_tile(color = "black") + geom_text(aes(label =
  scale_fill_gradient2(low = "#FFFFFF",
  mid = colorinos.bipolar[7],
  high = colorinos.bipolar[6],
  midpoint = 20,
  space = "Lab",
  na.value = "#FFFFFF",

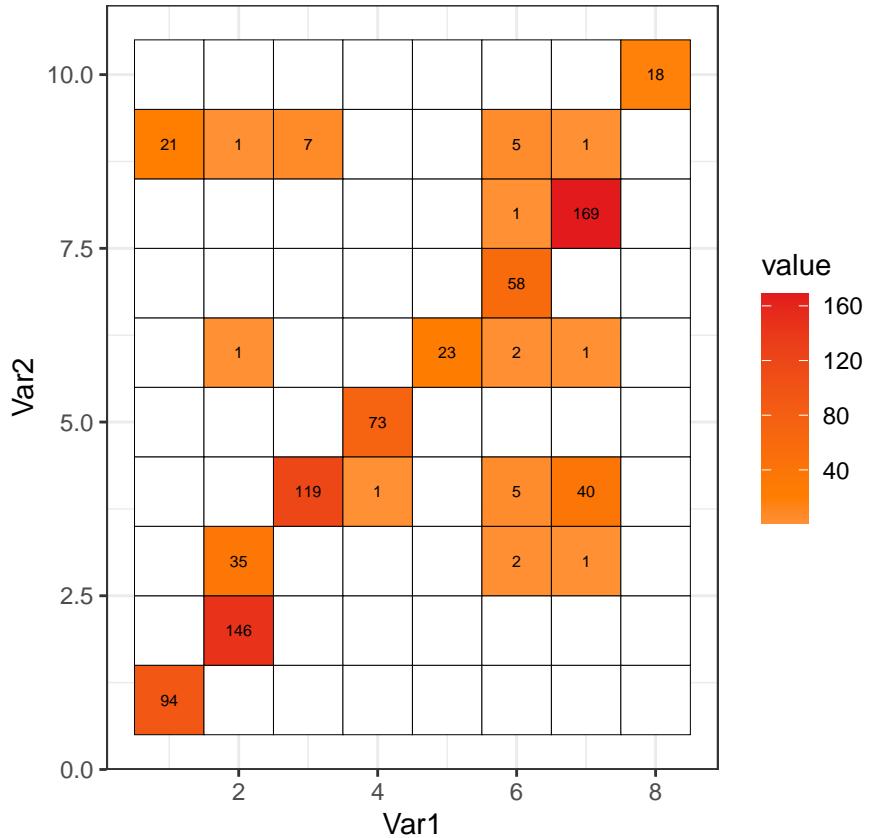
```

```

    guide = "colourbar",
    aesthetics = "fill"
) +
  coord_fixed() + theme_bw()

## Warning: Removed 57 rows containing missing values (geom_text).

```



Heatmap 2 Species vs bGMYC

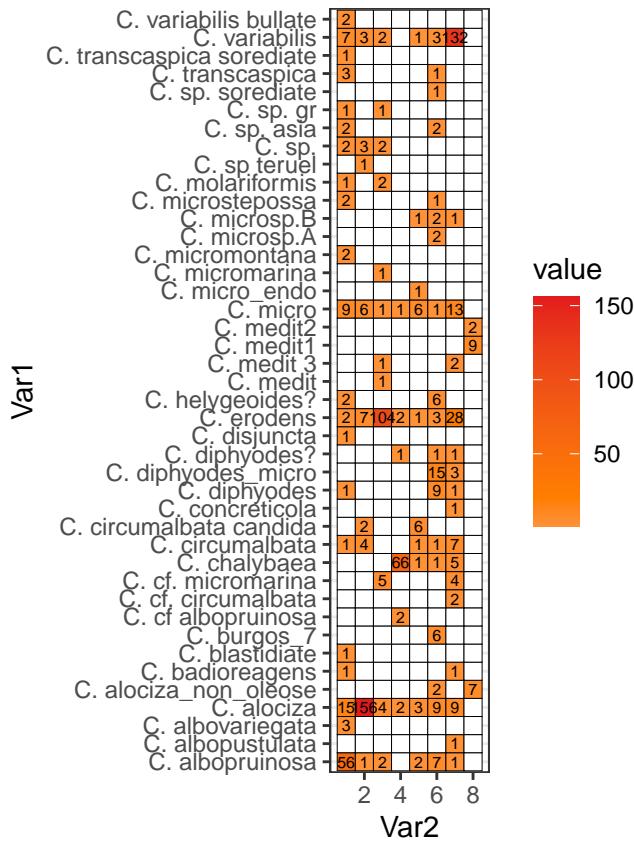
```

foo_tabla<-melt(table(condensed_baps_adm[names(foo_bgmyc_clusters),"Species"],as.numeric(foo_bgmyc_clusters)),varnames=c("Species","Cluster"))
foo_tabla$value[foo_tabla$value==0]<-NA

ggplot(foo_tabla,
       aes(x=Var2,y=Var1,fill=value)) +
  geom_tile(color = "black") +
  geom_text(aes(label = value), color = "black", size = 2) +
  scale_fill_gradient2(low = "#FFFFFF",
                       mid = colorinos.bipolar[7],
                       high = colorinos.bipolar[6],
                       midpoint = 20,
                       space = "Lab",
                       na.value = "#FFFFFF",
                       guide = "colourbar",
                       aesthetics = "fill") +
  coord_fixed() +
  theme_bw()

```

```
## Warning: Removed 239 rows containing missing values (geom_text).
```



```
assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters), "Species"], as.numeric(foo_bgmyc_clusters))

##          X^2   df P(> X^2)
## Likelihood Ratio 1867.6 287      0
## Pearson         3428.6 287      0
## 
## 
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.898
## Cramer's V        : 0.771

kable(chisq.residuals(table(condensed_baps_adm$Species, condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters), "Species"], as.numeric(foo_bgmyc_clusters))

## 
## Permutation test for conditional independence
## 
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters), "Species"], as.numeric(foo_bgmyc_clusters))
## f(x) = 23.216, p-value < 2.2e-16

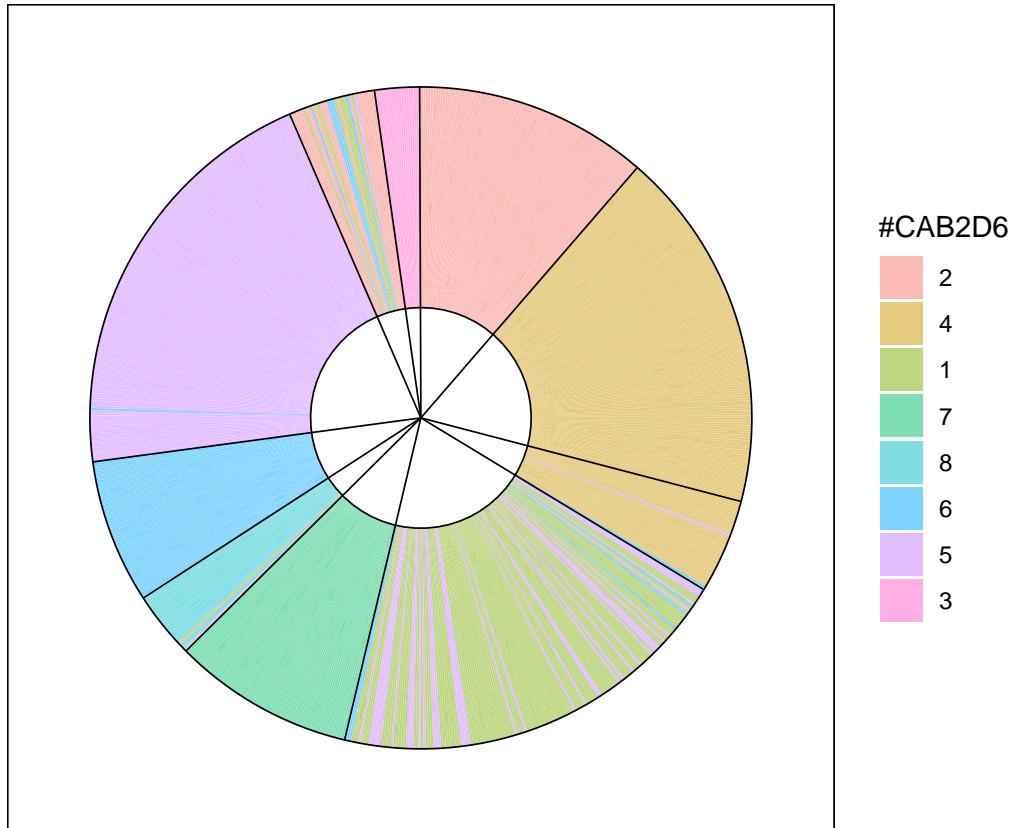
foo_bgmyc_clusters<-foo_bgmyc_clusters[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])), foo, clusters = foo_bgmyc_clusters[orden.foo])
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables
```

```

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1, fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(), axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



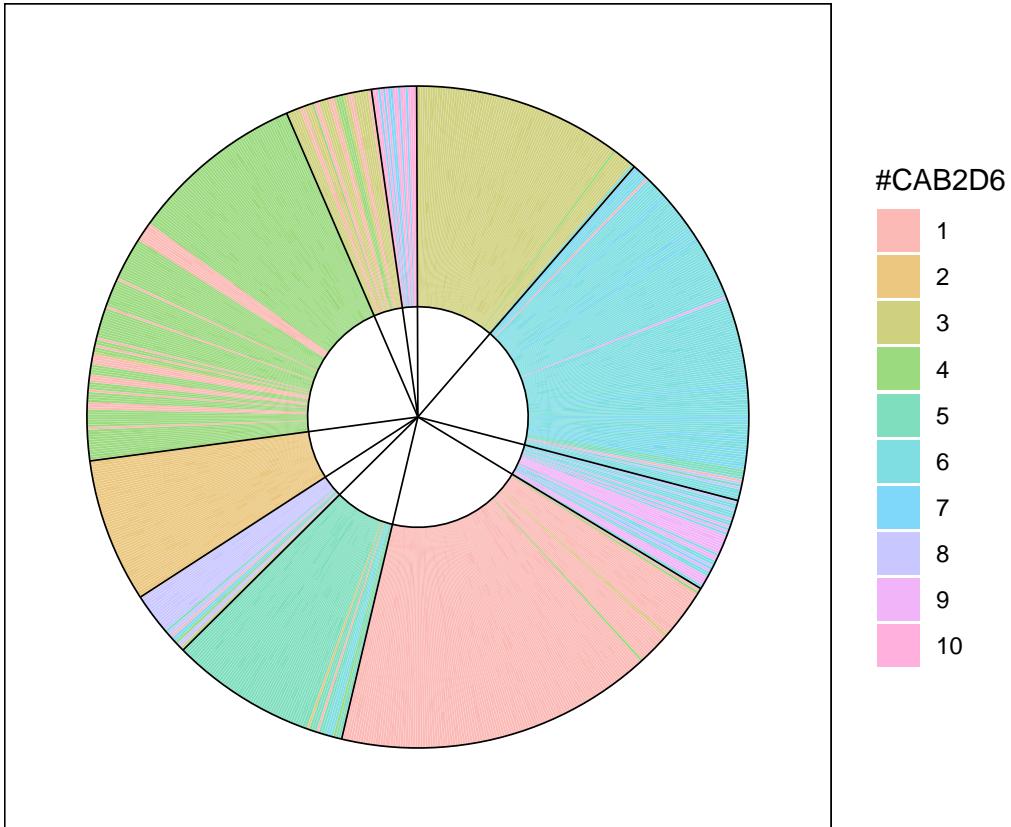
2.5 Single locus bGMYC

2.5.1 ITS

```
coco.its<-pamk(1-x1,2:10,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=clusters),
            stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)
```



```

## facet_wrap(vars(clusters)))

coco.its<-pamk(1-x1,2:100,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1, fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white", guide = "none") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +

```

```

theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
axis.text.x=element_blank(),
axis.ticks.x=element_blank(),axis.title.y=element_blank(),
axis.text.y=element_blank(),
axis.ticks.y=element_blank()) + coord_polar()
print(p + facet_wrap(vars(clusters)))

```



```

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"], as.numeric(foo_bgmyc_clusters

```

2.5.1.1 Association with BAPS

```

## X^2  df P(> X^2)

```

```

## Likelihood Ratio 2940.8 495      0
## Pearson          6200.3 495      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.94
## Cramer's V       : 0.914
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its),"name"],as.numeric(foo_bgmyc_clusters.its)))
## Permutation test for conditional independence
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 26.168, p-value < 2.2e-16

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its),"Species"],as.numeric(foo_bgmyc_clusters.its)))

2.5.1.2 Association with species

##           X^2   df P(> X^2)
## Likelihood Ratio 2545.2 2255 1.603e-05
## Pearson          12928.6 2255 0.000e+00
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.97
## Cramer's V       : 0.619
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its),"Species"],as.numeric(foo_bgmyc_clusters.its)))
## Permutation test for conditional independence
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 28.671, p-value = 0.224

assocstats(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)],as.numeric(foo_bgmyc_clusters.its)))

2.5.1.3 Association with multilocus bGMYC

##           X^2   df P(> X^2)
## Likelihood Ratio 2581.2 385      0
## Pearson          4797.9 385      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.924
## Cramer's V       : 0.912
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)],as.numeric(foo_bgmyc_clusters.its)))

```

```

## Permutation test for conditional independence
## data: table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]), as.numeric(foo_bgmyc_clusters.its)
## f(x) = 23.417, p-value < 2.2e-16

```

2.5.2 Beta Tubulin

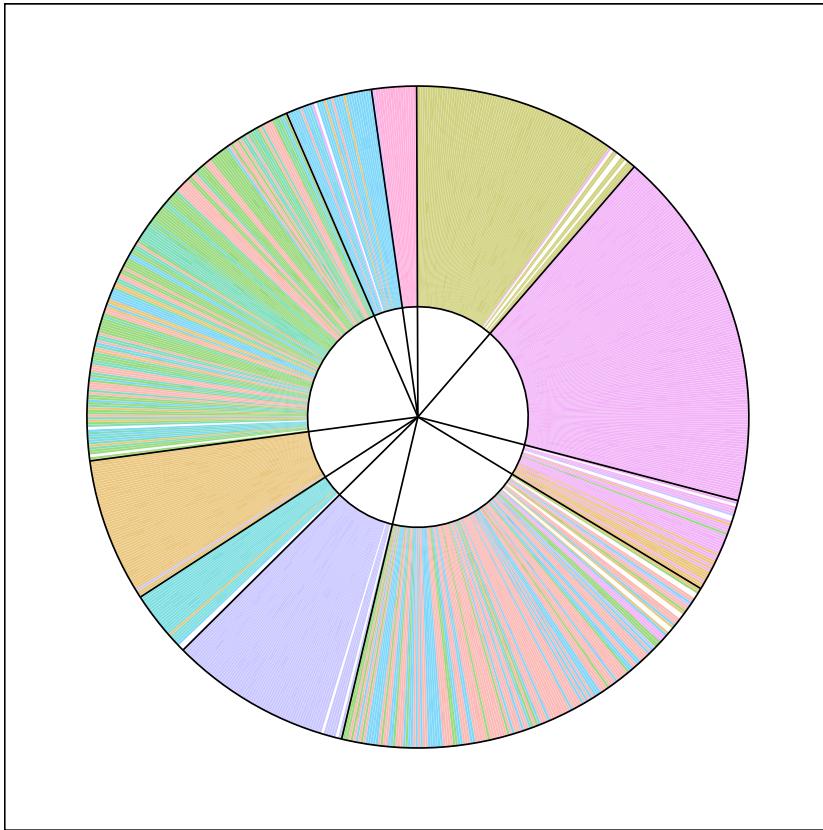
```

coco.its<-pamk(1-x2,2:10,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1, fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



#CAB2D6

	1
	2
	3
	4
	5
	6
	7
	8
	9
	10
	NA

```

## facet_wrap(vars(clusters)))

coco.its<-pamk(1-x2,2:100,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

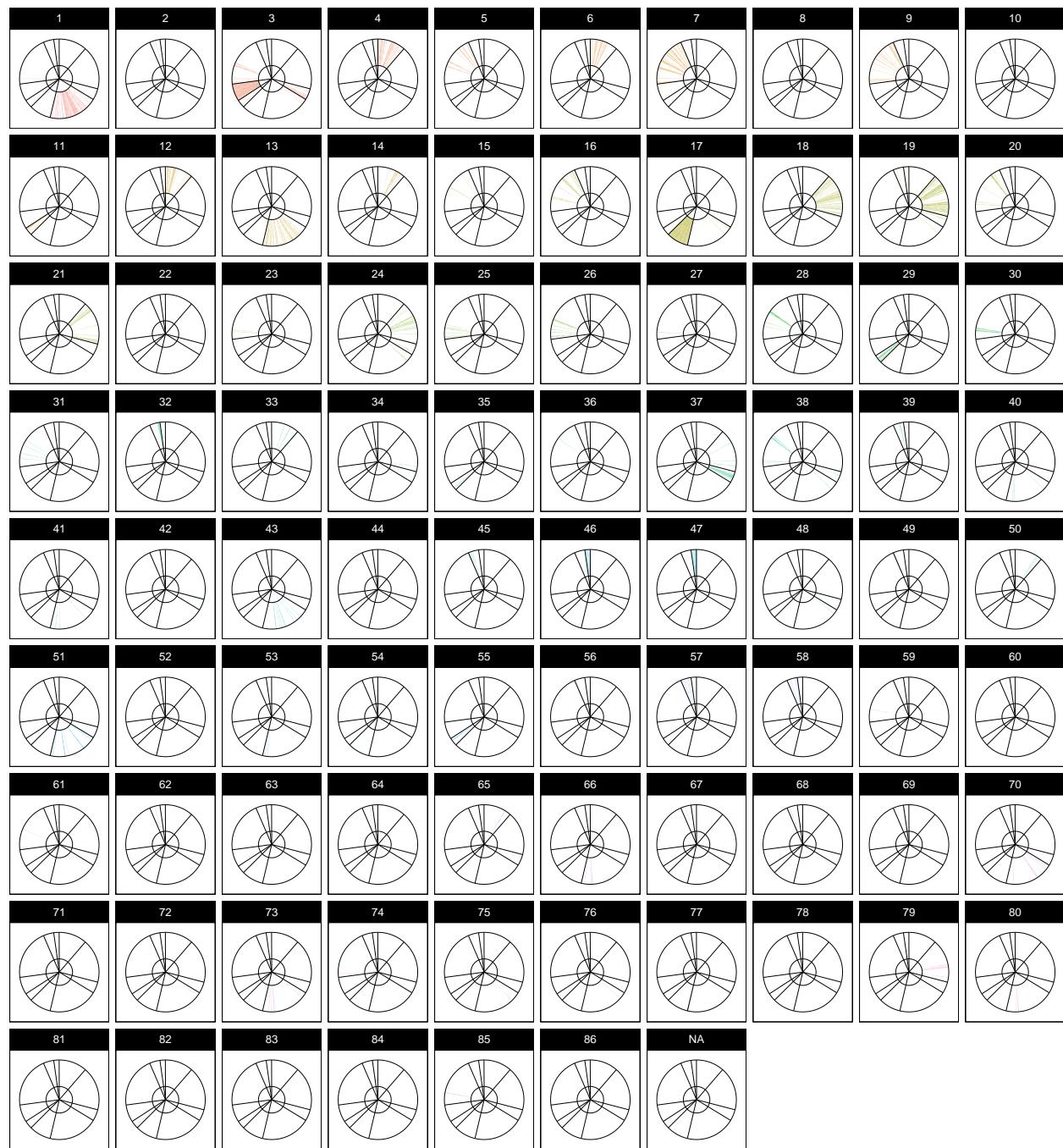
p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white", guide = "none") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +

```

```

theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
axis.text.x=element_blank(),
axis.ticks.x=element_blank(),axis.title.y=element_blank(),
axis.text.y=element_blank(),
axis.ticks.y=element_blank()) + coord_polar()
print(p + facet_wrap(vars(clusters)))

```



```

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"], as.numeric(foo_bgmyc_clusters

```

2.5.2.1 Association with BAPS

```
##          X^2   df P(> X^2)
## Likelihood Ratio 3005.0 765      0
## Pearson         6237.6 765      0
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.941
## Cramer's V       : 0.928
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"],as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 25.218, p-value < 2.2e-16

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"],as.numeric(foo_bgmyc_clusters.its)))
```

2.5.2.2 Association with species

```
##          X^2   df P(> X^2)
## Likelihood Ratio 2665 3315      1
## Pearson         12847 3315      0
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.97
## Cramer's V       : 0.64
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"],as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 28.32, p-value = 0.322
```

```
assocstats(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)],as.numeric(foo_bgmyc_clusters.its)))
```

2.5.2.3 Association with multilocus bGMYC

```
##          X^2   df P(> X^2)
## Likelihood Ratio 2713.4 595      0
## Pearson         5065.3 595      0
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.929
## Cramer's V       : 0.949
```

```

#kable(chisq.residuals(table(condensed_baps_adm$Species, condensed_baps_adm$name)))

coindep_test(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]),as.numeric(foo_bgmyc_clusters.its))

##
##  Permutation test for conditional independence
##
## data:  table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]), as.numeric(foo_bgmyc_clusters.its)
## f(x) = 25.395, p-value < 2.2e-16

```

2.5.3 Elongation factor alpha

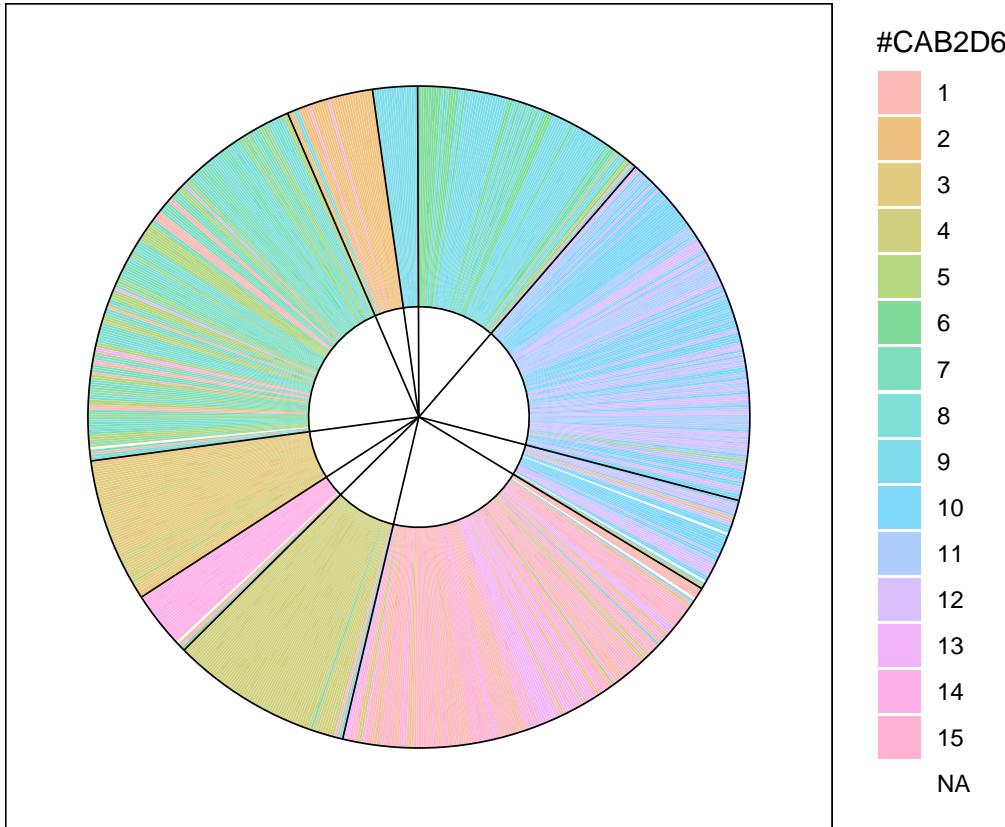
```

coco.its<-pamk(1-x3,2:15,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(),panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



```

## facet_wrap(vars(clusters)))

coco.its<-pamk(1-x3,2:15,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

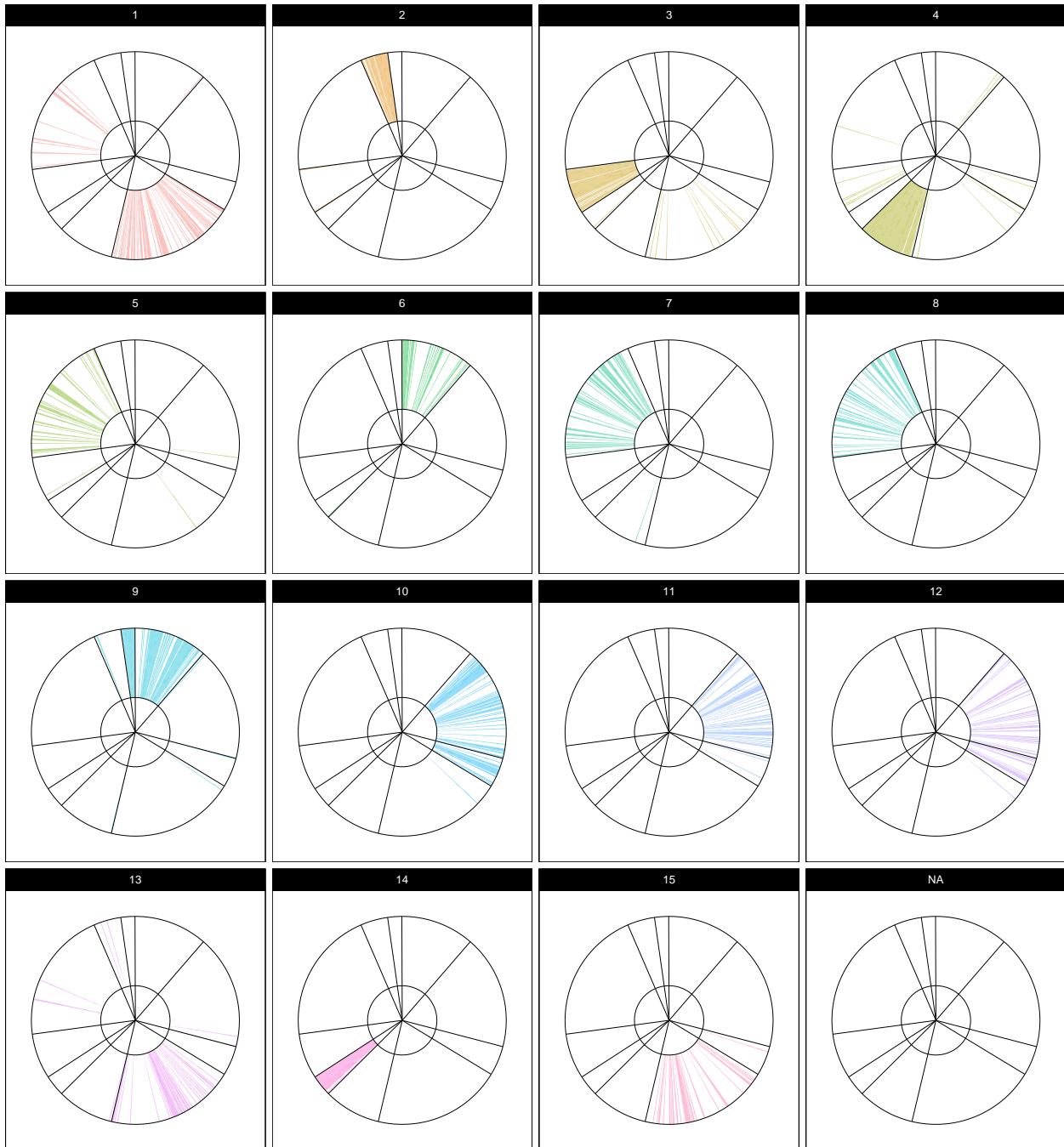
p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white", guide = "none") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +

```

```

theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
axis.text.x=element_blank(),
axis.ticks.x=element_blank(),axis.title.y=element_blank(),
axis.text.y=element_blank(),
axis.ticks.y=element_blank()) + coord_polar()
print(p + facet_wrap(vars(clusters)))

```



```

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"],as.numeric(foo_bgmyc_clusters

```

2.5.3.1 Association with BAPS

```
##          X^2  df P(> X^2)
## Likelihood Ratio 2658.7 126      0
## Pearson         4821.4 126      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.925
## Cramer's V        : 0.809
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"],as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 26.062, p-value < 2.2e-16

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"],as.numeric(foo_bgmyc_clusters.its)))
```

2.5.3.2 Association with species

```
##          X^2  df P(> X^2)
## Likelihood Ratio 1916.6 574      0
## Pearson         3283.7 574      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.895
## Cramer's V        : 0.535
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"],as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 20.653, p-value < 2.2e-16
```

```
assocstats(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)],as.numeric(foo_bgmyc_clusters.its)))
```

2.5.3.3 Association with multilocus bGMYC

```
##          X^2  df P(> X^2)
## Likelihood Ratio 2318.6 98      0
## Pearson         3804.6 98      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.907
## Cramer's V        : 0.815
```

```
#kable(chisq.residuals(table(condensed_baps_adm$Species, condensed_baps_adm$name)))
coindep_test(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]),as.numeric(foo_bgmyc_clusters.its))

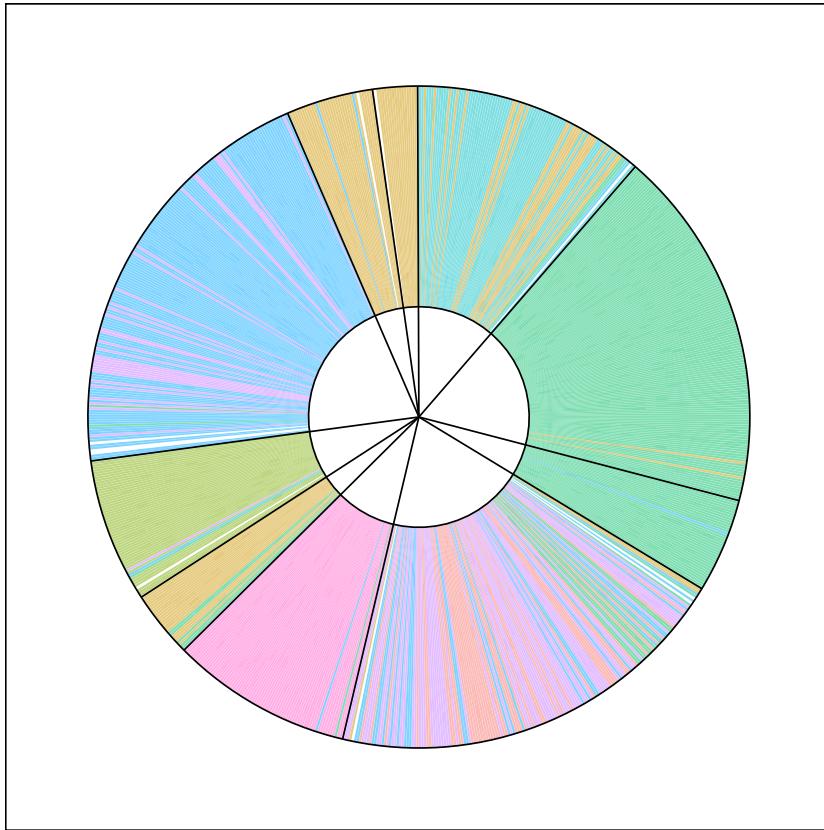
##
##  Permutation test for conditional independence
##
## data:  table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]), as.numeric(foo_bgmyc_clusters.its)
## f(x) = 26.57, p-value < 2.2e-16
```

2.5.4 MCM7

```
coco.its<-pamk(1-x4,2:10,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(),panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)
```



```

## facet_wrap(vars(clusters)))

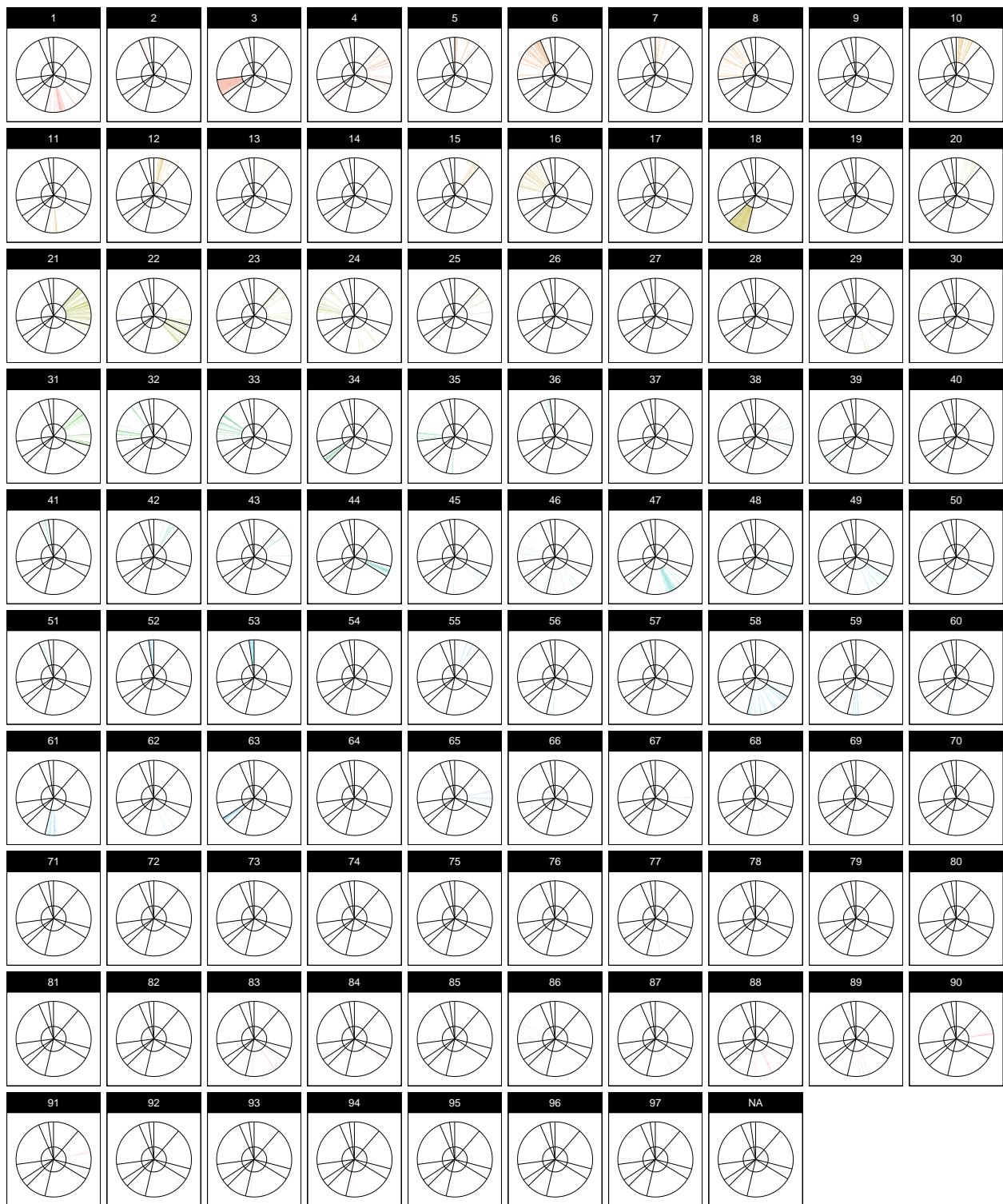
coco.its<-pamk(1-x4,2:100,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1, fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white", guide= "none") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +

```

```
theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
  axis.text.x=element_blank(),
  axis.ticks.x=element_blank(),axis.title.y=element_blank(),
  axis.text.y=element_blank(),
  axis.ticks.y=element_blank()) + coord_polar()
print(p + facet_wrap(vars(clusters)))
```



```
assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"], as.numeric(foo_bgmyc_clusters
```

2.5.4.1 Association with BAPS

```
## X^2 df P(> X^2)
```

```

## Likelihood Ratio 3091.4 864      0
## Pearson          6412.3 864      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.942
## Cramer's V       : 0.936

#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its),"name"],as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 25.342, p-value < 2.2e-16

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its),"Species"],as.numeric(foo_bgmyc_clusters.its))

2.5.4.2 Association with species

##           X^2   df P(> X^2)
## Likelihood Ratio 2806.5 3936      1
## Pearson        13734.2 3936      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.972
## Cramer's V       : 0.642

#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its),"Species"],as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 28.496, p-value = 0.306

assocstats(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)],as.numeric(foo_bgmyc_clusters.its)))

2.5.4.3 Association with multilocus bGMYC

##           X^2   df P(> X^2)
## Likelihood Ratio 2744.2 672      0
## Pearson        5085.6 672      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.928
## Cramer's V       : 0.945

#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

coindep_test(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)],as.numeric(foo_bgmyc_clusters.its)))

```

```

##  

##  Permutation test for conditional independence  

##  

## data:  table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]), as.numeric(foo_bgmyc_clusters.its)  

## f(x) = 24.68, p-value < 2.2e-16

```

2.5.5 RPB1

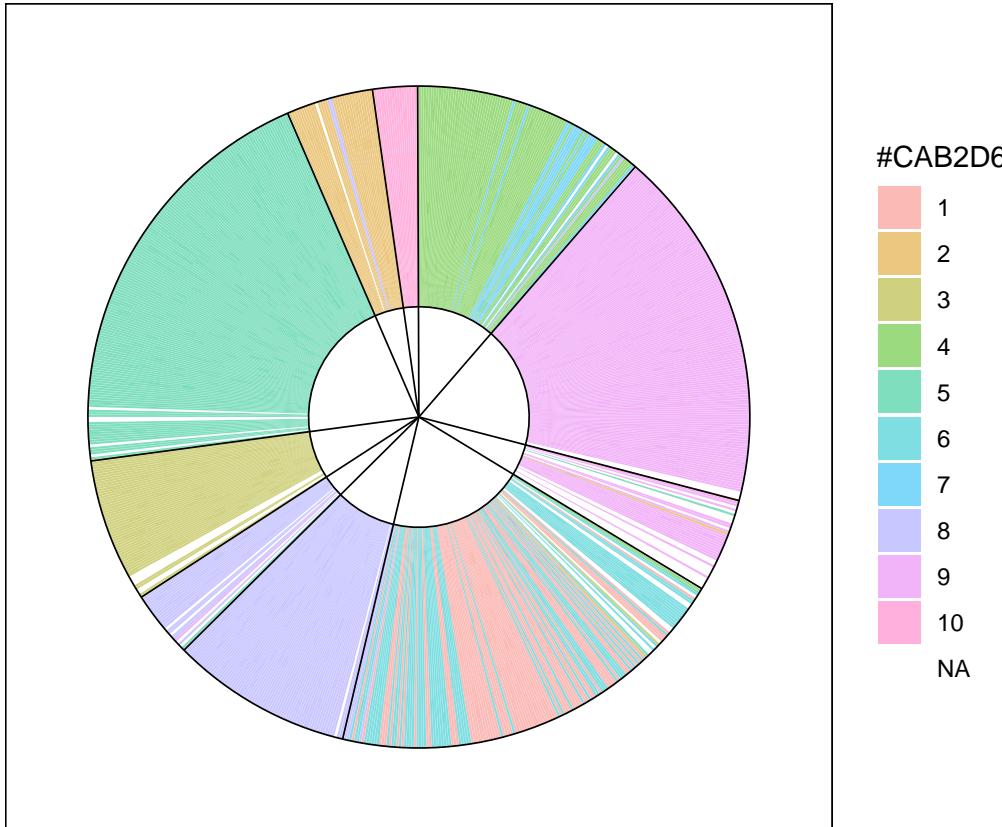
```

coco.its<-pamk(1-x5,2:10,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



```

## facet_wrap(vars(clusters)))

coco.its<-pamk(1-x5,2:100,diss=TRUE)
foo_bgmyc_clusters.its<-coco.its$pamobject$clustering
foo_bgmyc_clusters.its<-foo_bgmyc_clusters.its[rownames(condensed_baps_adm)]
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo,clusters = as.factor(foo_bgmyc_clusters.its[orden.foo]))
foo<-melt(foo[,c(1,26)])

## Using orden, clusters as id variables

p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1, fill=clusters),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos.bipolar, na.value="white", guide = "none") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +

```

```

theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
axis.text.x=element_blank(),
axis.ticks.x=element_blank(),axis.title.y=element_blank(),
axis.text.y=element_blank(),
axis.ticks.y=element_blank()) + coord_polar()
print(p + facet_wrap(vars(clusters)))

```



```

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"], as.numeric(foo_bgmyc_clusters.its)))

```

2.5.5.1 Association with BAPS

```

##          X^2   df P(> X^2)
## Likelihood Ratio 3075.4 531      0
## Pearson         6656.4 531      0
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.946
## Cramer's V       : 0.977

```

```

#kable(chisq.residuals(table(condensed_baps_adm$Species, condensed_baps_adm$name)))

```

```

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"], as.numeric(foo_bgmyc_clusters.its)))

```

```

## Permutation test for conditional independence
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "name"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 25.043, p-value < 2.2e-16

```



```

assocstats(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"], as.numeric(foo_bgmyc_clusters.its)))

```

2.5.5.2 Association with species

```

##          X^2   df P(> X^2)
## Likelihood Ratio 2654.8 2419 0.00049163
## Pearson         13451.3 2419 0.000000000
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.972
## Cramer's V       : 0.651

```

```

#kable(chisq.residuals(table(condensed_baps_adm$Species, condensed_baps_adm$name)))

```

```

coindep_test(table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"], as.numeric(foo_bgmyc_clusters.its)))

```

```

## Permutation test for conditional independence
## data: table(condensed_baps_adm[names(foo_bgmyc_clusters.its), "Species"] , as.numeric(foo_bgmyc_clusters.its))
## f(x) = 27.803, p-value = 0.176

```



```

assocstats(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)], as.numeric(foo_bgmyc_clusters.its)))

```

2.5.5.3 Association with multilocus bGMYC

```

##          X^2   df P(> X^2)
## Likelihood Ratio 2717.0 413      0
## Pearson         5119.2 413      0
##
## Phi-Coefficient : NA
## Contingency Coeff.: 0.932

```

```

## Cramer's V : 0.971
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))
coindep_test(table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]),as.numeric(foo_bgmyc_clusters.its))

##
## Permutation test for conditional independence
##
## data: table(foo_bgmyc_clusters[names(foo_bgmyc_clusters.its)]), as.numeric(foo_bgmyc_clusters.its)
## f(x) = 25.043, p-value < 2.2e-16
```

3 Part II. Mating type coocurrence

3.1 II.I Read data and CD-HIT

```

i=9
for (file in c(
  "/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/proteins/alpha_v13_exons.fasta",
  "/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/proteins/hmg_v13_Only_exons.fasta"
))
{
  sequences<-read.dna(file,format="fasta")
  seq.dataset[[i]]<-sequences
  names.dataset[[i]]<-strsplit(rownames(sequences),split="_")
  i<-i+1
}
# library(phangorn)
i=11
for (file in c(
  "/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/proteins/alpha_v13_translation.fasta",
  "/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/proteins/hmg_v13_shortened_translation."
))
{
  sequences<-read.aa(file,format="fasta")
  seq.dataset[[i]]<-sequences
  names.dataset[[i]]<-strsplit(names(sequences),split="_")
  i<-i+1
}

for ( i in 9:12)
{
  for (j in 1:length(names.dataset[[i]]))
  {
    names.dataset[[i]][[j]]<-names.dataset[[i]][[j]][1]
  }
  names.dataset[[i]]<-unlist(names.dataset[[i]])
}

#alpha
names.dataset[[9]][is.na(as.numeric(names.dataset[[9]]))]<-c("207","205")

## Warning in names.dataset[[9]][is.na(as.numeric(names.dataset[[9]]))]: 
##   c("207", : NAs introducidos por coerción
```

```

names.dataset$alpha_tr<-gsub("X","",names.dataset$alpha_tr)
names.dataset[[11]][is.na(as.numeric(names.dataset[[11]]))]<-c("207","205")

## Warning in names.dataset[[11]][is.na(as.numeric(names.dataset[[11]]))] <-
## c("207", : NAs introducidos por coerción

#hmg_tr"
names.dataset$hmg_tr<-gsub("X","",names.dataset$hmg_tr)
#
#
#
rownames(seq.dataset$alpha)<-names.dataset$alpha
rownames(seq.dataset$hmg)<-names.dataset$hmg
names(seq.dataset$alpha_tr)<-names.dataset$alpha_tr
names(seq.dataset$hmg_tr)<-names.dataset$hmg_tr
#
names.dataset[[8]][names.dataset[[8]]=="00"]<-"0"
names.dataset[[9]][names.dataset[[9]]=="00"]<-"0"
#
# Renumber doubled from Vondrak
#
a<-as.character(seq(2,56,2))
b<-as.character(seq(1,55,2))
for (i in 9:length(names.dataset))
{
  for (j in 1:28)
  {
    names.dataset[[i]][names.dataset[[i]]]==a[j]]<-b[j]
  }
}
rm(a,b)

reduced.dataset$alpha<-seq.dataset$alpha[names.dataset$alpha%in%rownames(dataset),]
reduced.dataset$hmg<-seq.dataset$hmg[names.dataset$hmg%in%rownames(dataset),]

reduced.dataset$alpha_tr<-subset(seq.dataset$alpha_tr,names(seq.dataset$alpha_tr)%in%names.dataset$alpha)
reduced.dataset$hmg_tr<-subset(seq.dataset$hmg_tr,names(seq.dataset$hmg_tr)%in%names.dataset$hmg_tr[nam

#
# 5. Export alignment files
#-----
#for (i in 9:(length(names.dataset)-2))
#{if (is.list(names.dataset[[i]])==TRUE)#
#  {
#    names(seq.dataset[[i]])<-names.dataset[[i]]
#    write.dna(seq.dataset[[i]][names.dataset[[i]]%in%rownames(dataset)],paste("/Users/Fernando/Desktop/
#  } else
#  {
#    rownames(seq.dataset[[i]])<-names.dataset[[i]]
#    write.dna(seq.dataset[[i]][names.dataset[[i]]%in%rownames(dataset)],paste("/Users/Fernando/Desktop/
#  }
#

```

```

#}
#
#
#
#
#
#
# Factor dataset for bipartite networks
#
alpha.haplo<-mat.or.vec(length(reduced.dataset$alpha_tr),2)
rownames(alpha.haplo)<-names(reduced.dataset$alpha_tr)
for (i in 1:dim(alpha.haplo)[1])
{
  alpha.haplo[i,1]<-paste(as.vector(reduced.dataset$alpha_tr)[[i]],collapse="")
}
alpha.haplo<-alpha.haplo[!(rownames(alpha.haplo)%in%c("377","1073","1170","1171")),]
alpha.haplo[,2]<-factor(alpha.haplo[,1])

hmg.haplo<-mat.or.vec(length(reduced.dataset$hmg_tr),2)
rownames(hmg.haplo)<-names(reduced.dataset$hmg_tr)
for (i in 1:dim(hmg.haplo)[1])
{
  hmg.haplo[i,1]<-paste(as.character(reduced.dataset$hmg_tr)[[i]],collapse="")
}
hmg.haplo<-hmg.haplo[!(rownames(hmg.haplo)%in%c("377","1073","1170","1171")),]
hmg.haplo[,2]<-factor(hmg.haplo[,1])
#
#
#
foo.alpha<-as.character(sort(as.numeric(rownames(alpha.haplo))))[duplicated(as.character(sort(as.numeric(
#
foo.hmg<-as.character(sort(as.numeric(rownames(hmg.haplo)))))[duplicated(as.character(sort(as.numeric(rownames(hmg.haplo))))))]
foo.both<-c(foo.alpha,foo.hmg)
foo.both<-foo.both[!duplicated(foo.both)]
foo.both<-as.character(sort(as.numeric(foo.both)))
foo.names<-c(rownames(alpha.haplo),rownames(hmg.haplo))
foo.names<-as.character(sort(as.numeric(foo.names[!duplicated(foo.names)])))
#
#
out.haps<-NULL
for (i in foo.names)
{
  if(i%in%rownames(alpha.haplo)&i%in%rownames(hmg.haplo))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,2]
    h<-hmg.haplo[rownames(hmg.haplo)==i,2]
    for(j in a)
    {
      for (k in h)
      {
        out.haps<-rbind(out.haps,c(i,j,k))
      }
    }
  }
}

```

```

} else if (i%in%rownames(alpha.haplo)&!(i%in%rownames(hmg.haplo)))
{
a<-alpha.haplo[rownames(alpha.haplo)==i,2]
out.haps<-rbind(out.haps,cbind(i,a,0))
} else if (!(i%in%rownames(alpha.haplo))&i%in%rownames(hmg.haplo))
{
a<-hmg.haplo[rownames(hmg.haplo)==i,2]
out.haps<-rbind(out.haps,cbind(i,0,a))
}
}
rownames(out.haps)<-out.haps[,1]
#
#
# 4. External Export for clustering in CD-Hit
#
#alpha.haplo.seq<-as.character(neurnames.reduced.dataset$alpha_tr)
#alpha.haplo.seq<-subset(alpha.haplo.seq,!duplicated(alpha.haplo[,2]))
#rownames(alpha.haplo.seq)<-paste("SeqID",alpha.haplo[!duplicated(alpha.haplo[,2]),2],"_",table(alpha.haplo[,2]))
#alpha.haplo.seq<-alpha.haplo.seq[order(table(alpha.haplo[,2]))][as.numeric(alpha.haplo[!duplicated(alpha.haplo[,2])])]

#hmg.haplo.seq<-as.character(neurnames.reduced.dataset$hmg_tr)
#hmg.haplo.seq<-subset(hmg.haplo.seq,!duplicated(hmg.haplo[,2]))
#rownames(hmg.haplo.seq)<-paste("SeqID",hmg.haplo[!duplicated(hmg.haplo[,2]),2],"_",table(hmg.haplo[,2]))
#hmg.haplo.seq<-hmg.haplo.seq[order(table(hmg.haplo[,2]))][as.numeric(hmg.haplo[!duplicated(hmg.haplo[,2])])]

#write(aa(alpha.haplo.seq,"/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/alpha_collapsed.fasta")
#write(aa(hmg.haplo.seq,"/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/hmg_collapsed.fasta")
#
# Import CD HIT
#
import.cd.hit<-function(file,reference)
{
require(stringr)
foo.read<-readLines(file)
foo.alpha99<-list()
a<-grep(">Cluster ",foo.read);
a<-c(a,length(foo.read))
for (i in 1:(length(a)-1))
{
  if((a[i]+1)==(a[i+1]-1))
  {
    foo.alpha99[[i]]<-foo.read[(a[i]+1)]
  }
  else
  {
    foo.alpha99[[i]]<-foo.read[(a[i]+1):(a[i+1]-1)]
  }
}
names(foo.alpha99)<-foo.read[a[-length(a)]]
for (i in 1:length(foo.alpha99)) foo.alpha99[[i]]<-str_extract(foo.alpha99[[i]], ">SeqID[0-9]+")
for (i in 1:length(foo.alpha99)) foo.alpha99[[i]]<-gsub(">SeqID","",foo.alpha99[[i]])
names(foo.alpha99)<-gsub(">Cluster","",names(foo.alpha99))
out<-mat.or.vec(length(reference[,2]),1)

```

```

for (i in 1:length(foo.alpha99))
{out[reference[,2]%in%foo.alpha99[[i]]]  
names(foo.alpha99)[i]}  
out<-as.numeric(out)+1  
return(out)  
}  
  
alpha.haplo<-cbind(alpha.haplo,import.cd.hit("/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/pr  
## Loading required package: stringr  
alpha.haplo<-cbind(alpha.haplo,import.cd.hit("/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/pr  
alpha.haplo<-cbind(alpha.haplo,import.cd.hit("/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/pr  
hmg.haplo<-cbind(hmg.haplo,import.cd.hit("/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/protein  
hmg.haplo<-cbind(hmg.haplo,import.cd.hit("/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/protein  
hmg.haplo<-cbind(hmg.haplo,import.cd.hit("/Users/Fernando/Desktop/01_Sanger_paper/6_Mating_types/protein  
  
#  
# 99%  
#  
out.99<-NULL  
out.97<-NULL  
out.95<-NULL  
  
for (i in foo.names)
{
  if(i%in%rownames(alpha.haplo)&i%in%rownames(hmg.haplo))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,3]
    h<-hmg.haplo[rownames(hmg.haplo)==i,3]
    for(j in a)
    {
      for (k in h)
      {
        out.99<-rbind(out.99,c(i,j,k))
      }
    }
  }
  if (i%in%rownames(alpha.haplo)&! (i%in%rownames(hmg.haplo)))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,3]
    out.99<-rbind(out.99,cbind(i,a,0))
  }
  else if (! (i%in%rownames(alpha.haplo))&i%in%rownames(hmg.haplo))
  {
    a<-hmg.haplo[rownames(hmg.haplo)==i,3]
    out.99<-rbind(out.99,cbind(i,0,a))
  }
}
rownames(out.99)<-out.99[,1]  
  
out.99<-out.99[!(rownames(out.99)%in%c("199","377","1073","1170","1171")),]  
#
# 97%

```

```

#
for (i in foo.names)
{
  if(i%in%rownames(alpha.haplo)&i%in%rownames(hmg.haplo))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,4]
    h<-hmg.haplo[rownames(hmg.haplo)==i,4]
    for(j in a)
    {
      for (k in h)
      {
        out.97<-rbind(out.97,c(i,j,k))
      }
    }
  }
  if (i%in%rownames(alpha.haplo)&! (i%in%rownames(hmg.haplo)))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,4]
    out.97<-rbind(out.97,cbind(i,a,0))
  }
  else if (! (i%in%rownames(alpha.haplo))&i%in%rownames(hmg.haplo))
  {
    a<-hmg.haplo[rownames(hmg.haplo)==i,4]
    out.97<-rbind(out.97,cbind(i,0,a))
  }
}
rownames(out.97)<-out.97[,1]

out.97<-out.97[!(rownames(out.97)%in%c("199","377","1073","1170","1171")),]
#
# 95% Similarity
#
for (i in foo.names)
{
  if(i%in%rownames(alpha.haplo)&i%in%rownames(hmg.haplo))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,5]
    h<-hmg.haplo[rownames(hmg.haplo)==i,5]
    for(j in a)
    {
      for (k in h)
      {
        out.95<-rbind(out.95,c(i,j,k))
      }
    }
  }
  if (i%in%rownames(alpha.haplo)&! (i%in%rownames(hmg.haplo)))
  {
    a<-alpha.haplo[rownames(alpha.haplo)==i,5]
    out.95<-rbind(out.95,cbind(i,a,0))
  }
  else if (! (i%in%rownames(alpha.haplo))&i%in%rownames(hmg.haplo))
  {

```

```

a<-hmg.haplo[rownames(hmg.haplo)==i,5]
out.95<-rbind(out.95,cbind(i,0,a))
}
}
rownames(out.95)<-out.95[,1]

out.95<-out.95[!(rownames(out.95)%in%c("199","377","1073","1170","1171")),]

```

3.2 II.II Compartmentalization and modularity

3.2.1 At haplotype level (Only compartments)

```

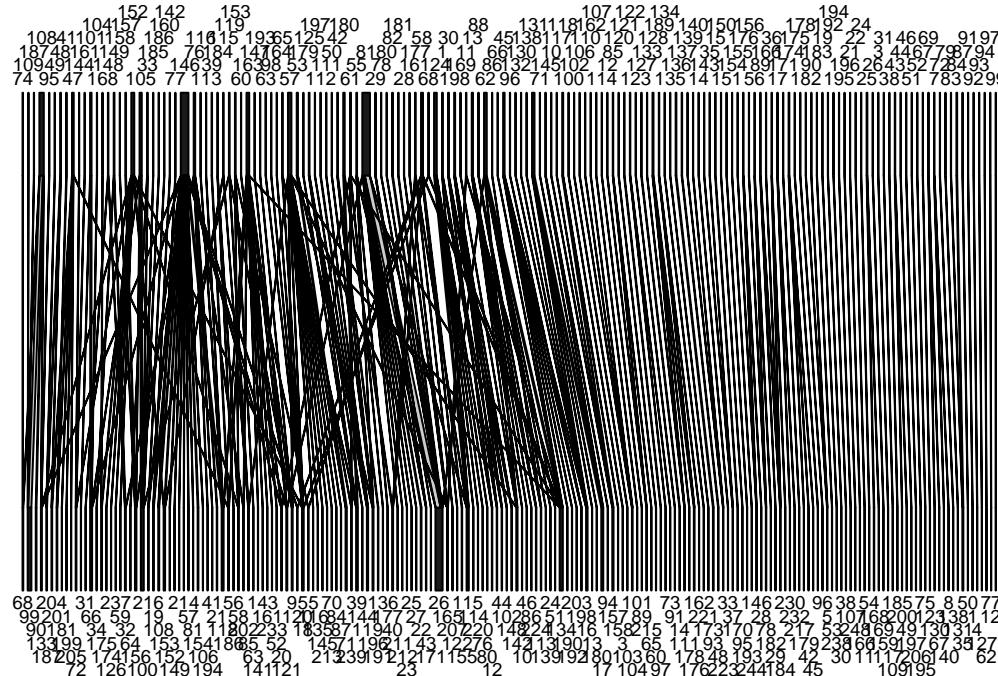
table.mating.types<-out.haps[,-1]
table.mating.types<-table(table.mating.types[,1],table.mating.types[,2])
table.mating.types<-table.mating.types[-1,-1]
table.mating.types<-table.mating.types[rowSums(table.mating.types)>0,colSums(table.mating.types)>0]
comps<-compart(table.mating.types)

```

```

colorinos_compartments<-colorRampPalette(colorinos.bipolar)(comps$n.compart)
plotweb(table.mating.types)

```



3.2.1.1 Network compartments

```

kable(networklevel(table.mating.types))

```

```

## Error in (function (cl, name, valueClass) :
##   assignment of an object of class "table" is not valid for @'originalWeb' in an object of class "mod"

```

	x
connectance	0.0097337
web asymmetry	-0.0909091
links per species	0.8760331

	x
number of compartments	66.0000000
compartment diversity	12.4520631
cluster coefficient	0.0050505
modularity Q	NA
nestedness	1.3055647
NODF	1.4900002
weighted nestedness	NaN
weighted NODF	0.3293185
interaction strength asymmetry	-0.0333291
specialisation asymmetry	0.0505732
linkage density	3.2394124
weighted connectance	0.0089240
Fisher alpha	556.2818877
Shannon diversity	5.5192298
interaction evenness	0.5309907
Alatalo interaction evenness	0.5824975
H2	0.4479515
number.of.species.HL	165.0000000
number.of.species.LL	198.0000000
mean.number.of.shared.partners.HL	0.0171471
mean.number.of.shared.partners.LL	0.0299954
cluster.coefficient.HL	0.0256999
cluster.coefficient.LL	0.0171788
weighted.cluster.coefficient.HL	0.0187563
weighted.cluster.coefficient.LL	0.0422438
niche.overlap.HL	0.0071341
niche.overlap.LL	0.0162541
togetherness.HL	0.0009580
togetherness.LL	0.0038503
C.score.HL	0.9867321
C.score.LL	0.9738783
V.ratio.HL	2.7936078
V.ratio.LL	0.8737068
discrepancy.HL	283.0000000
discrepancy.LL	288.0000000
extinction.slope.HL	1.3140338
extinction.slope.LL	1.3864882
robustness.HL	0.5689320
robustness.LL	0.5819856
functional.complementarity.HL	341.8393154
functional.complementarity.LL	339.7511160
partner.diversity.HL	0.9994908
partner.diversity.LL	0.6602675
generality.HL	4.1900761
vulnerability.LL	2.2887487

```
kable(grouplevel(table.mating.types))
```

	x
number.of.species.HL	165.0000000
number.of.species.LL	198.0000000

	x
mean.number.of.links.HL	5.0885781
mean.number.of.links.LL	2.8344988
mean.number.of.shared.partners.HL	0.0171471
mean.number.of.shared.partners.LL	0.0299954
cluster.coefficient.HL	0.0256999
cluster.coefficient.LL	0.0171788
weighted.cluster.coefficient.HL	0.0187563
weighted.cluster.coefficient.LL	0.0422438
niche.overlap.HL	0.0071341
niche.overlap.LL	0.0162541
togetherness.HL	0.0009580
togetherness.LL	0.0038503
C.score.HL	0.9867321
C.score.LL	0.9738783
V.ratio.HL	2.7936078
V.ratio.LL	0.8737068
discrepancy.HL	283.0000000
discrepancy.LL	288.0000000
extinction.slope.HL	1.3281663
extinction.slope.LL	1.3735409
robustness.HL	0.5705557
robustness.LL	0.5799338
functional.complementarity.HL	341.8393154
functional.complementarity.LL	339.7511160
partner.diversity.HL	0.9994908
partner.diversity.LL	0.6602675
generality.HL	4.1900761
vulnerability.LL	2.2887487

3.2.2 Comps vs species

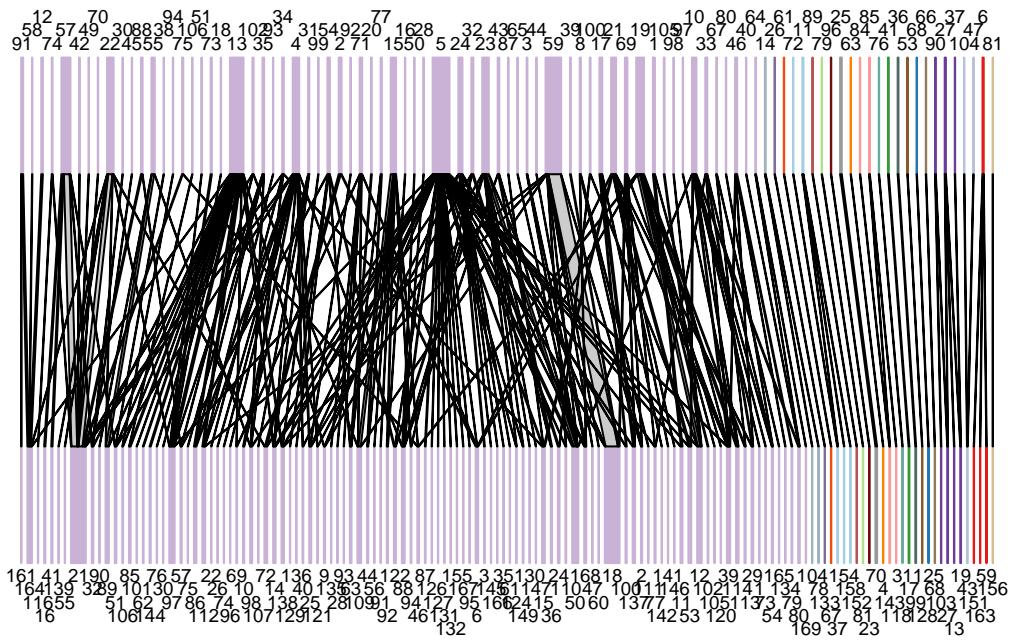
3.2.3 At 99% similarity level

```

table.mating.types<-out.99[,-1]
table.mating.types<-table(table.mating.types[,1],table.mating.types[,2])
table.mating.types<-table.mating.types[-1,-1]
table.mating.types<-table.mating.types[rowSums(table.mating.types)>0,colSums(table.mating.types)>0]
comps<-compart(table.mating.types)
class(table.mating.types)<-NULL
cubo<-as.matrix(table.mating.types)
class(cubo)<-"matrix"
modules99<-metaComputeModules(cubo,N=5, steps=1e+05)

colorinos_compartments<-colorRampPalette(colorinos.bipolar)(comps$n.compart)
plotweb(modules99@moduleWeb,
        col.high = colorinos_compartments[(apply(comps$cweb,2,min)*-1)[colnames(modules99@moduleWeb)]],
        col.low = colorinos_compartments[(apply(comps$cweb,1,min)*-1)[rownames(modules99@moduleWeb)]],
        bor.col.high = colorinos_compartments[(apply(comps$cweb,2,min)*-1)[colnames(modules99@moduleWeb)]],
        bor.col.low = colorinos_compartments[(apply(comps$cweb,1,min)*-1)[rownames(modules99@moduleWeb)]],
        bor.col.interaction = 1, y.width.low =0.15, y.width.high = 0.15)

```



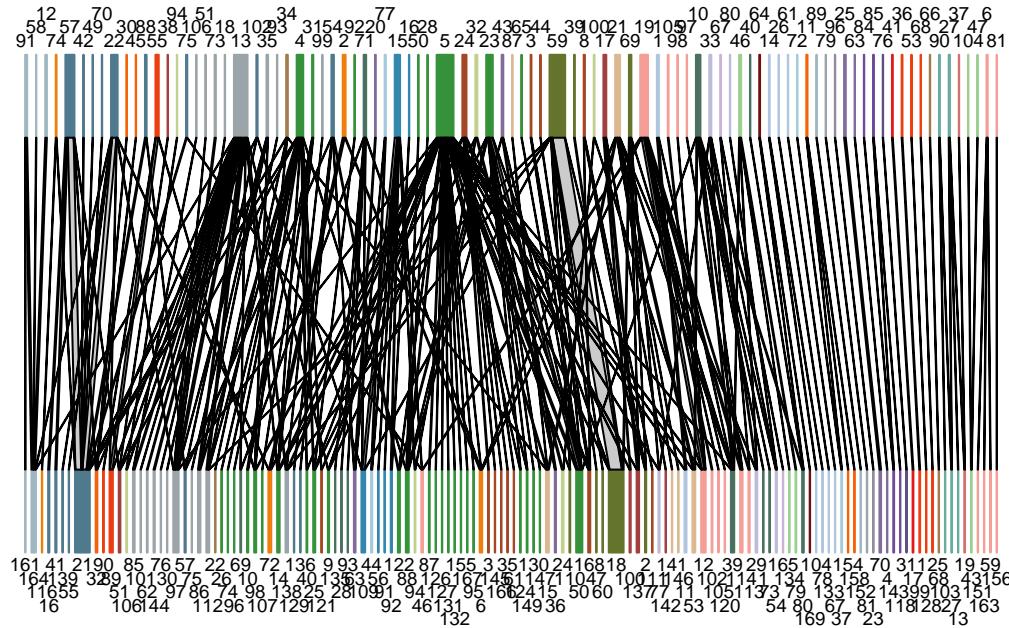
```

foo1<-modules99@modules[-1,-c(1,2)]
foo2<-foo1[, (1+dim(modules99@originalWeb)[1]):dim(foo1)[2]]
foo1<-foo1[,1:dim(modules99@originalWeb)[1]]
foo1<-apply(foo1,2,FUN = function(x){which(x!=0)})
names(foo1)<-rownames(modules99@originalWeb)
foo2<-apply(foo2,2,FUN = function(x){which(x!=0)})
names(foo2)<-colnames(modules99@originalWeb)

colorinos_modules<-colorRampPalette(colorinos.bipolar)(dim(modules99@modules)[1]-1)

plotweb(modules99@moduleWeb,
        col.high = colorinos_modules[foo2[colnames(modules99@moduleWeb)]],
        col.low = colorinos_modules[foo1[rownames(modules99@moduleWeb)]],
        bor.col.high = colorinos_modules[foo2[colnames(modules99@moduleWeb)]],
        bor.col.low = colorinos_modules[foo1[rownames(modules99@moduleWeb)]],
        bor.col.interaction = 1, y.width.low =0.1, y.width.high = 0.1)

```



```

out.99.bckup<-out.99
out.99<-cbind(out.99,0,0,0)
out.99<-out.99[,-1]
colnames(out.99)<-c("alpha","hmg","compartments","modules1","modules2")

for (i in 1:length(rownames(out.99)))
{
  if (out.99[i,1]!="0"&out.99[i,2]!="0")
  {
    out.99[i,3]<-comps$cweb[out.99[i,1],out.99[i,2]]
  }
  else if (out.99[i,1]!="0"&out.99[i,1]%in%rownames(comps$cweb))
  {
    out.99[i,3]<-min(as.numeric(comps$cweb[out.99[i,1],]))
  }
  else if (out.99[i,2]!="0"&out.99[i,2]%in%colnames(comps$cweb))
  {
    out.99[i,3]<-min(as.numeric(comps$cweb[,out.99[i,2]]))
  }
}
out.99[,4]<-foo1[as.character(out.99[,1])]
out.99[,5]<-foo1[as.character(out.99[,2])]

#out.99[is.na(out.99[,4]),4]<-foo2[as.character(out.99[,2])][is.na(out.99[,4])]
out.99[,3]<-as.numeric(out.99[,3])*-1
out.99[,4]<-as.numeric(out.99[,4])
out.99[,5]<-as.numeric(out.99[,5])
#
#
rownames(out.99)[duplicated(rownames(out.99))]<-paste(rownames(out.99)[duplicated(rownames(out.99))],"."

```

```

rownames(out.99)[duplicated(rownames(out.99))]<-gsub("\\.1","\\.2",rownames(out.99)[duplicated(rownames
rownames(out.99)[duplicated(rownames(out.99))]<-gsub("\\.2","\\.3",rownames(out.99)[duplicated(rownames
rownames(out.99)[duplicated(rownames(out.99))]<-gsub("\\.3","\\.4",rownames(out.99)[duplicated(rownames
#
#
```

```

foo_modules<-mat.or.vec(length(orden.foo),3)
rownames(foo_modules)<-orden.foo
colnames(foo_modules)<-colnames(out.99)[3:5]
foo_reduced<-out.99[rownames(out.99)%in%orden.foo,3:5]
foo_modules[rownames(foo_reduced),]<-foo_reduced
rm(foo_reduced)
#
#
#
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo, foo_modules[orden.foo,])
foo<-melt(foo[,c(1,26)])

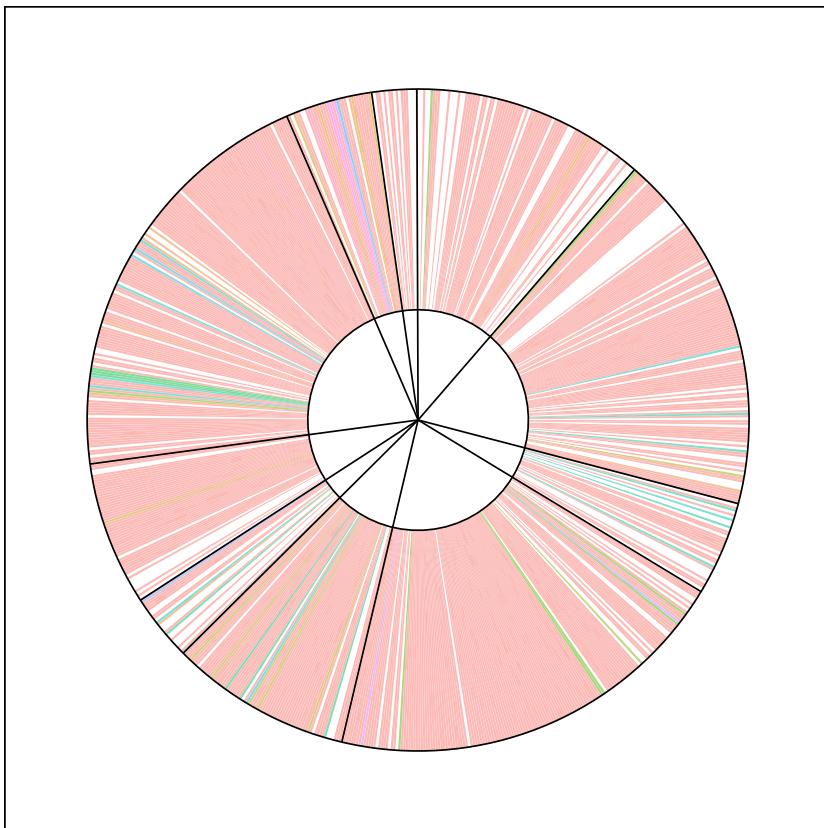
```

3.2.3.1 Donut plot compartments

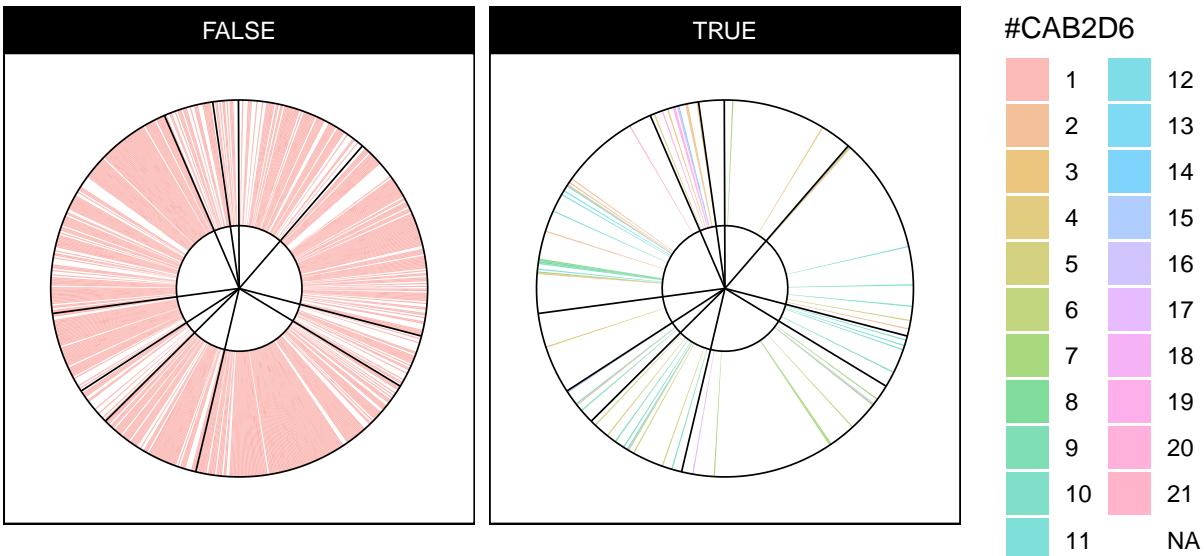
```

## Using orden, compartments as id variables
foo$compartments[foo$compartments==0]<-NA
foo$compartments<-factor(foo$compartments,levels=1:comps$n.compart)
p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=compartments),
            stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos_compartments,na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



```
print(p + facet_wrap(vars((compartments!=1|is.na(compartments)))))
```



```
foo<-condensed_baps_adm[orden.foo,]
foo<-cbind(orden=factor(c(1:dim(foo)[1])),foo, foo_modules[orden.foo,])
foo<-melt(foo[,c(1,28)])
```

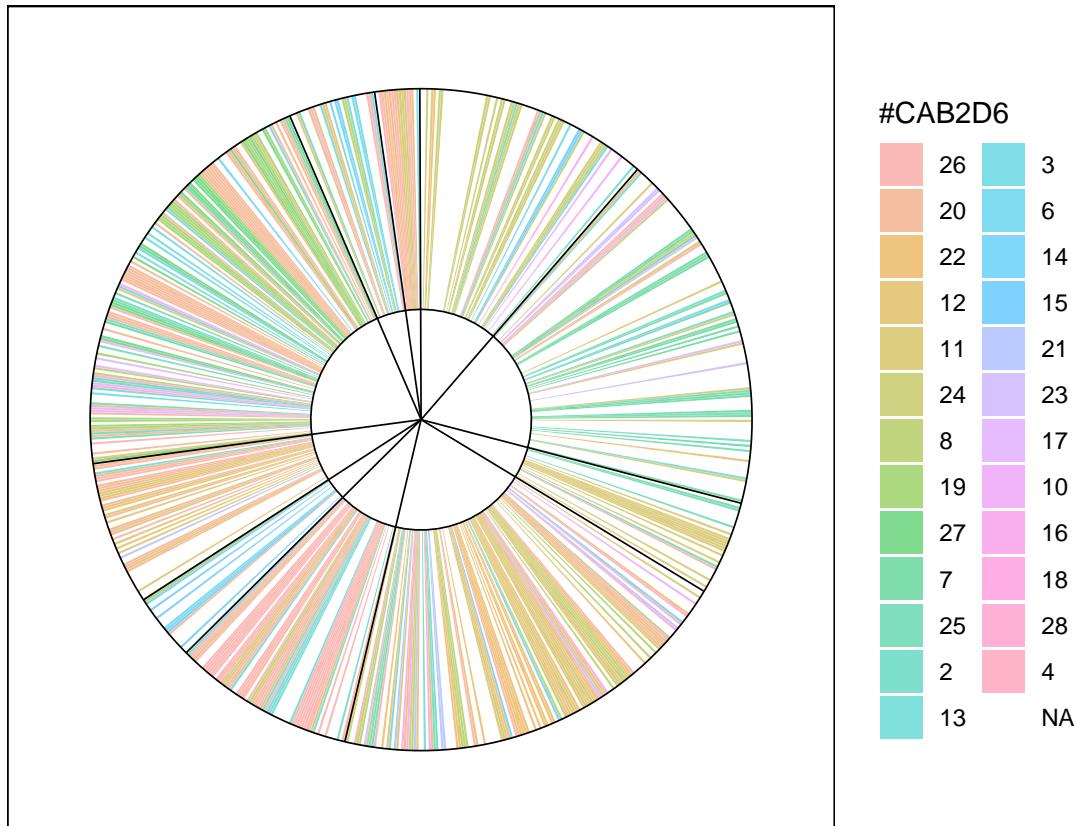
3.2.3.2 Donut plots Modules

```
## Using orden, modules2 as id variables
```

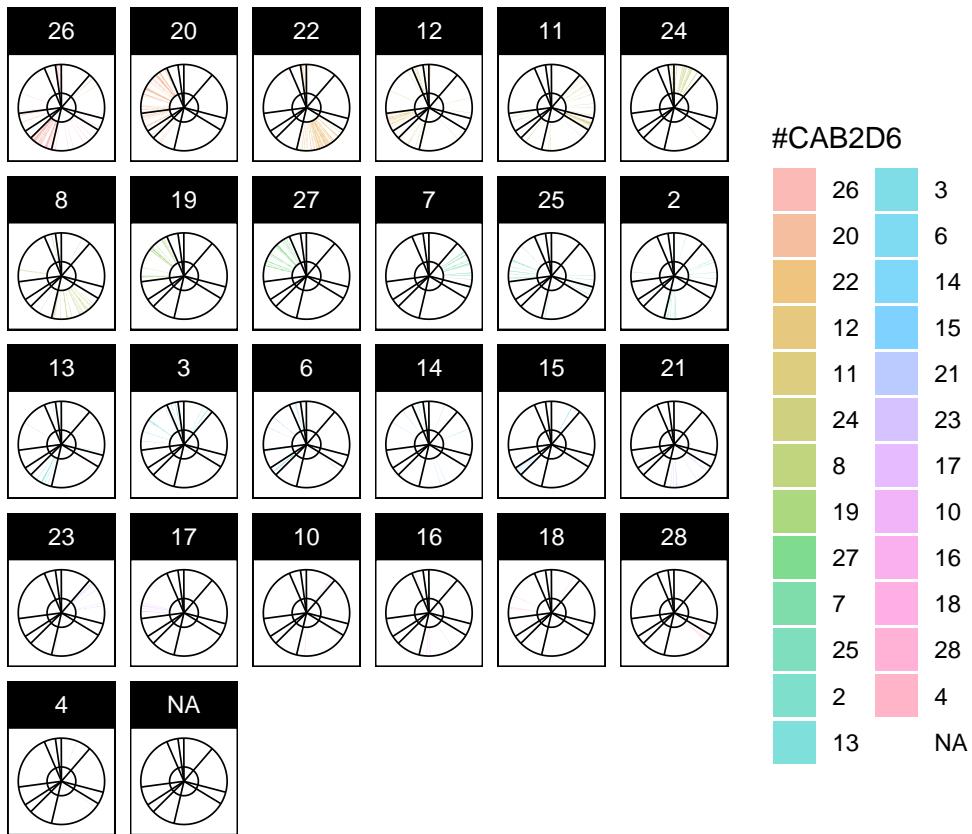
```

foo$modules2[foo$modules2==0] <-NA
foo$modules2<-factor(foo$modules2,levels=names(table(foo$modules2))[order(as.numeric(table(foo$modules2)))]
p<-ggplot(foo) +
  geom_bar(aes(x=orden, y=1,fill=modules2),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos_modules,na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(),panel.grid.major.y = element_blank(),
                          axis.text.x=element_blank(),
                          axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                          axis.text.y=element_blank(),
                          axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



```
print(p + facet_wrap(vars(modules2)))
```



```
kable(networklevel(table.mating.types))
```

	x
connectance	0.0218972
web asymmetry	-0.1982379
links per species	1.1938326
number of compartments	21.0000000
compartment diversity	3.4511332
cluster coefficient	0.0073529
modularity Q	0.7153134
nestedness	2.2983241
NODF	5.8353085
weighted nestedness	0.3378359
weighted NODF	1.6330296
interaction strength asymmetry	-0.0526979
specialisation asymmetry	0.0752745
linkage density	5.0572869
weighted connectance	0.0222788
Fisher alpha	315.9472254
Shannon diversity	5.2507149
interaction evenness	0.5571929
Alatalo interaction evenness	0.4894535
H2	0.4619052
number.of.species.HL	91.0000000
number.of.species.LL	136.0000000

	x
mean.number.of.shared.partners.HL	0.0759463
mean.number.of.shared.partners.LL	0.1172113
cluster.coefficient.HL	0.0648567
cluster.coefficient.LL	0.0432900
weighted.cluster.coefficient.HL	0.1161349
weighted.cluster.coefficient.LL	0.2020986
niche.overlap.HL	0.0191771
niche.overlap.LL	0.0431530
togetherness.HL	0.0027480
togetherness.LL	0.0114261
C.score.HL	0.9553825
C.score.LL	0.9141449
V.ratio.HL	6.1869741
V.ratio.LL	1.3942149
discrepancy.HL	210.0000000
discrepancy.LL	215.0000000
extinction.slope.HL	1.5362135
extinction.slope.LL	1.7249732
robustness.HL	0.6057715
robustness.LL	0.6313006
functional.complementarity.HL	285.5111560
functional.complementarity.LL	306.2279211
partner.diversity.HL	1.4568297
partner.diversity.LL	0.9011428
generality.HL	7.1765847
vulnerability.LL	2.9379890

```
kable(grouplevel(table.mating.types))
```

	x
number.of.species.HL	91.0000000
number.of.species.LL	136.0000000
mean.number.of.links.HL	8.8205128
mean.number.of.links.LL	3.9393939
mean.number.of.shared.partners.HL	0.0759463
mean.number.of.shared.partners.LL	0.1172113
cluster.coefficient.HL	0.0648567
cluster.coefficient.LL	0.0432900
weighted.cluster.coefficient.HL	0.1161349
weighted.cluster.coefficient.LL	0.2020986
niche.overlap.HL	0.0191771
niche.overlap.LL	0.0431530
togetherness.HL	0.0027480
togetherness.LL	0.0114261
C.score.HL	0.9553825
C.score.LL	0.9141449
V.ratio.HL	6.1869741
V.ratio.LL	1.3942149
discrepancy.HL	210.0000000
discrepancy.LL	215.0000000
extinction.slope.HL	1.5262411

	x
extinction.slope.LL	1.7328575
robustness.HL	0.6033901
robustness.LL	0.6329664
functional.complementarity.HL	285.5111560
functional.complementarity.LL	306.2279211
partner.diversity.HL	1.4568297
partner.diversity.LL	0.9011428
generality.HL	7.1765847
vulnerability.LL	2.9379890

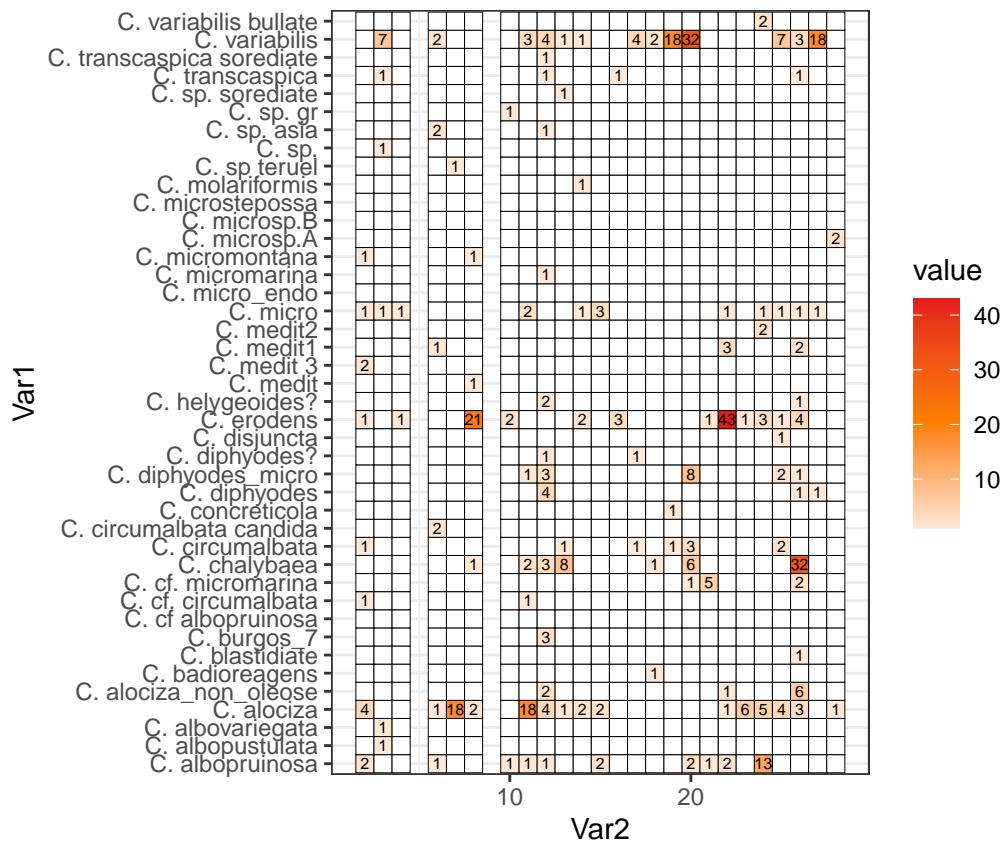
```
#save.image('/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v16final.Rdata')

# Heatmap 3 Species vs modules

foo_tabla<-melt(table(condensed_baps_adm[as.character(rownames(foo)),2],foo$modules))
foo_tabla$value[foo_tabla$value==0]<-NA

ggplot(foo_tabla,aes(x=Var2,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label =
  scale_fill_gradient2(low = "#FFFFFF",
  mid = colorinos.bipolar[7],
  high = colorinos.bipolar[6],
  midpoint = 20,
  space = "Lab",
  na.value = "#FFFFFF",
  guide = "colourbar",
  aesthetics = "fill"
) +
  coord_fixed() + theme_bw()

## Warning: Removed 925 rows containing missing values (geom_text).
```



```
write.table(cbind(condensed_baps_adm,foo_bgmyc_clusters[rownames(condensed_baps_adm)],out.99[rownames(condensed_baps_adm),]),"C:/Users/.../Desktop/.../out.99",sep=" ",row.names=FALSE)
```

3.3 II.III Networks at individual level

```
library(reshape2)
library(ggplot2)
library(fpc)
library(igraph)
library(robin)
library(scales)

##
## Attaching package: 'scales'
## The following object is masked from 'package:geiger':
##      rescale
#
# Create network of 99% similarity sequence clusters
#
network_indivs<-mat.or.vec(length(rownames(out.99))![duplicated(rownames(out.99))]),length(rownames(out.99)))
rownames(network_indivs)<-rownames(out.99)![duplicated(rownames(out.99))]
colnames(network_indivs)<-rownames(out.99)![duplicated(rownames(out.99))]
names_foo_network<-sapply(strsplit(rownames(out.99),"\\."),`[`,1)
for (foo.levels in levels(factor(out.99[,1]))[-1])
{
  foo_select<-names_foo_network[out.99[,1]==foo.levels]
```

```

    network_indivs[foo_select,foo_select]<-1
}
for (foo.levels in levels(factor(out.99[,2]))[-1])
{
  foo_select<-names_foo_network[out.99[,2]==foo.levels]
  network_indivs[foo_select,foo_select]<-network_indivs[foo_select,foo_select]+1
}
rownames(network_indivs)<-paste("s",rownames(network_indivs),sep="_")
colnames(network_indivs)<-paste("s",colnames(network_indivs),sep="_")
network_indivs<-network_indivs[!(rowSums(network_indivs)==diag(network_indivs)),!(rowSums(network_indivs)==2)<-1
network_indivs[network_indivs==3]<-1
uni_graph<-igraph::graph_from_adjacency_matrix(network_indivs, mode ="undirected",diag=FALSE)

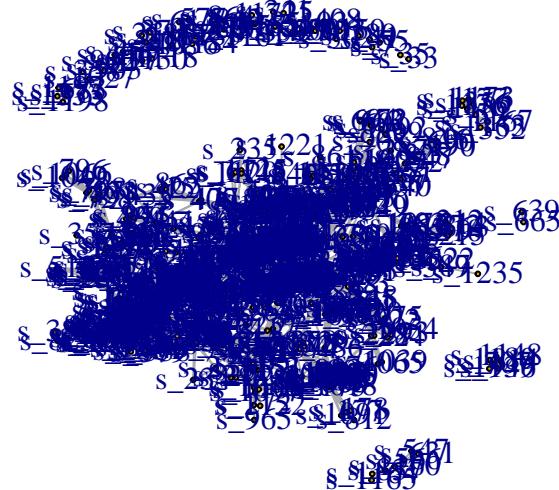
```

3.3.1 Compartmentalization

```

#
# Components
#
components<-igraph::components(uni_graph)
#
# Communities
#
communities_mat<-igraph::communities(components)
#
# Plot Graph with BAPS assignments
#
plot.igraph(uni_graph,layout=layout_with_fr(uni_graph),vertex.size=2, edge.arrow.size=0.2)

```



3.3.2 Test modularity algorythms

```

uni_graph2<-prepGraph(file=uni_graph, file.format="igraph")
attributes<-vertex_attr(uni_graph2, index = V(uni_graph2))
set.seed(10)
VI_In<-list()
comp<-list()

```

```

for (DA in c("walktrap", "louvain", "labelProp", "infomap"))
{
  members_In <- membershipCommunities(graph=uni_graph, method=DA)
  VI_In[[DA]] <- compare(components$membership, members_In, method="vi")
  for (DA1 in c("walktrap", "louvain", "labelProp", "infomap"))
  {
    if(DA!=DA1) {
      comp[[paste(DA,DA1,sep="_)]]<-robinCompare(graph=uni_graph2,method1 = DA, method2 = DA1, measure
    }
  }
}

## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges

```

```
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
```

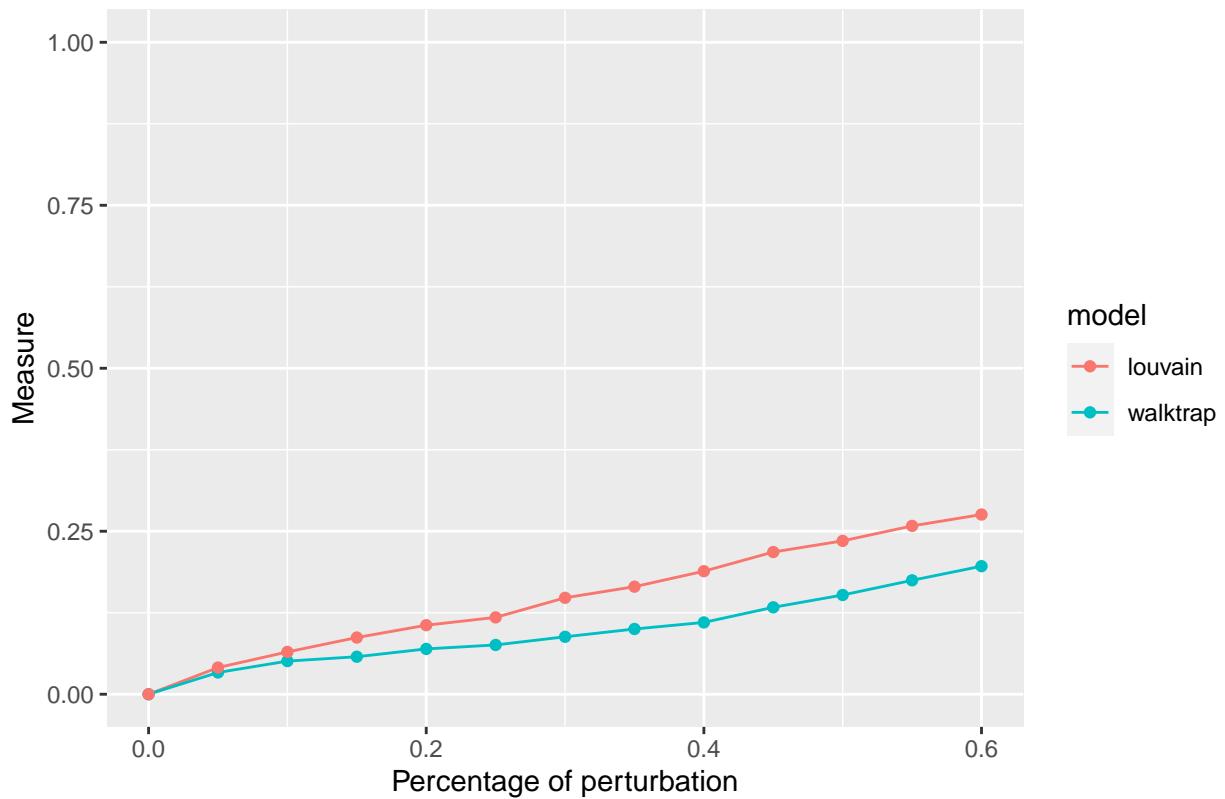
```
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
```

```

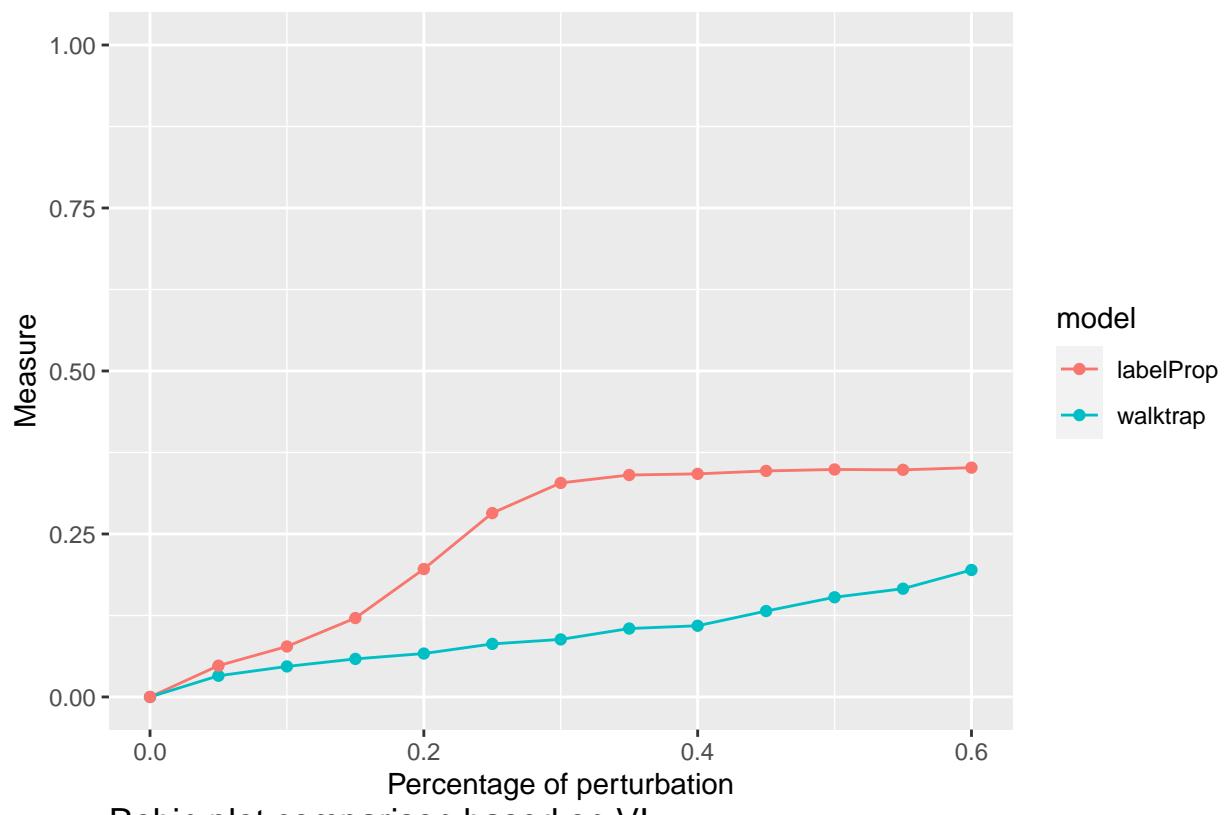
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
for (i in 1:length(comp))
{
  comp_foo<-comp[[i]]
  foo_bar1<-sapply(strsplit(names(comp)[i],"_"),`[`,1)
  foo_bar2<-sapply(strsplit(names(comp)[i],"_"),`[`,2)
  print(plotRobin(uni_graph2, model1=comp_foo$Mean1, model2=comp_foo$Mean2, legend = c(foo_bar1,foo_bar2),
                 title = "Robin plot comparison based on VI"))
}

```

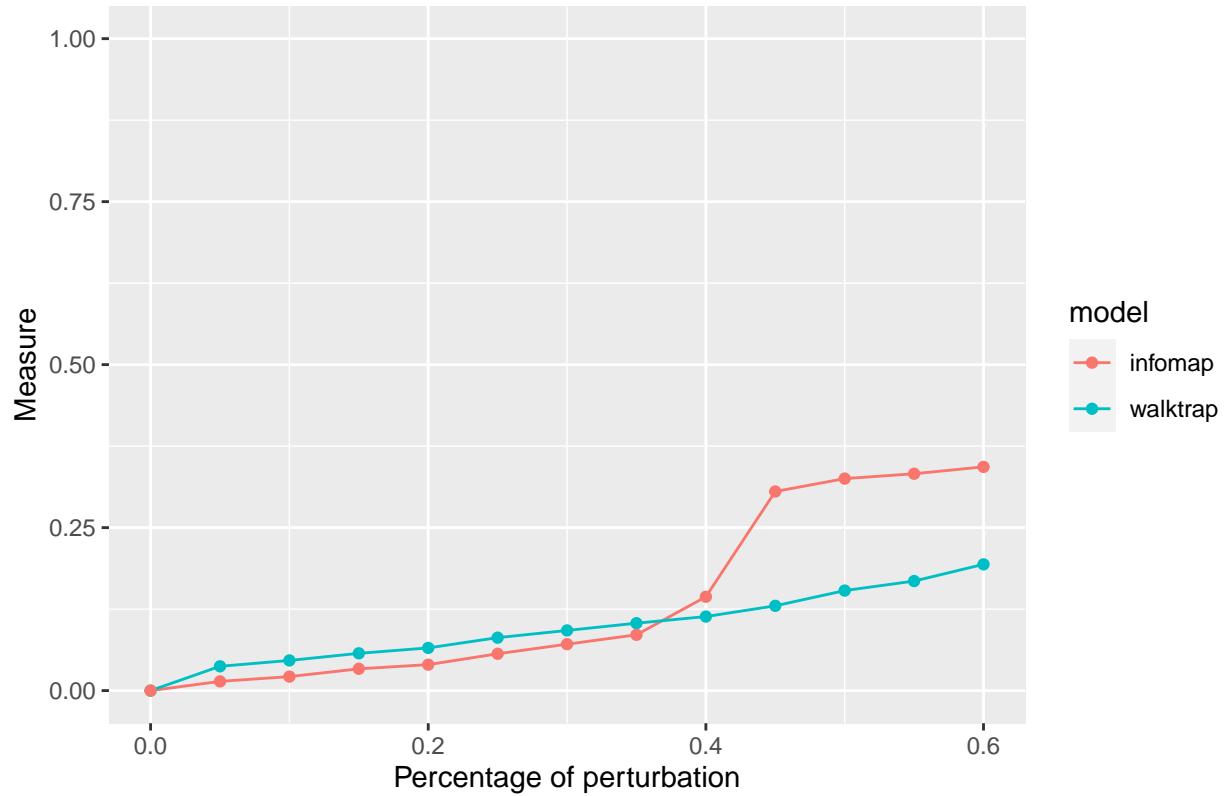
Robin plot comparison based on VI



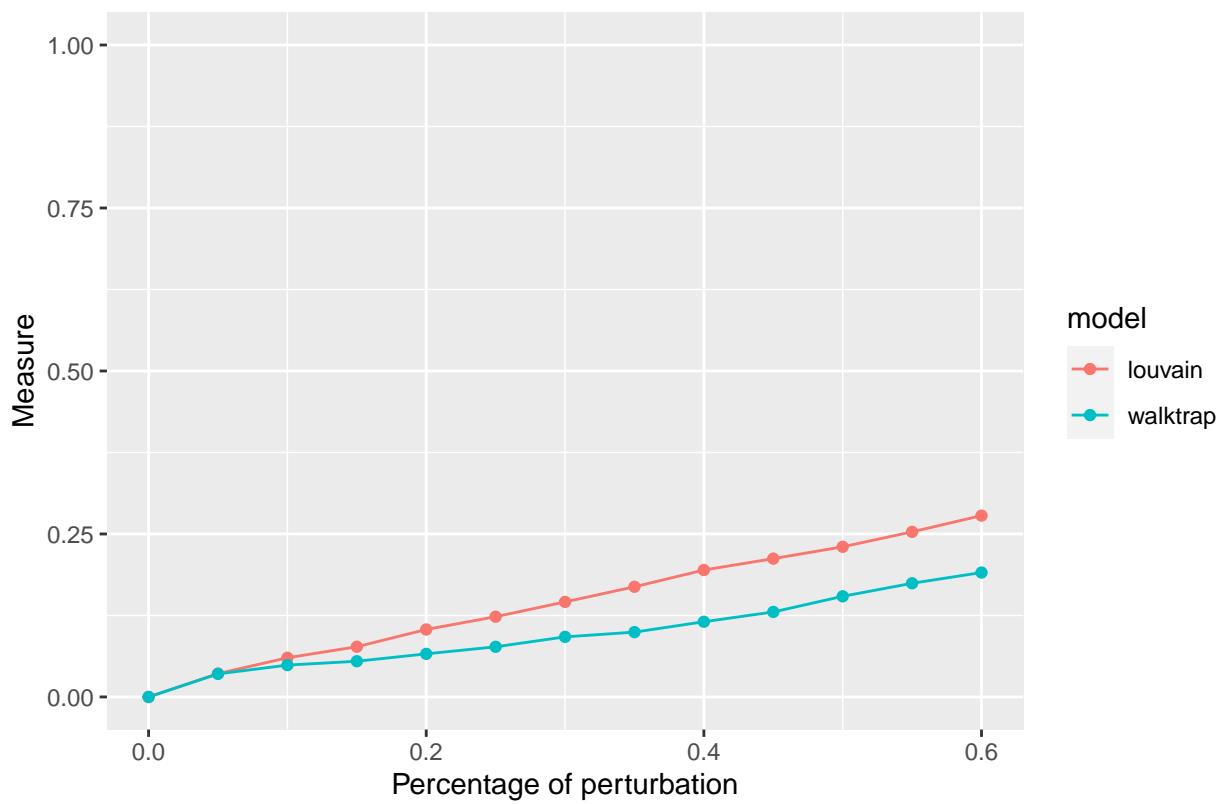
Robin plot comparison based on VI



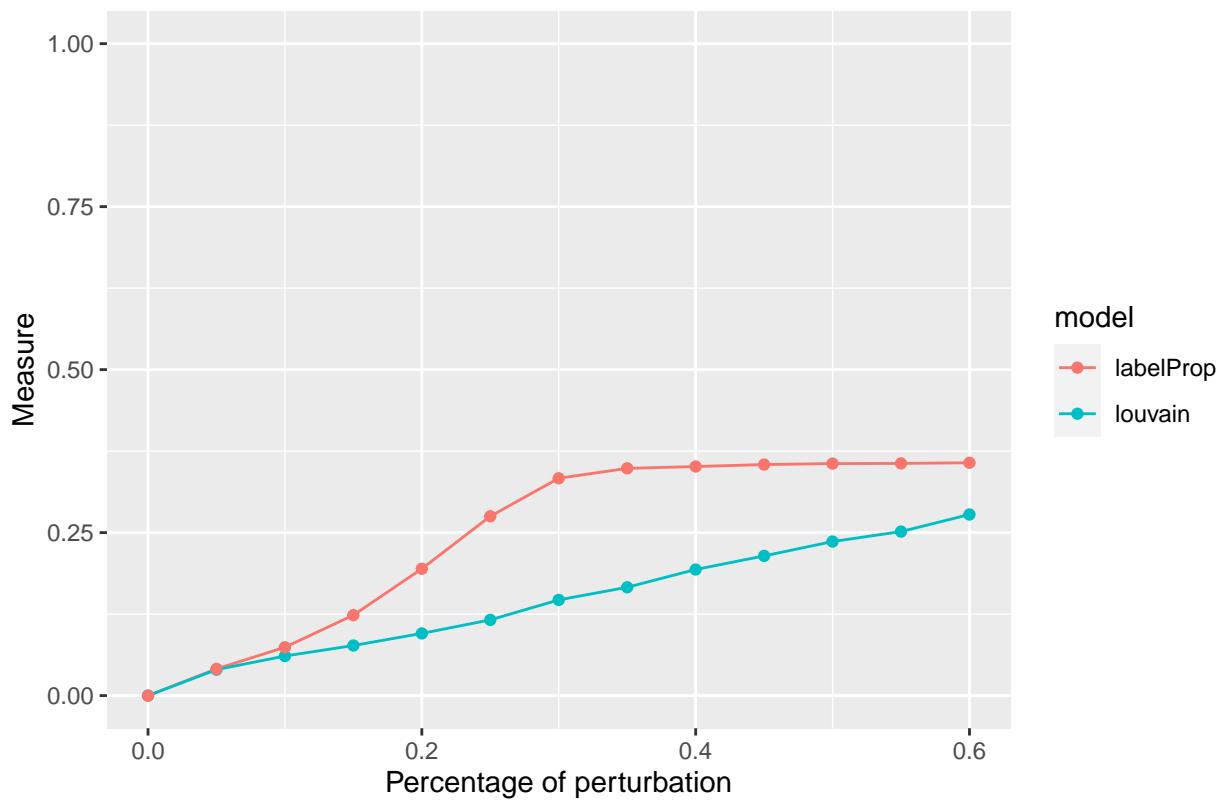
Robin plot comparison based on VI



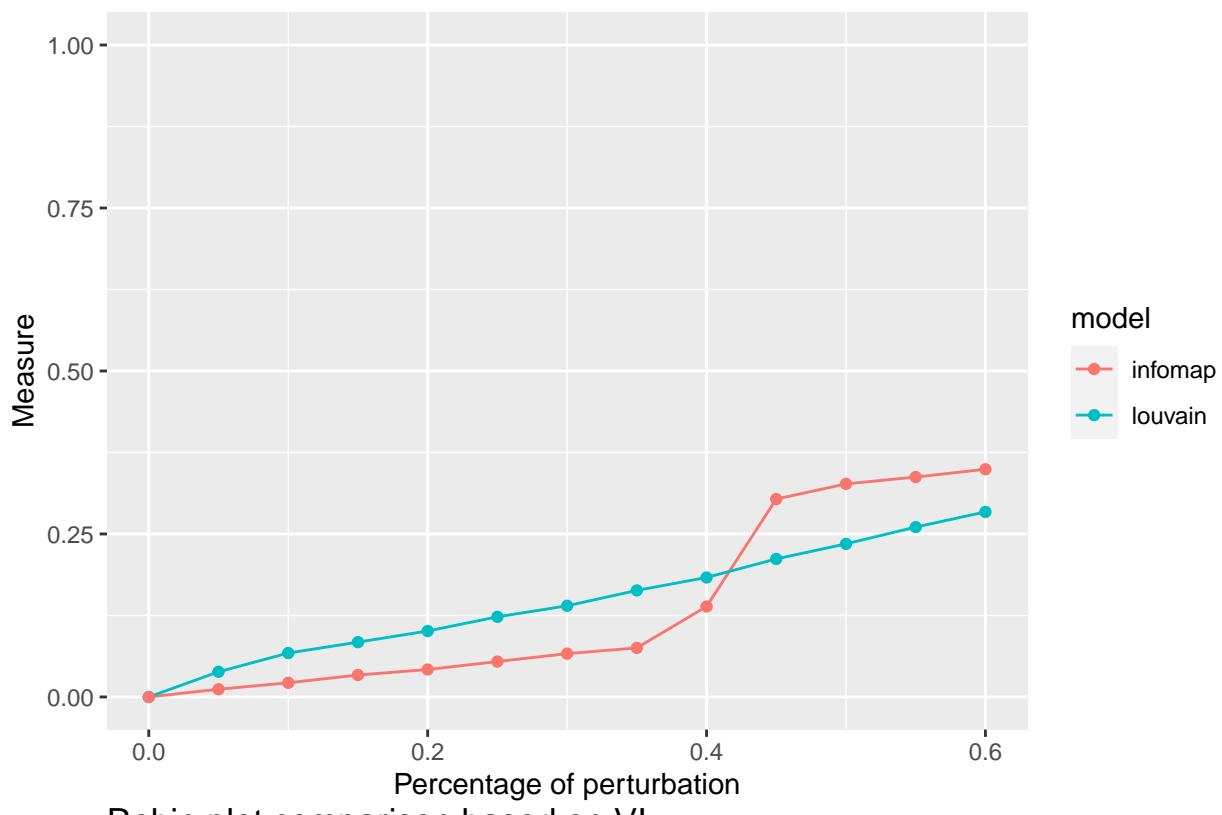
Robin plot comparison based on VI



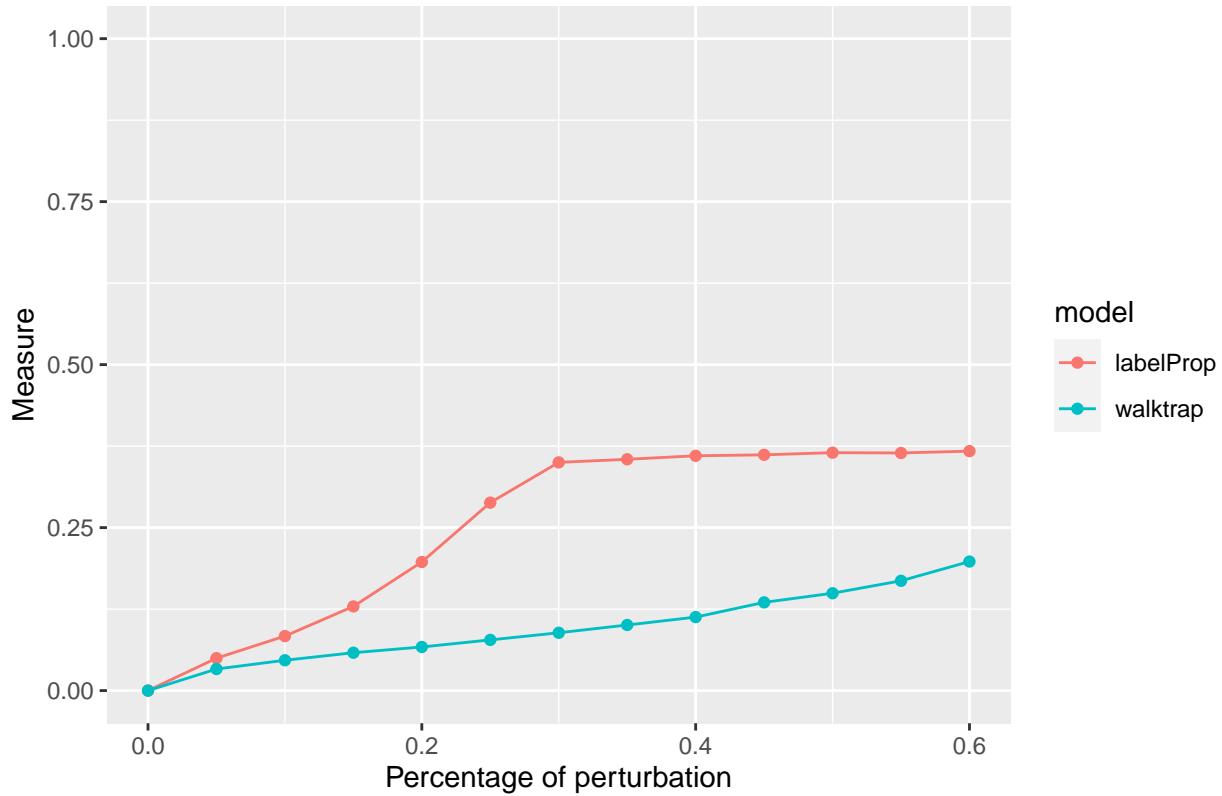
Robin plot comparison based on VI



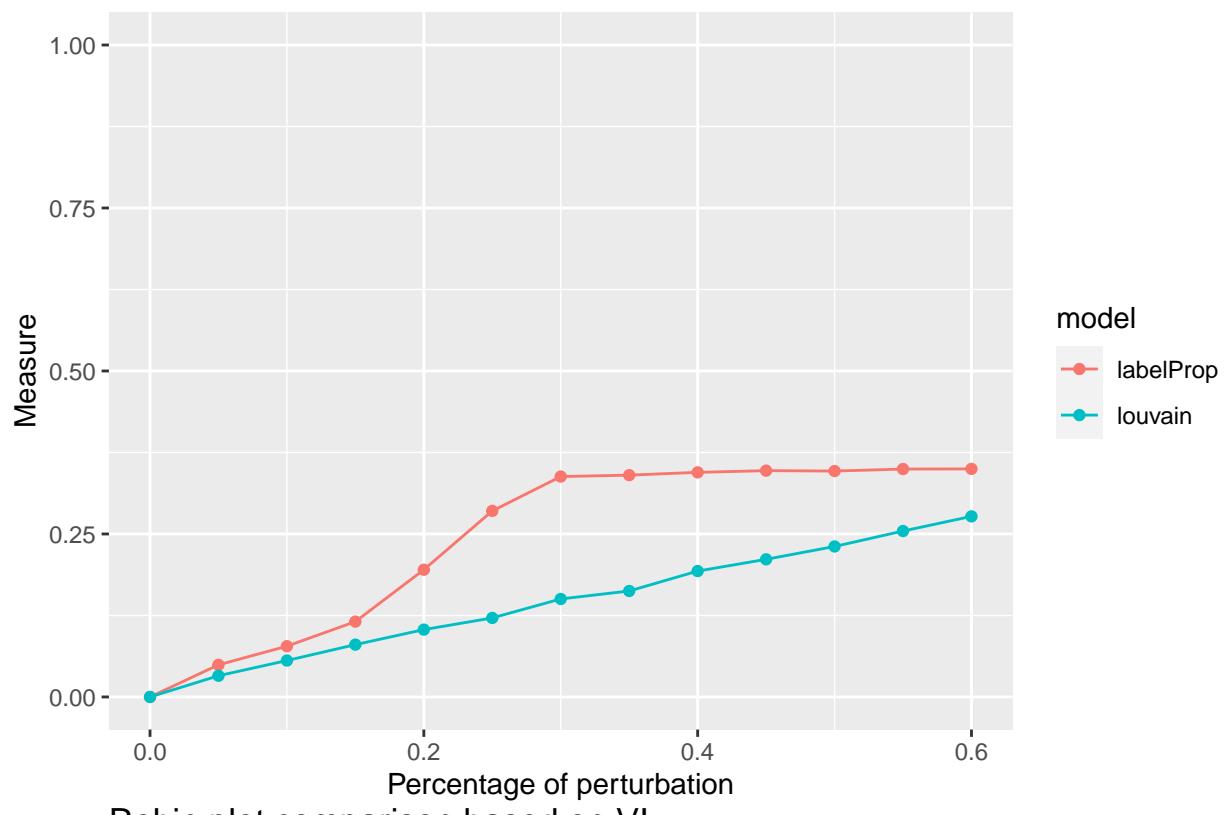
Robin plot comparison based on VI



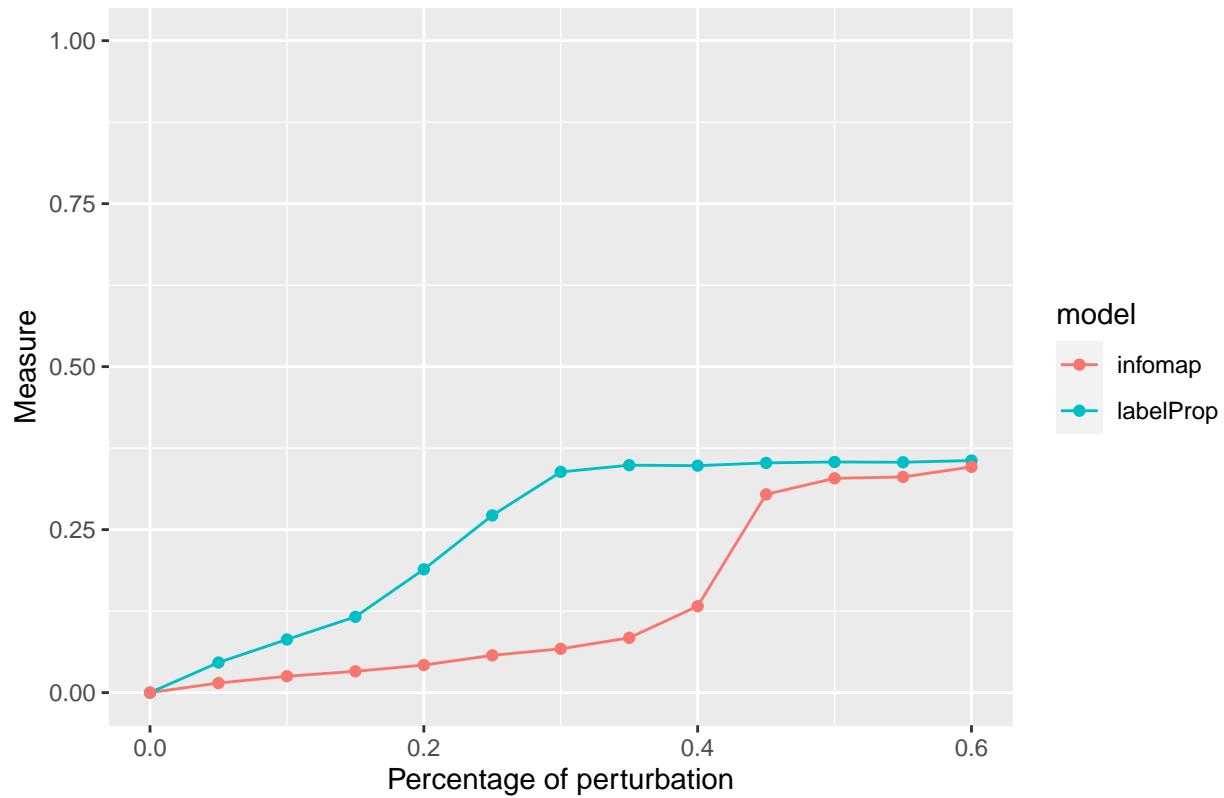
Robin plot comparison based on VI



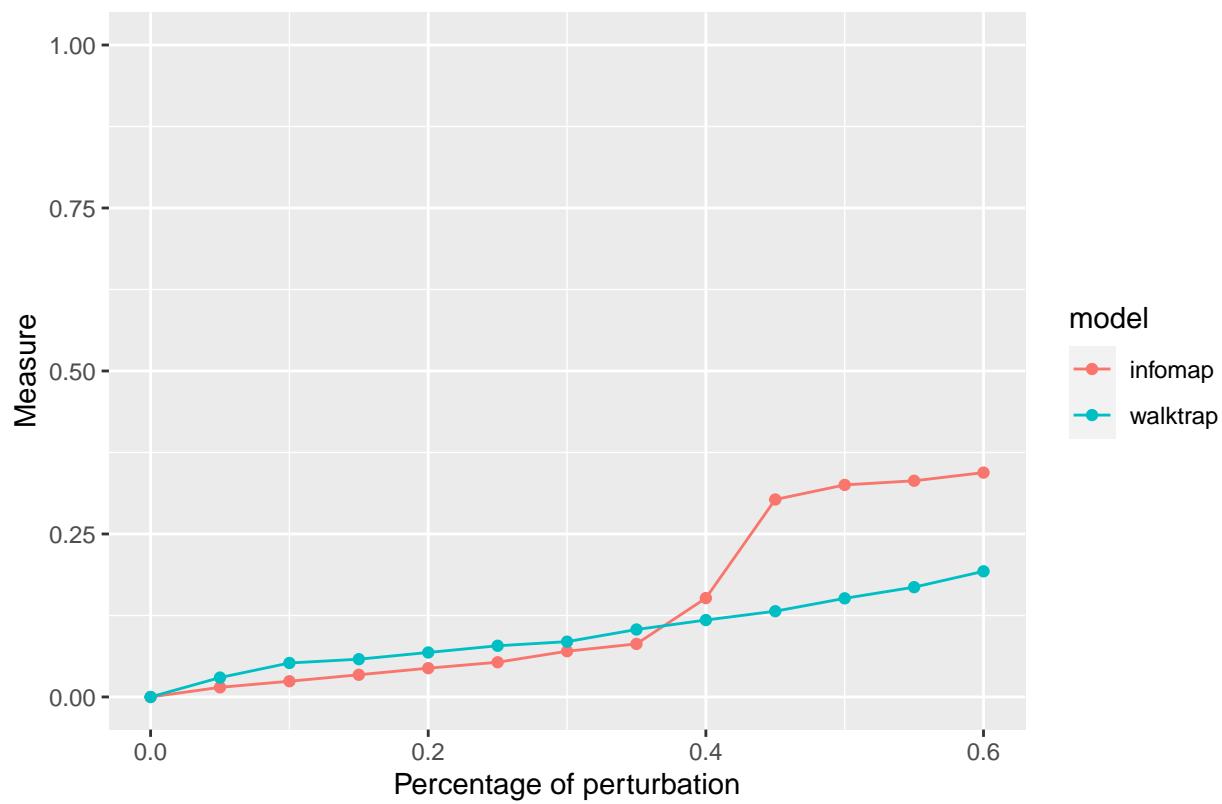
Robin plot comparison based on VI



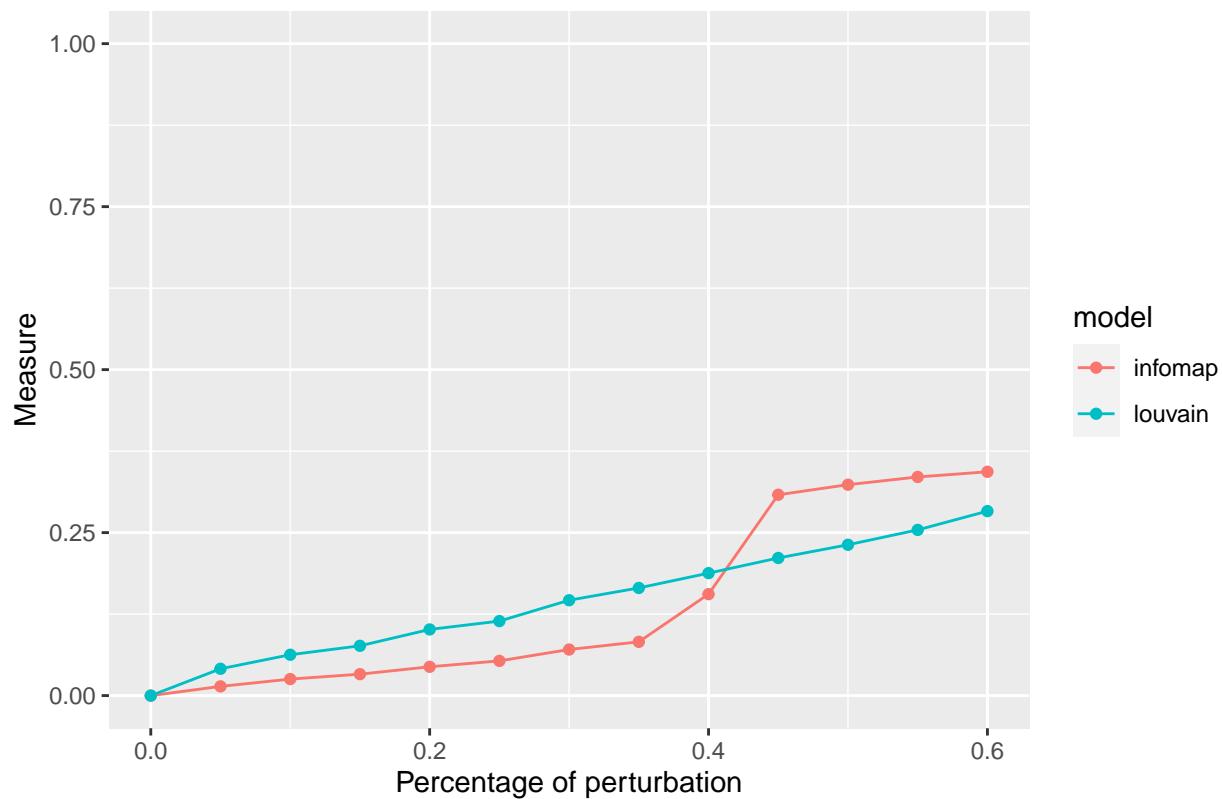
Robin plot comparison based on VI



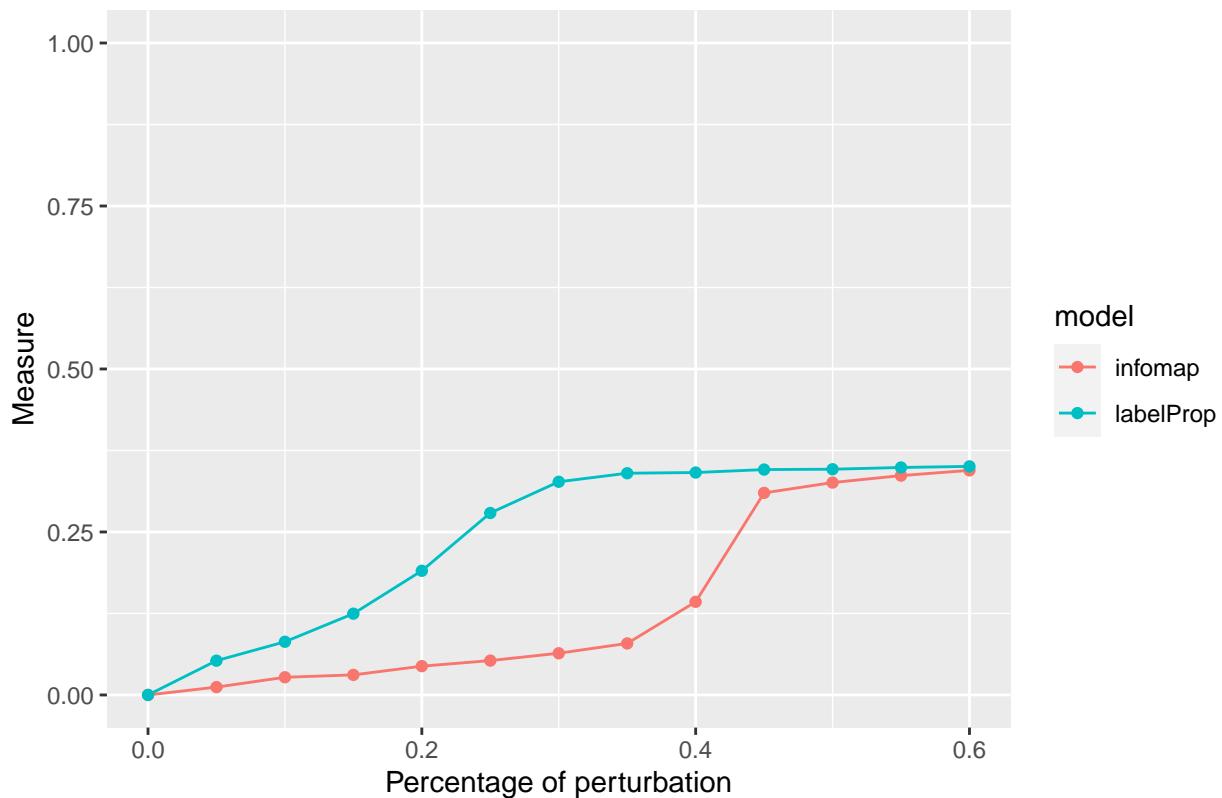
Robin plot comparison based on VI



Robin plot comparison based on VI



Robin plot comparison based on VI



3.3.3 Model selection based on BF

```
graphRandomCM <- random(graph=uni_graph2)
proc_CM<-list()
for (DA in c("walktrap", "louvain", "labelProp", "infomap"))
{
  proc_CM[[DA]] <- robinRobust(graph=uni_graph2, graphRandom=graphRandomCM,
                                 measure="vi", method=DA, type="independent")
}
```

3.3.3.1 Simple random model

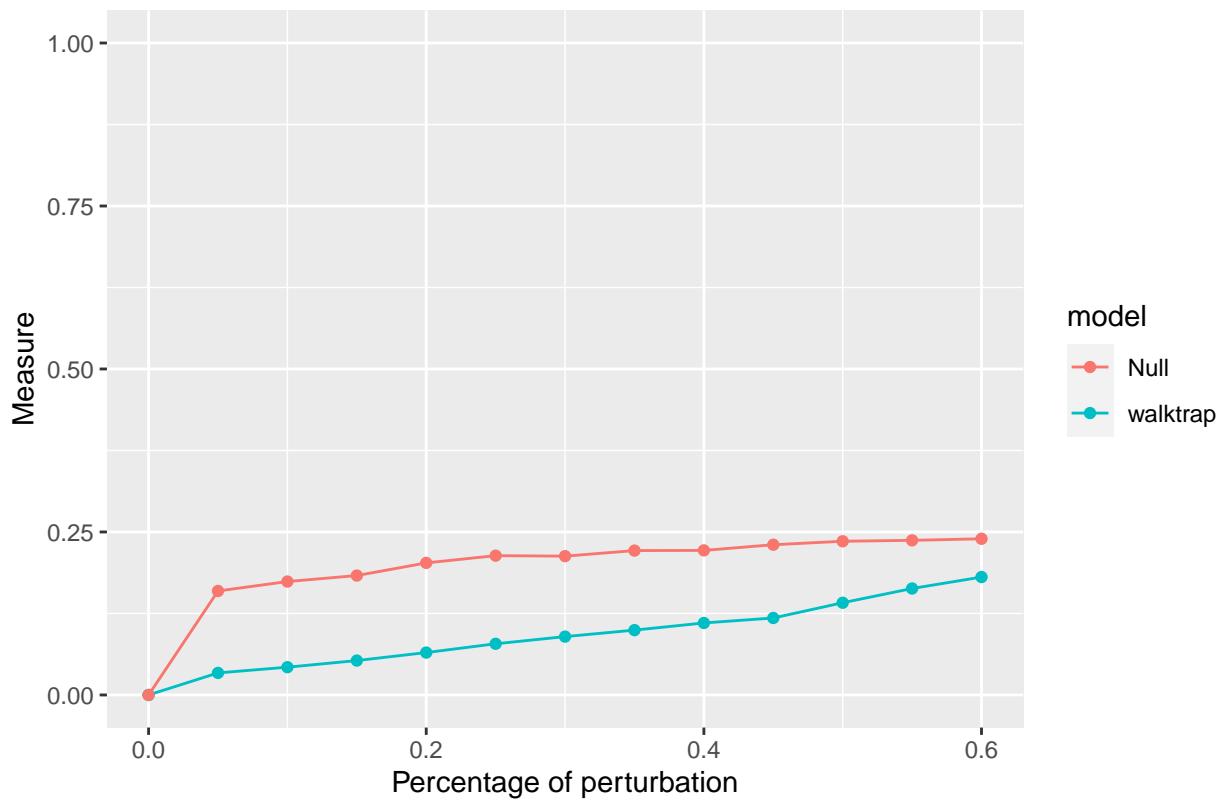
```
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
```

```

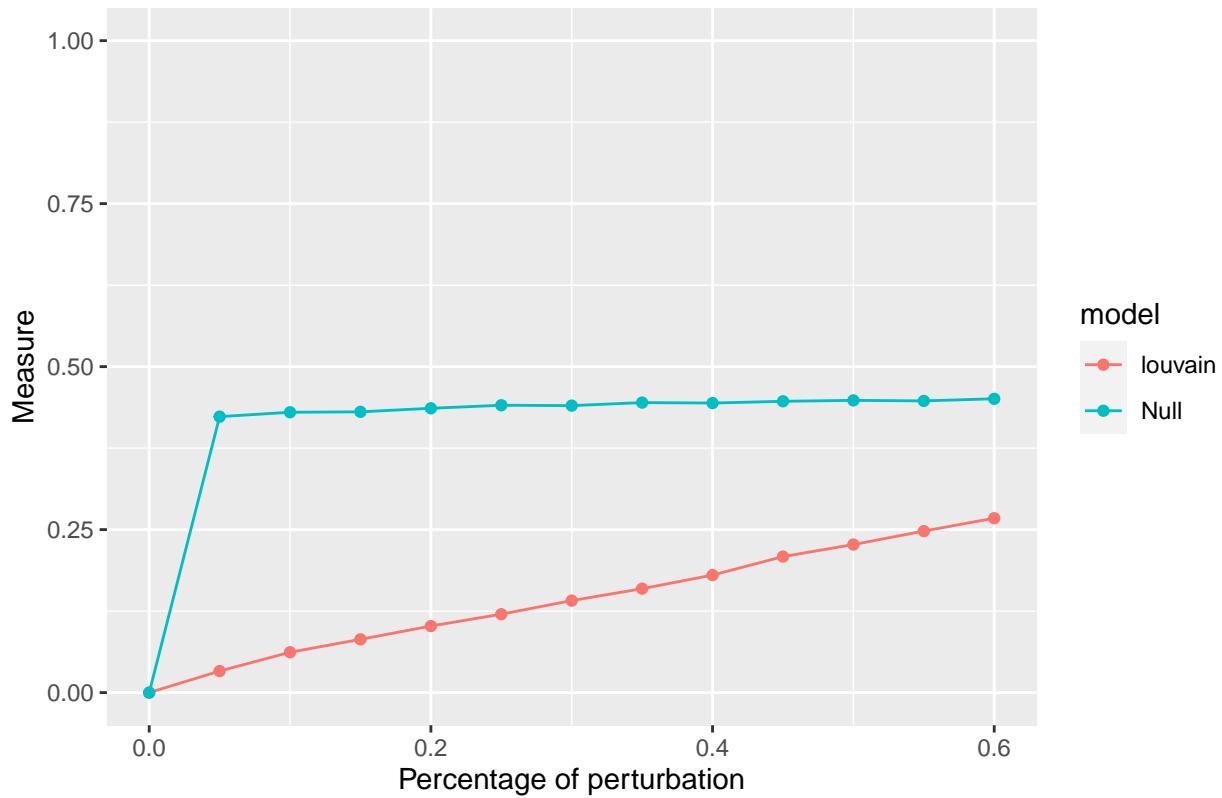
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
for (i in 1:length(proc_CM))
{
  comp_foo<-proc_CM[[i]]
  print(plotRobin(uni_graph2, model1=comp_foo$Mean, model2=comp_foo$MeanRandom, legend = c(names(proc_CM)))
  title = "Robin plot robustness based on VI"))
}

```

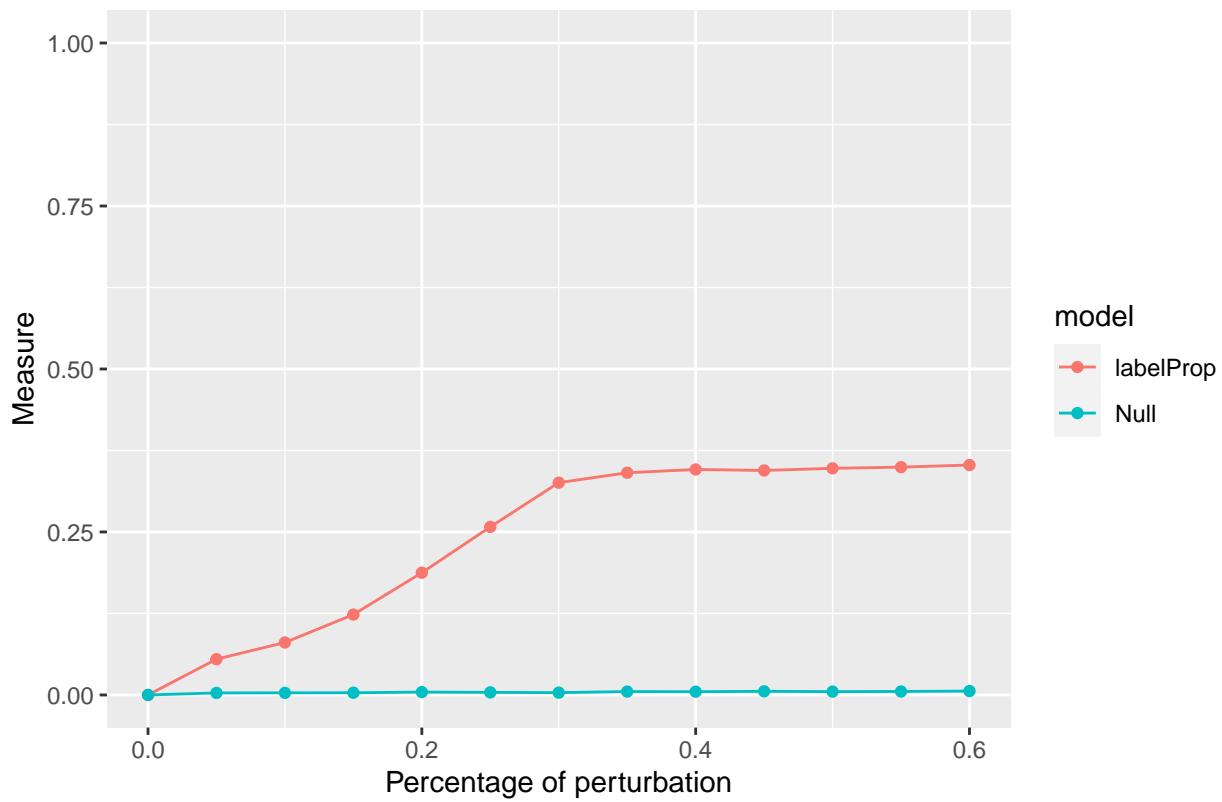
Robin plot robustness based on VI



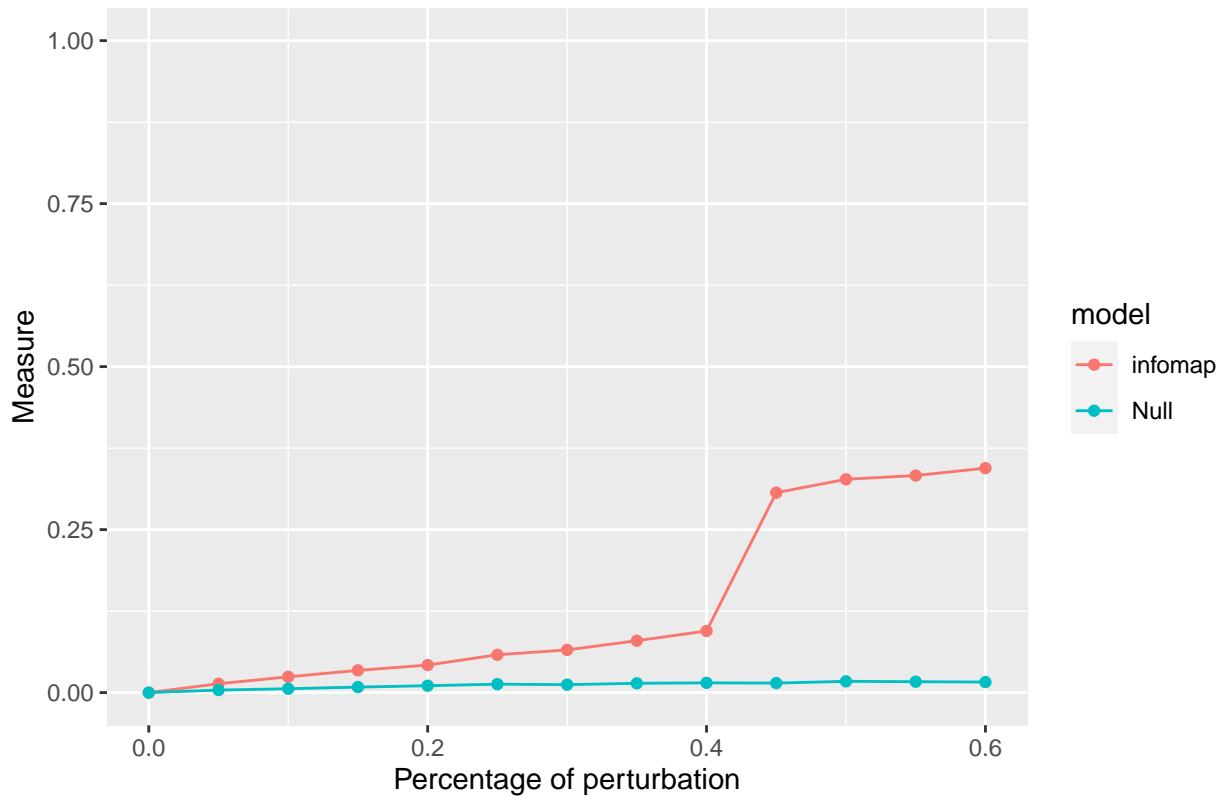
Robin plot robustness based on VI



Robin plot robustness based on VI



Robin plot robustness based on VI



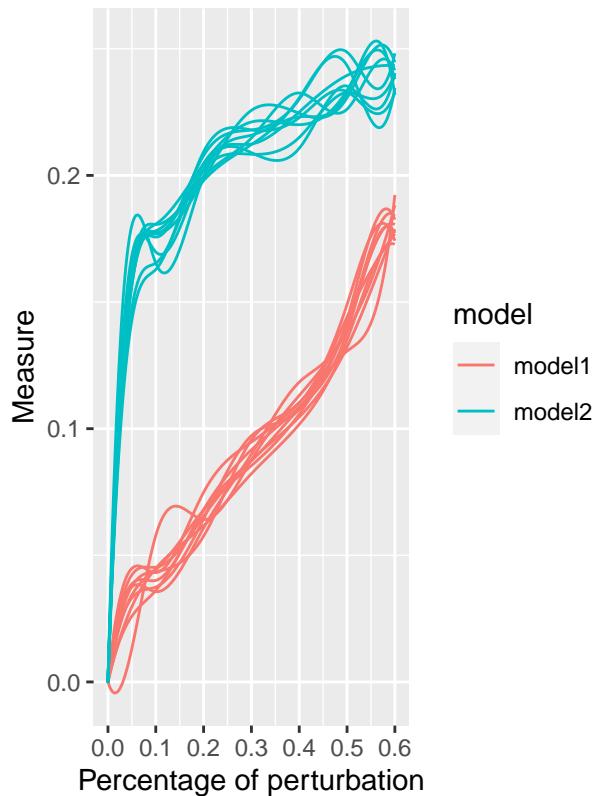
```

#
#
#
results_Robin<-mat.or.vec(length(proc_CM) ,4)
rownames(results_Robin)<-names(proc_CM)
colnames(results_Robin)<-c("bf_cm","auc_cm","bf_dk","auc_dk")
for (i in 1:length(proc_CM))
{
  results_Robin[i,1] <- robinGPTTest(model1=proc_CM[[i]]$Mean, model2=proc_CM[[i]]$MeanRandom)
AUC <- robinAUC(graph=uni_graph2, model1=proc_CM[[i]]$Mean,
                 model2=proc_CM[[i]]$MeanRandom)
results_Robin[i,2] <- AUC$area2/AUC$area1
robinFDATest(graph=uni_graph2, model1=proc_CM[[i]]$Mean, model2=proc_CM[[i]]$MeanRandom)
}

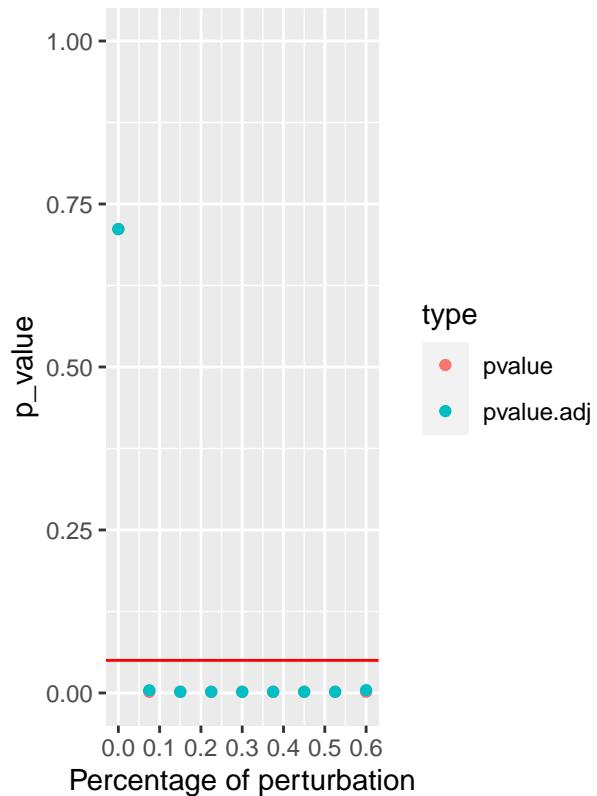
## Profile 1
## Profile 2
## [1] "First step: basis expansion"
## Swapping 'y' and 'argvals', because 'y' is simpler,
## and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## [1] "Second step: joint univariate tests"
## [1] "Third step: interval-wise combination and correction"
## [1] "creating the p-value matrix: end of row 2 out of 9"
## [1] "creating the p-value matrix: end of row 3 out of 9"
## [1] "creating the p-value matrix: end of row 4 out of 9"
## [1] "creating the p-value matrix: end of row 5 out of 9"
## [1] "creating the p-value matrix: end of row 6 out of 9"
## [1] "creating the p-value matrix: end of row 7 out of 9"
## [1] "creating the p-value matrix: end of row 8 out of 9"
## [1] "creating the p-value matrix: end of row 9 out of 9"
## [1] "Interval Testing Procedure completed"

```

Functional Data Analysis



P-values

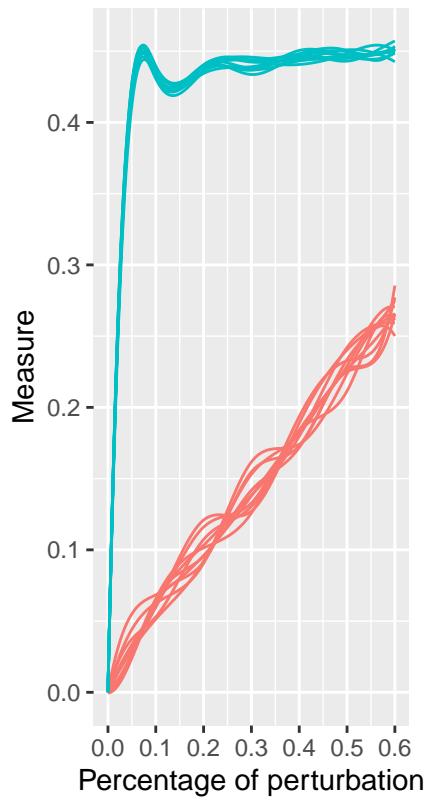


```

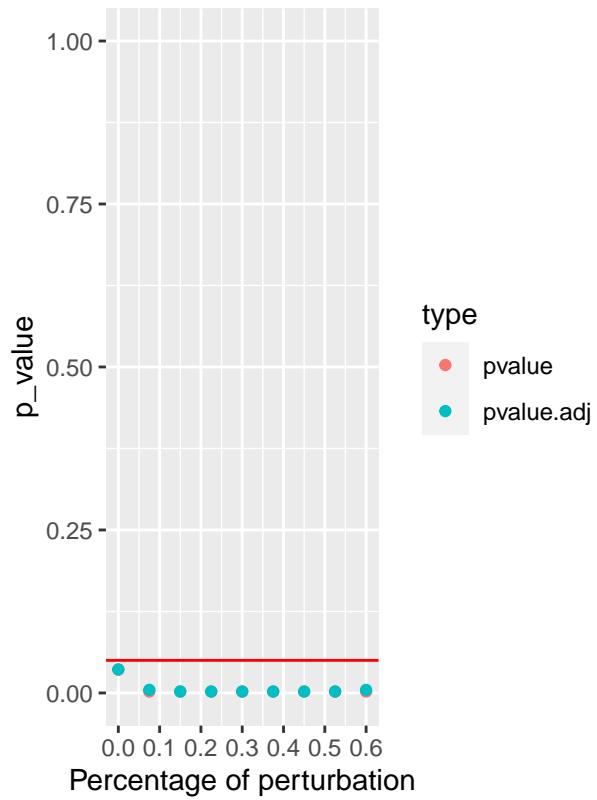
## TableGrob (1 x 2) "arrange": 2 grobs
##   z      cells    name      grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]
##   Profile 1
##   Profile 2
## [1] "First step: basis expansion"
## Swapping 'y' and 'argvals', because 'y' is simpler,
##   and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## [1] "Second step: joint univariate tests"
## [1] "Third step: interval-wise combination and correction"
## [1] "creating the p-value matrix: end of row 2 out of 9"
## [1] "creating the p-value matrix: end of row 3 out of 9"
## [1] "creating the p-value matrix: end of row 4 out of 9"
## [1] "creating the p-value matrix: end of row 5 out of 9"
## [1] "creating the p-value matrix: end of row 6 out of 9"
## [1] "creating the p-value matrix: end of row 7 out of 9"
## [1] "creating the p-value matrix: end of row 8 out of 9"
## [1] "creating the p-value matrix: end of row 9 out of 9"
## [1] "Interval Testing Procedure completed"

```

Functional Data Analysis



P-values

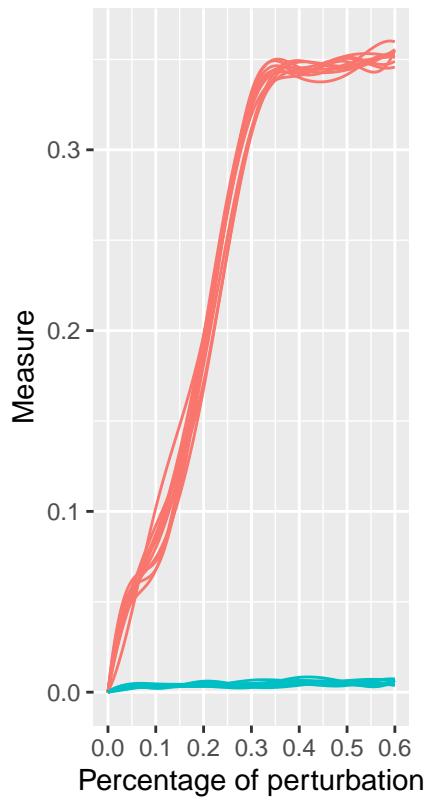


```

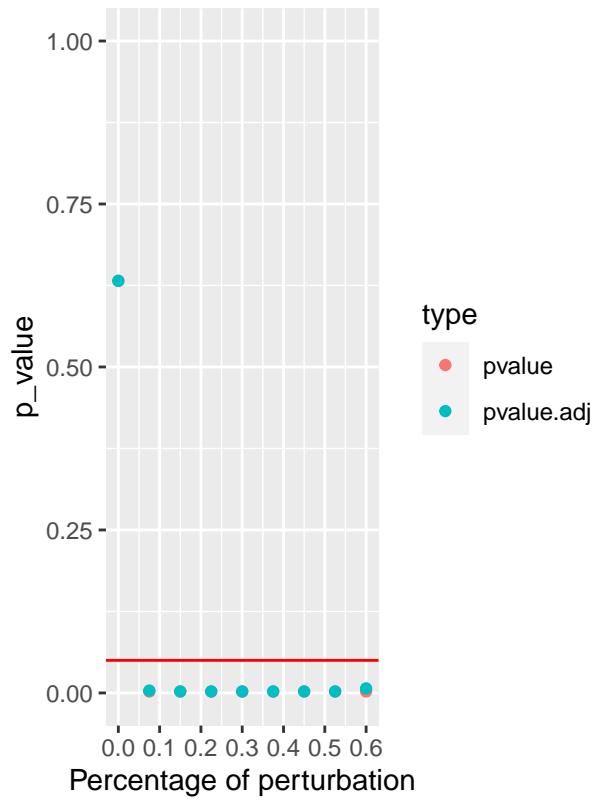
## TableGrob (1 x 2) "arrange": 2 grobs
##   z      cells    name      grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]
## Profile 1
## Profile 2
## [1] "First step: basis expansion"
## Swapping 'y' and 'argvals', because 'y' is simpler,
## and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## [1] "Second step: joint univariate tests"
## [1] "Third step: interval-wise combination and correction"
## [1] "creating the p-value matrix: end of row 2 out of 9"
## [1] "creating the p-value matrix: end of row 3 out of 9"
## [1] "creating the p-value matrix: end of row 4 out of 9"
## [1] "creating the p-value matrix: end of row 5 out of 9"
## [1] "creating the p-value matrix: end of row 6 out of 9"
## [1] "creating the p-value matrix: end of row 7 out of 9"
## [1] "creating the p-value matrix: end of row 8 out of 9"
## [1] "creating the p-value matrix: end of row 9 out of 9"
## [1] "Interval Testing Procedure completed"

```

Functional Data Analysis



P-values

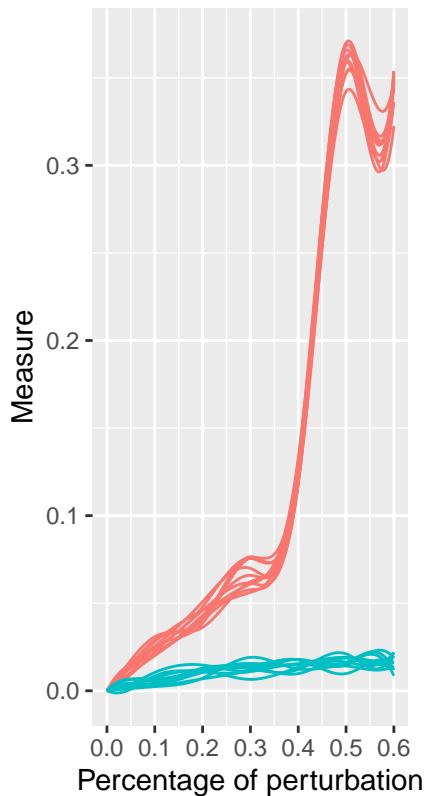


```

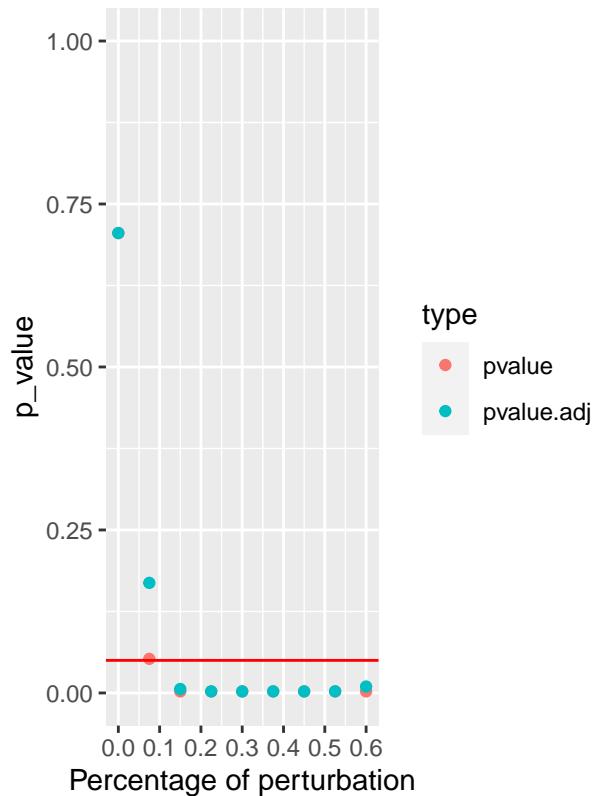
## #> #> ## TableGrob (1 x 2) "arrange": 2 grobs
## #> #>   z      cells    name      grob
## #> #>   1 1 (1-1,1-1) arrange gtable[layout]
## #> #>   2 2 (1-1,2-2) arrange gtable[layout]
## #> #> Profile 1
## #> #> Profile 2
## #> [1] "First step: basis expansion"
## #> Swapping 'y' and 'argvals', because 'y' is simpler,
## #> and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## #> [1] "Second step: joint univariate tests"
## #> [1] "Third step: interval-wise combination and correction"
## #> [1] "creating the p-value matrix: end of row 2 out of 9"
## #> [1] "creating the p-value matrix: end of row 3 out of 9"
## #> [1] "creating the p-value matrix: end of row 4 out of 9"
## #> [1] "creating the p-value matrix: end of row 5 out of 9"
## #> [1] "creating the p-value matrix: end of row 6 out of 9"
## #> [1] "creating the p-value matrix: end of row 7 out of 9"
## #> [1] "creating the p-value matrix: end of row 8 out of 9"
## #> [1] "creating the p-value matrix: end of row 9 out of 9"
## #> [1] "Interval Testing Procedure completed"

```

Functional Data Analysis



P-values



```
## TableGrob (1 x 2) "arrange": 2 grobs
##   z      cells    name      grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]
```

```
# 
# Complex random model dk-series
#
#write_graph(
#  uni_graph2,
#  "/Users/Fernando/Desktop/01_paper_sanger_drive/export_graph",
#  format = "edgelist")
#save.image('/Users/Fernando/Desktop/01_Sanger_paper/improvement_dataset.Rdata')
save.image('/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v17final.Rdata')

graphRandomDK <- prepGraph(file="/Users/Fernando/Desktop/01_paper_sanger_drive/dk2.1_export_graph",
                           file.format = "edgelist")
proc_DK<-list()
for (DA in c("walktrap", "louvain", "labelProp", "infomap"))
{
  proc_DK[[DA]] <- robinRobust(graph=uni_graph2, graphRandom=graphRandomDK,
                                 measure="vi", method=DA, type="independent")
}
```

3.3.3.2 Random model based on dk-series

```
## Detected robin method independent type
```

```

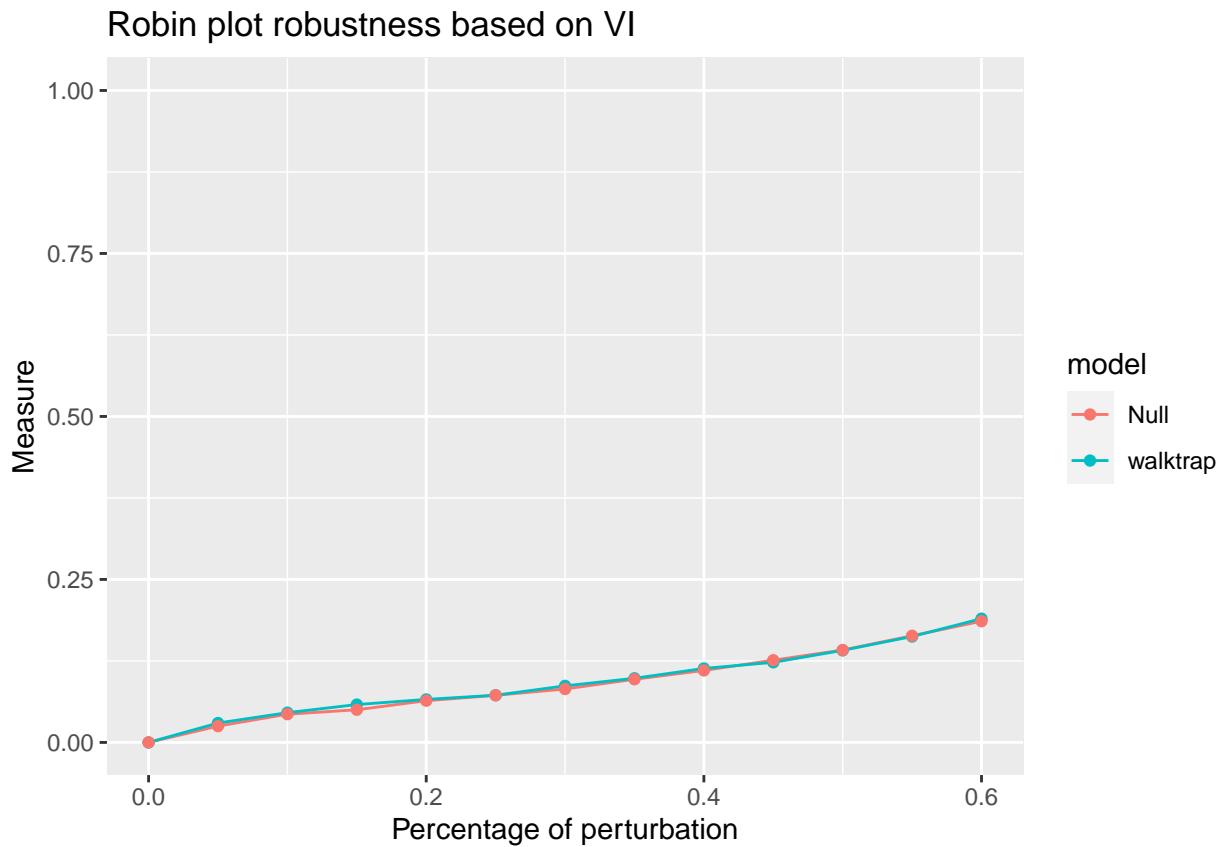
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
## Detected robin method independent type
## Perturbed 410 edges
## Perturbed 820 edges
## Perturbed 1230 edges
## Perturbed 1641 edges
## Perturbed 2051 edges
## Perturbed 2461 edges
## Perturbed 2871 edges
## Perturbed 3281 edges
## Perturbed 3691 edges
## Perturbed 4102 edges
## Perturbed 4512 edges
## Perturbed 4922 edges
for (i in 1:length(proc_DK))
{

```

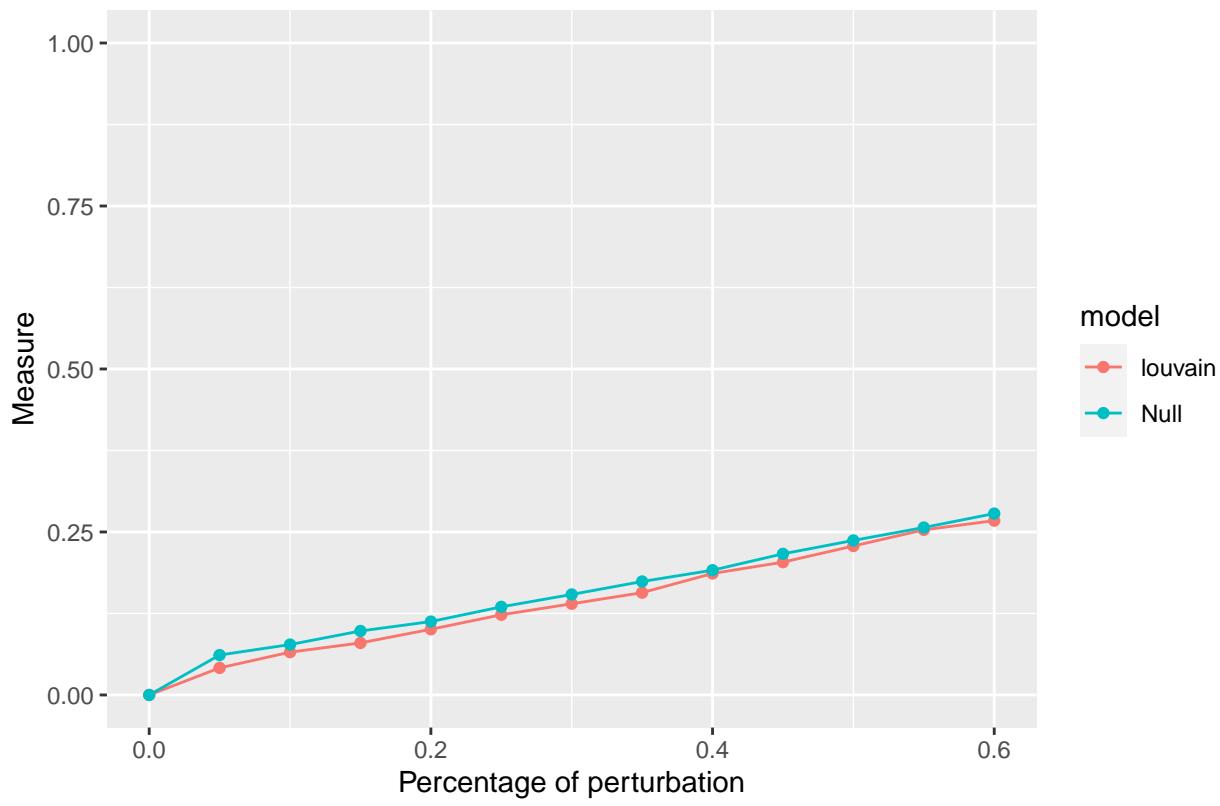
```

comp_foo<-proc_DK[[i]]
print(plotRobin(uni_graph2, model1=comp_foo$Mean, model2=comp_foo$MeanRandom, legend = c(names(proc_C),
                                         title = "Robin plot robustness based on VI"))
}

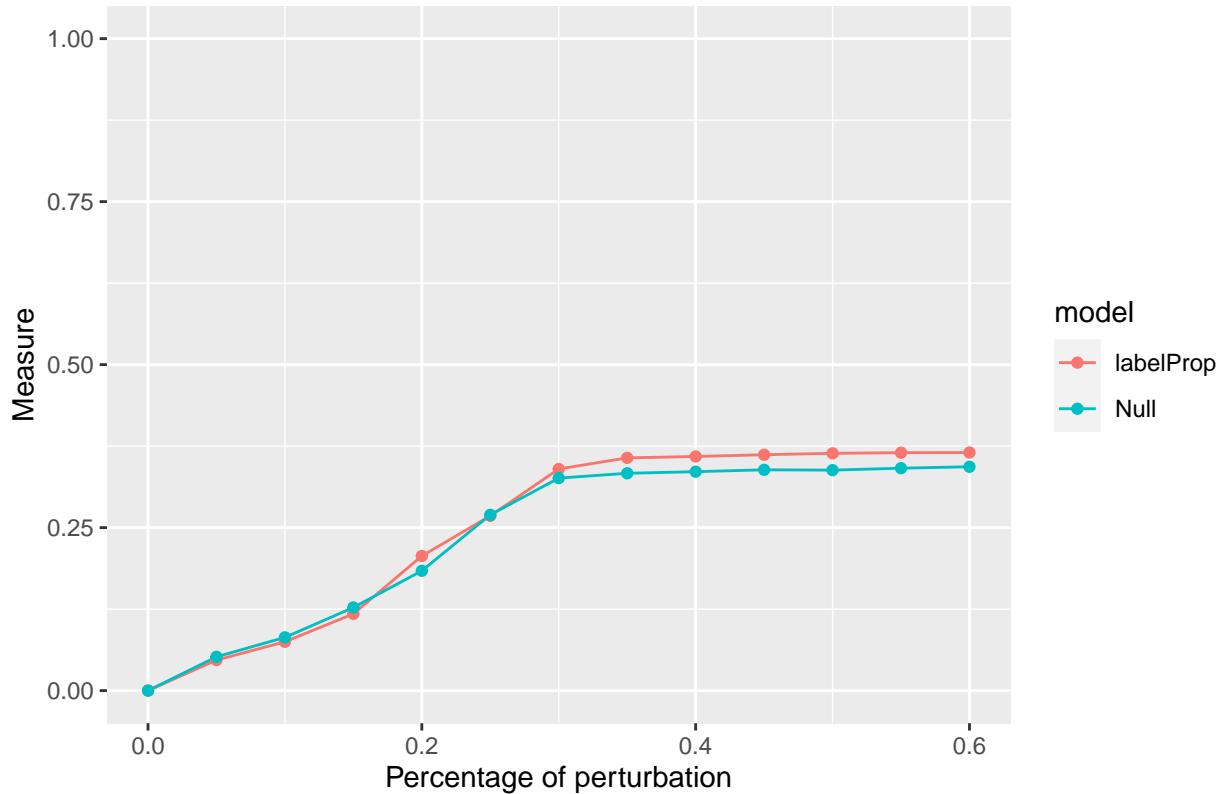
```



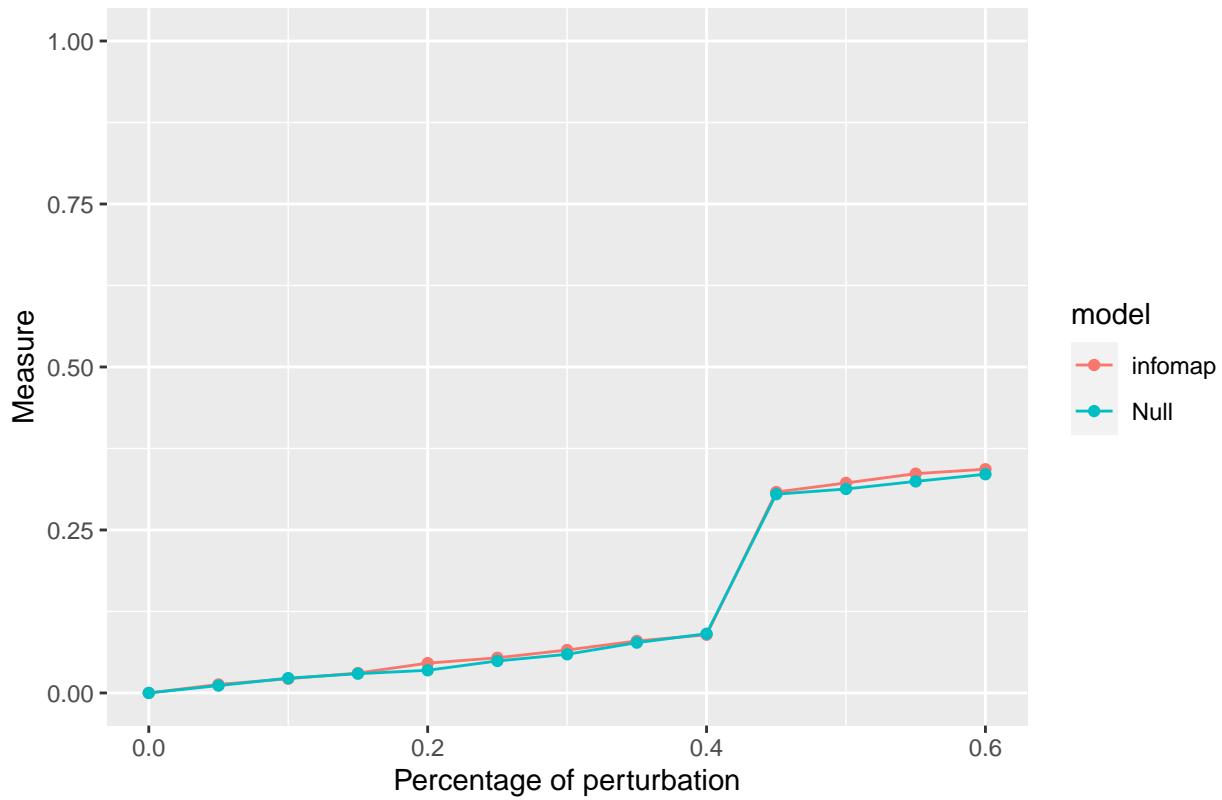
Robin plot robustness based on VI



Robin plot robustness based on VI



Robin plot robustness based on VI



```

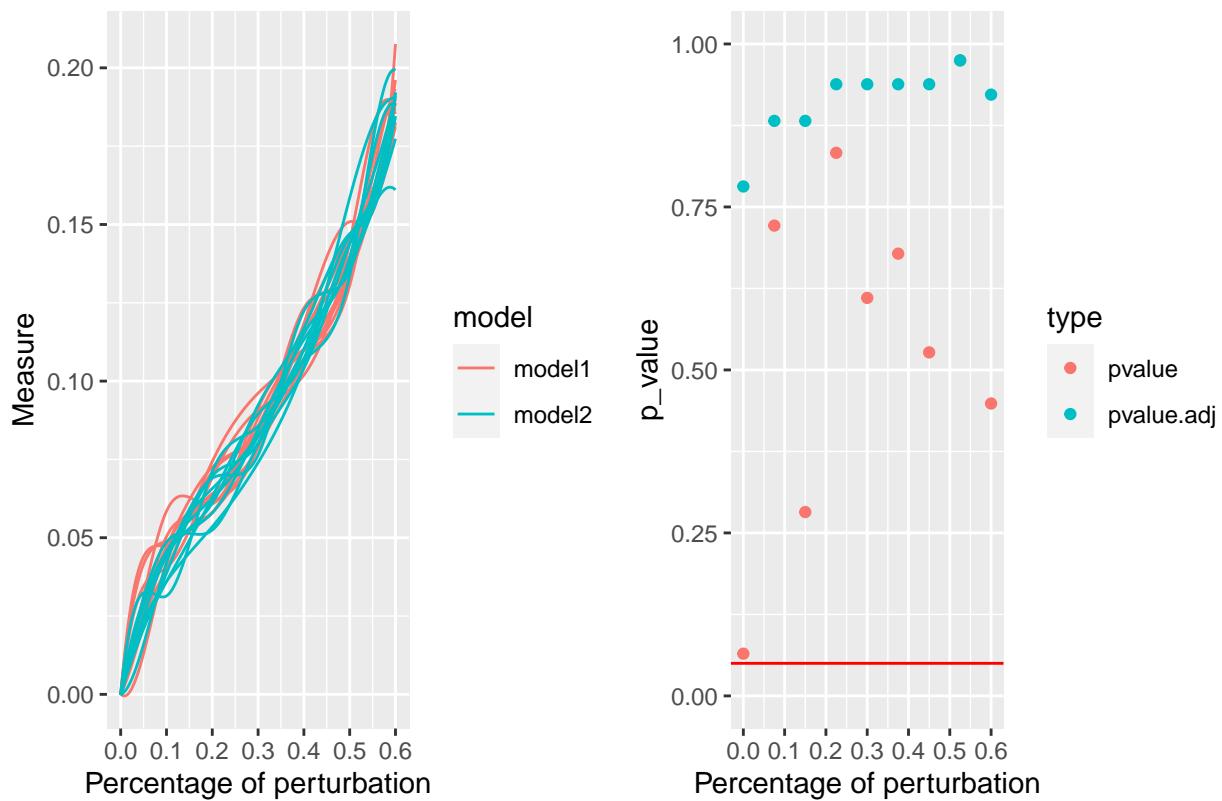
#
#
#
for (i in 1:length(proc_DK))
{
  results_Robin[i,3] <- robinGPTest(model1=proc_DK[[i]]$Mean, model2=proc_DK[[i]]$MeanRandom)
  AUC <- robinAUC(graph=uni_graph2,
                    model1=proc_DK[[i]]$Mean,
                    model2=proc_DK[[i]]$MeanRandom)
  results_Robin[i,4] <- AUC$area2/AUC$area1
  robinFDATest(graph=uni_graph2, model1=proc_DK[[i]]$Mean, model2=proc_DK[[i]]$MeanRandom)
}

## Profile 1
## Profile 2
## [1] "First step: basis expansion"
## Swapping 'y' and 'argvals', because 'y' is simpler,
## and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## [1] "Second step: joint univariate tests"
## [1] "Third step: interval-wise combination and correction"
## [1] "creating the p-value matrix: end of row 2 out of 9"
## [1] "creating the p-value matrix: end of row 3 out of 9"
## [1] "creating the p-value matrix: end of row 4 out of 9"
## [1] "creating the p-value matrix: end of row 5 out of 9"
## [1] "creating the p-value matrix: end of row 6 out of 9"
## [1] "creating the p-value matrix: end of row 7 out of 9"
## [1] "creating the p-value matrix: end of row 8 out of 9"

```

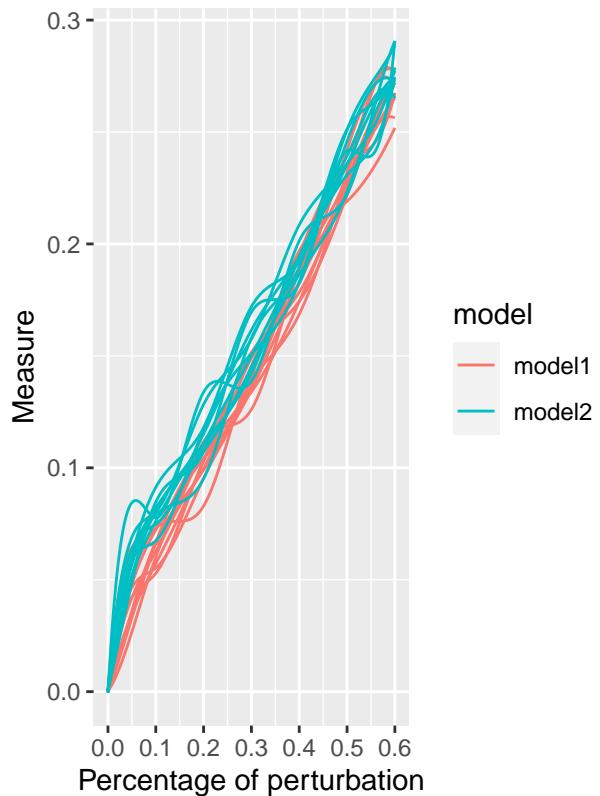
```
## [1] "creating the p-value matrix: end of row 9 out of 9"
## [1] "Interval Testing Procedure completed"
```

Functional Data Analysis

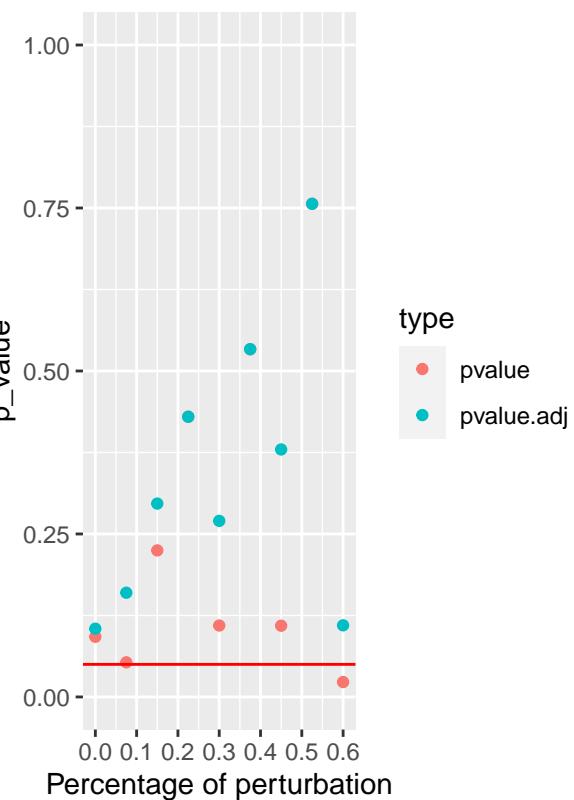


```
## TableGrob (1 x 2) "arrange": 2 grobs
##   z      cells    name    grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]
##   Profile 1
##   Profile 2
## [1] "First step: basis expansion"
## Swapping 'y' and 'argvals', because 'y' is simpler,
## and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## [1] "Second step: joint univariate tests"
## [1] "Third step: interval-wise combination and correction"
## [1] "creating the p-value matrix: end of row 2 out of 9"
## [1] "creating the p-value matrix: end of row 3 out of 9"
## [1] "creating the p-value matrix: end of row 4 out of 9"
## [1] "creating the p-value matrix: end of row 5 out of 9"
## [1] "creating the p-value matrix: end of row 6 out of 9"
## [1] "creating the p-value matrix: end of row 7 out of 9"
## [1] "creating the p-value matrix: end of row 8 out of 9"
## [1] "creating the p-value matrix: end of row 9 out of 9"
## [1] "Interval Testing Procedure completed"
```

Functional Data Analysis



P-values

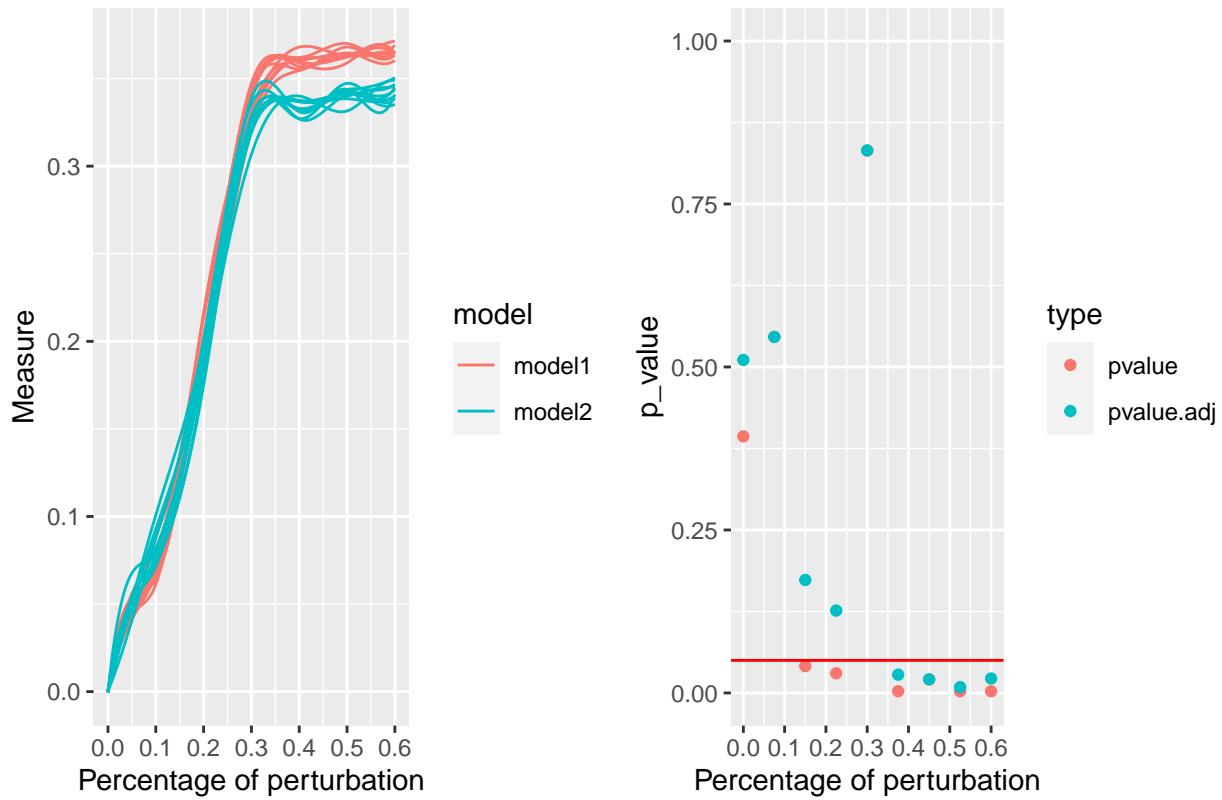


```

## #> #> ## TableGrob (1 x 2) "arrange": 2 grobs
## #> #>   z      cells      name      grob
## #> #> 1 1 (1-1,1-1) arrange gtable[layout]
## #> #> 2 2 (1-1,2-2) arrange gtable[layout]
## #> Profile 1
## #> Profile 2
## #> [1] "First step: basis expansion"
## #> Swapping 'y' and 'argvals', because 'y' is simpler,
## #> and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## #> [1] "Second step: joint univariate tests"
## #> [1] "Third step: interval-wise combination and correction"
## #> [1] "creating the p-value matrix: end of row 2 out of 9"
## #> [1] "creating the p-value matrix: end of row 3 out of 9"
## #> [1] "creating the p-value matrix: end of row 4 out of 9"
## #> [1] "creating the p-value matrix: end of row 5 out of 9"
## #> [1] "creating the p-value matrix: end of row 6 out of 9"
## #> [1] "creating the p-value matrix: end of row 7 out of 9"
## #> [1] "creating the p-value matrix: end of row 8 out of 9"
## #> [1] "creating the p-value matrix: end of row 9 out of 9"
## #> [1] "Interval Testing Procedure completed"

```

Functional Data Analysis

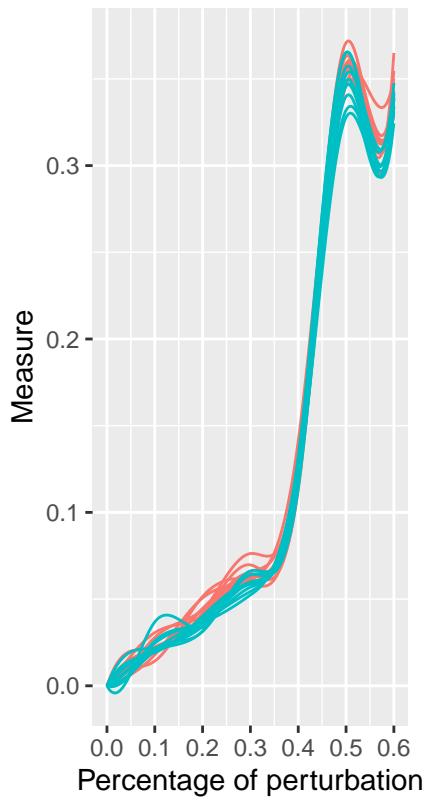


```

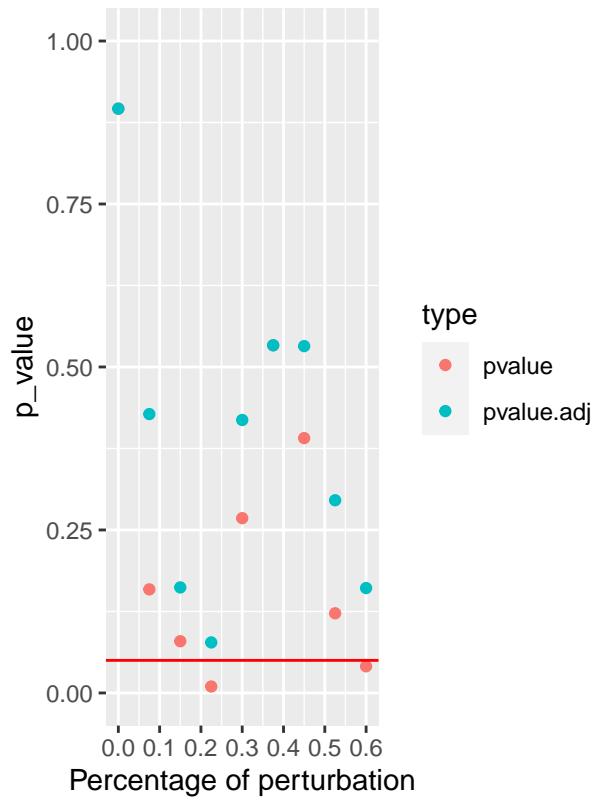
## # TableGrob (1 x 2) "arrange": 2 grobs
##   z      cells    name      grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]
## Profile 1
## Profile 2
## [1] "First step: basis expansion"
## Swapping 'y' and 'argvals', because 'y' is simpler,
## and 'argvals' should be; now dim(argvals) = 13 ; dim(y) = 13 x 20
## [1] "Second step: joint univariate tests"
## [1] "Third step: interval-wise combination and correction"
## [1] "creating the p-value matrix: end of row 2 out of 9"
## [1] "creating the p-value matrix: end of row 3 out of 9"
## [1] "creating the p-value matrix: end of row 4 out of 9"
## [1] "creating the p-value matrix: end of row 5 out of 9"
## [1] "creating the p-value matrix: end of row 6 out of 9"
## [1] "creating the p-value matrix: end of row 7 out of 9"
## [1] "creating the p-value matrix: end of row 8 out of 9"
## [1] "creating the p-value matrix: end of row 9 out of 9"
## [1] "Interval Testing Procedure completed"

```

Functional Data Analysis



P-values



```
## TableGrob (1 x 2) "arrange": 2 grobs
##   z      cells    name         grob
## 1 1 (1-1,1-1) arrange gtable[layout]
## 2 2 (1-1,2-2) arrange gtable[layout]

#save.image('/Users/Fernando/Desktop/01_Sanger_paper/improvement_dataset.Rdata')
#save.image('/Users/Fernando/Desktop/01_Sanger_paper/final_dataset_v18final.Rdata')
```

```
# 
# Modules
#
foo_comps<-membership(components)
names(foo_comps)<-sapply(strsplit(names(foo_comps),"_"),`[`,2)

#
#
foo<-condensed_baps_adm[orden.foo,]
foo<-data.frame(orden=factor(c(1:dim(foo)[1])),modules=factor(foo_comps[orden.foo],levels = order(table

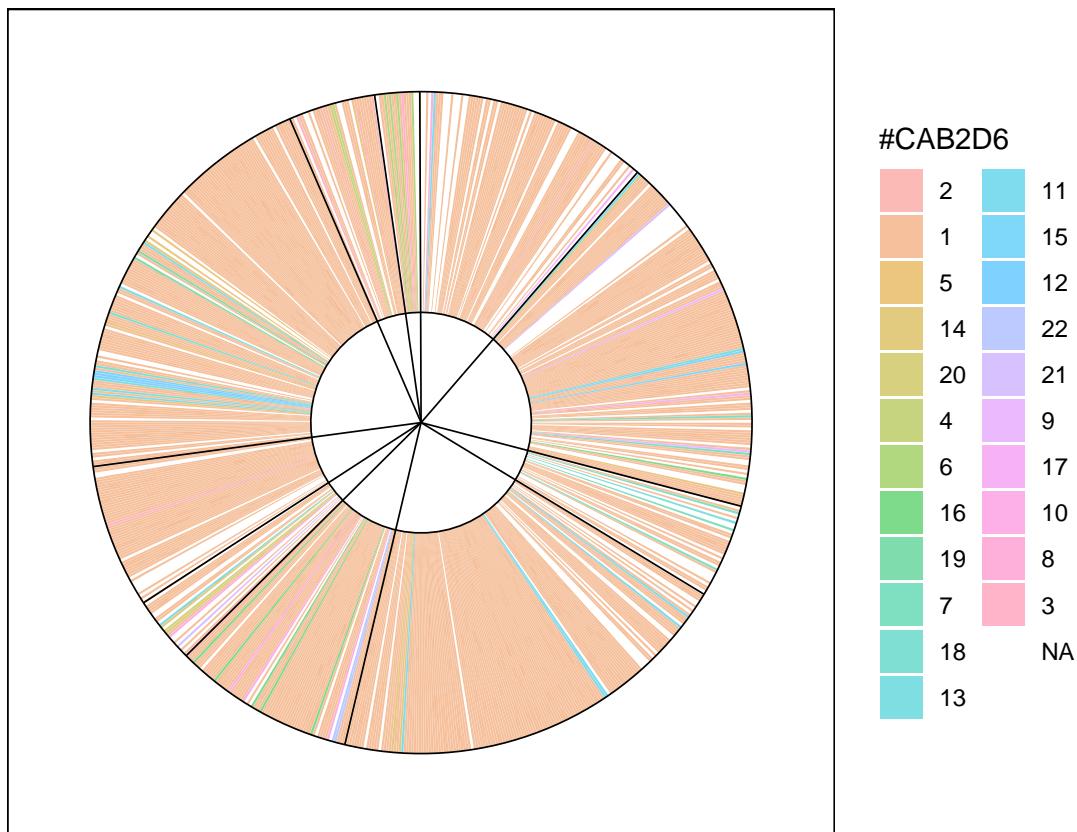
colorinos_modules<-colorRampPalette(colorinos.bipolar)(max(foo_comps))

p<-ggplot(data.frame(foo)) +
  geom_bar(aes(x=orden, y=1,fill=modules),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos_modules,na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
```

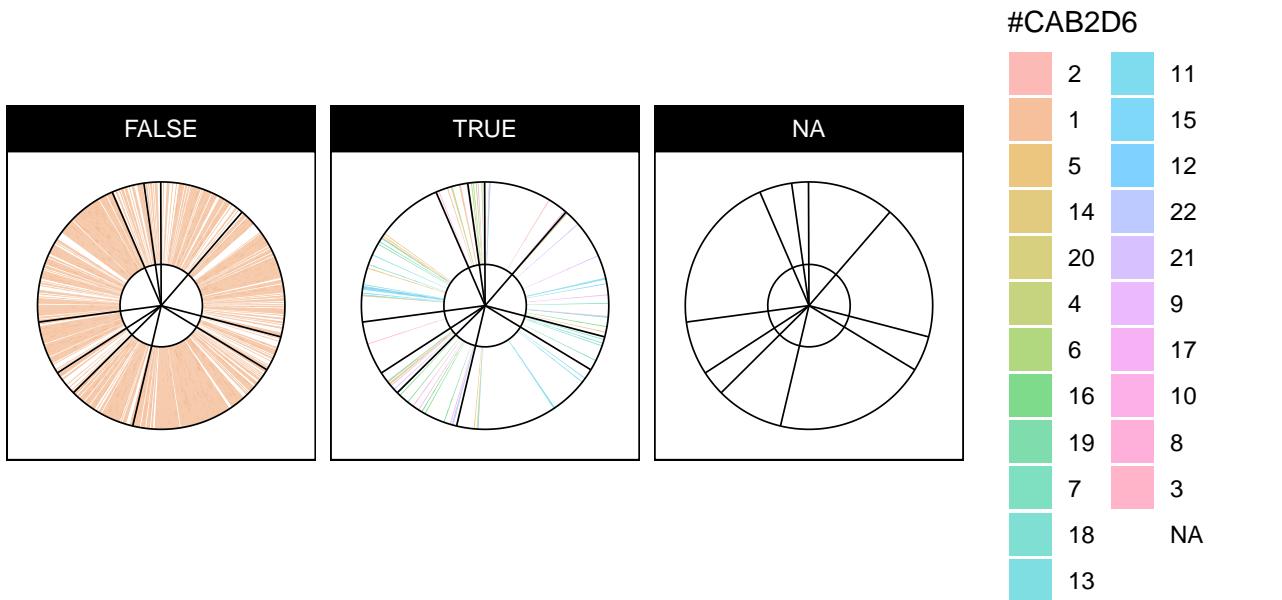
```

geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
ylim(c(-0.5,1)) +
theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
axis.text.x=element_blank(),
axis.ticks.x=element_blank(), axis.title.y=element_blank(),
axis.text.y=element_blank(),
axis.ticks.y=element_blank()) + coord_polar()
print(p)

```



```
print(p + facet_wrap(vars(modules!=1)))
```



```

final_mods<-igraph::cluster_louvain(uni_graph2)
foo_modules<-membership(final_mods)
names(foo_modules)<-sapply(strsplit(names(foo_modules), "_"), `[`, 2)

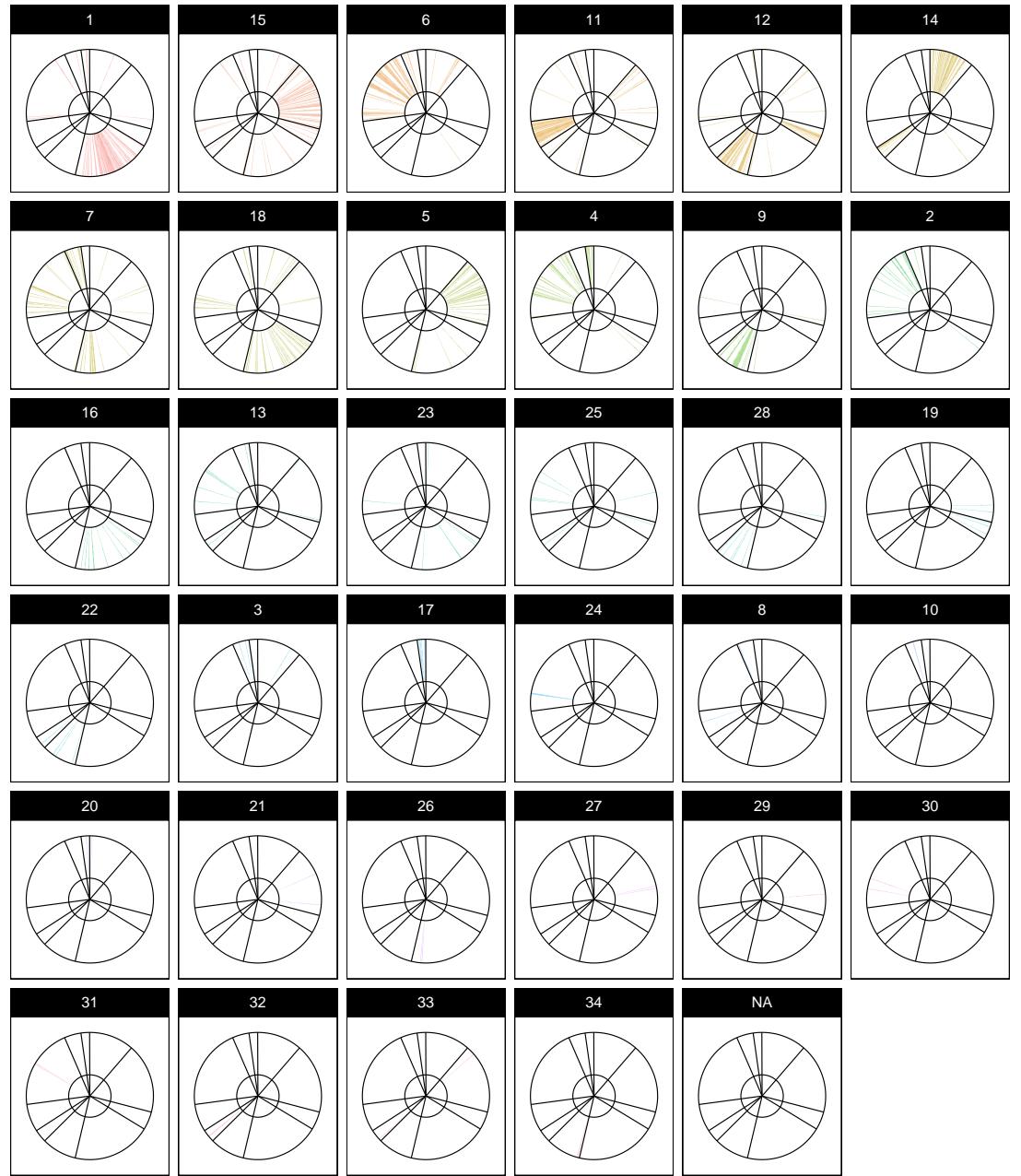
#
#
foo<-condensed_baps_adm[orden.foo,]
foo<-data.frame(orden=factor(c(1:dim(foo)[1])),modules=factor(foo_modules[orden.foo]),levels = order(table(foo)))

colorinos_modules<-colorRampPalette(colorinos.bipolar)(max(foo_modules))

p<-ggplot(data.frame(foo)) +
  geom_bar(aes(x=orden, y=1,fill=modules),
           stat="identity", alpha=0.5) +
  scale_fill_discrete(colorinos_modules,na.value="white") +
  geom_hline(yintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_hline(yintercept = 1, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 0, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 94, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 240, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 278, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 443, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 516, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 543, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 601, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 771, colour = 1, alpha=1, size=0.3) +
  geom_vline(xintercept = 806, colour = 1, alpha=1, size=0.3) +
  ylim(c(-0.5,1)) +
  theme_linedraw() + theme(panel.grid.major.x = element_blank(), panel.grid.major.y = element_blank(),
                           axis.text.x=element_blank(),
                           axis.ticks.x=element_blank(),axis.title.y=element_blank(),
                           axis.text.y=element_blank(),
                           axis.ticks.y=element_blank()) + coord_polar()

```

```
print(p + facet_wrap(vars(modules)))
```

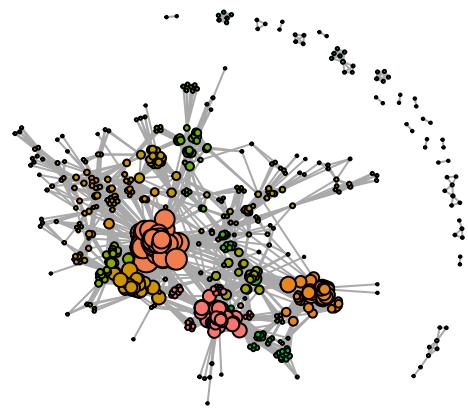


```
#  
# Plot beyond to illustrate the networks  
#  
colorinos_neo<-hue_pal()(34)[c(1,12,20,10,9,3,7,23,11,24,4,5,14,6,2,13,21,8,18,25,26,19,15,22,16,27,28,  
color_clusters<-foo_modules  
names(color_clusters)<-paste("s_",names(color_clusters),sep="")  
color_clusters<-color_clusters[names(V(uni_graph2))]  
plot(  
  uni_graph2,  
  vertex.size      = degree(uni_graph2)/10 +1,  
  vertex.label     = NA,
```

```

    edge.arrow.size = .25,
    vertex.color    = colorinos_neo[color_clusters]
)

```

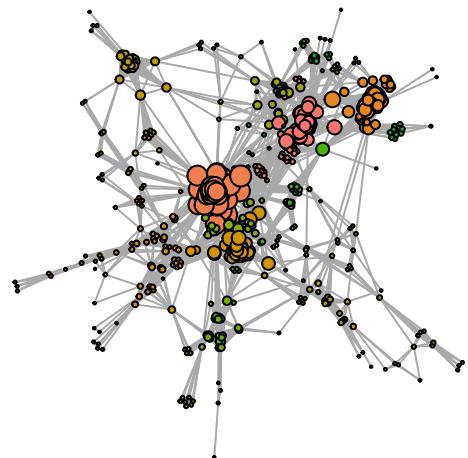


:::

```

foo<-induced_subgraph(uni_graph2,which(color_clusters%in%c(1,2,4,5,6,7,9,11,12,14,15,16,18)))
plot(
  foo,
  vertex.size    = degree(foo)/10 +1,
  vertex.label   = NA,
  edge.arrow.size = .25,
  vertex.color   = colorinos_neo[color_clusters[which(color_clusters%in%c(1,2,4,5,6,7,9,11,12,14,15,16
)

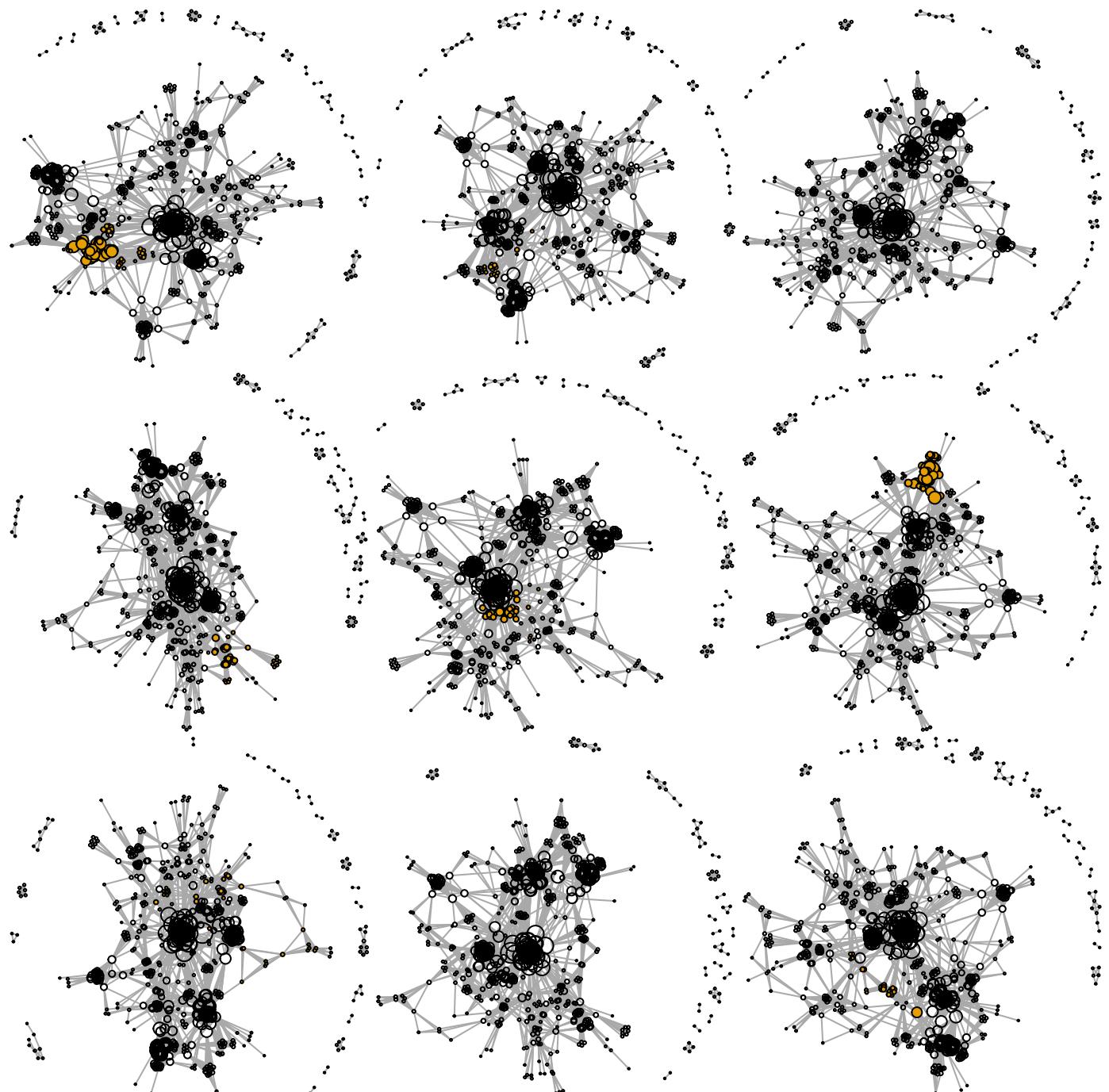
```

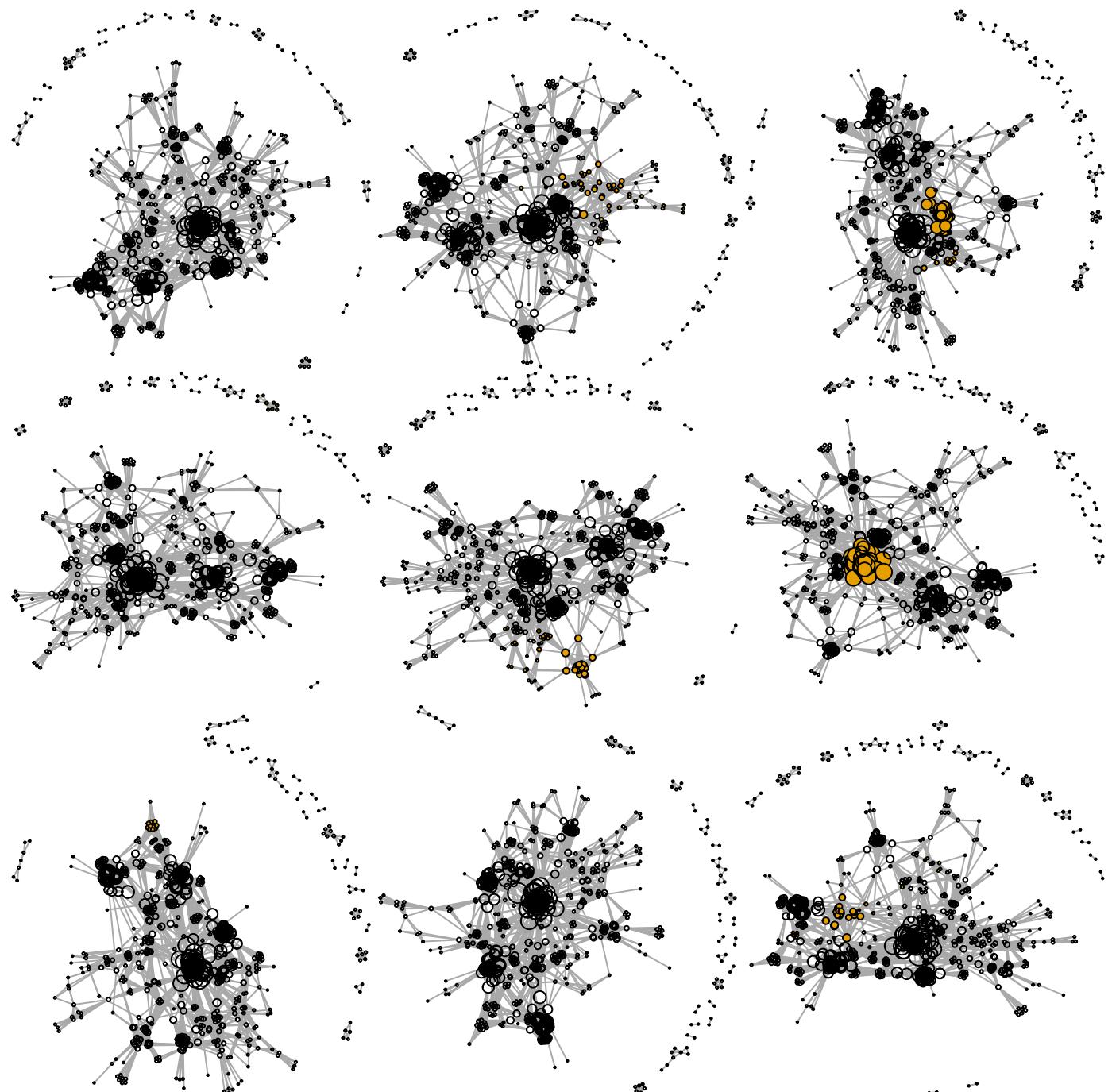


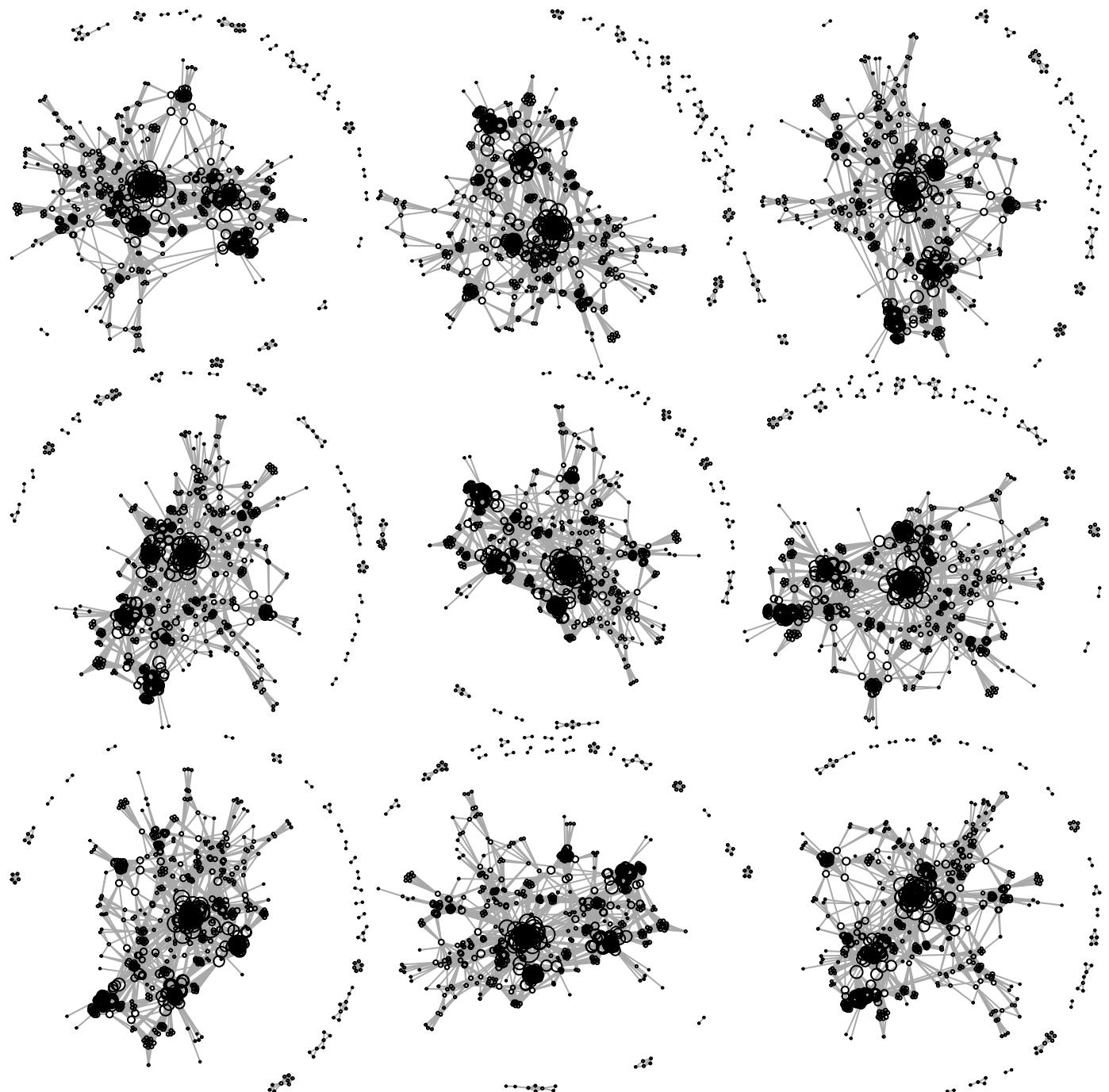
```

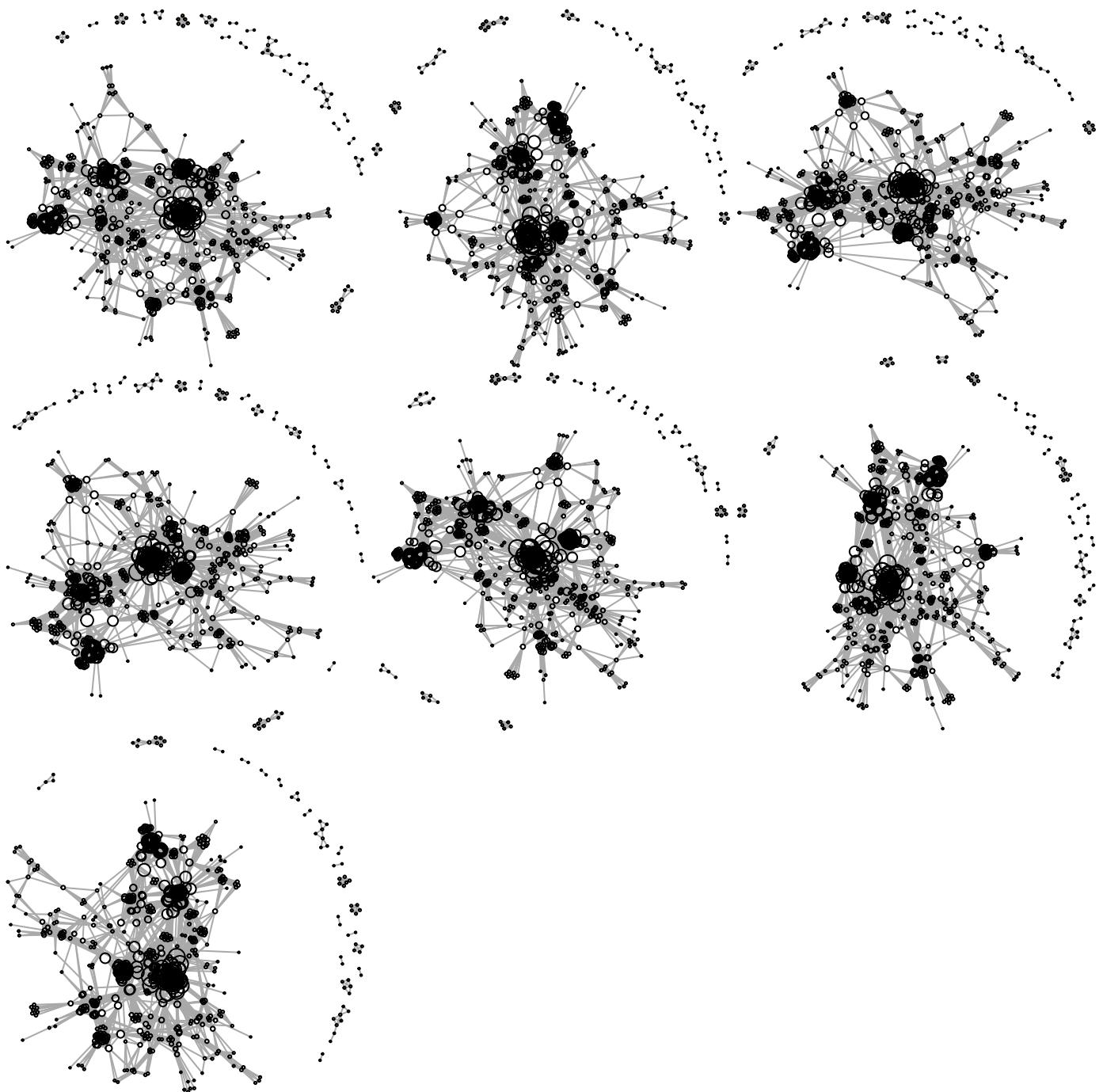
for (i in 1:34)
{
  plot(
    uni_graph2,
    vertex.size    = degree(uni_graph2)/10 +1,
    vertex.label   = NA,
    edge.arrow.size = .25,
    vertex.color   = color_clusters==i
  )
}

```









```

stats_degree<-list()
stats_desc<-list()
stats_networks<-list()
for (i in 1:34)
{
  foo<-induced_subgraph(uni_graph2,which(color_clusters==i))
  # Computing centrality measures for each vertex
  V(foo)$outdegree <- degree(foo, mode = "out")
  V(foo)$closeness <- closeness(foo, mode = "total", normalized = TRUE)
  V(foo)$betweenness <- betweenness(foo, normalized = TRUE)
}
  
```

```

# Extracting each vertex features as a data.frame
stats <- as_data_frame(foo, what = "vertices")
stats_networks[[i]]<-stats
# Computing quantiles for each variable
stats_degree[[i]] <- with(stats, {
  cbind(
    outdegree = quantile(outdegree, c(.025, .5, .975), na.rm = TRUE),
    closeness = quantile(closeness, c(.025, .5, .975), na.rm = TRUE),
    betweeness = quantile(betweeness, c(.025, .5, .975), na.rm = TRUE)
  )
})
stats_desc[[i]] <- cbind(
  size = vcount(foo),
  nedges = ecount(foo),
  density = edge_density(foo),
  recip = reciprocity(foo),
  centr = centr_betw(foo)$centralization,
  pathLen = mean_distance(foo)
)
}

foo<-induced_subgraph(uni_graph2,which(color_clusters%in%c(1,2,4,5,6,7,9,11,12,14,15,16,18)))
V(foo)$outdegree <- degree(foo, mode = "out")
V(foo)$closeness <- closeness(foo, mode = "total", normalized = TRUE)
V(foo)$betweeness <- betweenness(foo, normalized = TRUE)
stats <- as_data_frame(foo, what = "vertices")
stats_networks[[35]]<-stats
stats_degree[[35]] <- with(stats, {
  cbind(
    outdegree = quantile(outdegree, c(.025, .5, .975), na.rm = TRUE),
    closeness = quantile(closeness, c(.025, .5, .975), na.rm = TRUE),
    betweeness = quantile(betweeness, c(.025, .5, .975), na.rm = TRUE)
  )
})
stats_desc[[35]] <- cbind(
  size = vcount(foo),
  nedges = ecount(foo),
  density = edge_density(foo),
  recip = reciprocity(foo),
  centr = centr_betw(foo)$centralization,
  pathLen = mean_distance(foo)
)

foo<-uni_graph2
V(foo)$outdegree <- degree(foo, mode = "out")
V(foo)$closeness <- closeness(foo, mode = "total", normalized = TRUE)
V(foo)$betweeness <- betweenness(foo, normalized = TRUE)
stats <- as_data_frame(foo, what = "vertices")
stats_networks[[36]]<-stats
stats_degree[[36]] <- with(stats, {
  cbind(
    outdegree = quantile(outdegree, c(.025, .5, .975), na.rm = TRUE),
    closeness = quantile(closeness, c(.025, .5, .975), na.rm = TRUE),

```

```

    betweeness = quantile(betweeness, c(.025, .5, .975), na.rm = TRUE)
  )
})

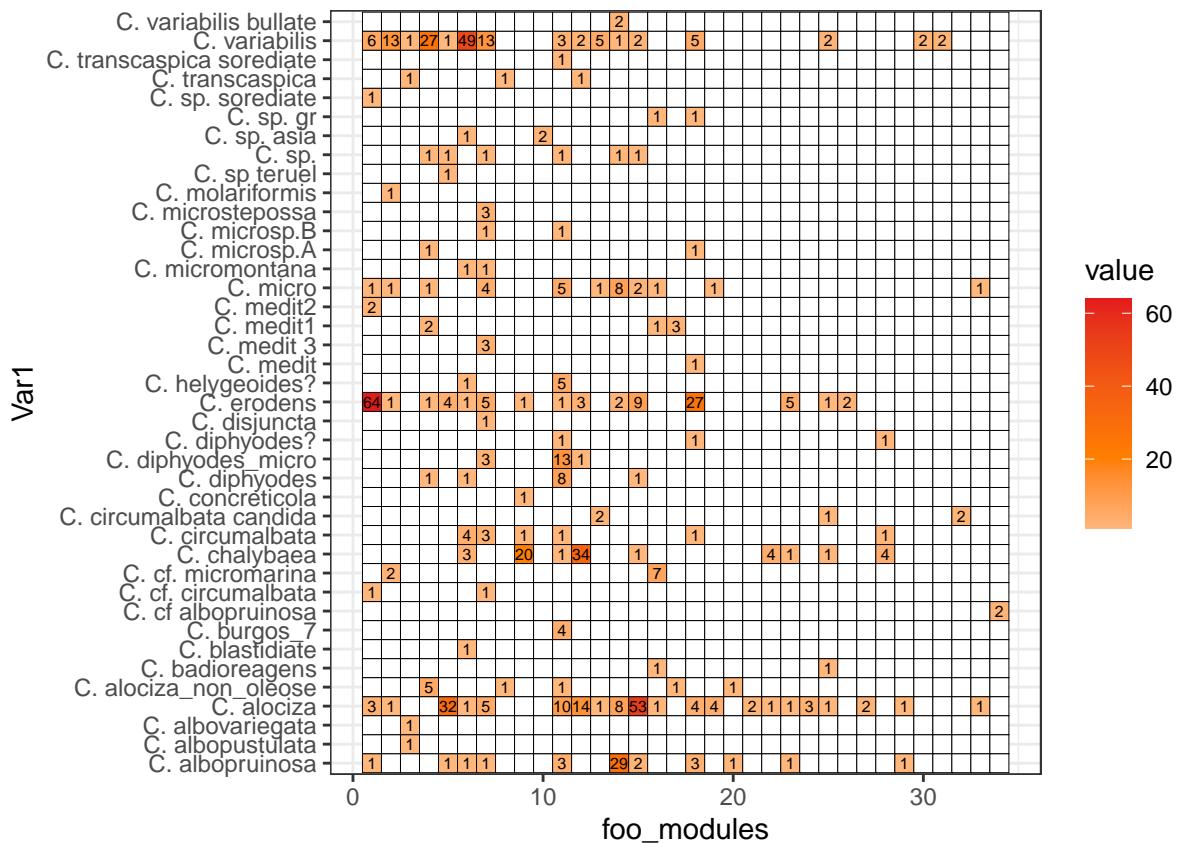
stats_desc[[36]] <- cbind(
  size    = vcount(foo),
  nedges  = ecount(foo),
  density = edge_density(foo),
  recip   = reciprocity(foo),
  centr   = centr_betw(foo)$centralization,
  pathLen = mean_distance(foo)
)
stats_degree_trim<-stats_degree
stats_desc_trim<-stats_desc

# Heatmap 3 Species vs modules
foo_tabla<-melt(table(condensed_baps_adm[as.character(names(foo_modules)),2],foo_modules))
foo_tabla$value[foo_tabla$value==0]<-NA

ggplot(foo_tabla,aes(x=foo_modules,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label =
  scale_fill_gradient2(low = "#FFFFFF",
                        mid = colorinos.bipolar[7],
                        high = colorinos.bipolar[6],
                        midpoint = 20,
                        space = "Lab",
                        na.value = "#FFFFFF",
                        guide = "colourbar",
                        aesthetics = "fill"
  ) +
  coord_fixed() + theme_bw()

## Warning: Removed 1207 rows containing missing values (geom_text).

```



```

#  

#  

#  

assocstats(table(condensed_baps_adm[as.character(names(foo_modules)),2],foo_modules))  

##          X^2    df   P(> X^2)  

## Likelihood Ratio 1644 1287 4.3692e-11  

## Pearson         4868 1287 0.0000e+00  

##  

##  Phi-Coefficient : NA  

##  Contingency Coeff.: 0.937  

##  Cramer's V       : 0.467  

#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))  

coindep_test(table(condensed_baps_adm[as.character(names(foo_modules)),2],foo_modules))  

##  

##  Permutation test for conditional independence  

##  

##  data:  table(condensed_baps_adm[as.character(names(foo_modules)), 2],      foo_modules)  

##  f(x) = 25.923, p-value = 0.001  

geo_distances<-mat.or.vec(length(condensed_baps_adm[as.character(names(foo_modules)),2]),length(condense  

for (X in 1:length(condensed_baps_adm[as.character(names(foo_modules)),2]))  

{  

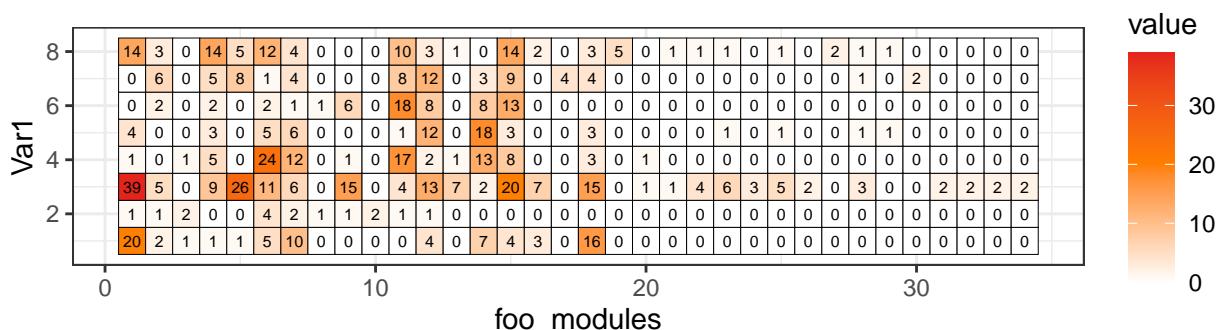
  geo_distances[,X]<-geosphere::distGeo(cbind(as.numeric(condensed_baps_adm[as.character(names(foo_modu

```

```
}  
  
regions<-pamk(geo_distances,krange=2:10,diss=TRUE)  
  
regions$pamobject$clustering
```

```
foo_tablea<-melt(table(regions$pamobject$clustering,foo_modules))
#foo_tablea$value[foo_tablea$value==0]<-NA
```

```
ggplot(foo_tabla,aes(x=foo_modules,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label=scale_fill_gradient2(low = "#FFFFFF",
  mid = colorinos.bipolar[7],
  high = colorinos.bipolar[6],
  midpoint = 20,
  space = "Lab",
  na.value = "#FFFFFF",
  guide = "colourbar",
  aesthetics = "fill"
) +
coord_fixed() + theme_bw()
```



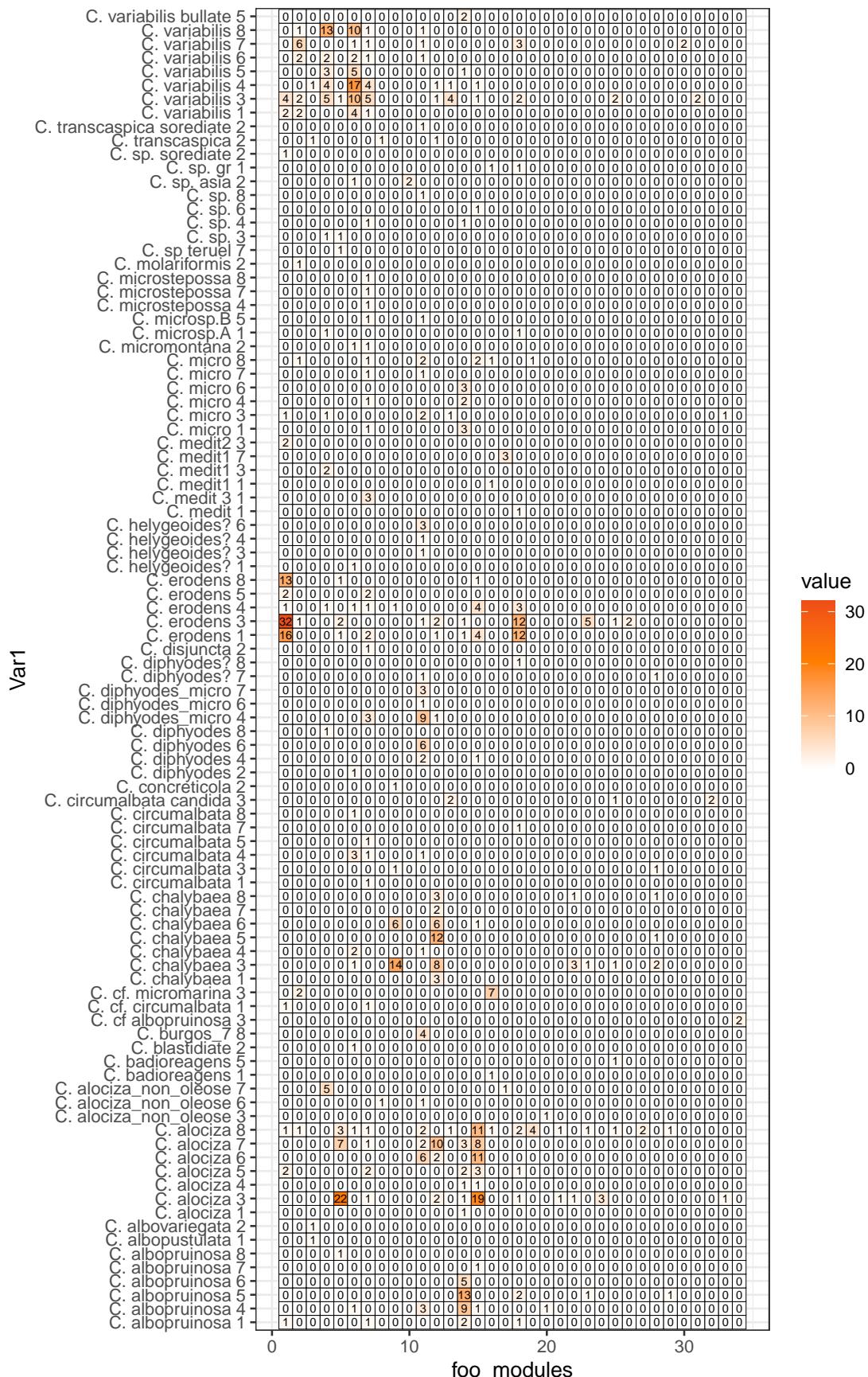
```
assocstats(table(regions$pamobject$clustering,foo modules))
```

```

##          X^2  df P(> X^2)
## Likelihood Ratio 632.37 231      0
## Pearson         755.86 231      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.727
## Cramer's V        : 0.4
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))
coindep_test(table(regions$pamobject$clustering,foo_modules))

##
## Permutation test for conditional independence
##
## data:  table(regions$pamobject$clustering, foo_modules)
## f(x) = 8.9748, p-value = 0.008
foo_tabla<-melt(table(paste(condensed_baps_adm[as.character(names(foo_modules)),2],regions$pamobject$clustering))
ggplot(foo_tabla,aes(x=foo_modules,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label = value,
scale_fill_gradient2(low = "#FFFFFF",
mid = colorinos.bipolar[7],
high = colorinos.bipolar[6],
midpoint = 20,
space = "Lab",
na.value = "#FFFFFF",
guide = "colourbar",
aesthetics = "fill"
) + coord_fixed() + theme_bw()

```



```

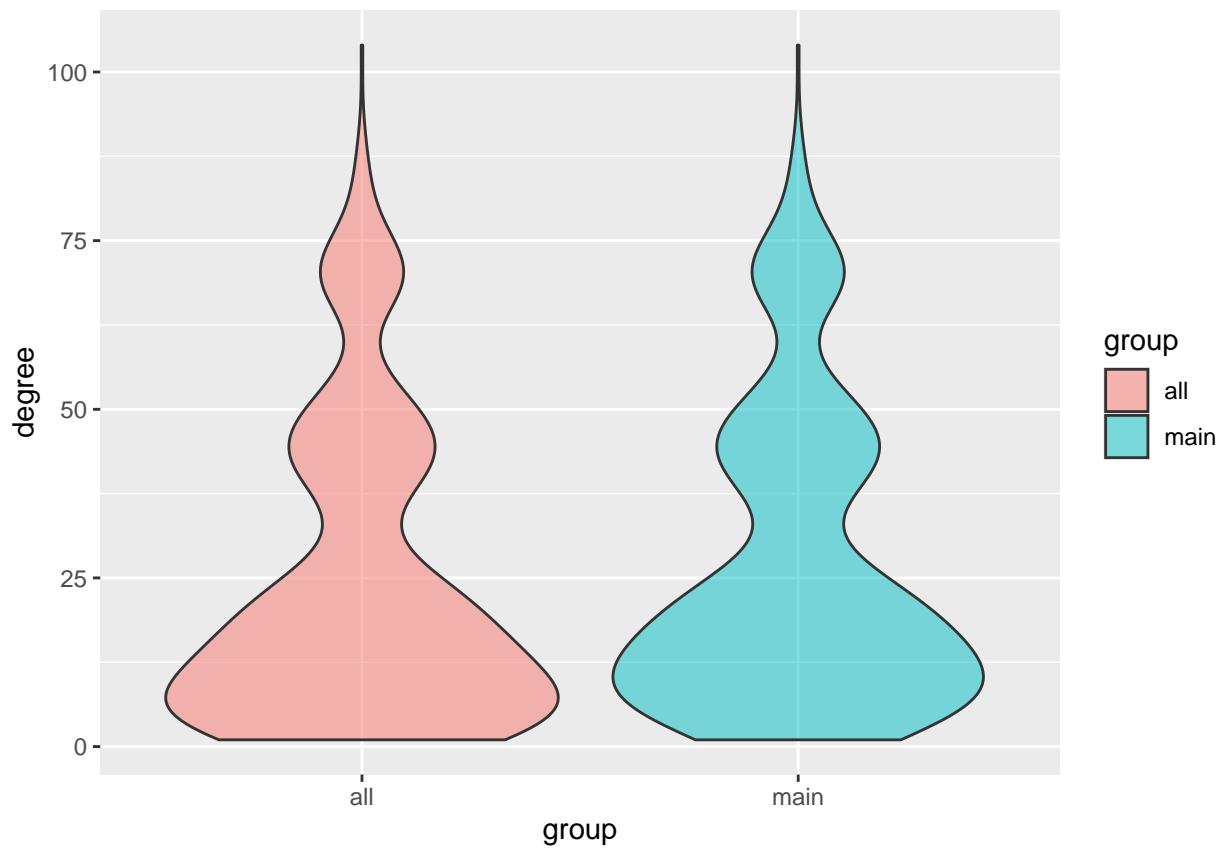
assocstats(table(paste(condensed_baps_adm[as.character(names(foo_modules)),2],regions$pamobject$cluster

##          X^2    df  P(> X^2)
## Likelihood Ratio 2270.6 3135      1
## Pearson         7258.0 3135      0
##
## Phi-Coefficient   : NA
## Contingency Coeff.: 0.956
## Cramer's V        : 0.57
#kable(chisq.residuals(table(condensed_baps_adm$Species,condensed_baps_adm$name)))

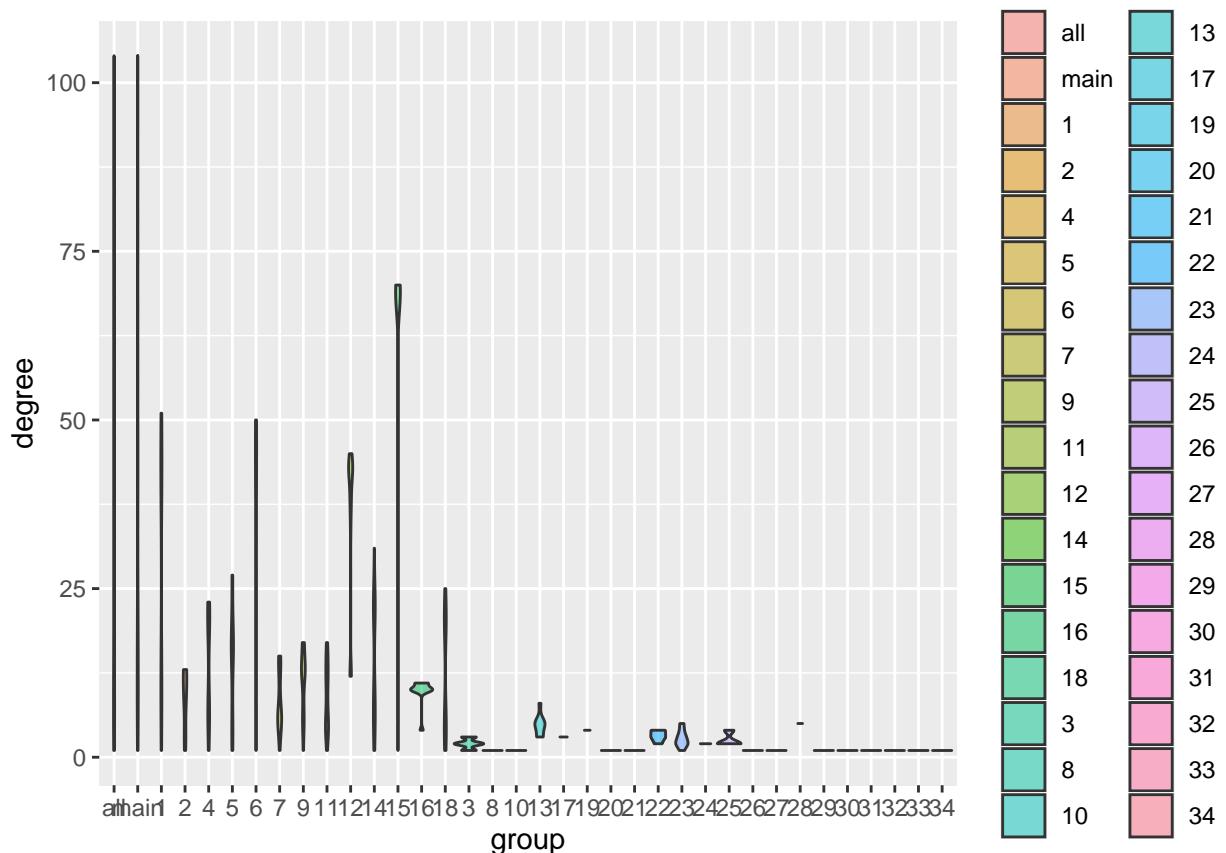
coindep_test(table(paste(condensed_baps_adm[as.character(names(foo_modules)),2],regions$pamobject$cluster

## Permutation test for conditional independence
##
## data: table(paste(condensed_baps_adm[as.character(names(foo_modules)),      2], regions$pamobject$clu
## f(x) = 25.923, p-value < 2.2e-16
#
# Boxplots
#
i="all"
values<-cbind(i,degree(uni_graph2, mode = "out"),closeness(uni_graph2, mode = "total", normalized = TRUE)
i="main"
foo<-induced_subgraph(uni_graph2,which(color_clusters%in%c(1,2,4,5,6,7,9,11,12,14,15,16,18)))
values<-rbind(values,cbind(i,degree(foo, mode = "out"),closeness(foo, mode = "total", normalized = TRUE
for (i in c(1,2,4,5,6,7,9,11,12,14,15,16,18,3,8,10,13,17,19:34))
{
  foo<-induced_subgraph(uni_graph2,which(color_clusters==i))
  # Computing centrality measures for each vertex
  values<-rbind(values,cbind(i,degree(foo, mode = "out"),closeness(foo, mode = "total", normalized = TRUE
}
#colnames(values)<-c("group","degree","close","between")
values<-
  data.frame(group=factor(values[,1],
                         levels=c("all","main",1,2,4,5,6,7,9,11,12,14,15,16,18,3,8,10,13,17,19:34)),
             degree=as.numeric(values[,2]),close=as.numeric(values[,3]),between=as.numeric(values[,4]))
ggplot(values[values$group%in%c("all","main"),],aes(x=group,y=degree,fill=group))+geom_violin(alpha=0.5

```

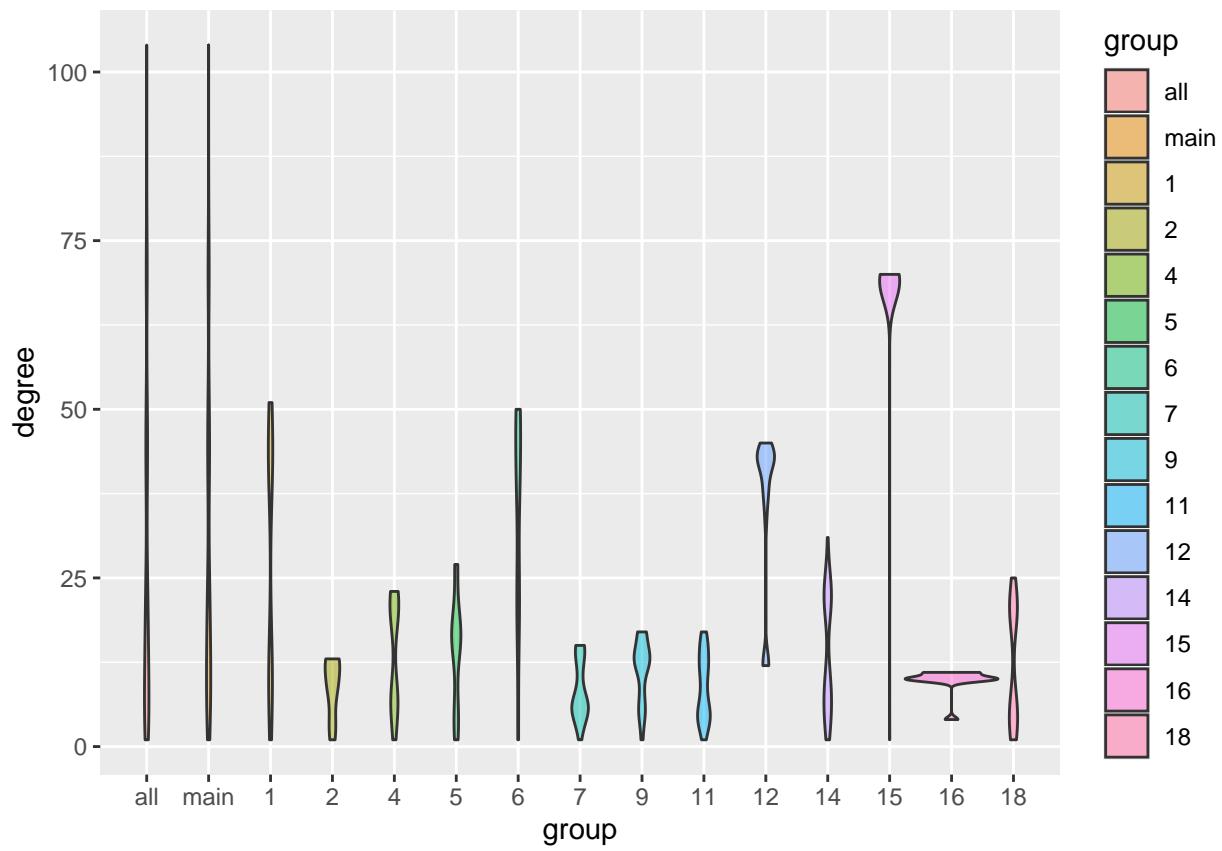


```
ggplot(values,aes(x=group,y=degree,fill=group))+geom_violin(alpha=0.5,width=1.25)  
## Warning: position_dodge requires non-overlapping x intervals
```

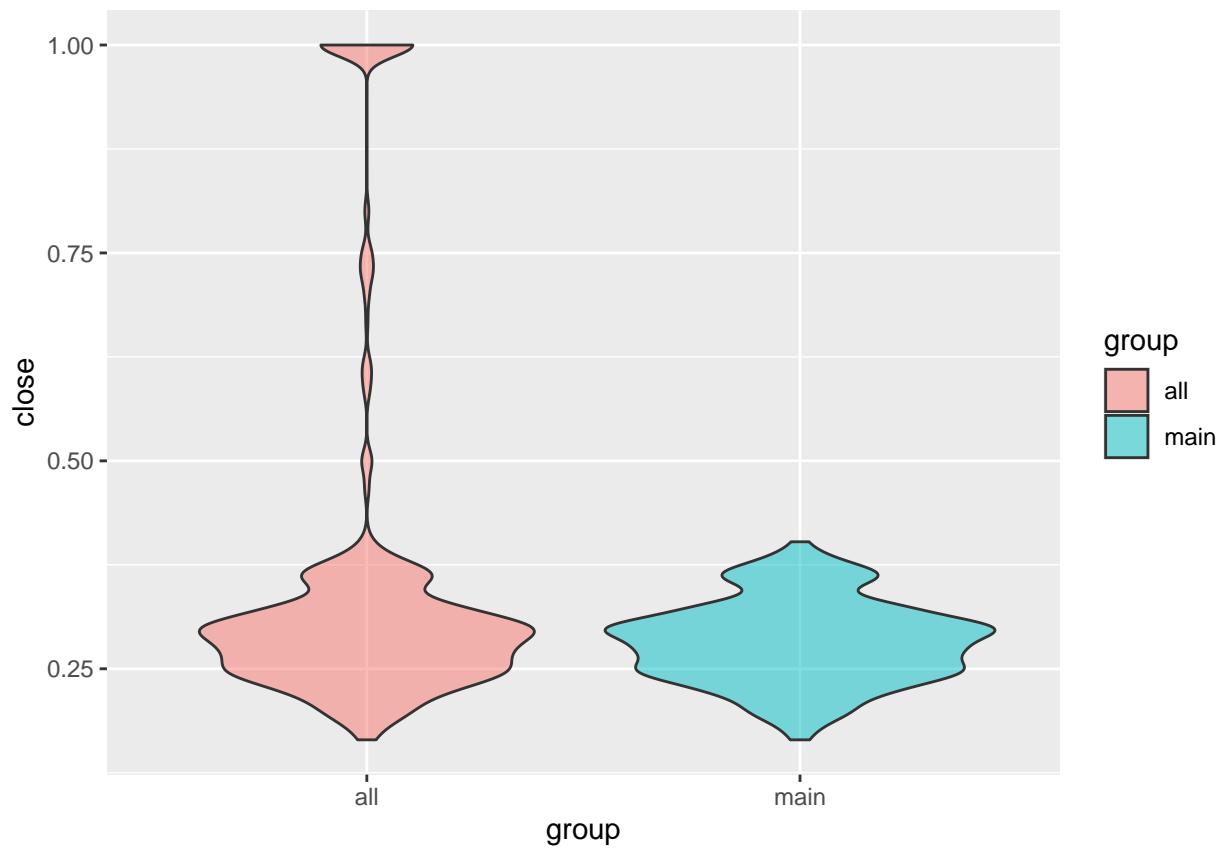


```
ggplot(values[values$group%in%c("all", "main", 1, 2, 4, 5, 6, 7, 9, 11, 12, 14, 15, 16, 18), ],  
       aes(x=group, y=degree, fill=group))+geom_violin(alpha=0.5, width=1.5)
```

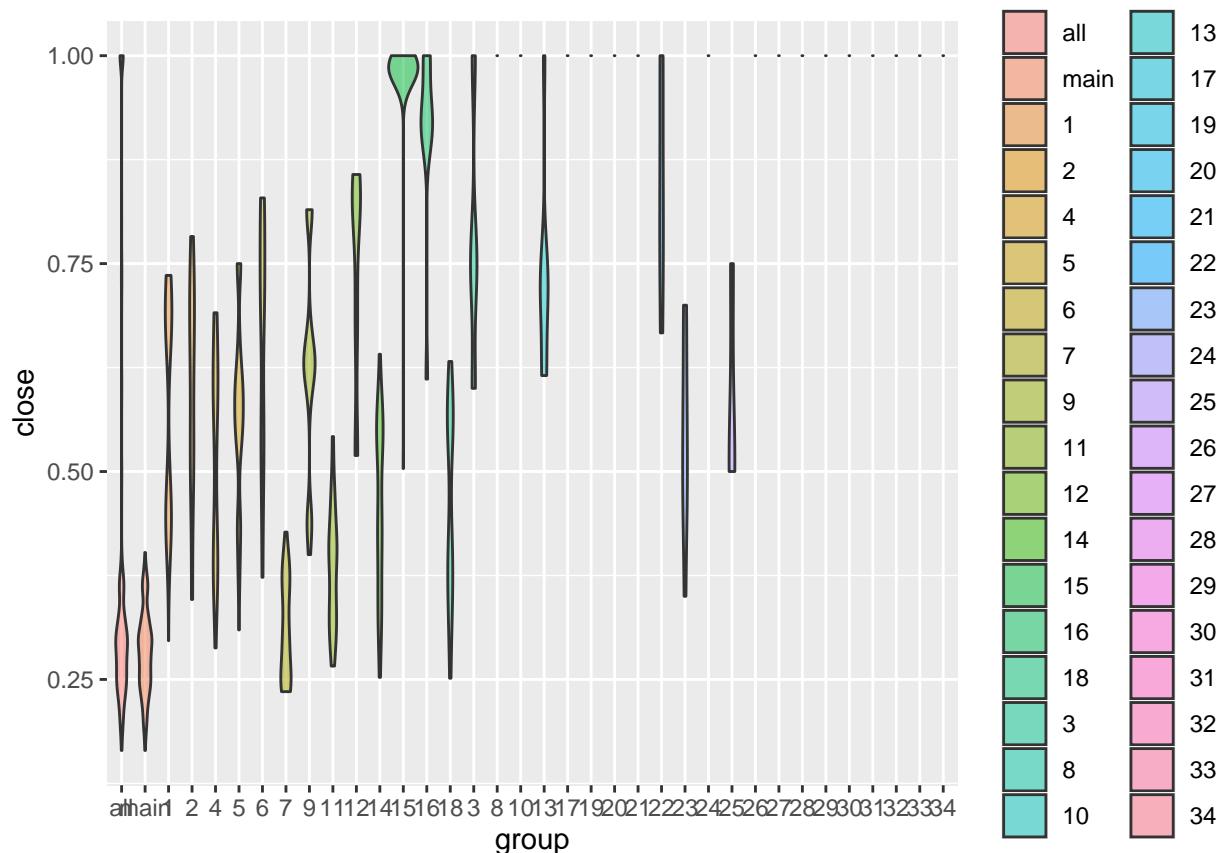
Warning: position_dodge requires non-overlapping x intervals



```
#  
ggplot(values[values$group%in%c("all", "main"),], aes(x=group, y=close, fill=group))+geom_violin(alpha=0.5)
```

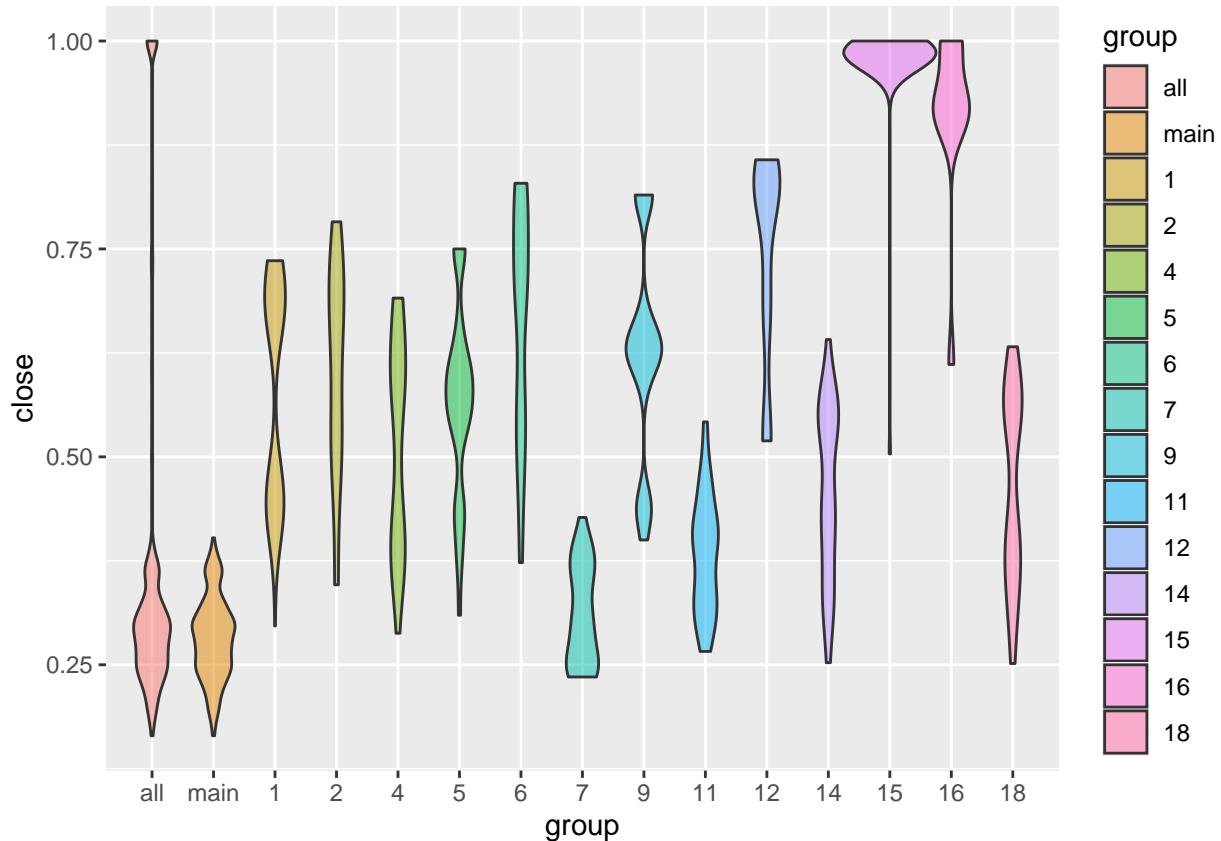


```
ggplot(values,aes(x=group,y=close,fill=group))+geom_violin(alpha=0.5,width=1.25)  
## Warning: position_dodge requires non-overlapping x intervals
```



```
ggplot(values[values$group%in%c("all", "main", 1, 2, 4, 5, 6, 7, 9, 11, 12, 14, 15, 16, 18), ],
       aes(x=group, y=close, fill=group))+geom_violin(alpha=0.5, width=1.5)
```

```
## Warning: position_dodge requires non-overlapping x intervals
```



values\$close

```
## [1] 0.3084833 0.2474227 0.7500000 0.2193784 0.2730997 0.2670227 0.2437043
## [8] 0.2835539 0.2671416 1.0000000 0.2638522 0.3387916 1.0000000 1.0000000
## [15] 0.3134796 0.2827521 1.0000000 0.2961500 0.2770083 0.2831524 0.2613240
## [22] 0.2613240 0.7500000 0.1973035 1.0000000 0.2970297 0.2970297 0.2721088
## [29] 0.2568493 0.2965892 0.2568493 0.2922552 0.2970297 0.2877698 0.2425222
## [36] 0.2492730 0.2426203 0.3025719 0.2568493 0.2568493 0.2922552 0.2439024
## [43] 0.2568493 0.3255562 0.2884615 0.3255562 0.3255562 0.3033367 0.1969150
## [50] 0.2710027 0.2828854 0.2732240 0.3799873 0.3001501 0.3612282 0.2732240
## [57] 0.2478315 0.2302379 0.2481390 0.2702703 0.3255562 0.2477291 0.2732240
## [64] 0.3007519 0.2539145 0.2556455 0.2027712 0.2027712 0.2670227 0.6000000
## [71] 0.3134796 0.3134796 0.2408671 0.2714932 0.2436054 0.2894356 0.1816530
## [78] 0.3255562 0.3255562 0.3255562 0.2976190 0.2954210 0.3033367 0.3816794
## [85] 0.2954210 0.2714932 0.3095975 0.3612282 0.2670227 0.2193784 1.0000000
## [92] 0.2193784 1.0000000 0.2193784 0.2193784 1.0000000 0.3201708 0.3225806
## [99] 0.2439024 0.3215434 0.2278769 0.2436054 0.2346500 0.2346500 0.3500583
## [106] 0.2902758 0.2436054 0.3293085 0.2902758 0.2254791 0.2154399 0.2897151
## [113] 0.2604167 0.1932990 0.2897151 0.2954210 0.2979146 0.2439024 0.2752294
## [120] 0.2408671 0.2588438 0.2824859 0.2898551 0.2955665 0.2309469 0.2214022
## [127] 0.2827521 0.3733665 0.3612282 0.3836317 0.2732240 0.2652520 0.2752294
## [134] 0.2400960 0.3007519 0.2400960 0.3224073 0.2962963 1.0000000 0.1837110
## [141] 0.3224073 0.2400960 0.3488372 0.3488372 0.2730997 0.3224073 0.2863962
## [148] 0.2373418 0.2484472 0.1998002 0.3612282 0.3634161 0.2400960 0.2480364
## [155] 0.1988731 0.3612282 0.2246350 0.2535926 0.3255562 0.2976190 0.3799873
## [162] 0.3623188 0.2714932 0.2962963 0.2590674 0.3095975 0.1857010 0.3757044
## [169] 0.2216476 0.3614458 0.3255562 0.2477291 0.3612282 0.3612282 0.2310358
```

```

## [176] 0.2310358 0.3612282 0.2214022 1.0000000 0.2876318 0.2876318 0.3010537
## [183] 0.2400960 0.2656042 0.3001501 0.2670227 0.2962963 0.2443992 0.6153846
## [190] 0.2962963 0.3790272 0.7272727 0.1861620 1.0000000 1.0000000 0.2286585
## [197] 0.2568493 0.2976190 0.2193784 0.2714932 0.2193784 1.0000000 0.2590674
## [204] 1.0000000 0.2590674 0.2748511 0.2235469 0.2748511 0.3656307 0.2748511
## [211] 0.2748511 0.2671416 0.2108963 0.2897151 0.2235469 0.2235469 0.2748511
## [218] 0.2897151 0.2954210 0.2235469 0.2748511 0.2985075 0.3260870 0.3260870
## [225] 0.3683241 0.3722084 0.2730997 0.3612282 0.3799873 0.5833333 0.3647416
## [232] 0.2974715 0.3050330 0.2858504 0.3041054 0.2737226 0.2976190 0.3799873
## [239] 1.0000000 0.3634161 0.3731343 0.2437043 0.3024194 0.2293578 0.3757044
## [246] 0.3757044 0.2929688 0.3064351 0.3612282 0.1996672 0.2031832 0.2460025
## [253] 0.3612282 0.2400960 0.3833866 0.3084833 0.2621232 0.3259098 1.0000000
## [260] 0.3612282 0.2730997 0.3612282 0.2977667 1.0000000 0.3262643 0.3680982
## [267] 0.3799873 0.4026846 0.3893576 0.3194888 0.3361345 0.2531646 0.3024194
## [274] 0.2748511 0.2748511 0.3710575 0.3612282 0.2443992 0.2801120 0.2985075
## [281] 0.2770083 0.2944063 0.3687769 0.2944063 0.3612282 0.3013561 0.2877698
## [288] 0.3833866 0.2646670 0.3048780 0.3500000 0.2535926 0.5000000 0.7000000
## [295] 0.4666667 0.7000000 0.2973241 0.3731343 0.2437043 0.2437043 0.1962067
## [302] 0.2535926 0.3054990 0.2373418 0.2702703 0.3324100 0.2437043 0.2702703
## [309] 0.2437043 0.3324100 0.2957122 0.2247191 0.2436054 0.2436054 0.2497918
## [316] 0.2445985 0.3225806 0.2285714 0.5000000 0.1968504 0.2497918 0.2727273
## [323] 0.2727273 0.3225806 0.3201708 0.7500000 0.3054990 0.3084833 0.3225806
## [330] 0.3058104 0.2957122 0.3134796 0.3488372 0.3519062 1.0000000 0.3051882
## [337] 0.2497918 0.3054990 0.3054990 0.2957122 0.3208556 0.3305785 0.2476269
## [344] 0.2897151 0.3051882 0.2761160 0.2976190 0.1990710 0.2976190 0.2957122
## [351] 0.2954210 0.2476269 1.0000000 0.3025719 0.2954210 0.2727273 0.3028773
## [358] 0.2476269 0.2475248 0.2954210 0.3134796 0.2727273 0.2282237 0.2954210
## [365] 0.3095975 0.2954210 0.5000000 0.2444988 0.3612282 0.2955665 0.3488372
## [372] 0.3612282 1.0000000 0.3412969 0.3838772 0.3488372 0.2535926 0.2497918
## [379] 0.3612282 0.2962963 0.2497918 0.3033367 1.0000000 0.3033367 0.2976190
## [386] 0.2727273 0.3612282 0.2954210 0.3034901 1.0000000 0.3134796 0.2954210
## [393] 0.2575107 0.2468120 0.1990710 0.3612282 0.2535926 0.8000000 0.2976190
## [400] 0.3612282 0.2252252 0.1816530 0.3255562 0.1990710 0.3033367 0.2436054
## [407] 0.2962963 0.3033367 0.2150538 0.2962963 0.2670227 1.0000000 0.2791996
## [414] 0.2727273 0.2532714 0.3189793 0.3612282 0.3612282 0.3612282 0.2958580
## [421] 0.3506721 0.3612282 0.2902758 0.2897151 0.2535926 0.2954210 0.3084833
## [428] 0.1996672 0.3893576 0.3134796 0.3084833 0.3084833 0.2954210 0.3084833
## [435] 0.3084833 0.2902758 0.2954210 0.2954210 0.3506721 0.3084833 0.3391747
## [442] 0.2284844 0.4026846 0.2897151 0.2897151 0.2340094 0.2964427 0.2897151
## [449] 0.2801120 0.2954210 0.2954210 0.3084833 0.3255562 0.2770083 0.3255562
## [456] 0.3255562 0.1996672 0.3084833 0.2476269 0.1667593 0.1998668 0.1998668
## [463] 0.2535926 0.2536998 0.2024291 0.2535926 1.0000000 0.2408671 0.2583979
## [470] 0.1747234 0.3134796 0.3255562 0.1932990 0.2108963 0.3612282 0.3612282
## [477] 0.7500000 0.2436054 0.2262443 0.3612282 0.3612282 0.1816530 0.2216476
## [484] 0.2752294 0.3255562 0.3612282 0.2962963 0.3033367 0.3033367 0.2340094
## [491] 1.0000000 0.2207506 1.0000000 0.2437043 1.0000000 0.2150538 1.0000000
## [498] 0.3255562 1.0000000 0.3612282 0.2730997 0.3973510 0.2400960 0.2400960
## [505] 0.2340094 1.0000000 1.0000000 0.2730997 0.1988731 0.3255562 0.2188982
## [512] 0.2710027 0.2063983 0.2401922 0.3255562 0.2400960 1.0000000 0.2400960
## [519] 0.2400960 0.2445985 0.2702703 0.1990710 0.1835424 0.2702703 0.2702703
## [526] 0.2188982 0.2876318 0.2876318 0.3612282 0.2535926 0.2535926 0.3612282
## [533] 0.2535926 0.2824859 0.2278769 0.3255562 0.2477291 0.2425222 0.2425222
## [540] 0.2816901 0.1953125 0.2748511 0.3612282 0.2539145 0.2748511 0.2748511
## [547] 0.2748511 0.2748511 0.2748511 1.0000000 0.5833333 1.0000000 0.2235469

```

```

## [554] 0.2235469 0.2053388 0.2535926 0.2535926 0.2670227 0.1667593 0.2235469
## [561] 0.2278769 0.2770083 0.2053388 0.1667593 0.2816901 0.2235469 0.2770083
## [568] 0.2670227 0.2770083 0.2770083 0.2150538 0.2770083 0.2535926 0.2150538
## [575] 0.2535926 0.2535926 0.3255562 0.2334630 0.2027712 0.2713704 0.2535926
## [582] 0.2535926 0.3255562 0.2334630 0.3255562 0.2334630 0.3255562 0.2846300
## [589] 0.3206841 0.2535926 0.2535926 0.3255562 0.2846300 0.3105590 0.3022670
## [596] 0.3022670 0.3022670 0.3022670 0.3022670 0.3022670 1.0000000 0.2976190
## [603] 0.2468120 0.3022670 0.3022670 0.2445985 0.2548853 0.3105590 0.3105590
## [610] 0.2444988 0.2590674 1.0000000 0.3255562 0.2443992 0.2846300 0.3105590
## [617] 0.2446982 0.2446982 0.3105590 0.2727273 1.0000000 0.3359462 0.3255562
## [624] 0.3255562 0.3255562 0.2548853 0.3000000 0.3255562 1.0000000 0.3612282
## [631] 0.2248033 0.1837110 0.2248033 0.2670227 1.0000000 0.4666667 0.6000000
## [638] 1.0000000 0.6153846 0.5000000 0.5000000 0.6153846 1.0000000 0.7272727
## [645] 0.7272727 0.7272727 0.7272727 1.0000000 1.0000000 1.0000000 1.0000000
## [652] 0.1988731 0.2475248 0.6666667 0.8000000 0.3612282 0.2670227 0.2714932
## [659] 0.2295333 0.1965924 0.3612282 0.2285714 0.2285714 0.2759890 0.3033367
## [666] 0.2714932 0.3033367 1.0000000 0.1645639 0.3255562 0.2235469 0.2730997
## [673] 0.3084833 0.3218884 0.3224073 0.2670227 0.3084833 0.2474227 0.2193784
## [680] 0.2730997 0.2670227 0.2437043 0.2835539 0.2671416 0.2638522 0.3387916
## [687] 0.3134796 0.2827521 0.2961500 0.2770083 0.2831524 0.2613240 0.2613240
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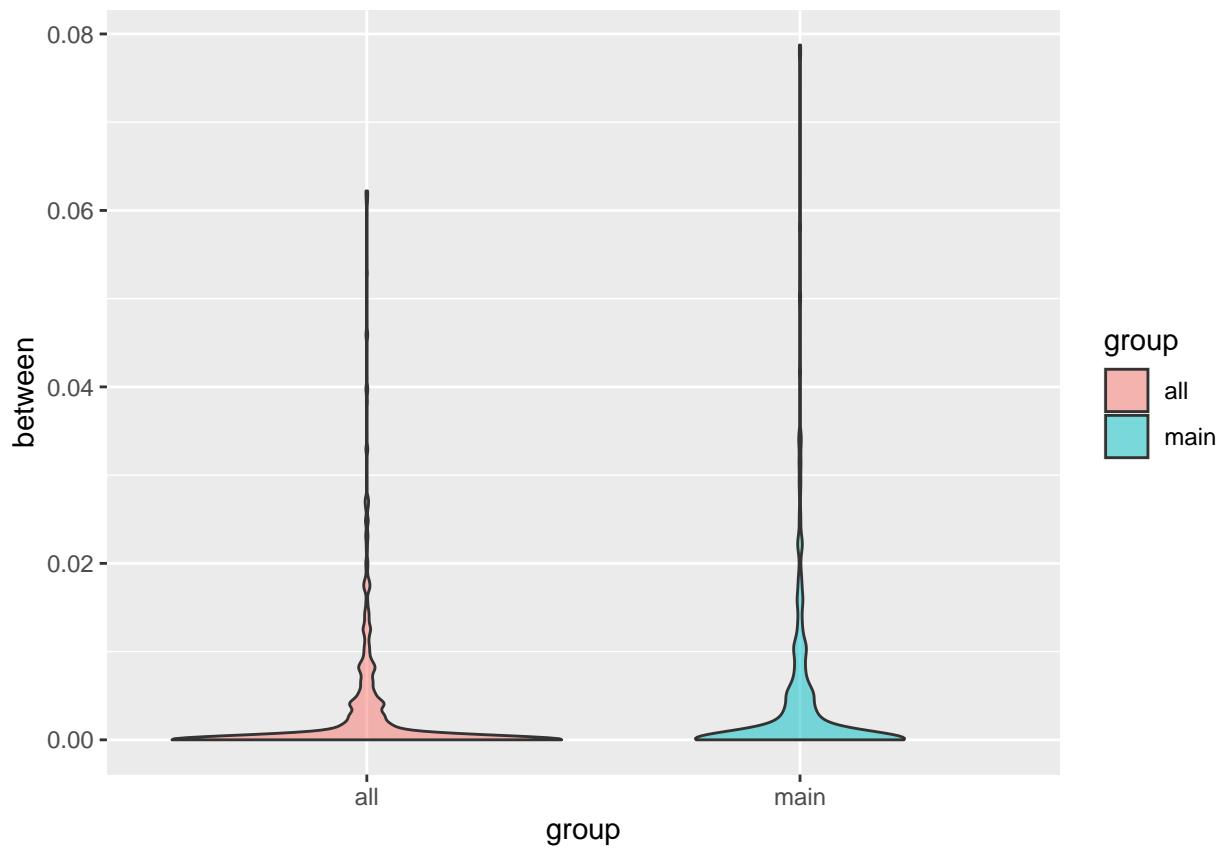
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#
ggplot(values[values$group%in%c("all","main"),],aes(x=group,y=between,fill=group))+geom_violin(alpha=0.5)

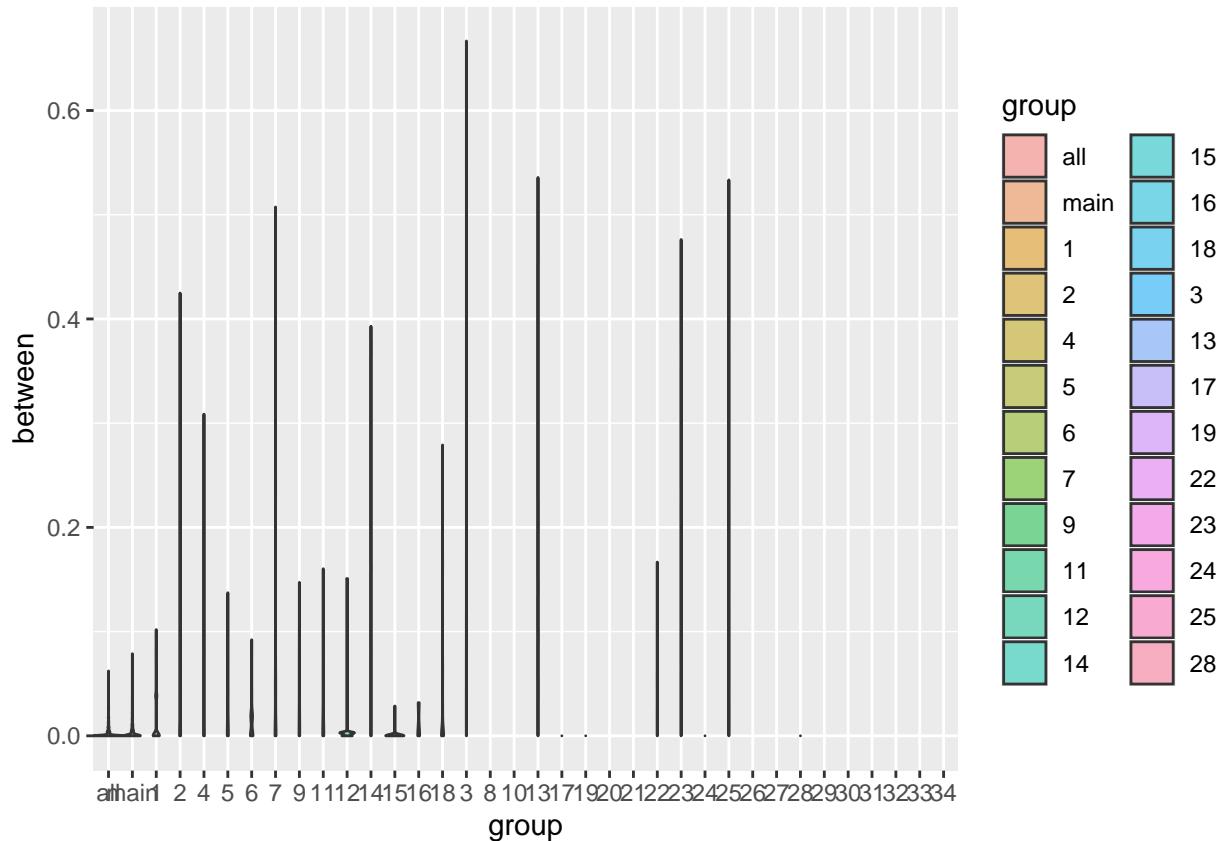
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```
ggplot(values,aes(x=group,y=between,fill=group))+geom_violin(alpha=0.5,width=1.25)

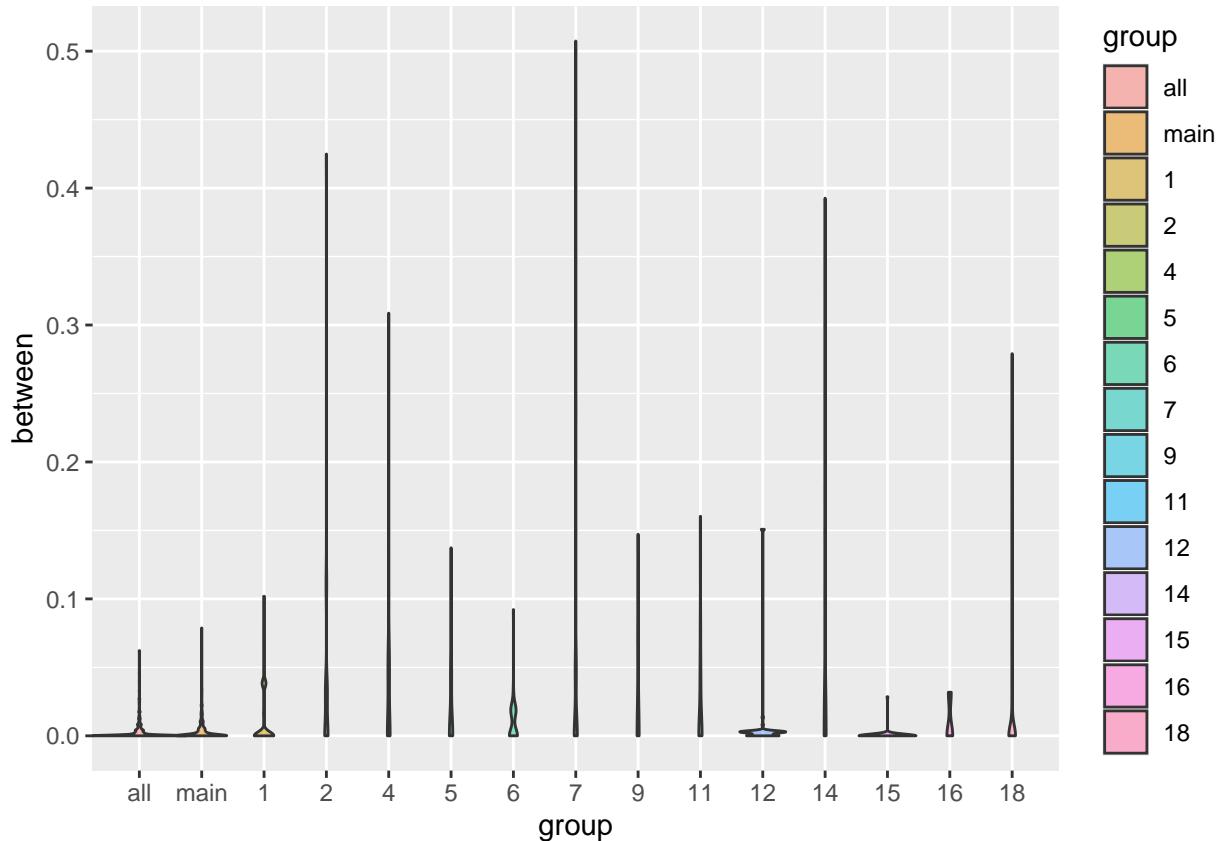
## Warning: Removed 24 rows containing non-finite values (stat_ydensity).

## Warning: position_dodge requires non-overlapping x intervals
```



```
ggplot(values[values$group%in%c("all", "main", 1, 2, 4, 5, 6, 7, 9, 11, 12, 14, 15, 16, 18), ],
       aes(x=group, y=between, fill=group))+geom_violin(alpha=0.5, width=1.5)
```

```
## Warning: position_dodge requires non-overlapping x intervals
```



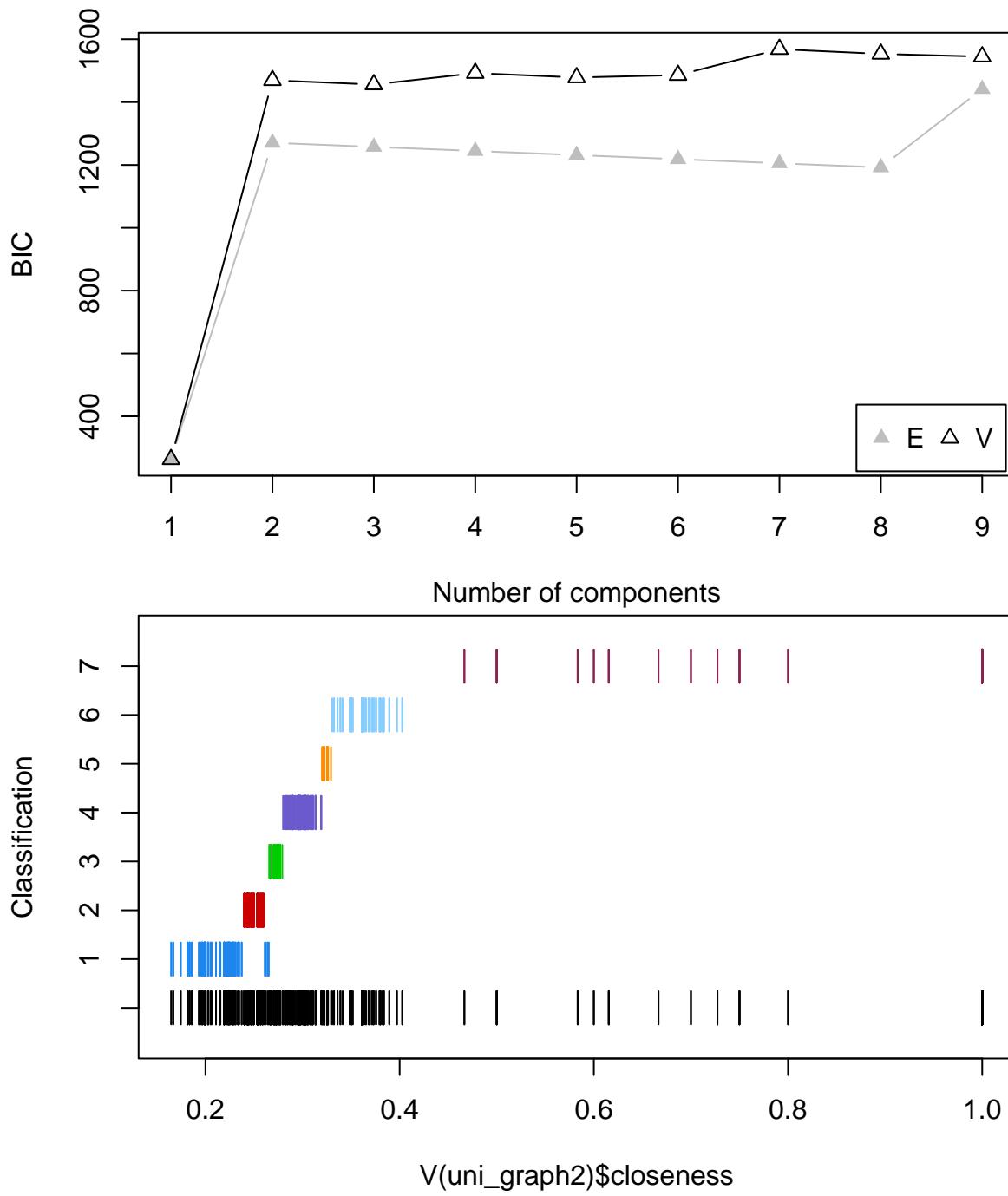
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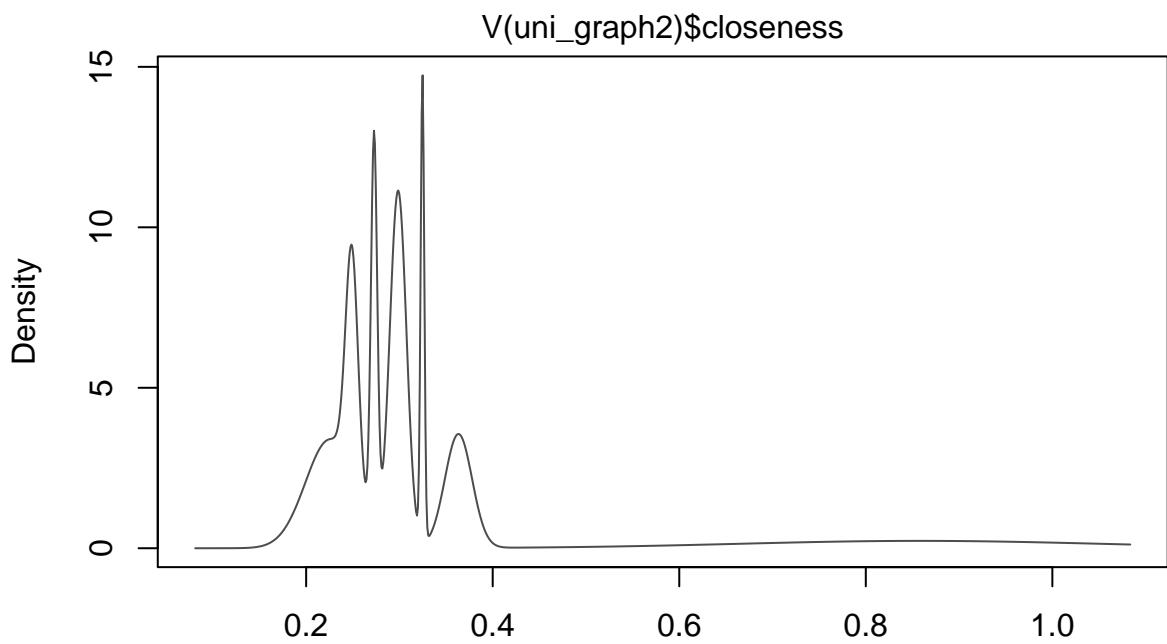
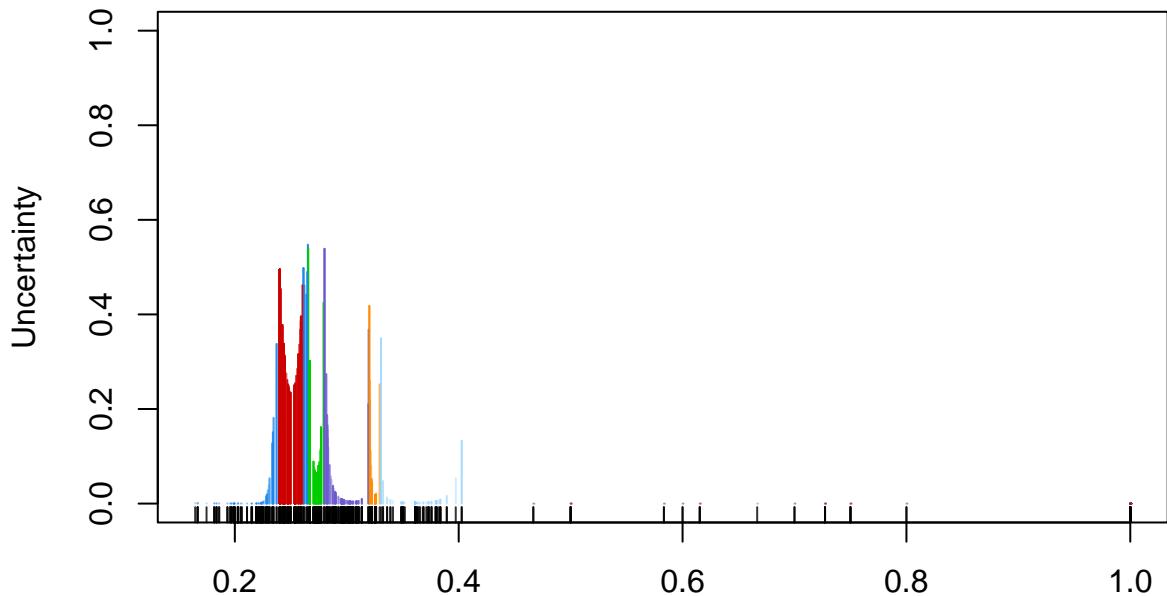
#
#
#
#
# Cuantos grupos de closeness hay usando una mezcla de normales?
#
library(mclust)

## Package 'mclust' version 5.4.9
## Type 'citation("mclust")' for citing this R package in publications.
##
## Attaching package: 'mclust'
## The following object is masked from 'package:maps':
##      map

V(uni_graph2)$outdegree  <- degree(uni_graph2, mode = "out")
V(uni_graph2)$closeness   <- closeness(uni_graph2, mode = "total", normalized = TRUE)
V(uni_graph2)$betweenness <- betweenness(uni_graph2, normalized = TRUE)
clustering_closeness<-Mclust(V(uni_graph2)$closeness)
plot(clustering_closeness)

```





V(uni_graph2)\$closeness

```
table(clustering_closeness$classification)
```

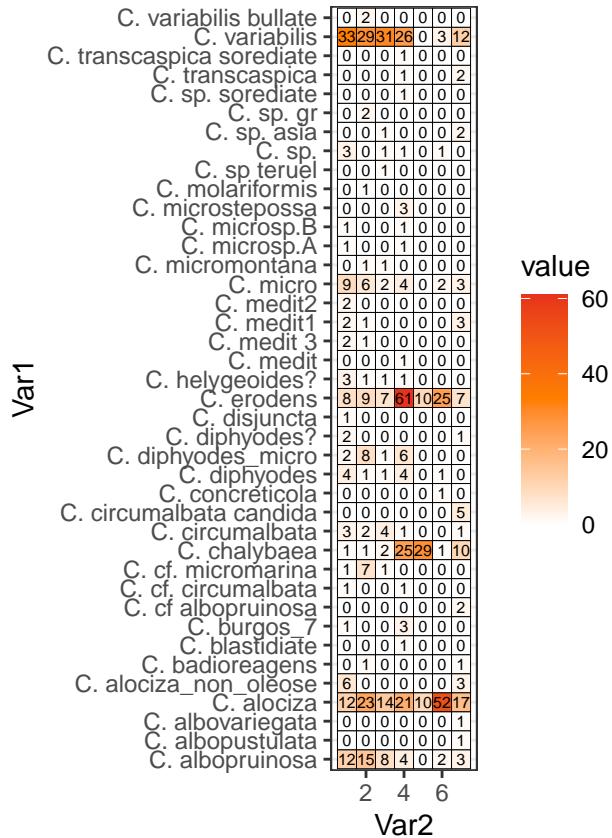
```
##  
##   1   2   3   4   5   6   7  
## 110 111   76 168   49   88   74
```

```
foo_tabla<-melt(table(condensed_baps_adm[sapply(strsplit(names(V(uni_graph2)), "_"), `^`, 2), 2], clustering_closeness$classification))  
ggplot(foo_tabla,aes(x=Var2,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label = value))  
  scale_fill_gradient2(low = "#FFFFFF",  
                      mid = colorinos.bipolar[7],  
                      high = colorinos.bipolar[6],  
                      midpoint = 33,
```

```

        space = "Lab",
        na.value = "#FFFFFF",
        guide = "colourbar",
        aesthetics = "fill"
) + coord_fixed() + theme_bw()

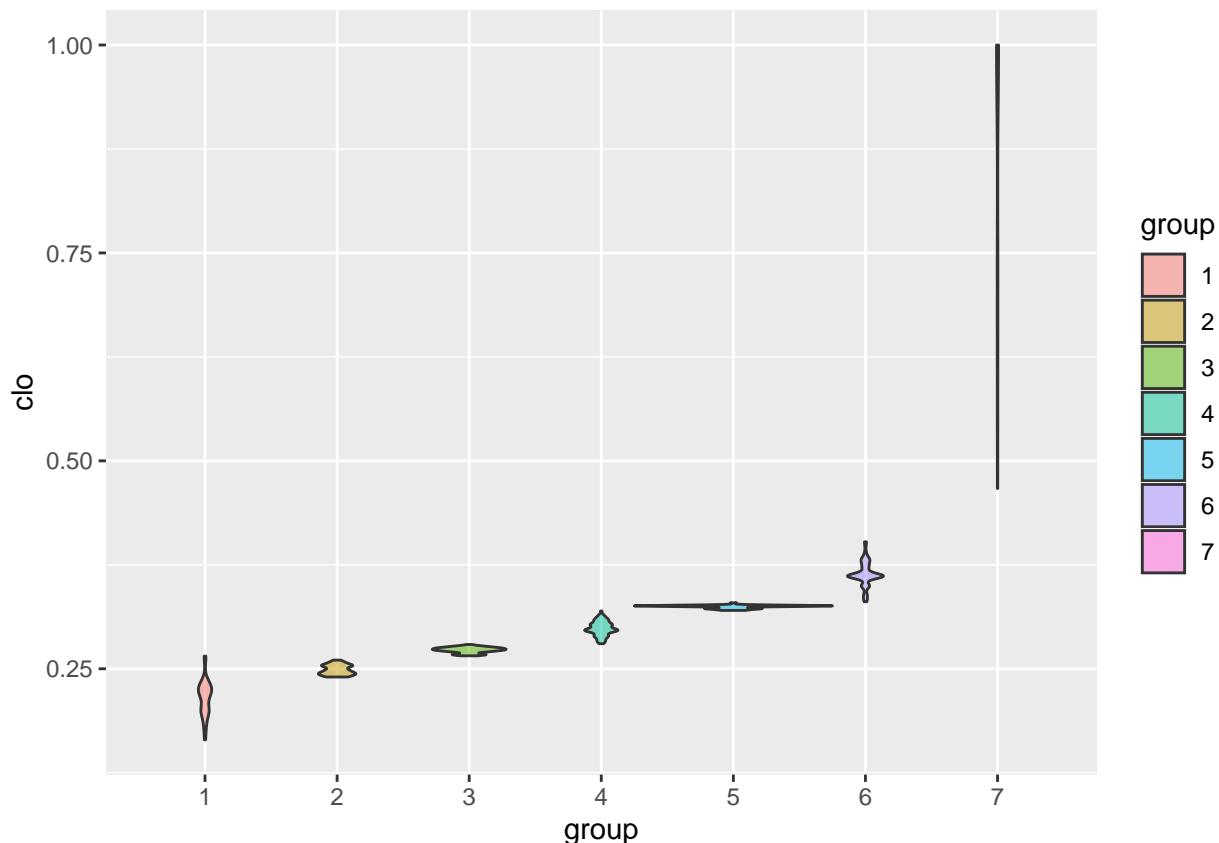
```

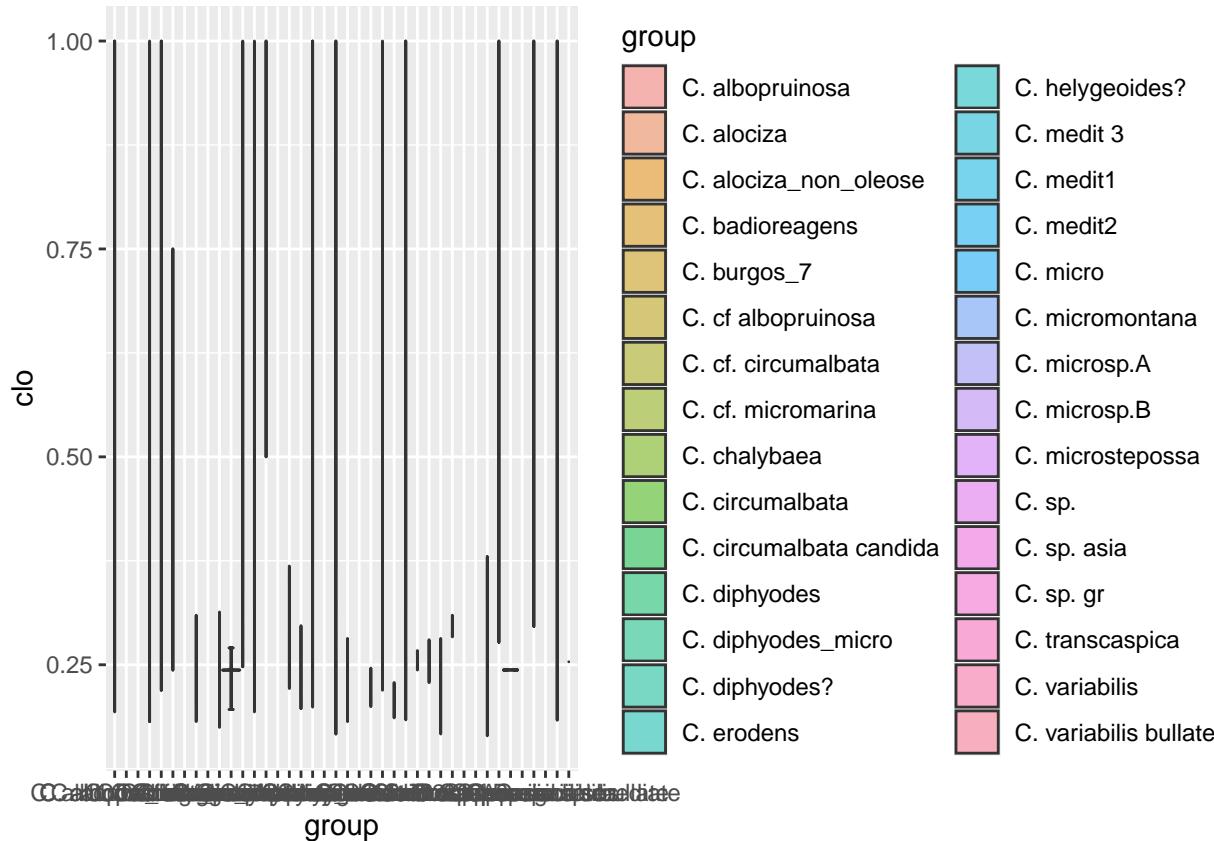


```

ggplot(data.frame(clo = V(uni_graph2)$closeness, group=factor(clustering_closeness$classification)),aes(
## Warning: position_dodge requires non-overlapping x intervals

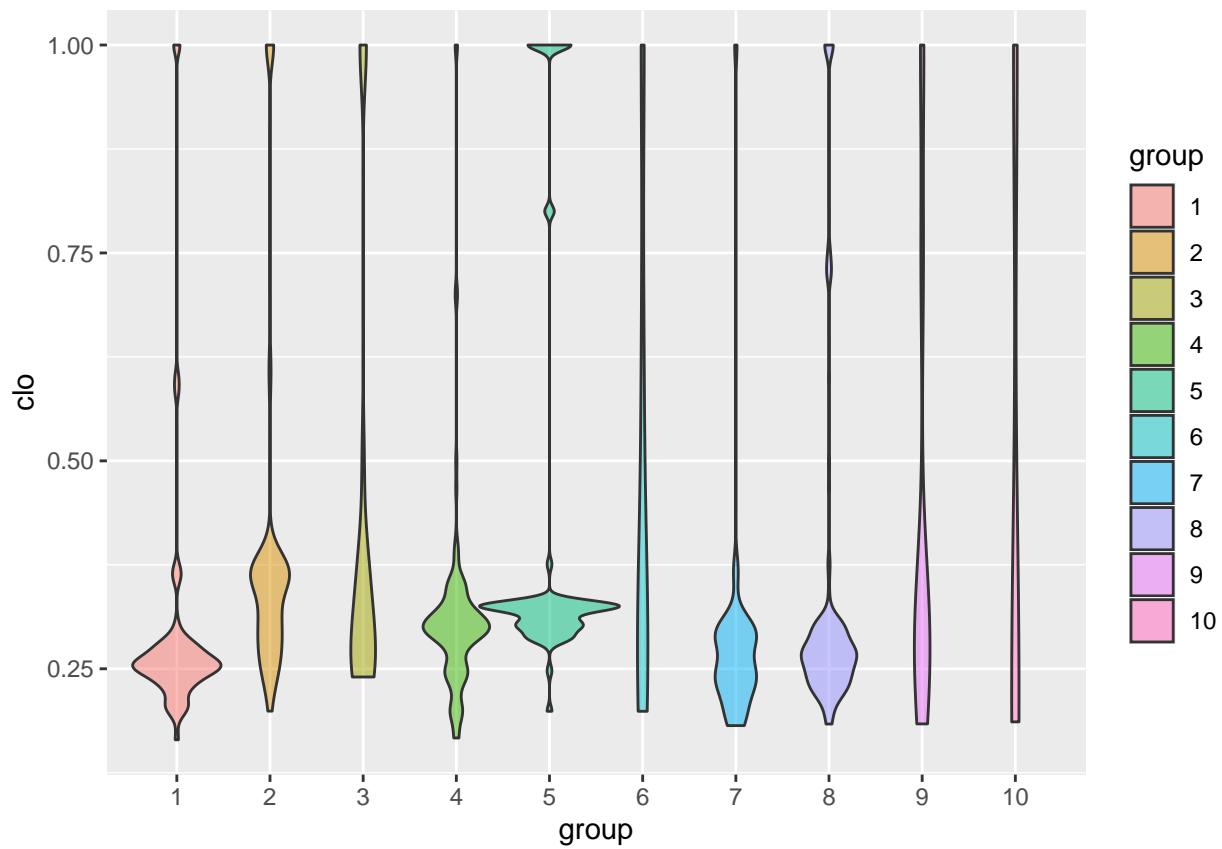
```





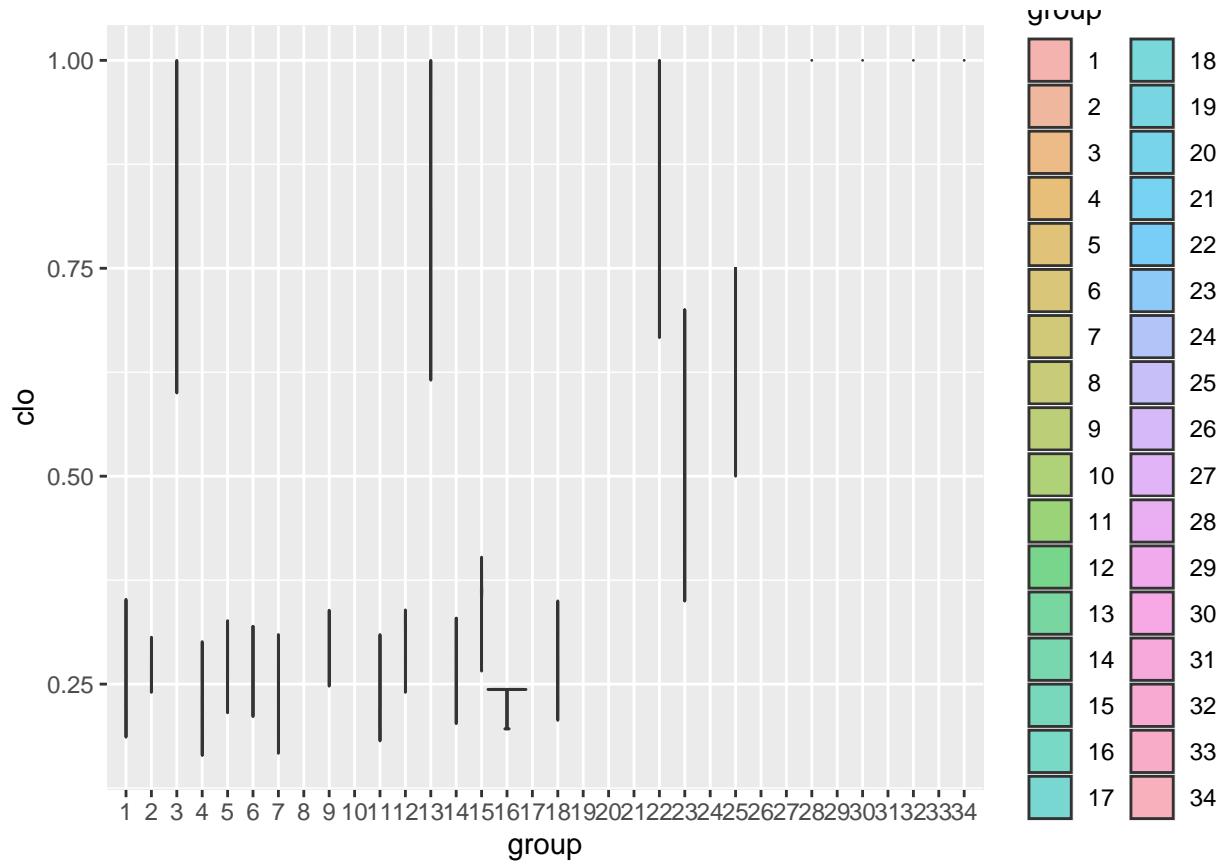
```
ggplot(data.frame(clo = V(uni_graph2)$closeness, group=factor(condensed_baps_adm[sapply(strsplit(names(V
```

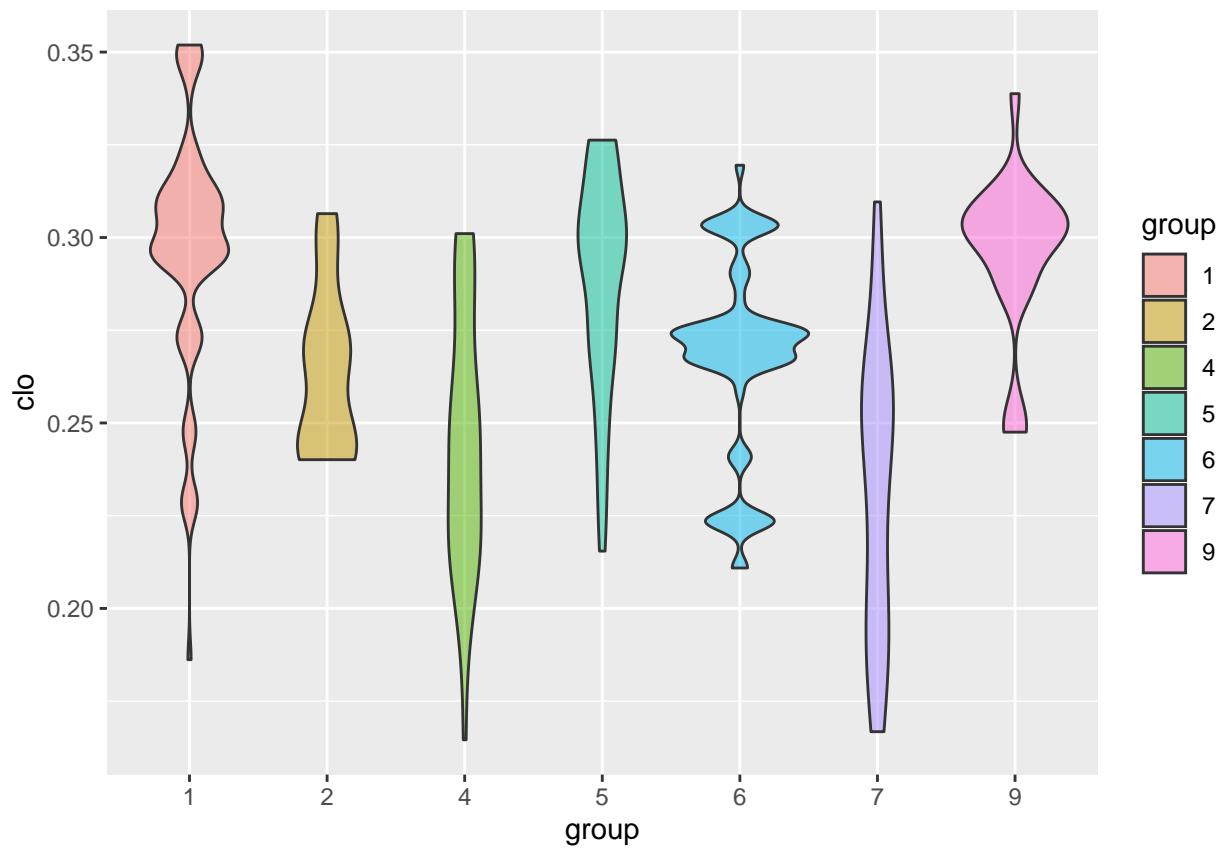
Warning: position_dodge requires non-overlapping x intervals



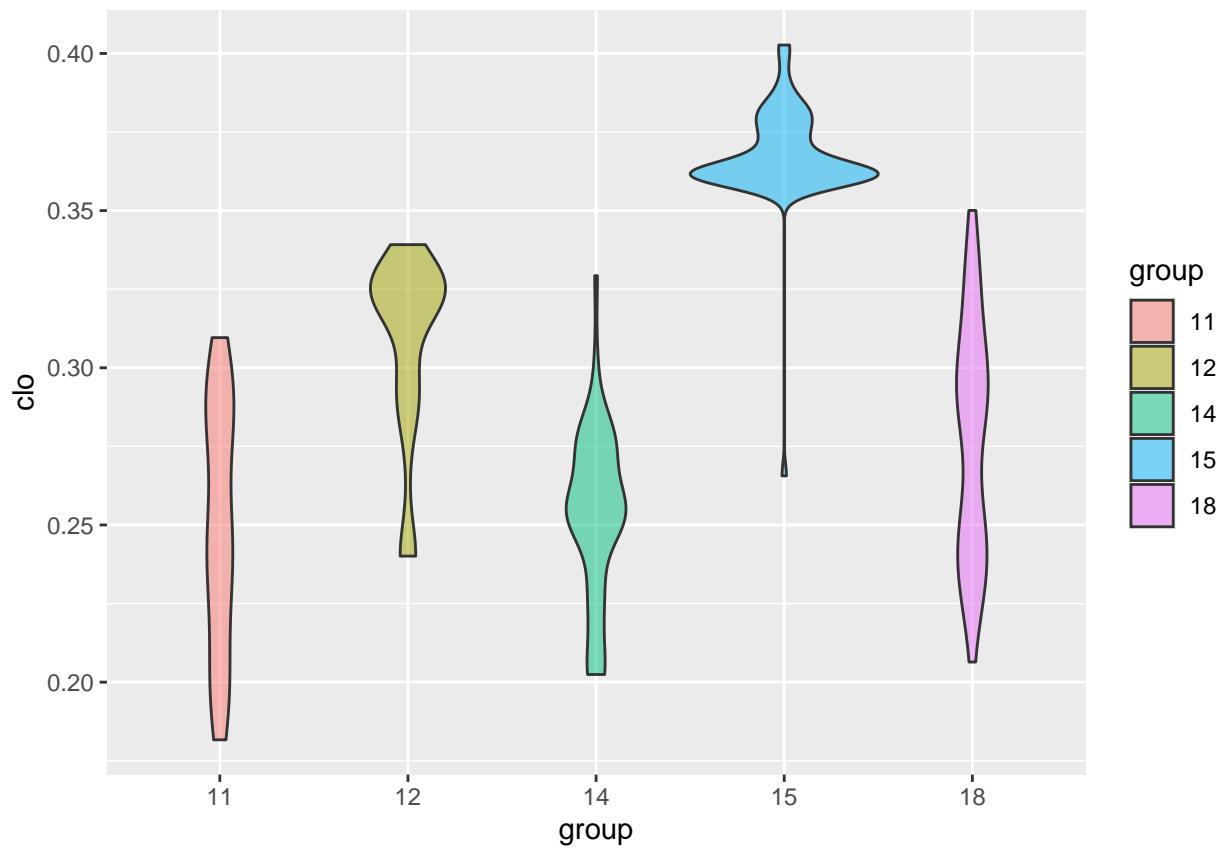
```
ferdframe<-data.frame(clo = V(uni_graph2)$closeness,group=factor(foo_modules[sapply(strsplit(names(V(uni
ggplot(ferdframe,
      aes(x=group,y=clo,fill=group))+geom_violin(alpha=0.5,width=1.5)
```

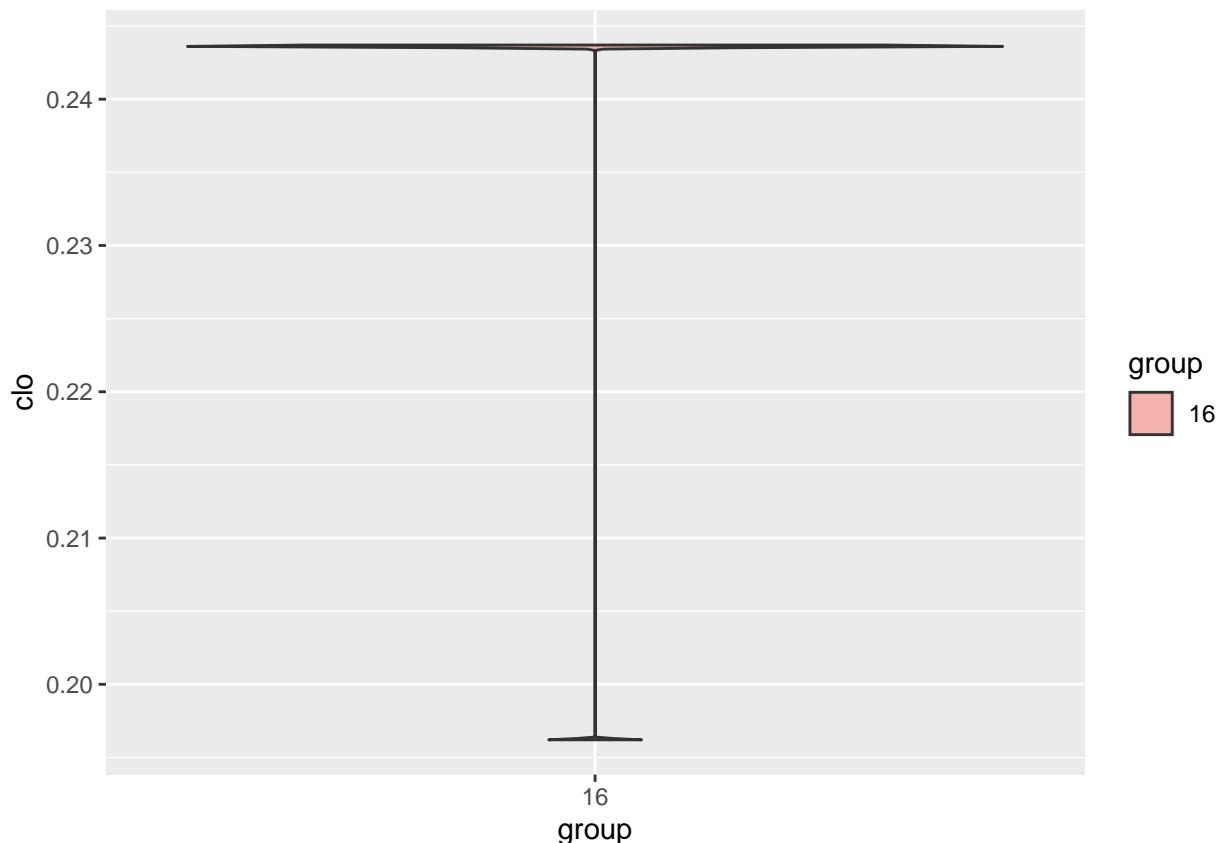
```
## Warning: position_dodge requires non-overlapping x intervals
```





```
ggplot(ferdframe[ferdframe$group%in%c(11,12,14,15,18),],  
       aes(x=group,y=clo,fill=group))+geom_violin(alpha=0.5,width=1)
```





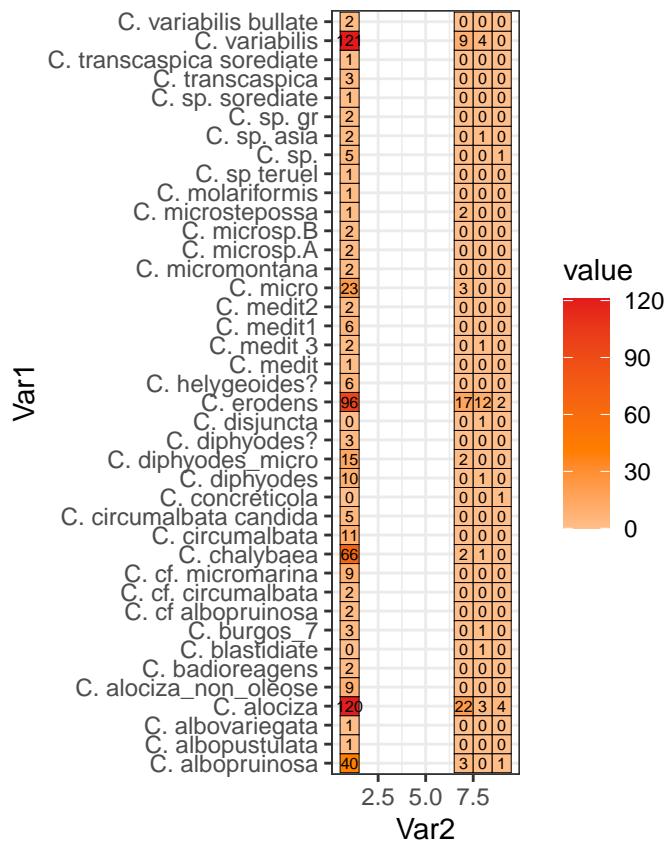
```

#
# Betweenness
#
clustering_closeness<-Mclust(V(uni_graph2)$betweeness)
table(clustering_closeness$classification)

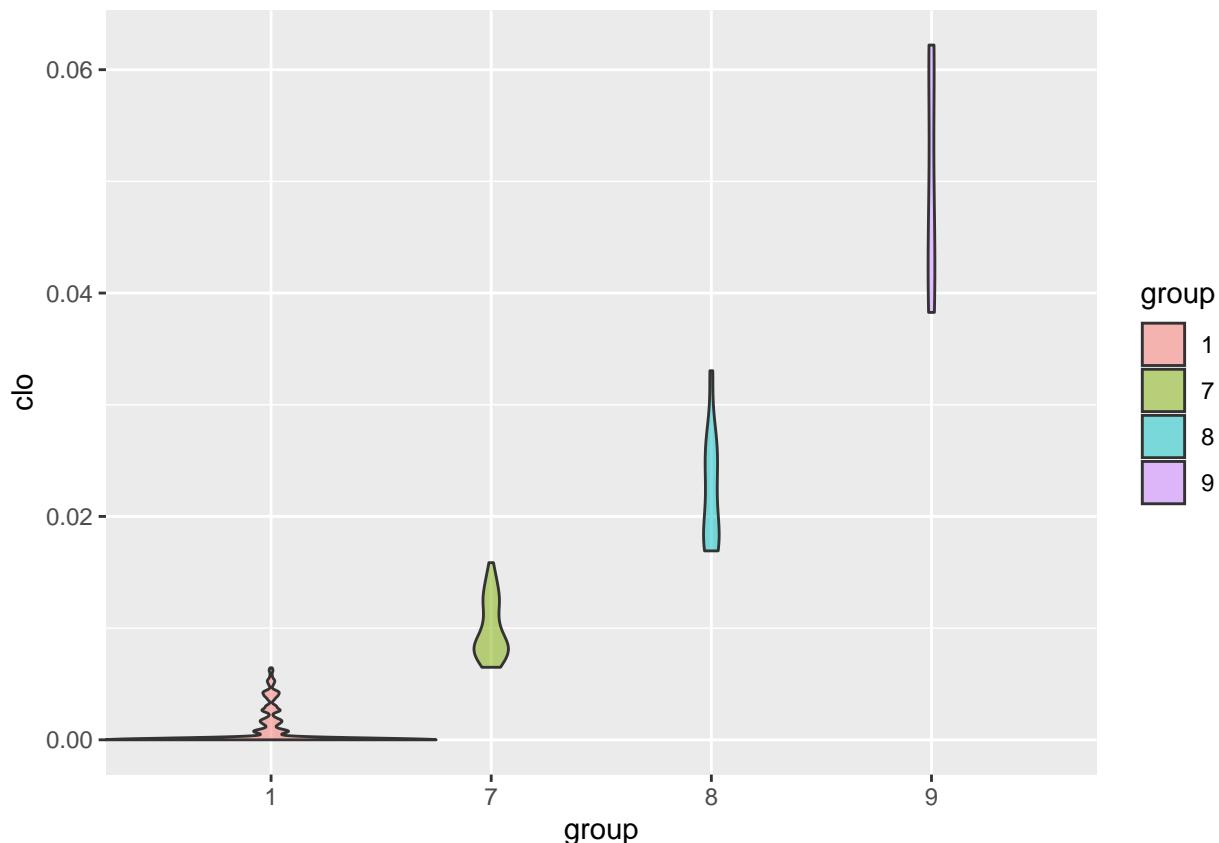
##
##    1    7    8    9
## 581   60   26    9

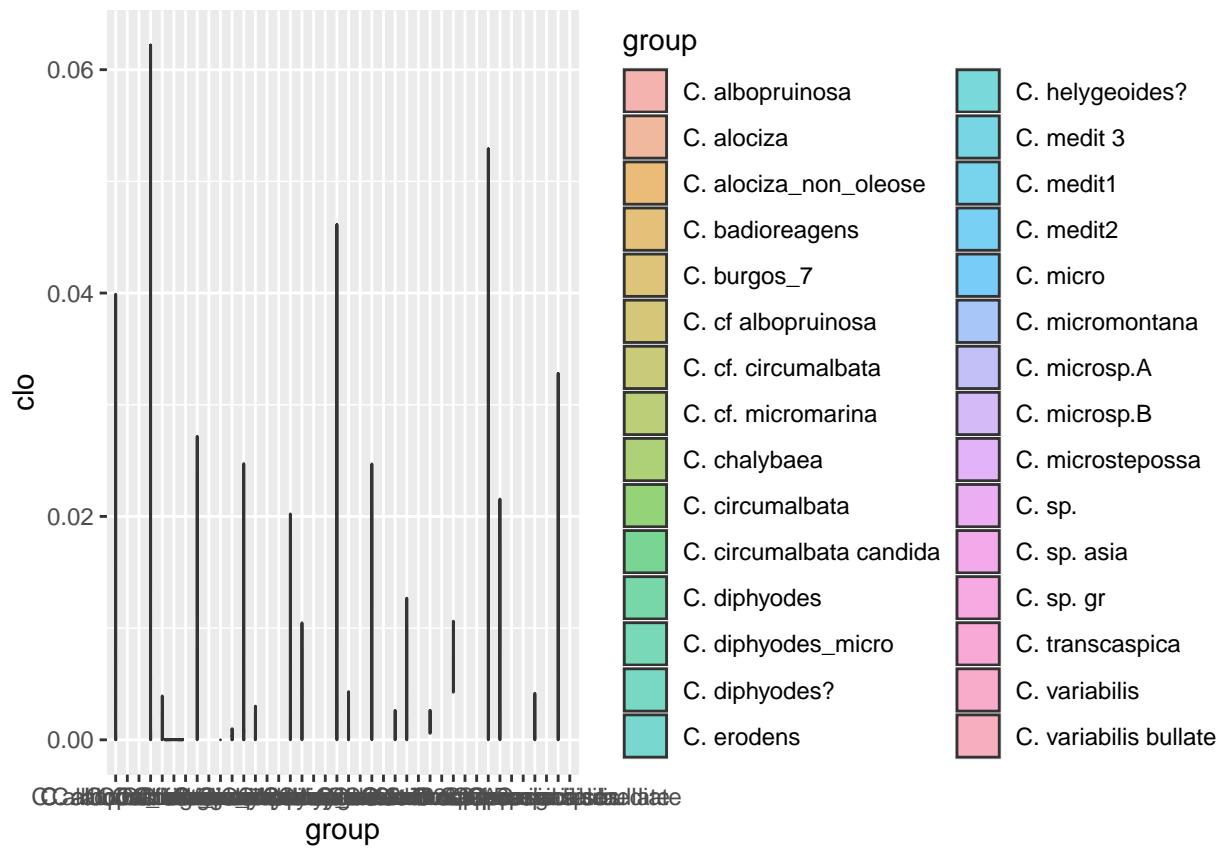
foo_tabla<-melt(table(condensed_baps_adm[sapply(strsplit(names(V(uni_graph2)),"_"),`[`,2),2],clustering_closeness))
ggplot(foo_tabla,aes(x=Var2,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label = value))
  scale_fill_gradient2(low = "#FFFFFF",
                        mid = colorinos.bipolar[7],
                        high = colorinos.bipolar[6],
                        midpoint = 40,
                        space = "Lab",
                        na.value = "#FFFFFF",
                        guide = "colourbar",
                        aesthetics = "fill"
  ) + coord_fixed() + theme_bw()

```



```
ggplot(data.frame(clo = V(uni_graph2)$betweeness,group=factor(clustering_closeness$classification)),aes
## Warning: position_dodge requires non-overlapping x intervals
```

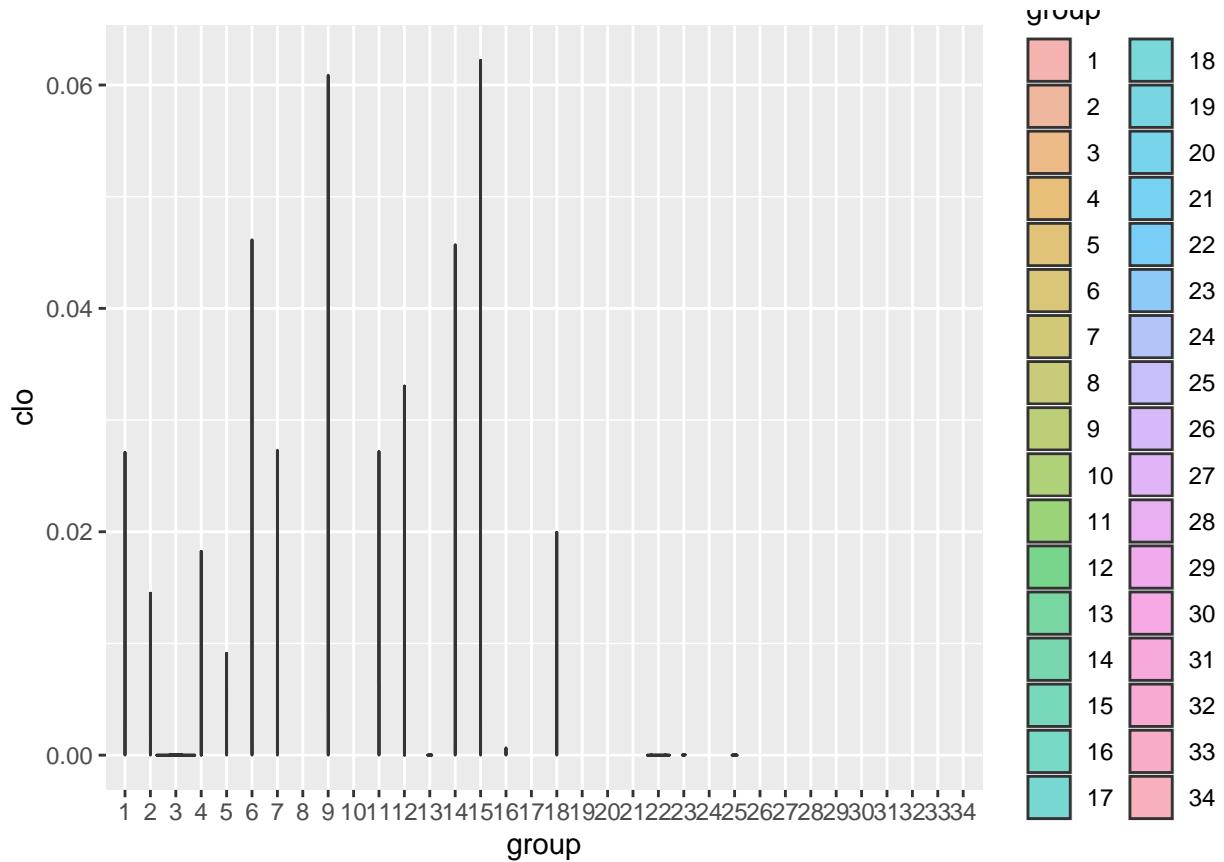




```
ggplot(data.frame(clo = V(uni_graph2)$betweenness, group=factor(foo_modules[sapply(strsplit(names(V(uni_g
    aes(x=group,y=clo,fill=group))+geom_violin(alpha=0.5,width=1.5)

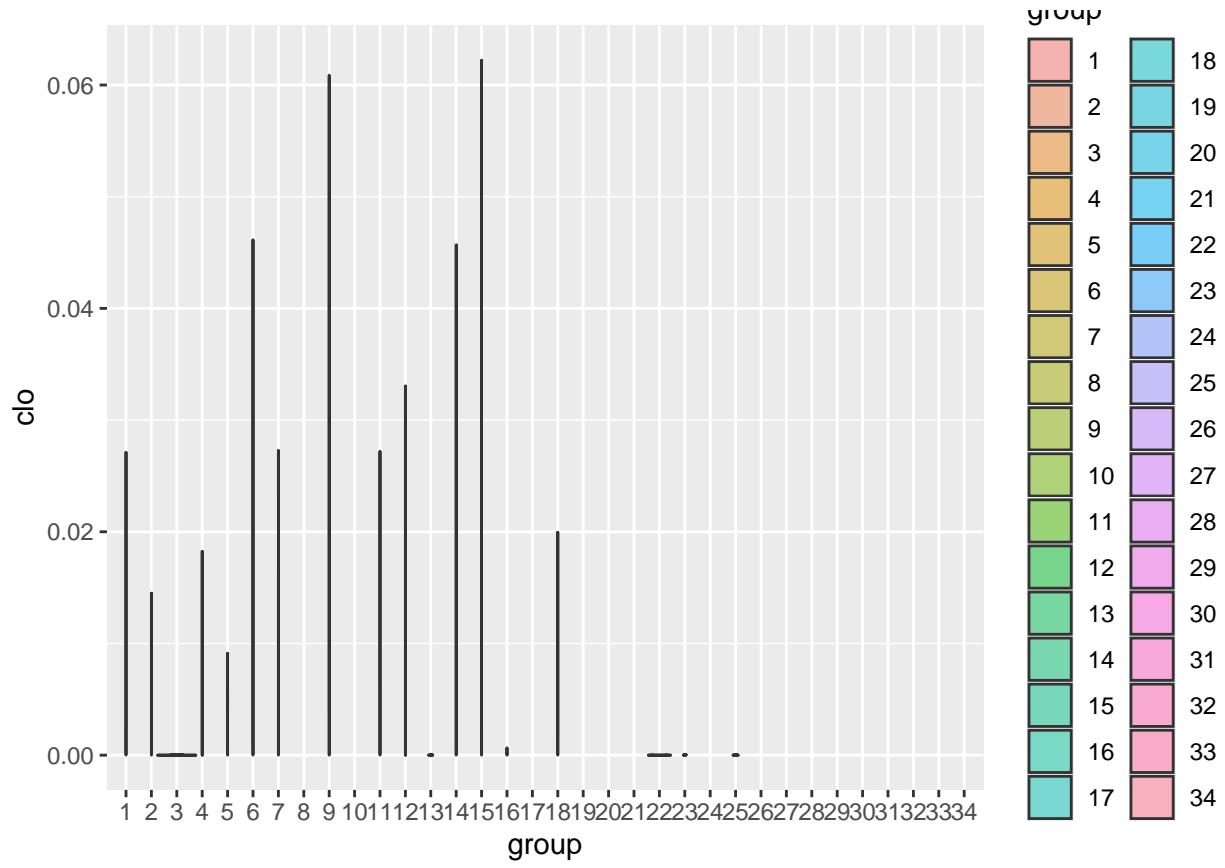
```

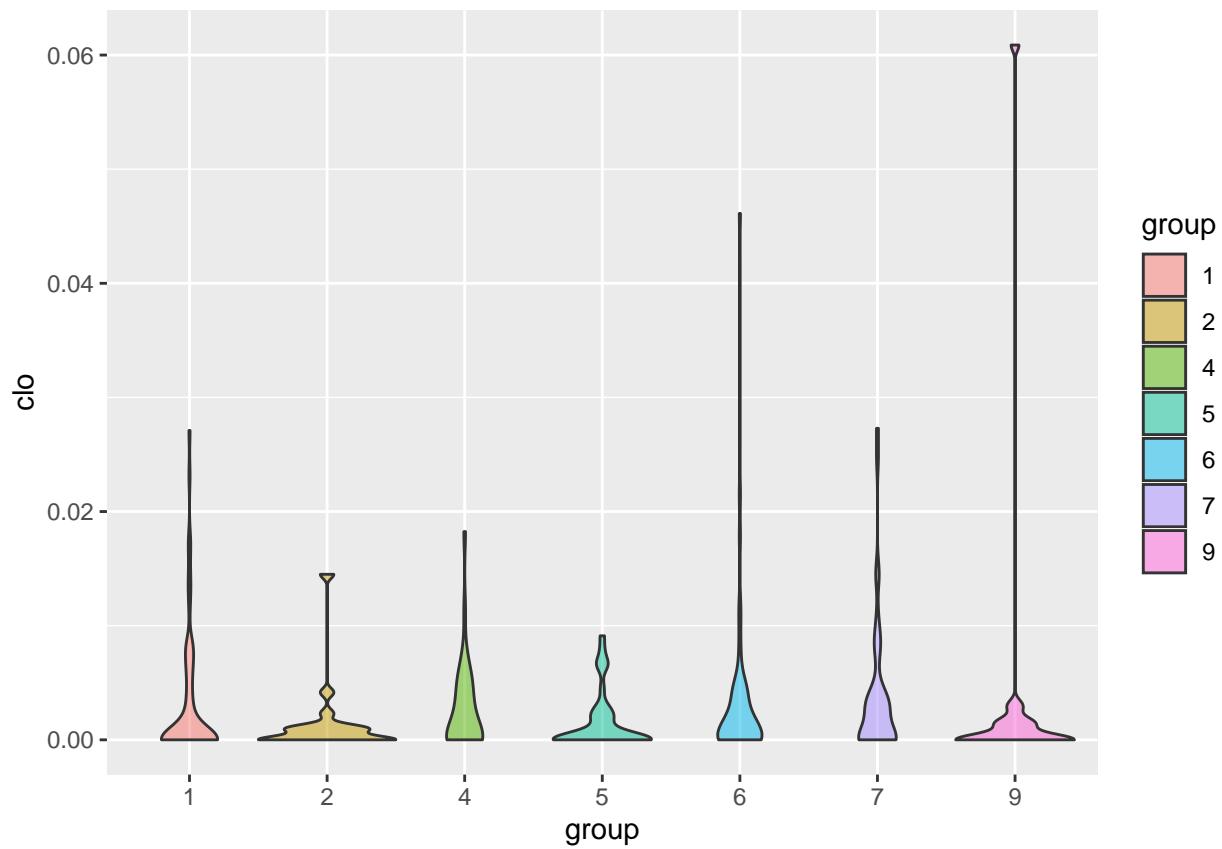
```
## Warning: position_dodge requires non-overlapping x intervals
```

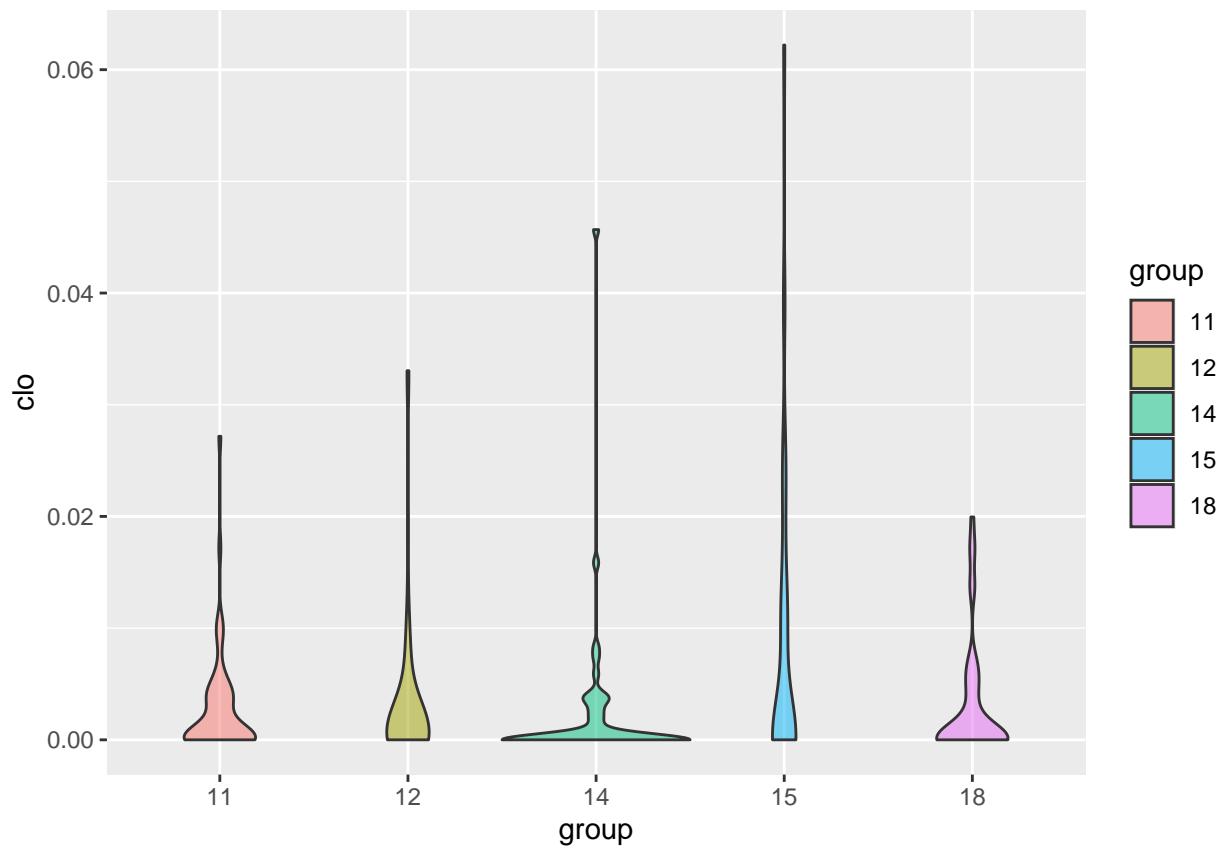


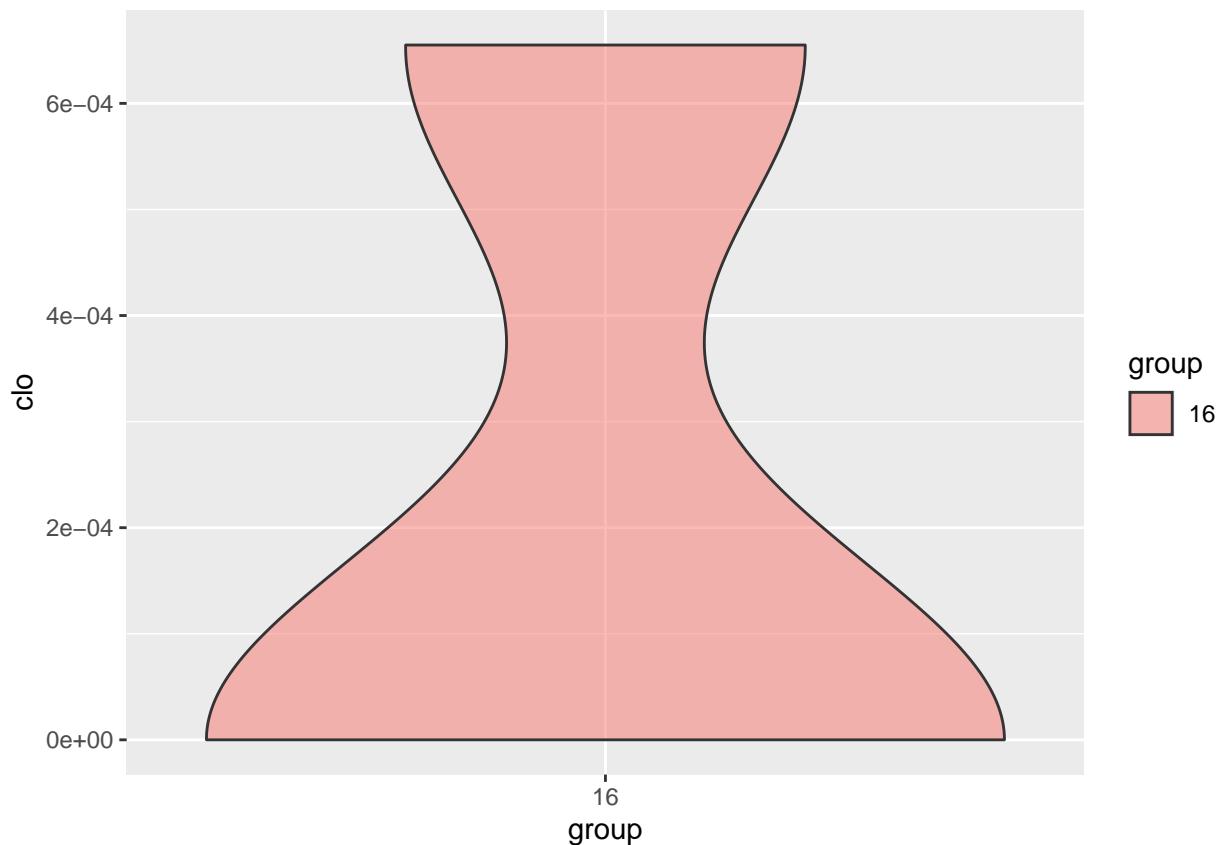
```
ferdframe<-data.frame(clo = V(uni_graph2)$betweenness,group=factor(foo_modules[sapply(strsplit(names(V(uni
ggplot(ferdframe,
    aes(x=group,y=clo,fill=group))+geom_violin(alpha=0.5,width=1.5)
```

```
## Warning: position_dodge requires non-overlapping x intervals
```









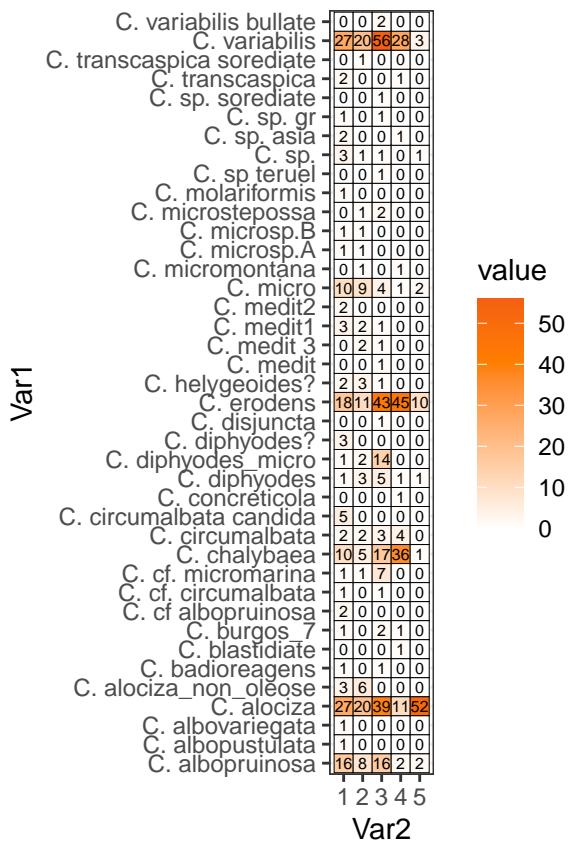
```

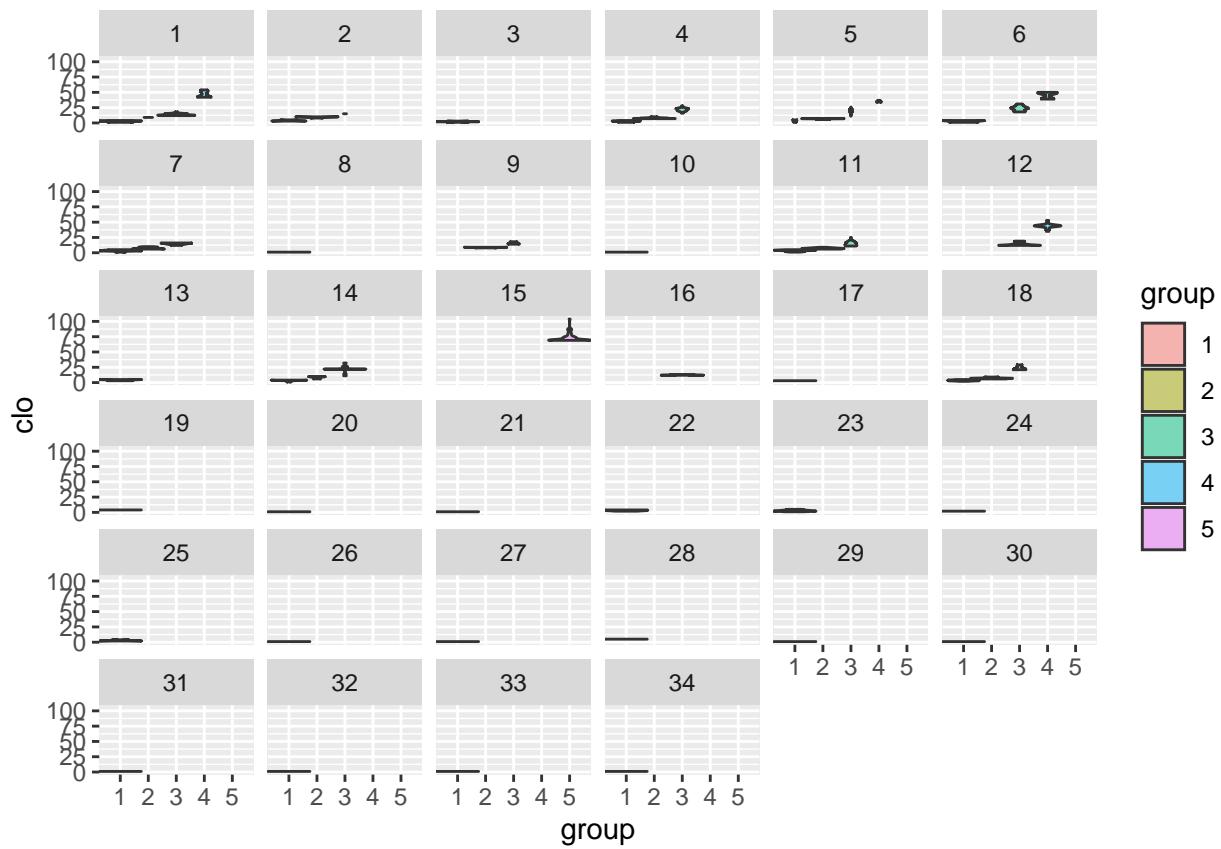
#
# Degree
#
clustering_closeness<-Mclust(V(uni_graph2)$outdegree)
table(clustering_closeness$classification)

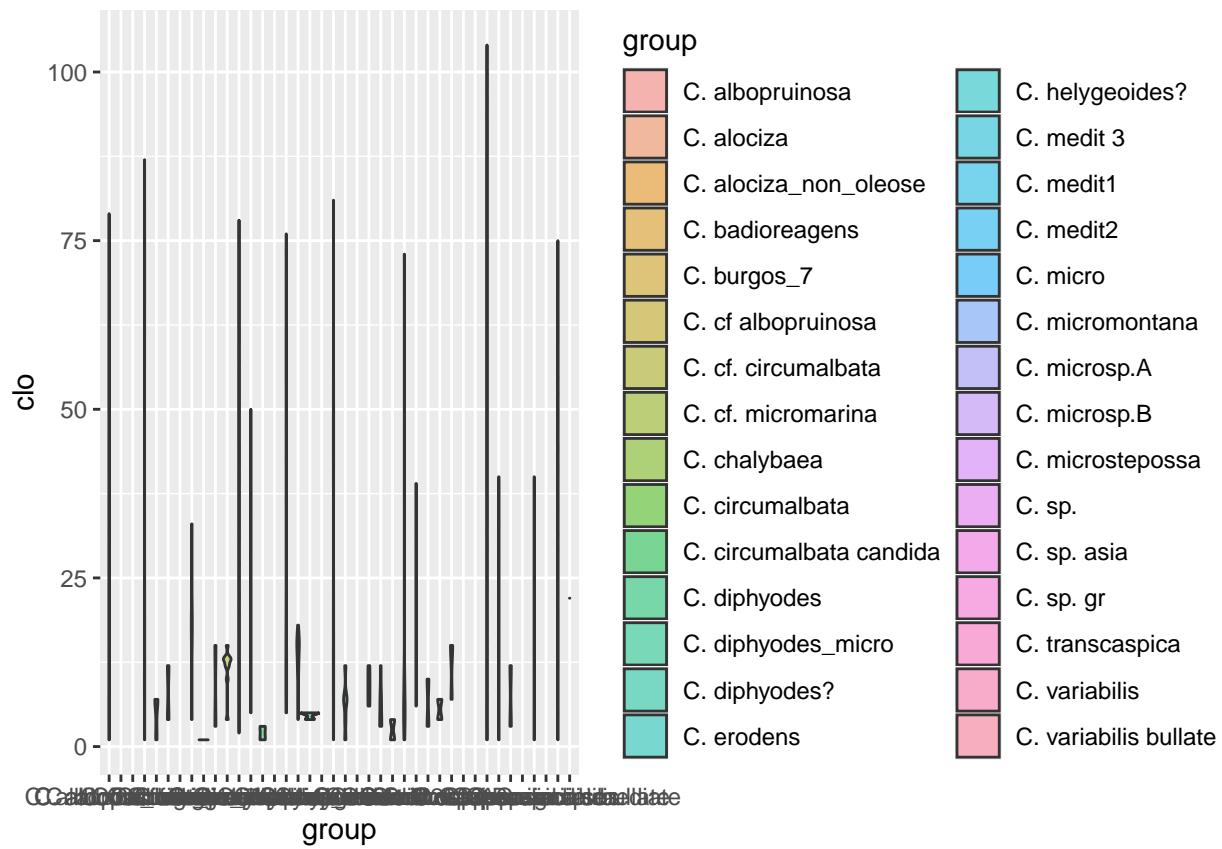
##
##    1    2    3    4    5
## 149 100 221 134  72

foo_tabla<-melt(table(condensed_baps_adm[sapply(strsplit(names(V(uni_graph2)),"_"),`[`,2),2],clustering_closeness))
ggplot(foo_tabla,aes(x=Var2,y=Var1,fill=value)) + geom_tile(color = "black") + geom_text(aes(label = value))
  scale_fill_gradient2(low = "#FFFFFF",
                        mid = colorinos.bipolar[7],
                        high = colorinos.bipolar[6],
                        midpoint = 40,
                        space = "Lab",
                        na.value = "#FFFFFF",
                        guide = "colourbar",
                        aesthetics = "fill"
  ) + coord_fixed() + theme_bw()

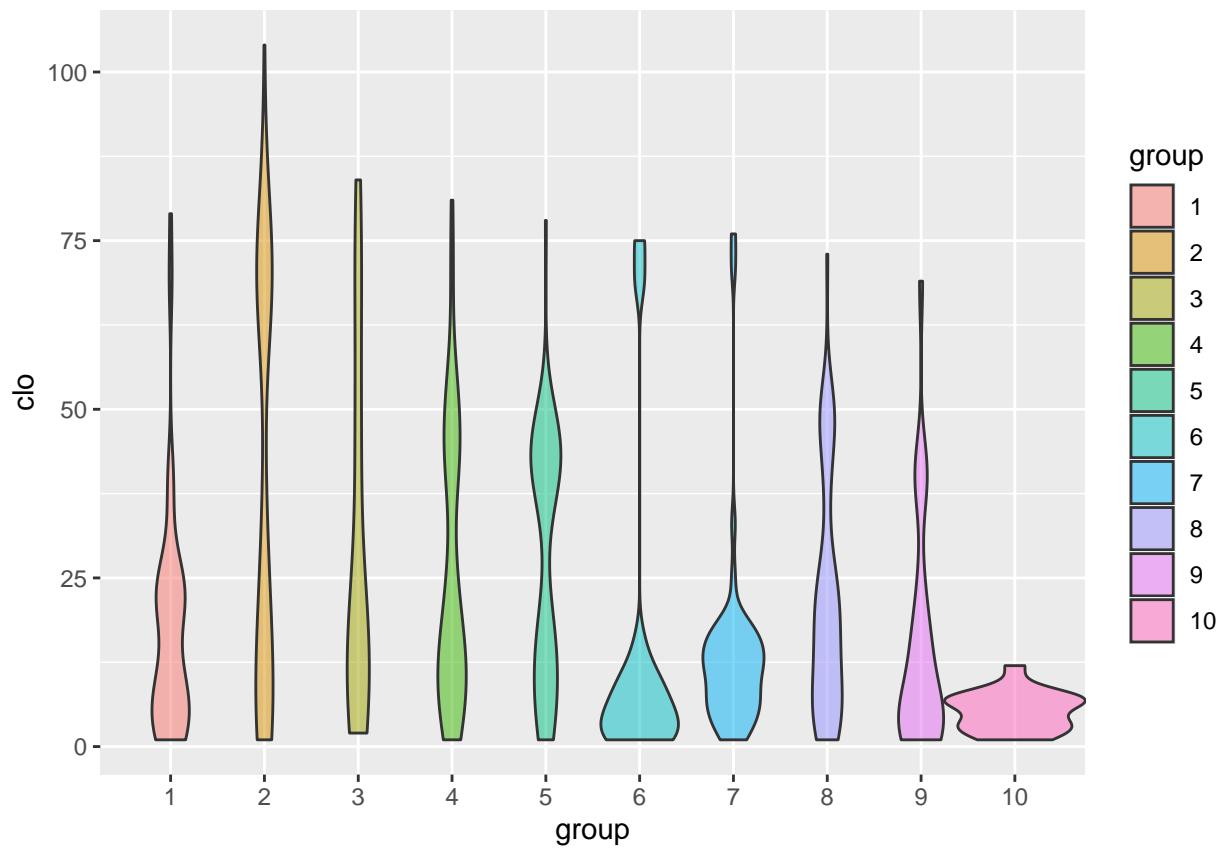
```







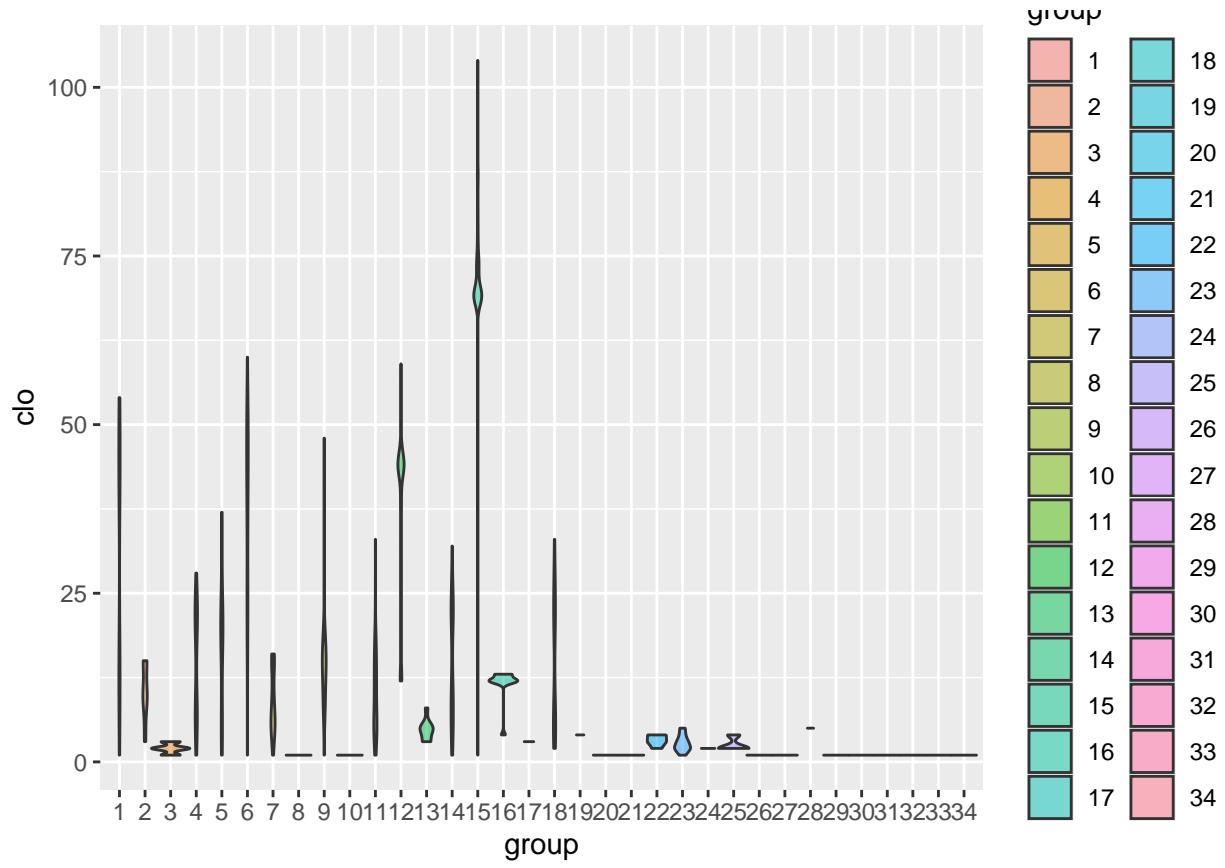
```
ggplot(data.frame(clo = V(uni_graph2)$outdegree, group=factor(condensed_baps_adm[sapply(strsplit(names(V(uni_graph2)), " "), trim=TRUE)]))) {  
  geom_dotplot(binwidth=1, dotsize=1, fill="white", dotinterior=c("black", "white"),  
               position=position_dodge(1))  
}  
## Warning: position_dodge requires non-overlapping x intervals
```

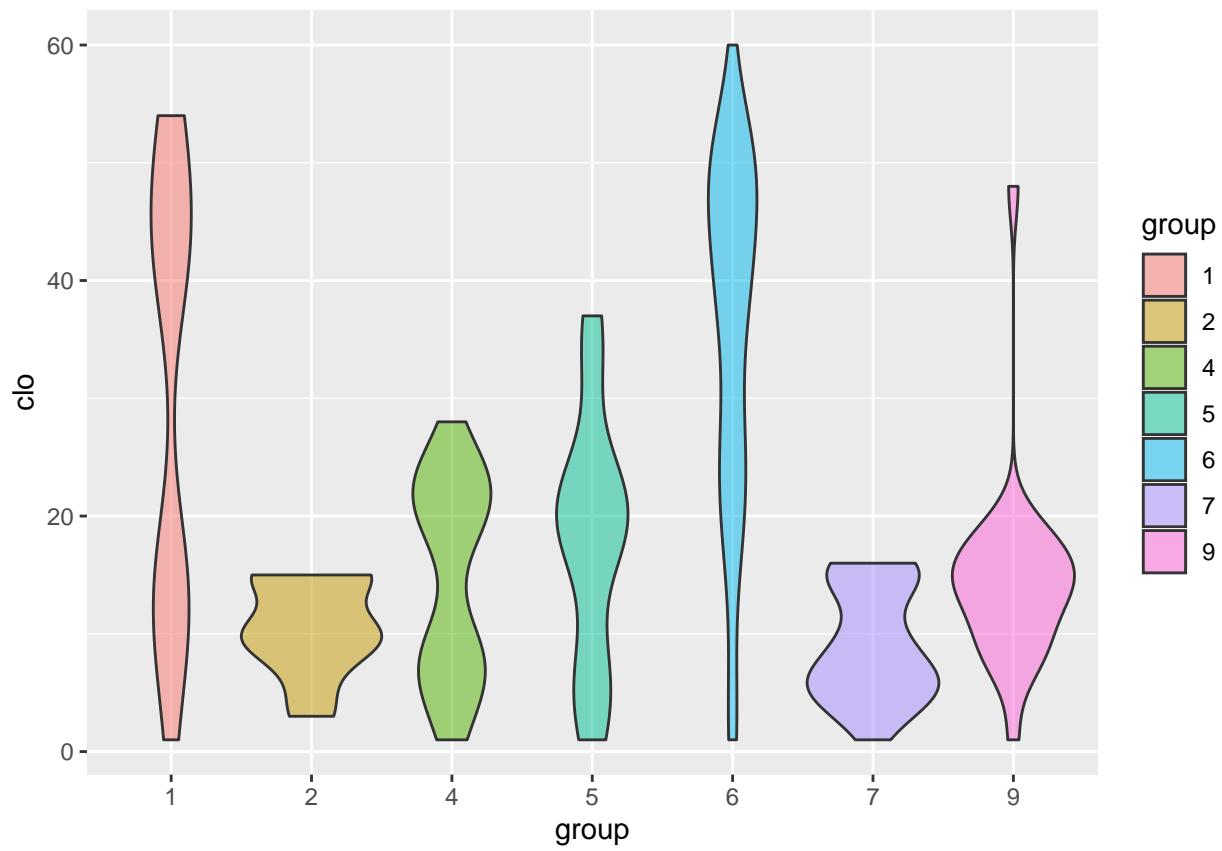


```

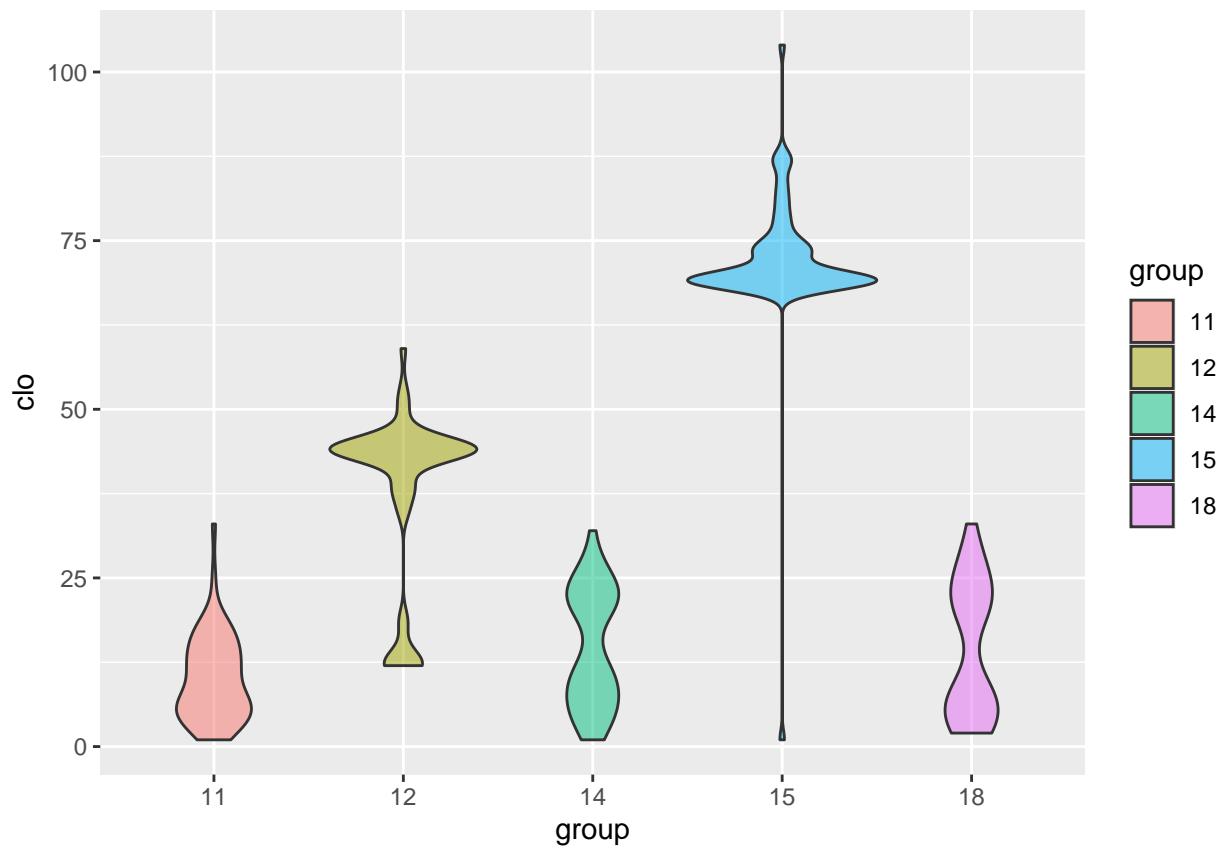
ferdframe<-data.frame(clo = V(uni_graph2)$outdegree,group=factor(foo_modules[sapply(strsplit(names(V(uni
ggplot(ferdframe,
    aes(x=group,y=clo,fill=group))+geom_violin(alpha=0.5,width=1.5)
## Warning: position_dodge requires non-overlapping x intervals

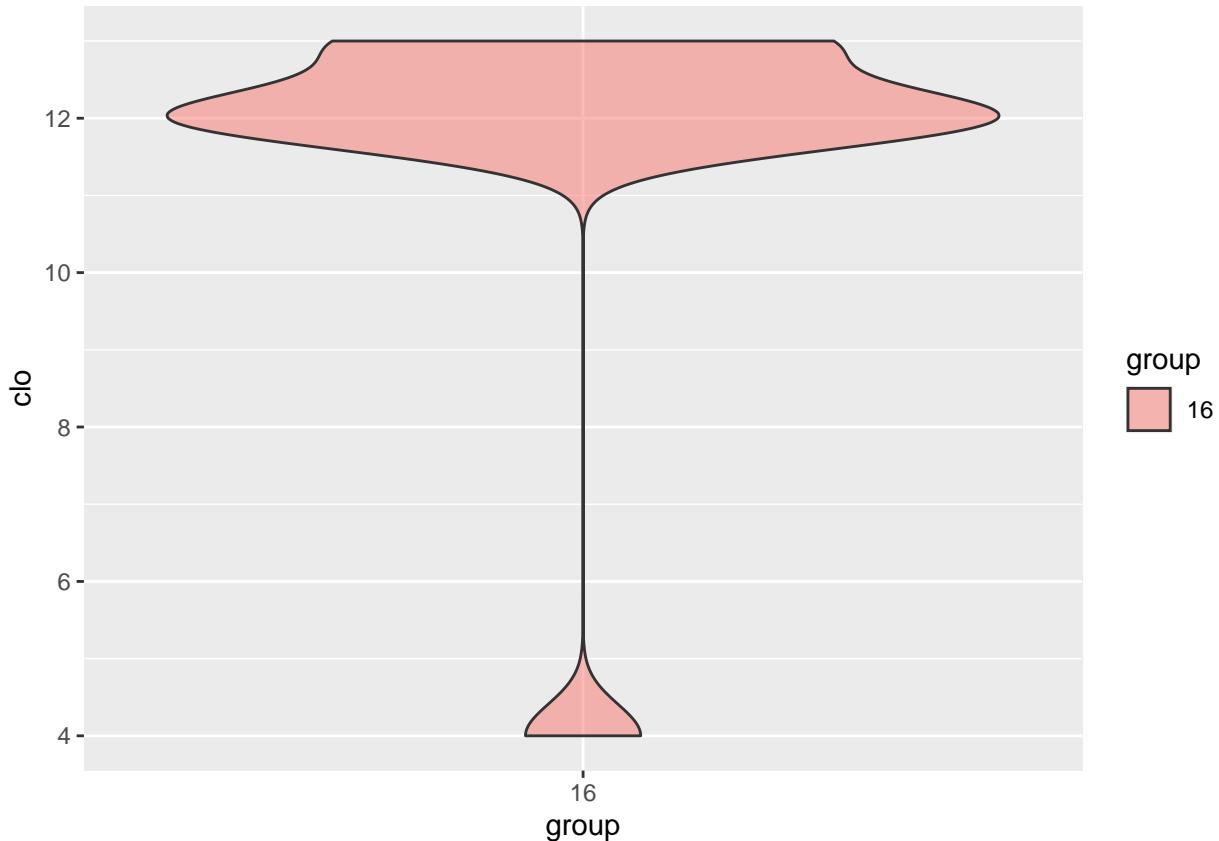
```





```
ggplot(ferdframe[ferdframe$group%in%c(11,12,14,15,18),],  
       aes(x=group,y=clo,fill=group))+geom_violin(alpha=0.5,width=1)
```





```

#
V(uni_graph2)$closeness[condensed_baps_adm[sapply(strsplit(names(V(uni_graph2)), "_"), `^`, 2), 13]==1]

## [1] 0.2670227 0.2437043 0.2539145 0.2556455 0.2027712 0.2027712 0.2670227
## [8] 0.6000000 0.2439024 0.2278769 0.2346500 0.2346500 0.2439024 0.2671416
## [15] 0.2108963 0.3612282 0.3710575 0.2770083 0.3612282 0.3013561 0.2877698
## [22] 0.2535926 0.2535926 0.2535926 0.2770083 0.2476269 0.2535926 0.2536998
## [29] 0.2024291 0.2535926 0.2583979 0.2535926 0.2535926 0.2535926 0.2824859
## [36] 0.2278769 0.2539145 1.0000000 0.5833333 1.0000000 0.2053388 0.2535926
## [43] 0.2535926 0.2278769 0.2770083 0.2053388 0.2770083 0.2670227 0.2770083
## [50] 0.2770083 0.2770083 0.2535926 0.2535926 0.2334630 0.2027712 0.2713704
## [57] 0.2535926 0.2535926 0.2334630 0.2334630 0.2535926 0.2535926 0.1645639

#
# Not recalculate vertex stuff
#
stats_degree<-list()
stats_desc<-list()
V(uni_graph2)$outdegree <- degree(uni_graph2, mode = "out")
V(uni_graph2)$closeness <- closeness(uni_graph2, mode = "total", normalized = TRUE)
V(uni_graph2)$betweenness <- betweenness(uni_graph2, normalized = TRUE)
for (i in 1:34)
{
  foo<-induced_subgraph(uni_graph2,which(color_clusters==i))
  # Extracting each vertex features as a data.frame
  stats <- as_data_frame(foo, what = "vertices")
  # Computing quantiles for each variable
}

```

```

stats_degree[[i]] <- with(stats, {
  cbind(
    outdegree = quantile(outdegree, c(.025, .5, .975), na.rm = TRUE),
    closeness = quantile(closeness, c(.025, .5, .975), na.rm = TRUE),
    betweeness = quantile(betweeness, c(.025, .5, .975), na.rm = TRUE)
  )
})
stats_desc[[i]] <- cbind(
  size     = vcount(foo),
  nedges   = ecount(foo),
  density  = edge_density(foo),
  recip    = reciprocity(foo),
  centr    = centr_betw(foo)$centralization,
  pathLen = mean_distance(foo)
)
}

foo<-induced_subgraph(uni_graph2,which(color_clusters%in%c(1,2,4,5,6,7,9,11,12,14,15,16,18)))
stats <- as_data_frame(foo, what = "vertices")
stats_degree[[35]] <- with(stats, {
  cbind(
    outdegree = quantile(outdegree, c(.025, .5, .975), na.rm = TRUE),
    closeness = quantile(closeness, c(.025, .5, .975), na.rm = TRUE),
    betweeness = quantile(betweeness, c(.025, .5, .975), na.rm = TRUE)
  )
})
stats_desc[[35]] <- cbind(
  size     = vcount(foo),
  nedges   = ecount(foo),
  density  = edge_density(foo),
  recip    = reciprocity(foo),
  centr    = centr_betw(foo)$centralization,
  pathLen = mean_distance(foo)
)

foo<-uni_graph2
stats <- as_data_frame(foo, what = "vertices")
stats_degree[[36]] <- with(stats, {
  cbind(
    outdegree = quantile(outdegree, c(.025, .5, .975), na.rm = TRUE),
    closeness = quantile(closeness, c(.025, .5, .975), na.rm = TRUE),
    betweeness = quantile(betweeness, c(.025, .5, .975), na.rm = TRUE)
  )
})
stats_desc[[36]] <- cbind(
  size     = vcount(foo),
  nedges   = ecount(foo),
  density  = edge_density(foo),
  recip    = reciprocity(foo),
  centr    = centr_betw(foo)$centralization,
  pathLen = mean_distance(foo)
)
}

```

```

print(stats_degree)

## [[1]]
##      outdegree closeness betweeness
## 2.5%        2.9 0.2285540 0.0000000
## 50%       42.0 0.2958580 0.0000000
## 97.5%     54.0 0.3506721 0.01759249
##
## [[2]]
##      outdegree closeness betweeness
## 2.5%        3 0.2400960 0.0000000
## 50%       10 0.2702703 0.0000000
## 97.5%     15 0.3046280 0.00984555
##
## [[3]]
##      outdegree closeness    betweeness
## 2.5%        1.075 0.61125 0.000000e+00
## 50%        2.000 0.75000 0.000000e+00
## 97.5%      2.925 0.98125 8.132762e-06
##
## [[4]]
##      outdegree closeness betweeness
## 2.5%        1.95 0.1949910 0.0000000
## 50%       19.00 0.2444988 0.00131443
## 97.5%     24.20 0.2965342 0.01168070
##
## [[5]]
##      outdegree closeness    betweeness
## 2.5%        1 0.2290098 0.000000000
## 50%       19 0.2976190 0.000000000
## 97.5%     37 0.3260914 0.007906799
##
## [[6]]
##      outdegree closeness    betweeness
## 2.5%        2.725 0.2181704 0.000000000
## 50%      39.000 0.2714932 0.001698865
## 97.5%     50.000 0.3033367 0.019397525
##
## [[7]]
##      outdegree closeness    betweeness
## 2.5%        3 0.1667593 0.000000000
## 50%       9 0.2437043 0.002624464
## 97.5%     16 0.2985075 0.023682604
##
## [[8]]
##      outdegree closeness    betweeness
## 2.5%        1        1        0
## 50%        1        1        0
## 97.5%     1        1        0
##
## [[9]]
##      outdegree closeness    betweeness
## 2.5%        4.85 0.2475248 0.0000000
## 50%       14.00 0.3022670 0.0000000

```

```

## 97.5%      31.50 0.3232637 0.02902508
##
## [[10]]
##      outdegree closeness betweeness
## 2.5%          1          1          0
## 50%          1          1          0
## 97.5%         1          1          0
##
## [[11]]
##      outdegree closeness   betweeness
## 2.5%        2.00 0.1816530 0.0000000000
## 50%        8.00 0.2477291 0.0004457213
## 97.5%       22.75 0.3038569 0.0141659932
##
## [[12]]
##      outdegree closeness   betweeness
## 2.5%       12.0 0.2400960 0.0000000000
## 50%       44.0 0.3255562 0.000772224
## 97.5%      52.3 0.3323097 0.028047272
##
## [[13]]
##      outdegree closeness   betweeness
## 2.5%       3.0 0.6153846 0.000000e+00
## 50%       5.0 0.7272727 0.000000e+00
## 97.5%      7.4 0.9454545 5.275305e-05
##
## [[14]]
##      outdegree closeness   betweeness
## 2.5%       4.0 0.2027712 0.00000000
## 50%       10.0 0.2535926 0.00000000
## 97.5%      27.5 0.2979595 0.01396839
##
## [[15]]
##      outdegree closeness   betweeness
## 2.5%       69 0.3612282 0.00000000
## 50%       69 0.3612282 0.00000000
## 97.5%      87 0.3986844 0.05511925
##
## [[16]]
##      outdegree closeness   betweeness
## 2.5%       6.2 0.2092413 0.0000000000
## 50%       12.0 0.2436054 0.0000000000
## 97.5%      13.0 0.2437043 0.000655017
##
## [[17]]
##      outdegree closeness   betweeness
## 2.5%       3          1          0
## 50%       3          1          0
## 97.5%      3          1          0
##
## [[18]]
##      outdegree closeness   betweeness
## 2.5%       3 0.2257045 0.00000000
## 50%       9 0.2897151 0.00000000

```

```

## 97.5%      29 0.3358551 0.01729053
##
## [[19]]
##      outdegree closeness betweeness
## 2.5%        4          1          0
## 50%         4          1          0
## 97.5%       4          1          0
##
## [[20]]
##      outdegree closeness betweeness
## 2.5%        1          1          0
## 50%         1          1          0
## 97.5%       1          1          0
##
## [[21]]
##      outdegree closeness betweeness
## 2.5%        1          1          0
## 50%         1          1          0
## 97.5%       1          1          0
##
## [[22]]
##      outdegree closeness   betweeness
## 2.5%        2.1        0.68 0.000000e+00
## 50%         3.0        0.80 0.000000e+00
## 97.5%       4.0        1.00 4.396087e-06
##
## [[23]]
##      outdegree closeness   betweeness
## 2.5%        1.175  0.3704167 0.000000e+00
## 50%         2.500  0.5416667 0.000000e+00
## 97.5%       4.825  0.7000000 4.396087e-05
##
## [[24]]
##      outdegree closeness betweeness
## 2.5%        2          1          0
## 50%         2          1          0
## 97.5%       2          1          0
##
## [[25]]
##      outdegree closeness   betweeness
## 2.5%        2          0.50 0.000000e+00
## 50%         2          0.50 0.000000e+00
## 97.5%       4          0.75 3.51687e-05
##
## [[26]]
##      outdegree closeness betweeness
## 2.5%        1          1          0
## 50%         1          1          0
## 97.5%       1          1          0
##
## [[27]]
##      outdegree closeness betweeness
## 2.5%        1          1          0
## 50%         1          1          0

```

```

## 97.5%      1      1      0
##
## [[28]]
##      outdegree closeness betweeness
## 2.5%      5      1      0
## 50%      5      1      0
## 97.5%     5      1      0
##
## [[29]]
##      outdegree closeness betweeness
## 2.5%      1      1      0
## 50%      1      1      0
## 97.5%     1      1      0
##
## [[30]]
##      outdegree closeness betweeness
## 2.5%      1      1      0
## 50%      1      1      0
## 97.5%     1      1      0
##
## [[31]]
##      outdegree closeness betweeness
## 2.5%      1      1      0
## 50%      1      1      0
## 97.5%     1      1      0
##
## [[32]]
##      outdegree closeness betweeness
## 2.5%      1      1      0
## 50%      1      1      0
## 97.5%     1      1      0
##
## [[33]]
##      outdegree closeness betweeness
## 2.5%      1      1      0
## 50%      1      1      0
## 97.5%     1      1      0
##
## [[34]]
##      outdegree closeness betweeness
## 2.5%      1      1      0
## 50%      1      1      0
## 97.5%     1      1      0
##
## [[35]]
##      outdegree closeness betweeness
## 2.5%      2 0.1953125 0.00000000
## 50%      18 0.2816901 0.00000000
## 97.5%     74 0.3790272 0.02635734
##
## [[36]]
##      outdegree closeness betweeness
## 2.5%      1.0 0.1965442 0.00000000
## 50%      15.5 0.2936875 0.00000000

```

```

## 97.5%      74.0 1.0000000 0.02476439
print(stats_desc)

## [[1]]
##      size nedges   density recip      centr pathLen
## [1,]    79     1124 0.3648166      1 0.09235636 1.824732
##
## [[2]]
##      size nedges   density recip      centr pathLen
## [1,]    19      84 0.4912281      1 0.4015977 1.754386
##
## [[3]]
##      size nedges   density recip      centr pathLen
## [1,]     4       4 0.6666667      1 0.6666667 1.333333
##
## [[4]]
##      size nedges   density recip      centr pathLen
## [1,]    39     271 0.365722      1 0.2875271 2.055331
##
## [[5]]
##      size nedges   density recip      centr pathLen
## [1,]    40     289 0.3705128      1 0.1180861 1.841026
##
## [[6]]
##      size nedges   density recip      centr pathLen
## [1,]    64     1105 0.5481151      1 0.0840709 1.583333
##
## [[7]]
##      size nedges   density recip      centr pathLen
## [1,]    45     188 0.189899      1 0.4630021 3.351515
##
## [[8]]
##      size nedges density recip centr pathLen
## [1,]    2       1       1       1   NaN       1
##
## [[9]]
##      size nedges   density recip      centr pathLen
## [1,]    23     132 0.5217391      1 0.1206218 1.667984
##
## [[10]]
##      size nedges density recip centr pathLen
## [1,]    2       1       1       1   NaN       1
##
## [[11]]
##      size nedges   density recip      centr pathLen
## [1,]    59     259 0.1513735      1 0.1326637 2.704267
##
## [[12]]
##      size nedges   density recip      centr pathLen
## [1,]    55     979 0.6592593      1 0.1460444 1.394613
##
## [[13]]
##      size nedges   density recip      centr pathLen
## [1,]     9      21 0.5833333      1 0.5357143 1.416667

```

```

## 
## [[14]]
##      size nedges   density recip      centr pathLen
## [1,]    51     355 0.2784314      1 0.3732898 2.307451
##
## [[15]]
##      size nedges   density recip      centr pathLen
## [1,]    71     2416 0.9722334      1 0.02857143 1.027767
##
## [[16]]
##      size nedges   density recip      centr pathLen
## [1,]    12      59 0.8939394      1 0.0231405 1.106061
##
## [[17]]
##      size nedges density recip centr pathLen
## [1,]    4       6      1      1      0       1
##
## [[18]]
##      size nedges   density recip      centr pathLen
## [1,]    44     268 0.2832981      1 0.2535734 2.312896
##
## [[19]]
##      size nedges density recip centr pathLen
## [1,]    5      10      1      1      0       1
##
## [[20]]
##      size nedges density recip centr pathLen
## [1,]    2       1      1      1      NaN      1
##
## [[21]]
##      size nedges density recip centr pathLen
## [1,]    2       1      1      1      NaN      1
##
## [[22]]
##      size nedges density recip centr pathLen
## [1,]    5       8      0.8      1 0.125      1.2
##
## [[23]]
##      size nedges   density recip      centr pathLen
## [1,]    8      11 0.3928571      1 0.3673469 1.928571
##
## [[24]]
##      size nedges density recip centr pathLen
## [1,]    3       3      1      1      0       1
##
## [[25]]
##      size nedges   density recip      centr pathLen
## [1,]    7       9 0.4285714      1 0.4444444 1.761905
##
## [[26]]
##      size nedges density recip centr pathLen
## [1,]    2       1      1      1      NaN      1
##
## [[27]]

```

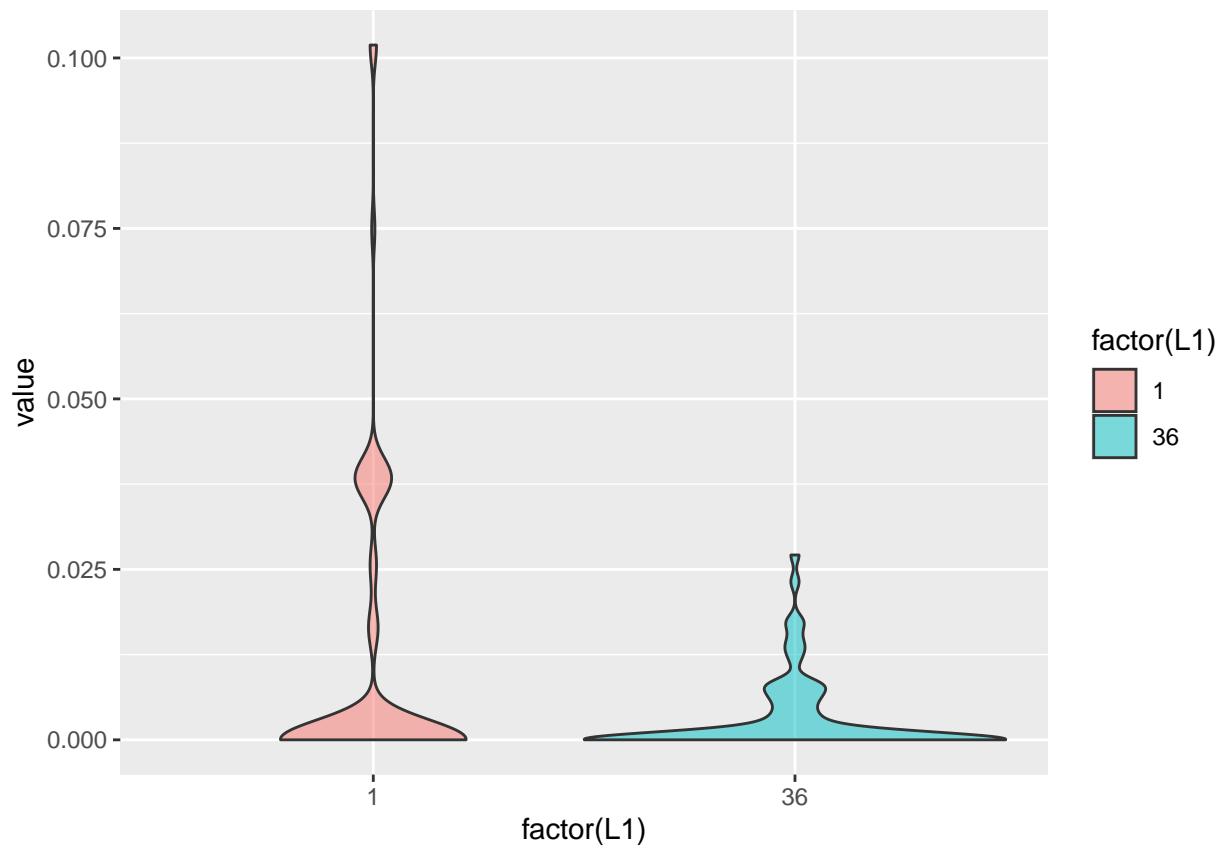


```

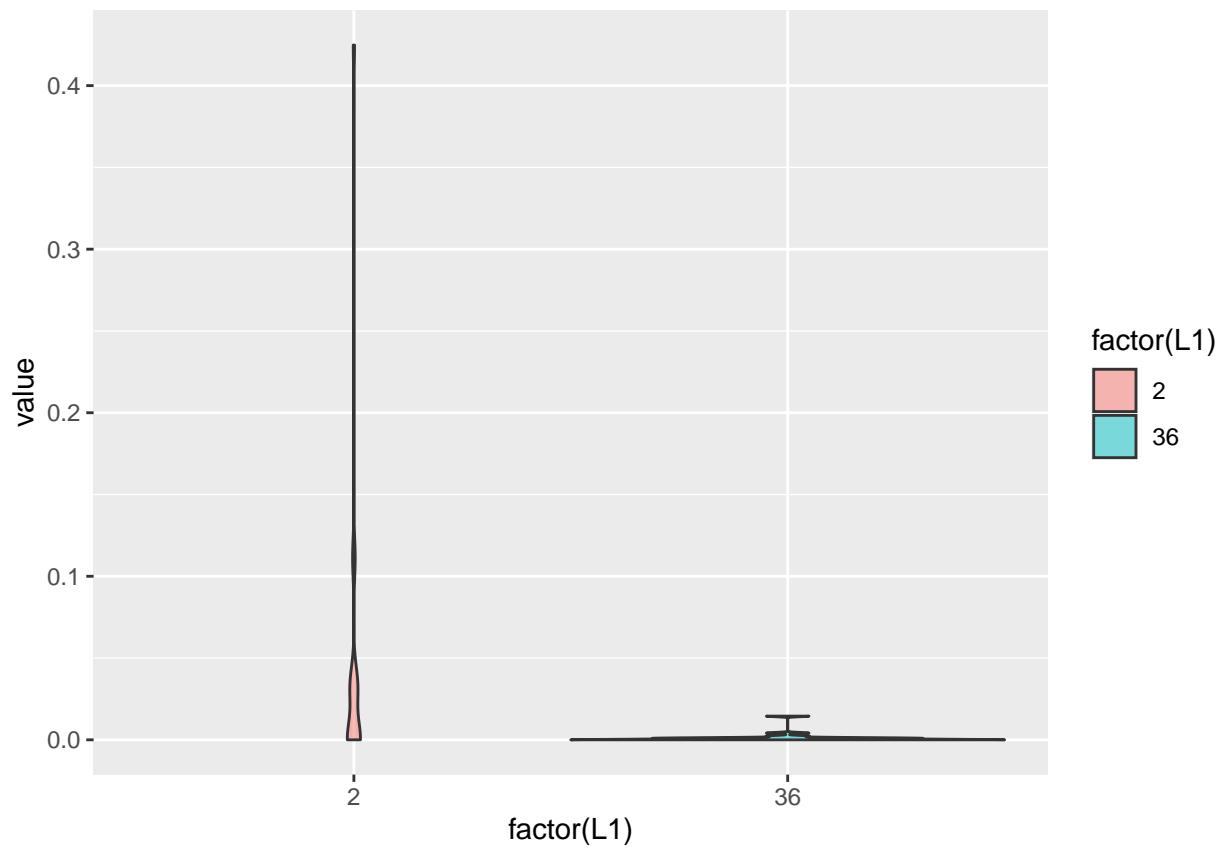
## Using name as id variables
library(stargazer)

##
## Please cite as:
## Hlavac, Marek (2022). stargazer: Well-Formatted Regression and Summary Statistics Tables.
## R package version 5.2.3. https://CRAN.R-project.org/package=stargazer
for (i in c(1,2,4,5,6,7,9,11,12,14,15,16,18))
{
vertices_select<-stats_networksmelt[stats_networksmelt$L1==i,1]
foo<-stats_networksmelt[stats_networksmelt[,1]%in%vertices_select,]
print(ggplot(foo[foo$variable=="betweenness"&foo$L1!=35,],
            aes(x=factor(L1),y=value,z=variable,fill=factor(L1)))+geom_violin(alpha=0.5,width=1))
stargazer(anova(lm(value~factor(L1),data=foo[foo$variable=="betweenness"&foo$L1!=35,])),type = "text")
}

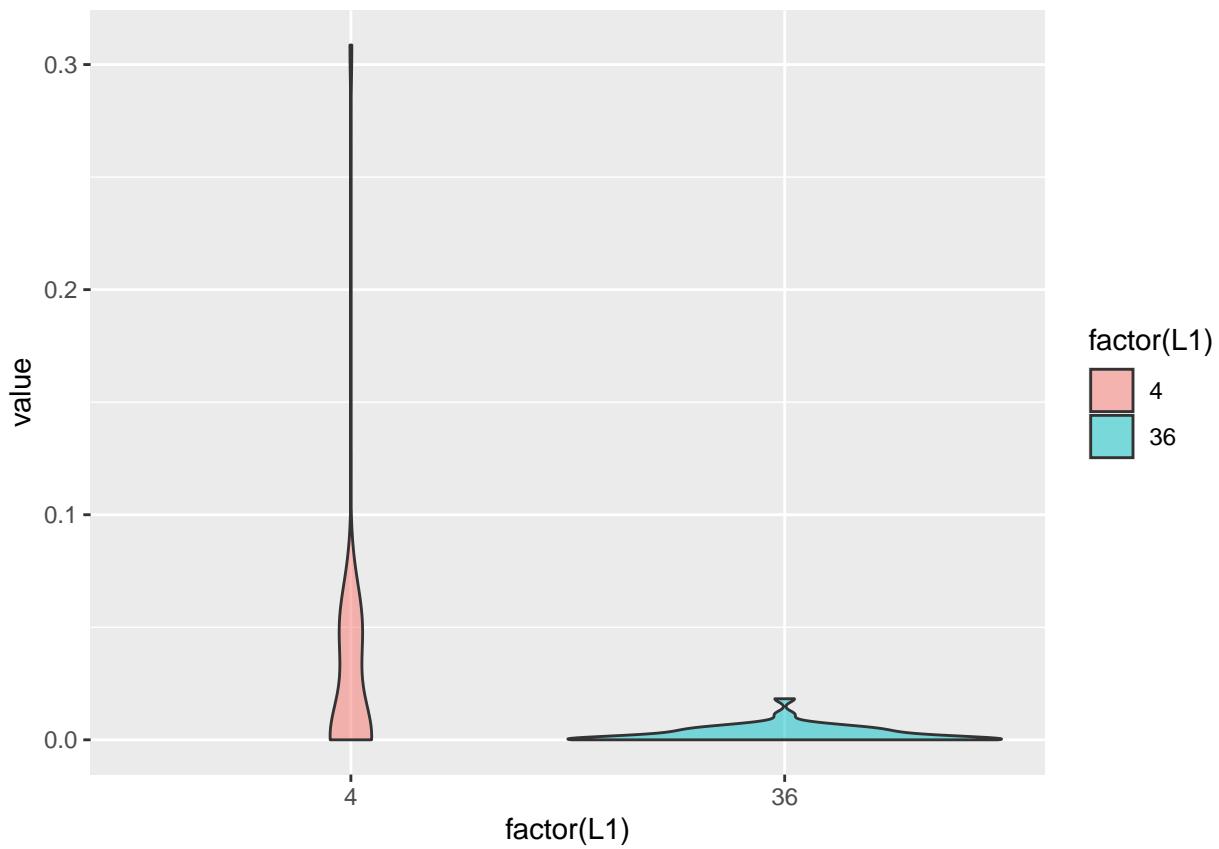
```



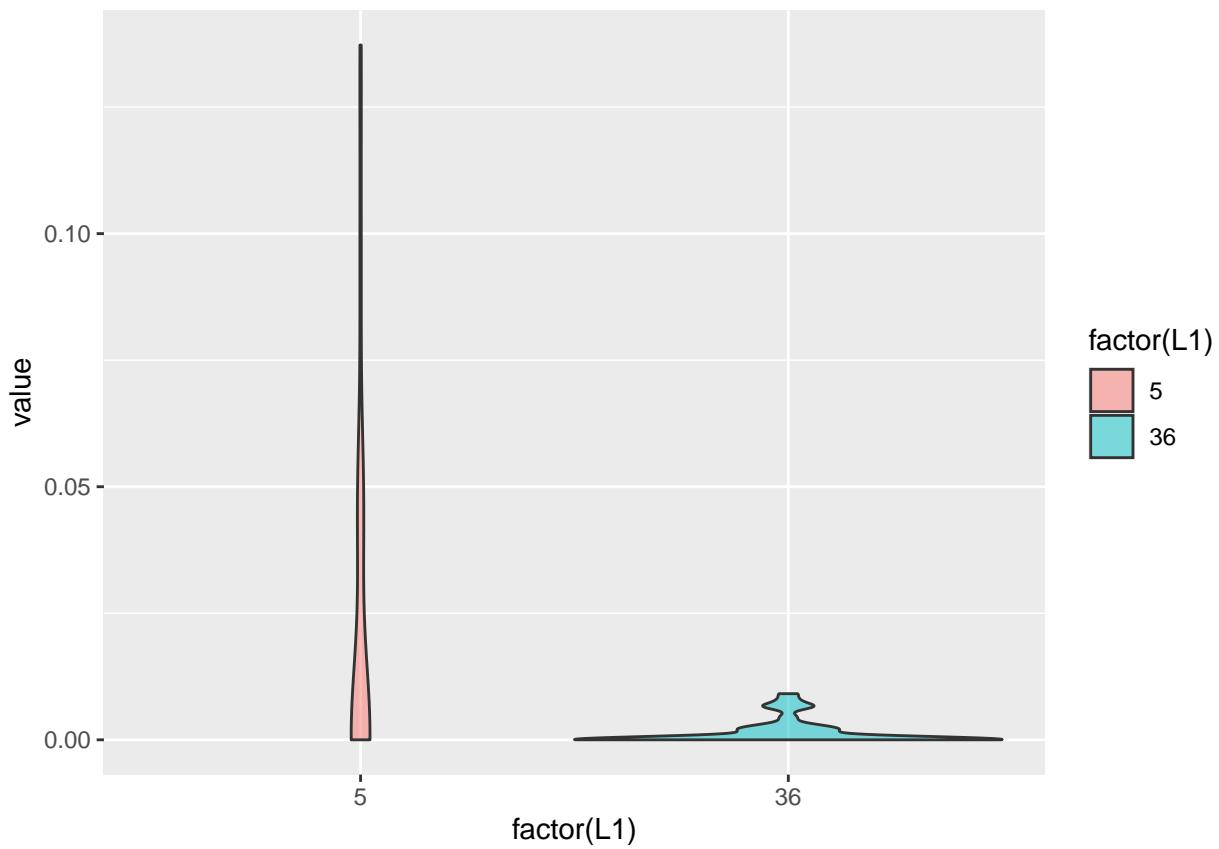
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min    Max  
## -----  
## Df      2 78.500 109.602     1     156  
## Sum Sq  2 0.021   0.026    0.002  0.040  
## Mean Sq 2 0.001   0.001    0.0003 0.002  
## F value 1 9.059          9.059  9.059  
## Pr(> F) 1 0.003          0.003  0.003  
## -----
```



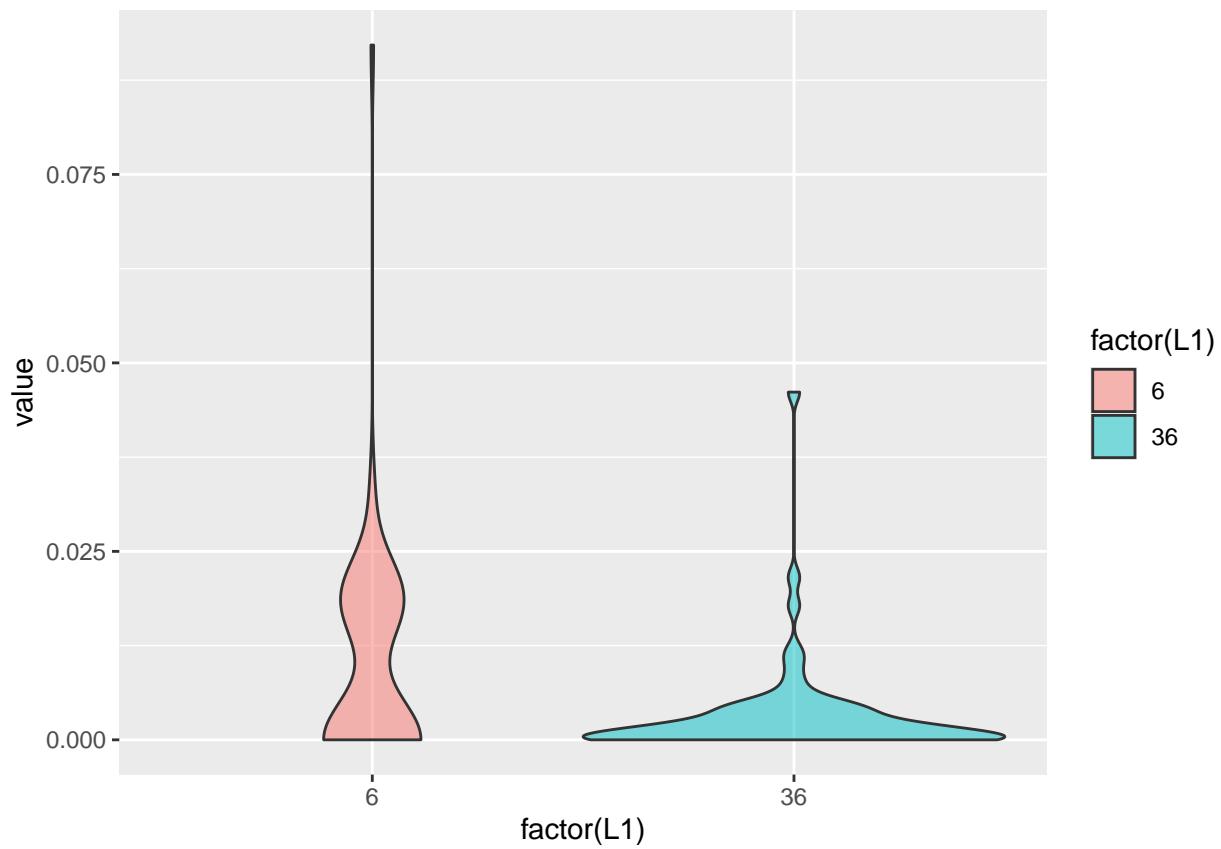
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min   Max  
## -----  
## Df      2 18.500  24.749    1    36  
## Sum Sq  2 0.096   0.111   0.018 0.174  
## Mean Sq 2 0.011   0.009   0.005 0.018  
## F value 1 3.620          3.620 3.620  
## Pr(> F) 1 0.065          0.065 0.065  
## -----
```



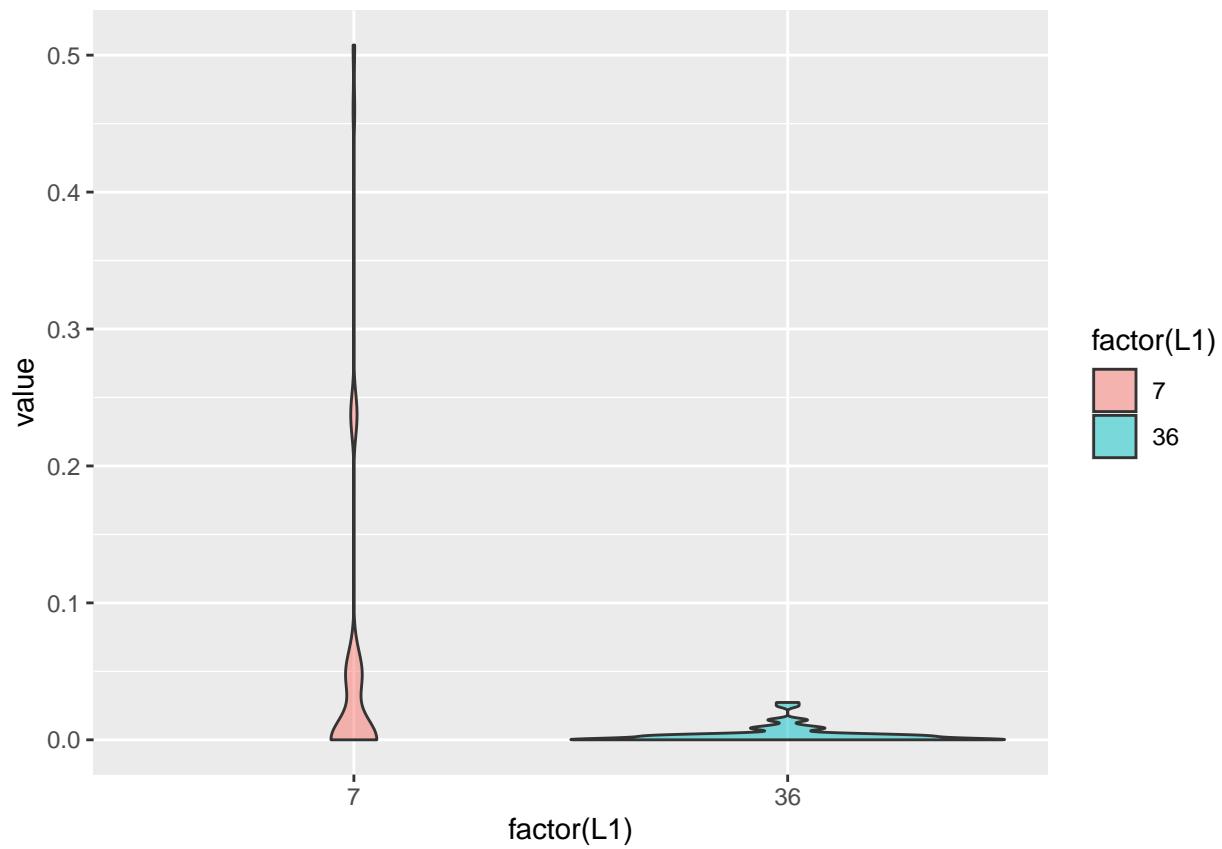
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min   Max  
## -----  
## Df      2 38.500  53.033    1    76  
## Sum Sq  2 0.059   0.065    0.013 0.106  
## Mean Sq 2 0.007   0.008    0.001 0.013  
## F value 1 9.411          9.411 9.411  
## Pr(> F) 1 0.003          0.003 0.003  
## -----
```



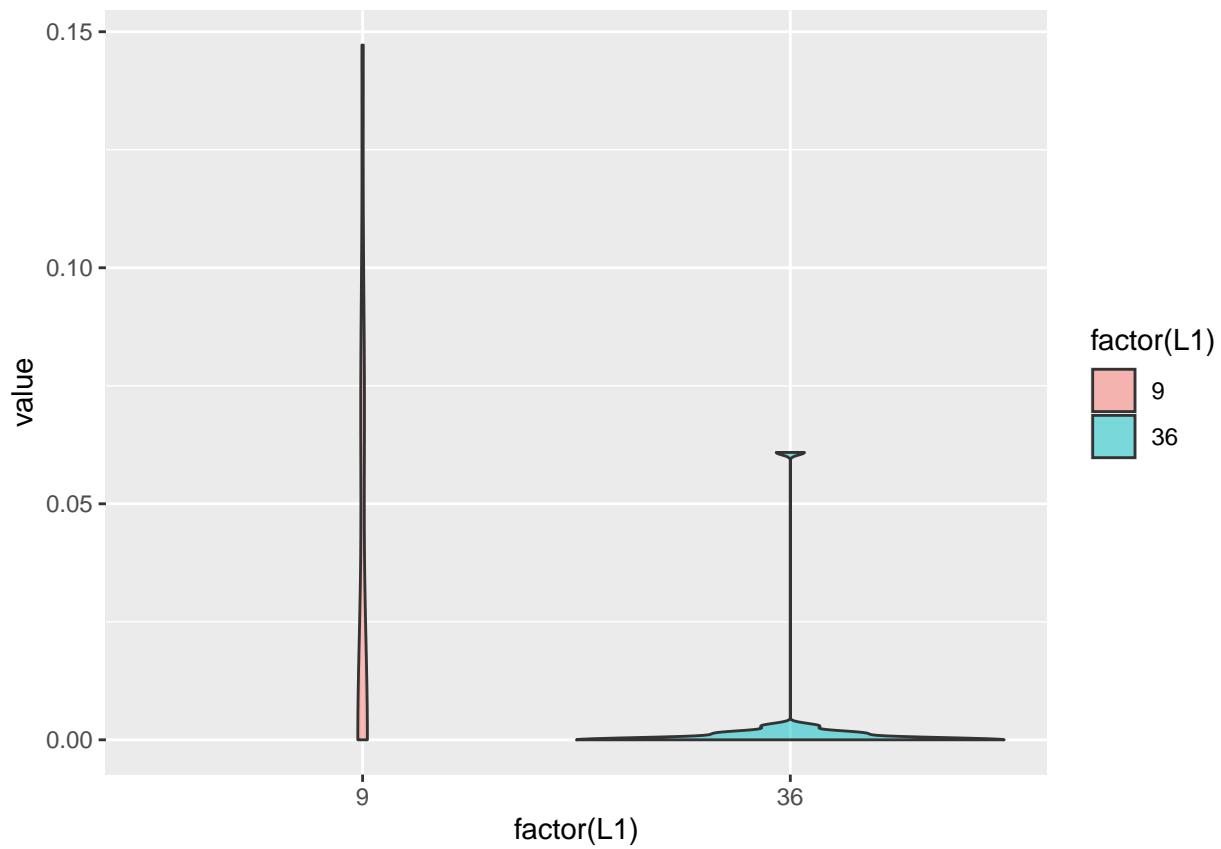
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min    Max  
## -----  
## Df      2 39.500  54.447    1     78  
## Sum Sq  2 0.030   0.031   0.009  0.052  
## Mean Sq 2 0.005   0.006   0.001  0.009  
## F value 1 12.712          12.712 12.712  
## Pr(> F) 1 0.001          0.001  0.001  
## -----
```



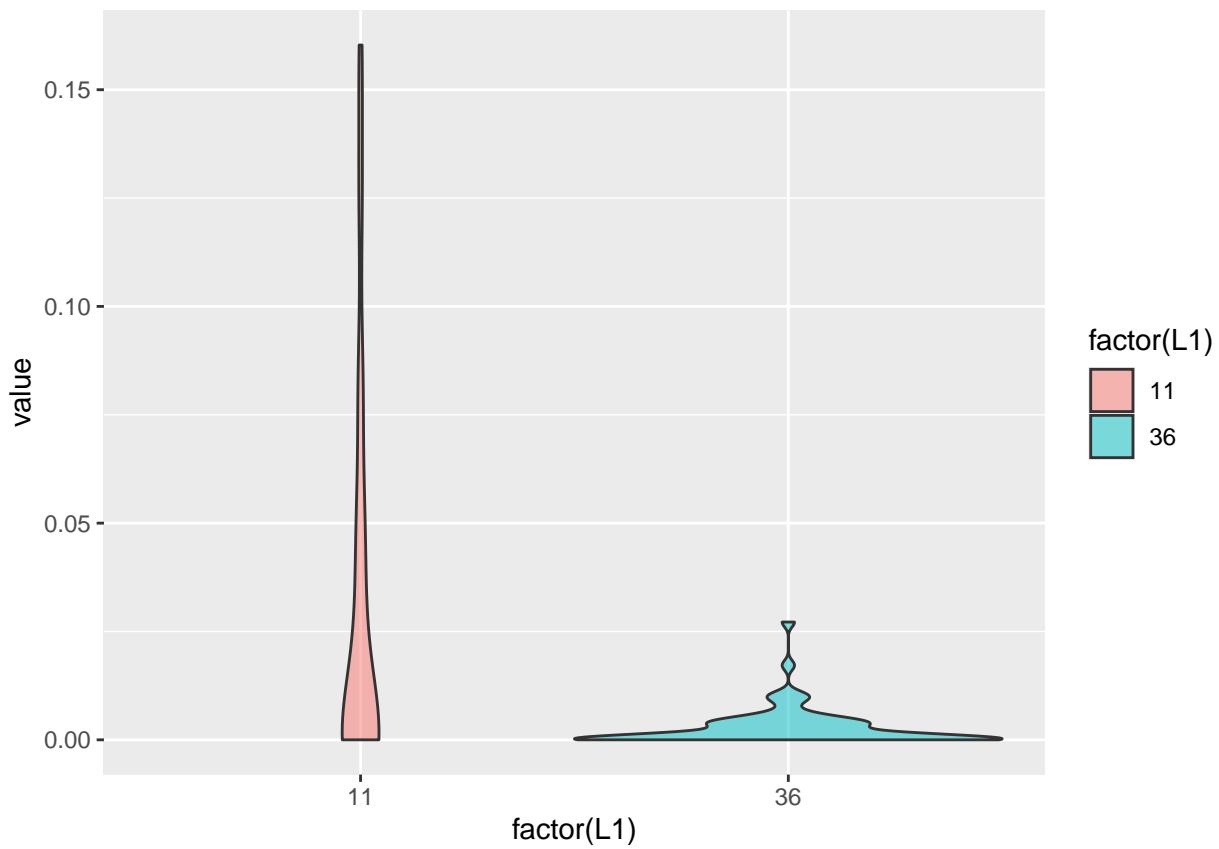
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min    Max  
## -----  
## Df      2 63.500  88.388     1    126  
## Sum Sq  2 0.009   0.010     0.001  0.016  
## Mean Sq 2 0.001   0.001     0.0001 0.001  
## F value 1 9.880          9.880  9.880  
## Pr(> F) 1 0.002          0.002  0.002  
## -----
```



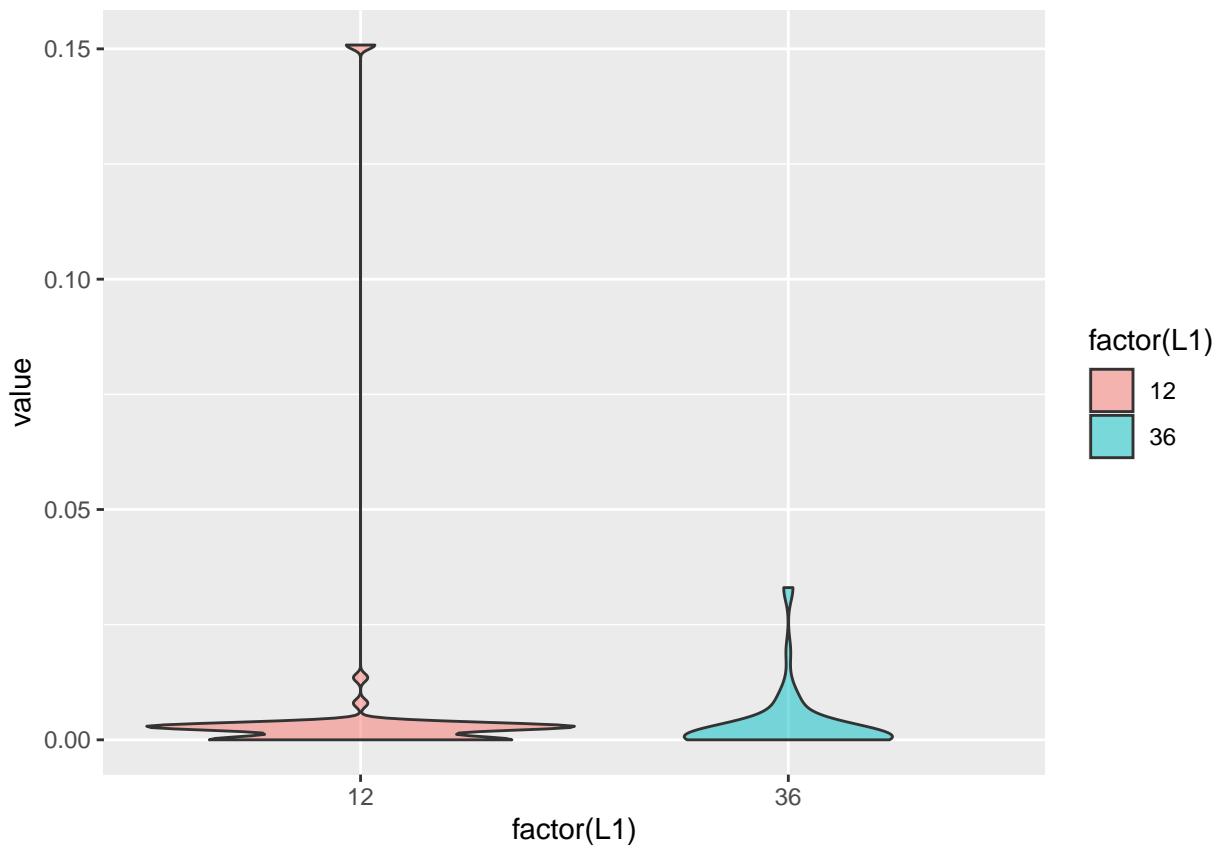
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min   Max  
## -----  
## Df      2 44.500  61.518    1     88  
## Sum Sq  2 0.323   0.375    0.058  0.589  
## Mean Sq 2 0.032   0.036    0.007  0.058  
## F value 1 8.692          8.692 8.692  
## Pr(> F) 1 0.004          0.004 0.004  
## -----
```



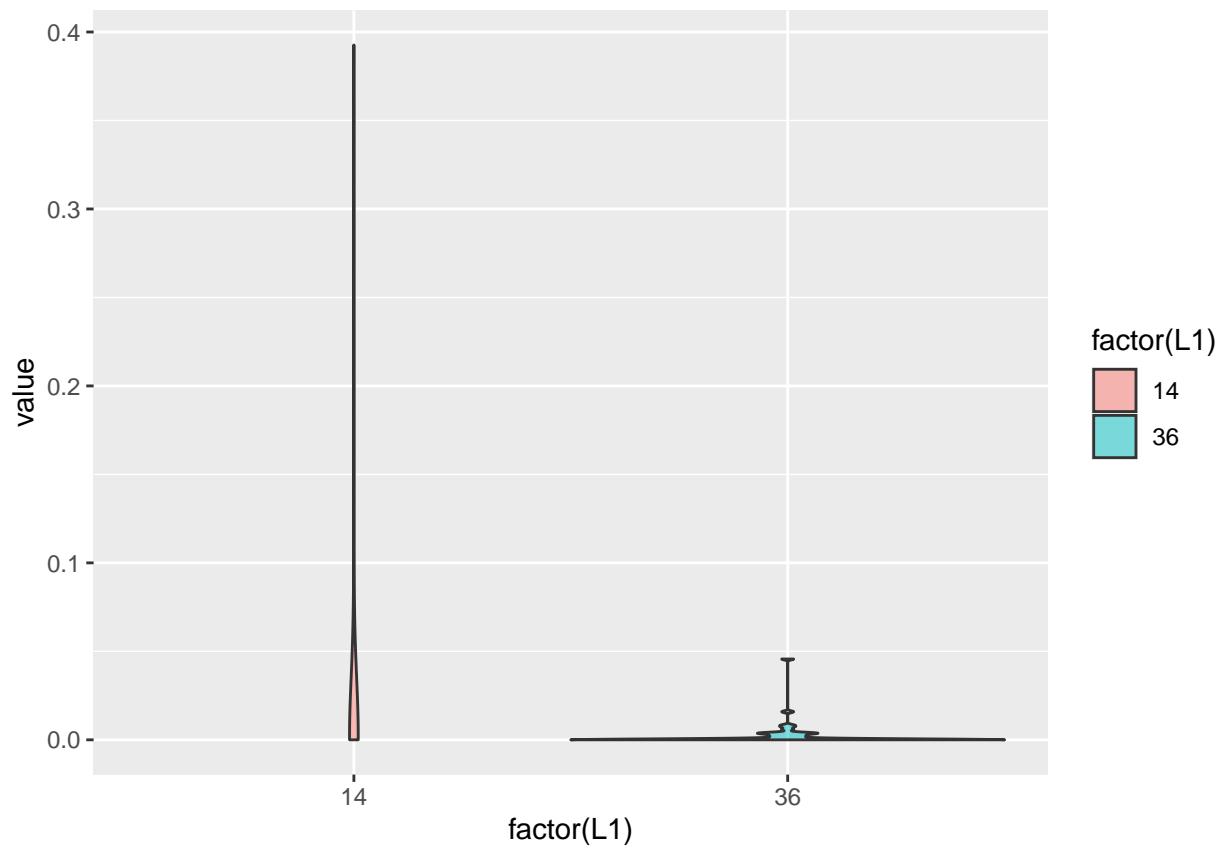
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min   Max  
## -----  
## Df      2 22.500  30.406    1    44  
## Sum Sq  2 0.033   0.033   0.009  0.056  
## Mean Sq 2 0.005   0.006   0.001  0.009  
## F value 1 7.411        7.411 7.411  
## Pr(> F) 1 0.009        0.009 0.009  
## -----
```



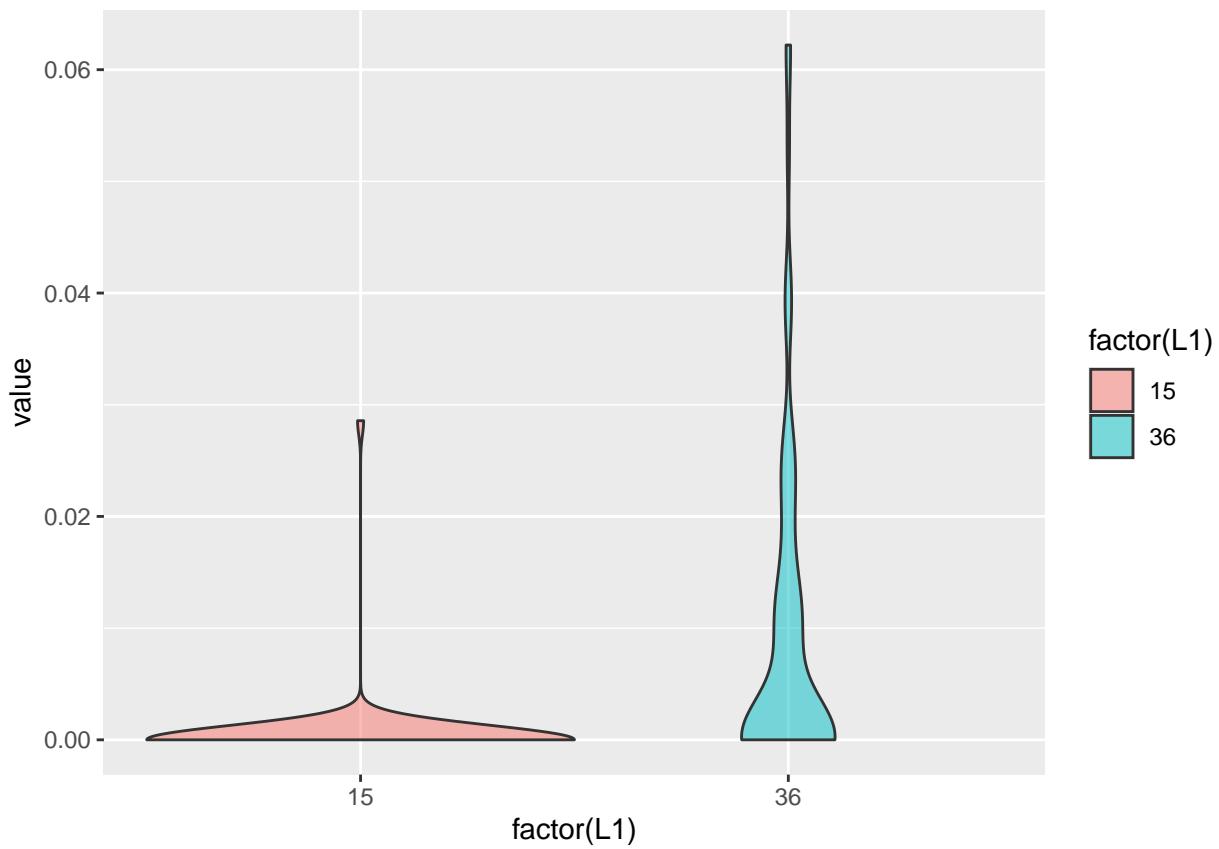
```
##  
## -----  
## Statistic N  Mean   St. Dev.   Min    Max  
## -----  
## Df      2 58.500  81.317     1    116  
## Sum Sq  2  0.071  0.070     0.022  0.121  
## Mean Sq 2  0.011  0.015     0.001  0.022  
## F value 1 20.911          20.911 20.911  
## Pr(> F) 1 0.00001    0.00001 0.00001  
## -----
```



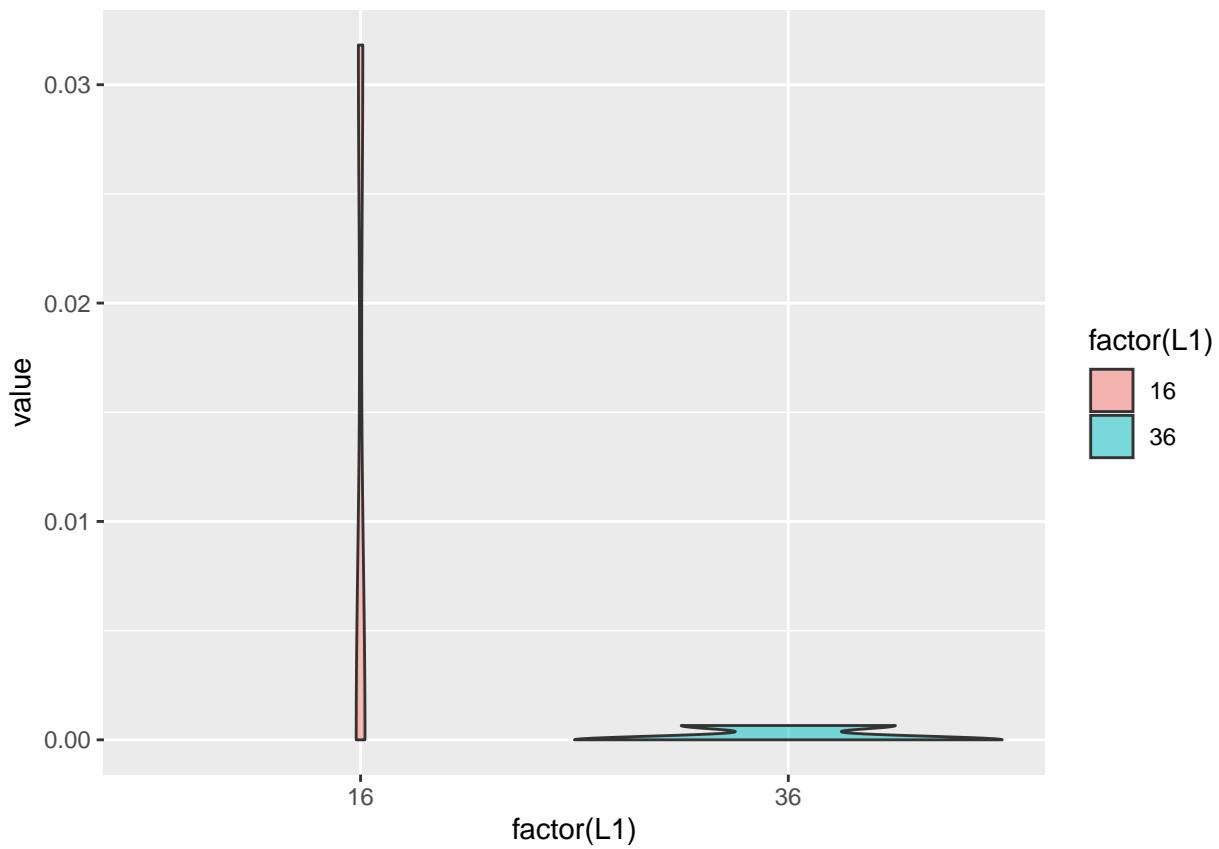
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min    Max  
## -----  
## Df      2 54.500  75.660     1    108  
## Sum Sq  2 0.023   0.032     0.001  0.045  
## Mean Sq 2 0.0005  0.0001    0.0004 0.001  
## F value 1 1.275          1.275  1.275  
## Pr(> F) 1 0.261          0.261  0.261  
## -----
```



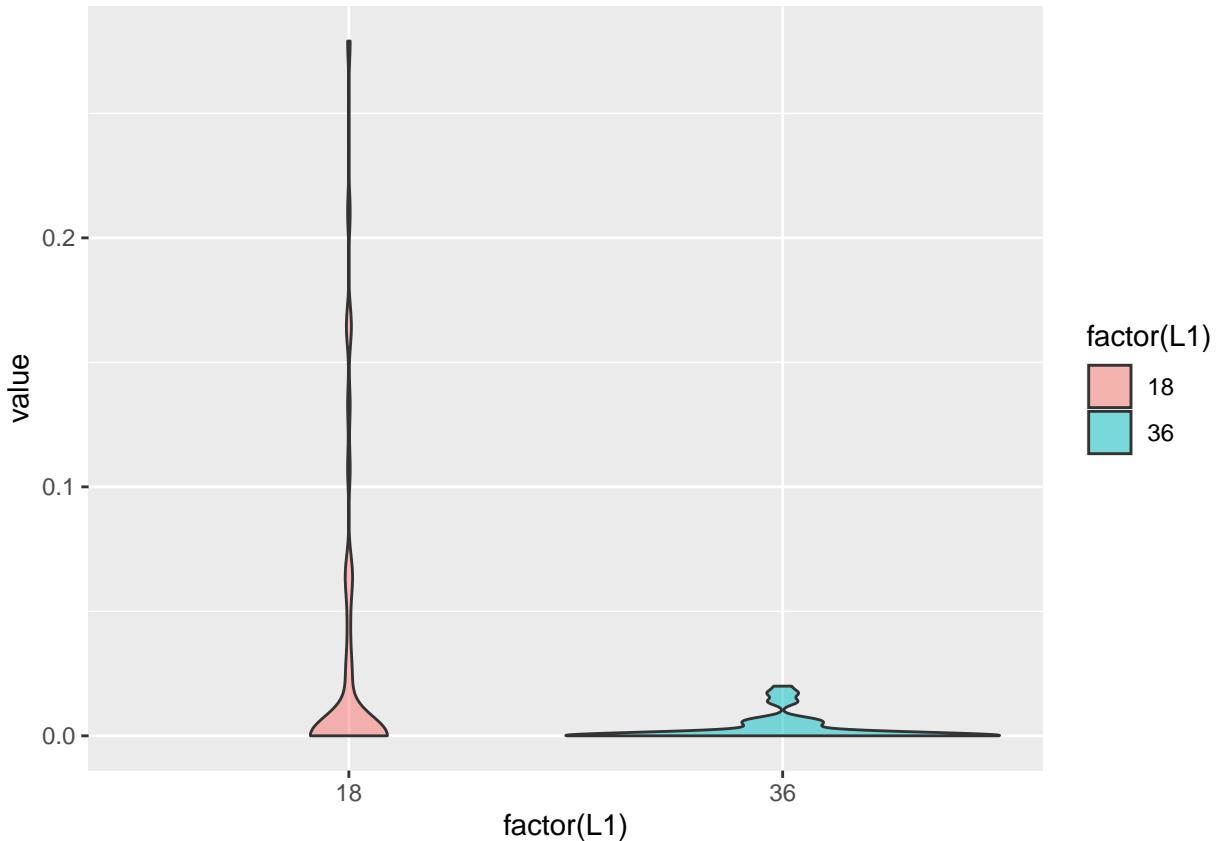
```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min   Max  
## -----  
## Df      2 50.500  70.004    1    100  
## Sum Sq  2 0.160   0.204    0.015  0.304  
## Mean Sq 2 0.009   0.009    0.003  0.015  
## F value 1 5.032          5.032 5.032  
## Pr(> F) 1 0.027          0.027 0.027  
## -----
```



```
##  
## -----  
## Statistic N  Mean   St. Dev.   Min    Max  
## -----  
## Df      2 70.500  98.288     1    140  
## Sum Sq  2  0.010  0.010     0.003  0.016  
## Mean Sq 2  0.001  0.002     0.0001  0.003  
## F value 1 23.646            23.646 23.646  
## Pr(> F) 1 0.00000          0.00000 0.00000  
## -----
```



```
##  
## -----  
## Statistic N  Mean   St. Dev.  Min    Max  
## -----  
## Df      2 11.500 14.849     1     22  
## Sum Sq  2 0.002  0.001  0.001  0.003  
## Mean Sq 2 0.0004 0.0004 0.0001 0.001  
## F value 1 5.274          5.274  5.274  
## Pr(> F) 1 0.032          0.032  0.032  
## -----
```



```

## 
## =====
## Statistic N  Mean  St. Dev.  Min   Max
## -----
## Df      2 43.500  60.104    1    86
## Sum Sq   2 0.099   0.115  0.018 0.180
## Mean Sq   2 0.010   0.011  0.002 0.018
## F value  1 8.402          8.402 8.402
## Pr(> F)  1 0.005          0.005 0.005
## -----
ggplot(data.frame(clo = V(uni_graph2)$outdegree,group=factor(clustering_closeness$classification)),aes(
  facet_wrap(vars(factor(foo_modules[sapply(strsplit(names(V(uni_graph2)),"_"),`[`,2)]])))
))

## Warning: Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.

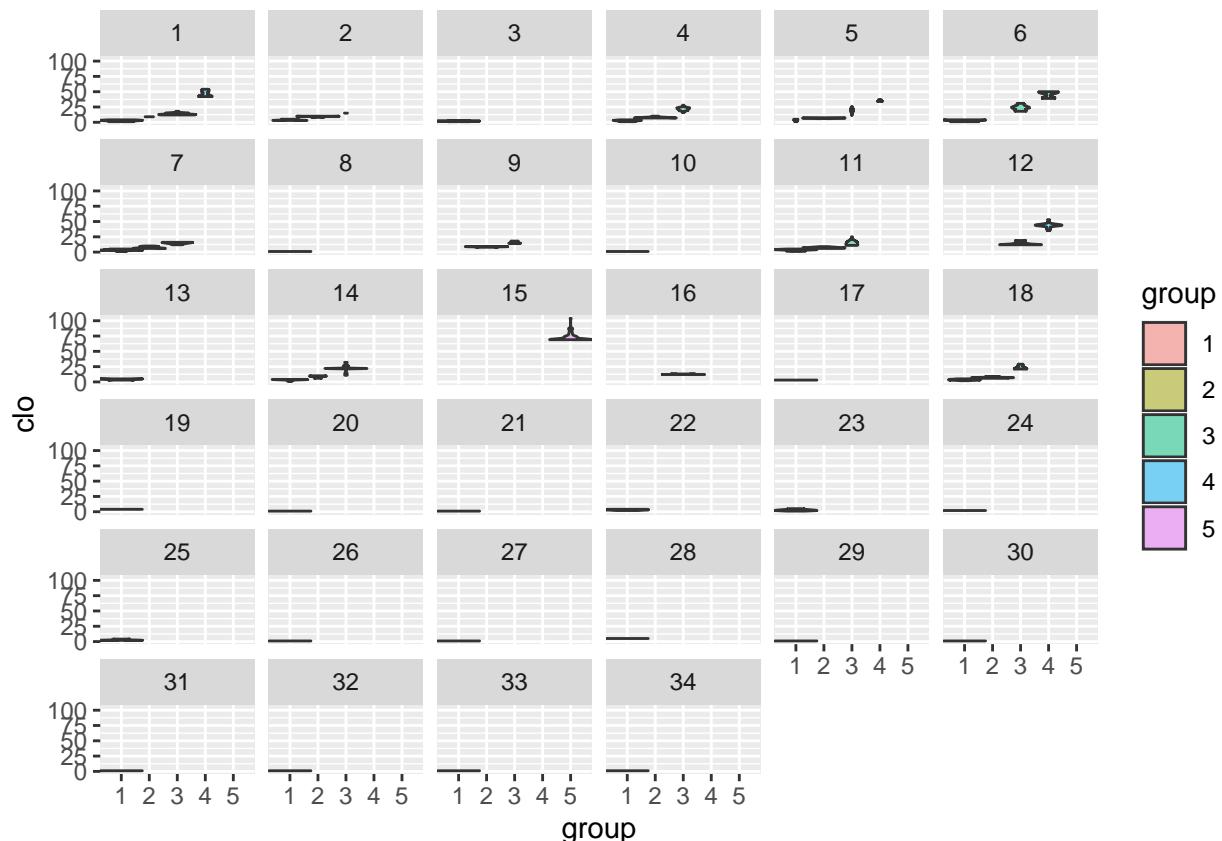
## Warning: position_dodge requires non-overlapping x intervals
## position_dodge requires non-overlapping x intervals
## position_dodge requires non-overlapping x intervals
## position_dodge requires non-overlapping x intervals

```

```

## position_dodge requires non-overlapping x intervals

```



```

ggplot(data.frame(clo = V(uni_graph2)$outdegree, group=factor(clustering_closeness$classification)),aes(
  geom_violin(alpha=0.5,width=1.5)+ 
  facet_wrap(vars(factor(condensed_baps_adm[as.character(sapply(strsplit(names(V(uni_graph2)), "_"), `^` ,`[`)))])))
  ## Warning: Groups with fewer than two data points have been dropped.
  ## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
  ## Warning: Computation failed in `stat_ydensity()`:
  ## replacement has 1 row, data has 0
  ## Warning: Groups with fewer than two data points have been dropped.
  ## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
  ## Warning: Computation failed in `stat_ydensity()`:
  ## replacement has 1 row, data has 0
  ## Warning: Groups with fewer than two data points have been dropped.
  ## Groups with fewer than two data points have been dropped.
  ## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
  ## Warning: Computation failed in `stat_ydensity()`:

```

```

## replacement has 1 row, data has 0
## Warning: Groups with fewer than two data points have been dropped.
## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
## Warning: Computation failed in `stat_ydensity()`:
## replacement has 1 row, data has 0

## Warning: Groups with fewer than two data points have been dropped.
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## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
## Warning: Computation failed in `stat_ydensity()`:
## replacement has 1 row, data has 0

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## replacement has 1 row, data has 0

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## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
## Warning: Computation failed in `stat_ydensity()`:
## replacement has 1 row, data has 0

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## Warning: Computation failed in `stat_ydensity()`:
## replacement has 1 row, data has 0

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## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
## Warning: Computation failed in `stat_ydensity()`:
## replacement has 1 row, data has 0

## Warning: Groups with fewer than two data points have been dropped.
## Groups with fewer than two data points have been dropped.

## Warning in max(data$density): ningun argumento finito para max; retornando -Inf
## Warning: Computation failed in `stat_ydensity()`:
## replacement has 1 row, data has 0

```



```
## position_dodge requires non-overlapping x intervals
## position_dodge requires non-overlapping x intervals
```

