ACN: Analysis of Leaf-Modifier Interaction Networks



Weighted and probabilistic analyses:

```
### load pit data
source('../src/loadPitdata.R')
head(summary(tree.info))
```

```
leaf.type
                                geno
                                             leaves
                  tree
   "live:36 " "np12.04: 2 " "1000 :12 " "Min. : 0.00 "
##
##
   "sen :36 " "np12.07: 2 " "1008
                                   :10 " "1st Qu.: 38.75 "
              "np13.10: 2 " "1017
                                   :10 " "Median : 50.00 "
##
              "np2.07 : 2 " "1023
                                   :10 " "Mean : 61.26 "
  NA
              "np2.08 : 2 " "11
                                   :10 " "3rd Qu.: 50.00 "
##
   NA
              "np2.10 : 2 " "996
                                   :10 " "Max. :464.00 "
```

head(summary(tree.arth))

```
##
                    Length Class
                                        Mode
## live np12.04 1017 "16" "data.frame" "list"
## live np12.07 1017 "16"
                           "data.frame" "list"
## live np13.10 1017 "16"
                           "data.frame" "list"
## live np2.07 1000 "16"
                          "data.frame" "list"
## live np2.08 996
                    "16"
                           "data.frame" "list"
                           "data.frame" "list"
## live np2.10 996
                    "16"
head(summary(arth.mats))
```

```
## Length Class Mode

## live np12.04 1017 "800" "-none-" "numeric"

## live np12.07 1017 "800" "-none-" "numeric"

## live np13.10 1017 "800" "-none-" "numeric"

## live np2.07 1000 "800" "-none-" "numeric"

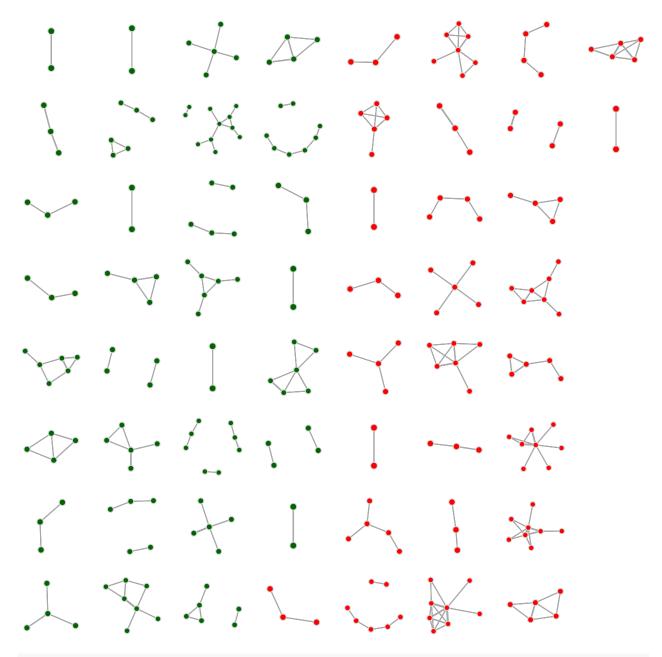
## live np2.08 996 "800" "-none-" "numeric"

## live np2.10 996 "800" "-none-" "numeric"
```

Generate the network using the co-occurrences of each arthropod on a leaf.

```
library(sna)
nets.plot <- lapply(tree.nets,rmZeros)

par(mfcol=c(8,9),mai=rep(0.1,4))
for (i in 1:length(nets.plot)){
    if (sum(dim(nets.plot[[i]])) != 0){
        if (tree.info[i,1] == 'sen'){
            vc <- 'red'
        }else{vc <- 'darkgreen'}
        gplot(nets.plot[[i]],gmode='graph',
            edge.col='darkgrey',vertex.col=vc,
            vertex.border='lightgrey',
            edge.lwd=nets.plot[[i]],vertex.cex=2)
}</pre>
```

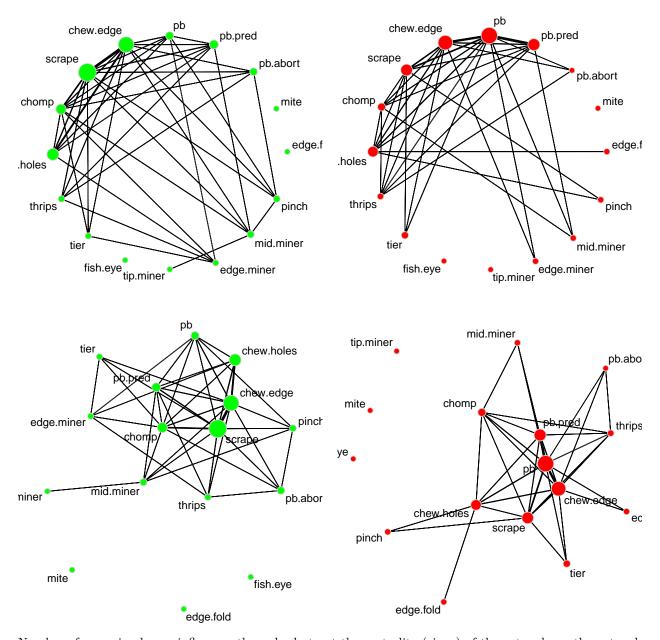


t.test(I(liv.cen-sen.cen))

```
##
## One Sample t-test
##
## data: I(liv.cen - sen.cen)
## t = -1.3324, df = 35, p-value = 0.1914
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
## -0.22098995    0.04585768
## sample estimates:
## mean of x
## -0.08756614
```

Analyze the mean networks for live and senescent leaves.

```
# average structure and variance
liv.mu <- meanNet(liv.nets)</pre>
liv.var <- varNet(liv.nets)</pre>
sen.mu <- meanNet(sen.nets)</pre>
sen.var <- varNet(sen.nets)</pre>
par(mfrow=c(2,2),mai=rep(0.1,4))
gplot(liv.mu,gmode='graph',
      edge.lwd=liv.mu/max(liv.mu)*3, vertex.col='green',
      vertex.border='lightgrey',
      edge.col=grey(liv.var/max(liv.var)),
      vertex.cex=apply(liv.spc,2,mean) * 3 + 0.5,
      mode='circle',displaylabels=TRUE)
gplot(sen.mu,gmode='graph',
      edge.lwd=sen.mu/max(sen.mu)*3,vertex.col='red',
      vertex.border='lightgrey',
      edge.col=grey(sen.var/max(sen.var)),
      vertex.cex=apply(sen.spc,2,mean) * 3 + 0.5,
      mode='circle',displaylabels=TRUE)
gplot(liv.mu,gmode='graph',
      edge.lwd=liv.mu/max(liv.mu)*3, vertex.col='green',
      vertex.border='lightgrey',
      edge.col=grey(liv.var/max(liv.var)),
      vertex.cex=apply(liv.spc,2,mean) * 3 + 0.5,
      displaylabels=TRUE)
gplot(sen.mu,gmode='graph',
      edge.lwd=sen.mu/max(sen.mu)*3,vertex.col='red',
      vertex.border='lightgrey',
      edge.col=grey(sen.var/max(sen.var)),
      vertex.cex=apply(sen.spc,2,mean) * 3 + 0.5,
      displaylabels=TRUE)
```



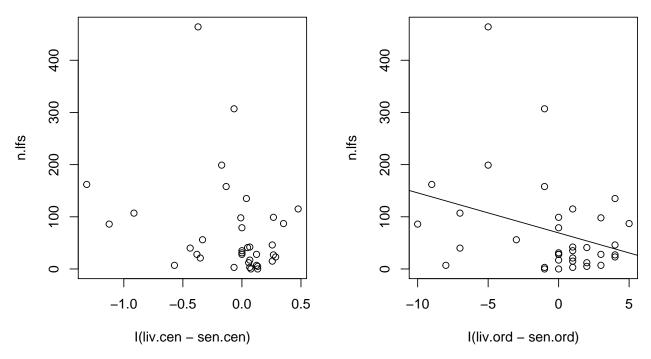
Number of senescing leaves influences the order but not the centrality (eigen) of the networks or the network similarity of senescing leaves.

```
n.lfs <- tree.info$leaves[tree.info$leaf.type == 'sen']
cor.test(n.lfs,I(liv.cen-sen.cen))

##
## Pearson's product-moment correlation
##
## data: n.lfs and I(liv.cen - sen.cen)
## t = -1.5167, df = 34, p-value = 0.1386
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.53594682  0.08372385</pre>
```

sample estimates:

```
cor
## -0.2517362
cor.test(n.lfs,I(liv.ord-sen.ord))
##
##
   Pearson's product-moment correlation
##
## data: n.lfs and I(liv.ord - sen.ord)
## t = -1.9501, df = 34, p-value = 0.05945
\mbox{\tt \#\#} alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.5847730 0.0126857
## sample estimates:
          cor
## -0.3171719
adonis(distNet(tree.nets[tree.info$leaf.type == 'sen'])~n.lfs)
##
## Call:
## adonis(formula = distNet(tree.nets[tree.info$leaf.type == "sen"]) ~
##
## Permutation: free
## Number of permutations: 999
## Terms added sequentially (first to last)
##
##
             Df SumsOfSqs MeanSqs F.Model
                                               R2 Pr(>F)
                   37.85 37.849 1.3597 0.03845 0.194
## n.lfs
            1
                   946.43 27.836
## Residuals 34
                                          0.96155
## Total
            35
                   984.28
                                          1.00000
par(mfrow=c(1,2))
plot(I(liv.cen-sen.cen),n.lfs)
plot(I(liv.ord-sen.ord),n.lfs)
abline(lm(n.lfs~I(liv.ord-sen.ord)))
```



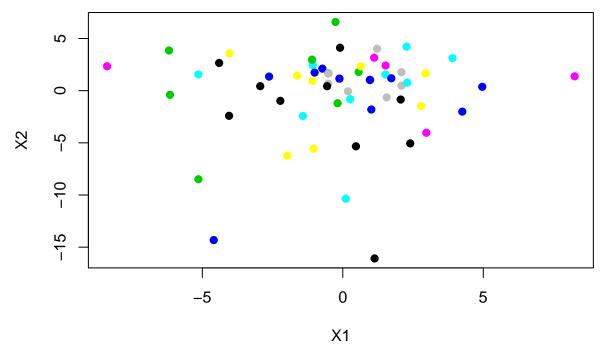
How much variance in network structure does genotype explain?

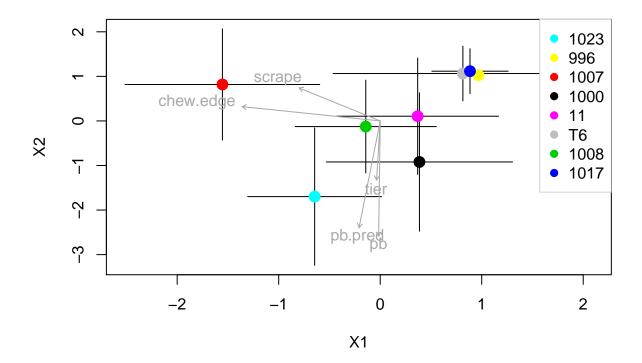
Total

About 8% of the variation in network structure was attributable to tree genotype. This was primarily due to genetic effects on re-wiring of the network rather than changes to the structure. Leaf senescence strongly impacted network modularity.

```
library(BiodiversityR)
library(ecodist)
dn.tree <- distNet(tree.nets)</pre>
adonis(dn.tree~factor(leaf.type)*factor(geno),data=tree.info, strata=tree.info$tree)
##
## Call:
## adonis(formula = dn.tree ~ factor(leaf.type) * factor(geno),
                                                                       data = tree.info, strata = tree.in
##
## Blocks: strata
## Permutation: free
## Number of permutations: 999
##
## Terms added sequentially (first to last)
##
                                   Df SumsOfSqs MeanSqs F.Model
##
                                                                      R2 Pr(>F)
## factor(leaf.type)
                                    1
                                         118.53 118.528 5.3315 0.07390
                                                                          0.001
## factor(geno)
                                    7
                                         123.52
                                                 17.646
                                                          0.7937 0.07702
                                                                          0.001
## factor(leaf.type):factor(geno)
                                    7
                                         116.79
                                                 16.684
                                                          0.7505 0.07282
                                                                          0.661
## Residuals
                                   56
                                        1244.97
                                                 22.232
                                                                 0.77626
## Total
                                   71
                                        1603.81
                                                                 1.00000
##
## factor(leaf.type)
                                   ***
## factor(geno)
## factor(leaf.type):factor(geno)
## Residuals
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
ord.tree <- nmds.min(nmds(dn.tree,2,2),dims=2)</pre>
## Using random start configuration
## Minimum stress for given dimensionality: 0.16264
## r^2 for minimum stress configuration: 0.9422117
spp.vectors <- envfit(ord.tree,spp.tot)</pre>
spp.vectors <- envfit(ord.tree,spp.tot[,spp.vectors$vectors$pvals <= 0.05])</pre>
plot(ord.tree,pch=19,
     col=as.numeric(factor(tree.info$geno)))
```





```
""{r}
```

 $adonis(distNet(liv.nets)\sim factor(geno), data = tree.info[tree.info$leaf.type == 'live',])$

 $adonis(distNet(sen.nets)\sim factor(geno), data = tree.info[tree.info$leaf.type == 'sen',])$

"

```
library(bipartite)
### centrality
tree.cen <- unlist(lapply(tree.nets,function(x) centralization(x,FUN='degree')))
tree.mod <- dget(file='.../data/tree.mod') # see src/treeMods.R

summary(aov(tree.cen~tree+factor(leaf.type)*factor(geno),data=tree.info))</pre>
```

```
## Df Sum Sq Mean Sq F value Pr(>F)
## tree 35 2.9209 0.08345 1.311 0.232
## factor(leaf.type) 1 0.1380 0.13802 2.168 0.152
## factor(leaf.type):factor(geno) 7 0.6164 0.08805 1.383 0.251
## Residuals 28 1.7824 0.06366
```

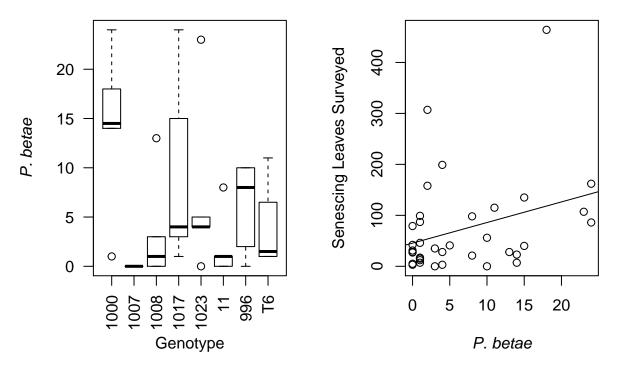
```
summary(aov(tree.mod~tree+factor(leaf.type)*factor(geno),data=tree.info))
```

```
## tree Df Sum Sq Mean Sq F value Pr(>F)
## tree 35 1.0698 0.0306 0.903 0.616910
## factor(leaf.type) 1 0.5749 0.5749 16.976 0.000304 ***
```

```
## factor(leaf.type):factor(geno) 7 0.2974 0.0425 1.255 0.307767
## Residuals 28 0.9482 0.0339
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

tree.info\$leaf.type == 'sen',]))

```
Genotype does not directly influence senescence, but may indirectly influence senescence through pb.
summary(aov(I(leaves^0.5)~factor(geno)*pb,
           data=data.frame(tree.info,spp.tot)[tree.info$leaf.type == 'sen',]))
                  Df Sum Sq Mean Sq F value Pr(>F)
## factor(geno)
                   7 171.2 24.46 1.178 0.3564
## pb
                   1
                       98.8
                              98.82 4.760 0.0406 *
## factor(geno):pb 6
                       79.5
                              13.25
                                      0.638 0.6985
## Residuals
                  21 436.0
                              20.76
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
summary(aov(I(pb^0.5) ~ factor(geno),
           data=data.frame(tree.info,spp.tot)[tree.info$leaf.type == 'sen',]))
               Df Sum Sq Mean Sq F value Pr(>F)
## factor(geno) 7 30.03
                          4.290
                                   2.114 0.0751 .
## Residuals
               28 56.81
                           2.029
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
par(mfrow=c(1,2))
plot(pb~geno,
    data=data.frame(tree.info,spp.tot)[tree.info$leaf.type == 'sen',],
    xlab='Genotype',ylab=expression(italic('P. betae')),las=2)
plot(leaves~pb,
    data=data.frame(tree.info,spp.tot)[tree.info$leaf.type == 'sen',],
    xlab=expression(italic('P. betae')),ylab='Senescing Leaves Surveyed')
abline(lm(leaves~pb,data=data.frame(tree.info,spp.tot)[
```



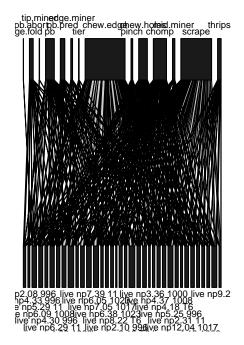
Stand level network modularity

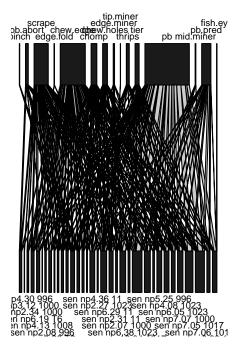
```
liv.bpn <- spp.tot[tree.info$leaf.type == 'live',]
sen.bpn <- spp.tot[tree.info$leaf.type == 'sen',]

liv.modules <- dget('../data/liv.modules')
sen.modules <- dget('../data/sen.modules')

par(mfrow=c(1,2))
plotweb(liv.bpn);title(main='Live')
plotweb(sen.bpn);title(main='Senescent')</pre>
```

Live Senescent

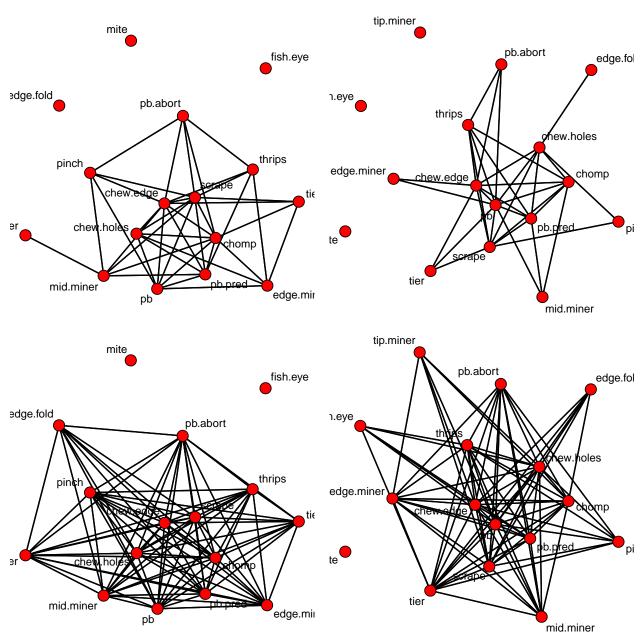




How does the mean interaction network compare to the bipartite to unipartite projection?

```
liv.b2u <- t(liv.bpn) %*% liv.bpn
sen.b2u <- t(sen.bpn) %*% sen.bpn

par(mfrow=c(2,2),mai=rep(0.1,4))
liv.coo <- gplot(liv.mu,gmode='graph',displaylabels=TRUE)
sen.coo <- gplot(sen.mu,gmode='graph',displaylabels=TRUE)
gplot(liv.b2u,coord=liv.coo,gmode='graph',displaylabels=TRUE)
gplot(sen.b2u,coord=sen.coo,gmode='graph',displaylabels=TRUE)</pre>
```



This question isn't very interesting since the effect of genotype doesn't differ between live and senescing leaves. What does the unipartite projection look like for the trees and genotypes?