

BMI 206: Networks Lab

```

#turned sergio's code into functions for ease.

sergio_ggplot <- function(pvals){
  observed <- sort(pvals$GenePvalue)
  lobs <- -(log10(observed))

  expected <- c(1:length(observed))
  lexp <- -(log10(expected / (length(expected)+1)))

  g1 <- ggplot(data = data.frame(cbind(lexp, lobs)), aes(x=lexp, y=lobs)) +
  geom_point() +
  xlab("Expected (-logP)") + ylab("Observed (-logP)") +
  theme_bw() +
  scale_x_continuous(breaks=c(1:7), limits = c(0,7)) +
  scale_y_continuous(breaks=c(1:7), limits = c(0,7)) +
  geom_abline(intercept = 0, slope = 1, color="red", size=1)
  NULL
  return(g1)
}

sergio_manhattan <- function(wtcc){
  wtcc$Start <- wtcc$Start/1000
  for(j in 2:22){
    wtcc[wtcc$Chr==j,"Start"] <- max(wtcc[wtcc$Chr==(j-1),"Start"])+wtcc[wtcc$Chr==j,"Start"]
    wtcc[wtcc$Chr==j, "Tick"] <- (min(wtcc[wtcc$Chr==j,"Start"]) +
      max(wtcc[wtcc$Chr==j,"Start"]))/2}
  wtcc[wtcc$Chr==1,"Tick"] <- (min(wtcc[wtcc$Chr==1,"Start"]) + max(wtcc[wtcc$Chr==1,"Start"]))/2
  wtcc$Discovery_log <- -log10(wtcc$GenePvalue)
  wtcc$Color_Dis <- wtcc$Chr %% 2
  wtcc$Color_Dis <-ifelse(wtcc$GenePvalue< 0.05, (wtcc$Chr %% 2)+2, wtcc$Color_Dis)

  colours <- c("#D3D3D3", "#808080", brewer.pal(n = 3, name = "Set1"))

#pdf("Manhattan_plot.pdf",width=12,height=6)
  g1 <- ggplot(wtcc, aes(Start, Discovery_log)) +
  geom_point(size=1.5,alpha=0.6,aes(colour=as.factor(Color_Dis)))+
  scale_colour_manual(values = colours) +
  #scale_color_brewer(palette="Set1")+
  geom_hline(yintercept=-log10(0.05),size=0.5, colour="gray")+
  ylab(expression(paste(-log[10]~'P value')))+
  theme_bw()+
  theme(legend.position = "none",
    panel.grid.major.x = element_blank(),
    panel.grid.minor.x = element_blank()) +
  scale_x_continuous(name = "Chromosome", breaks = unique(wtcc$Tick), labels = unique(wtcc$Chr),expand=c(0.01,0))

  return(g1)
}

```

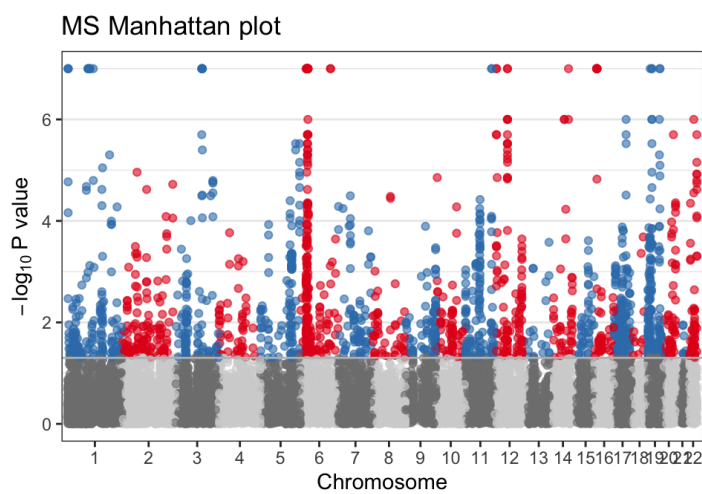
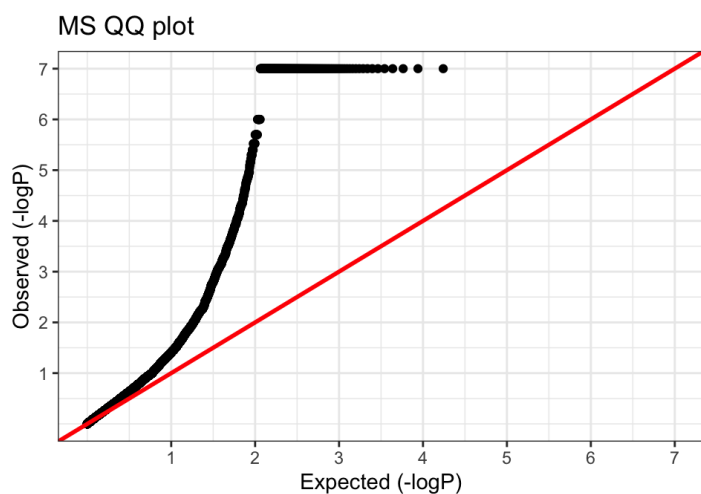
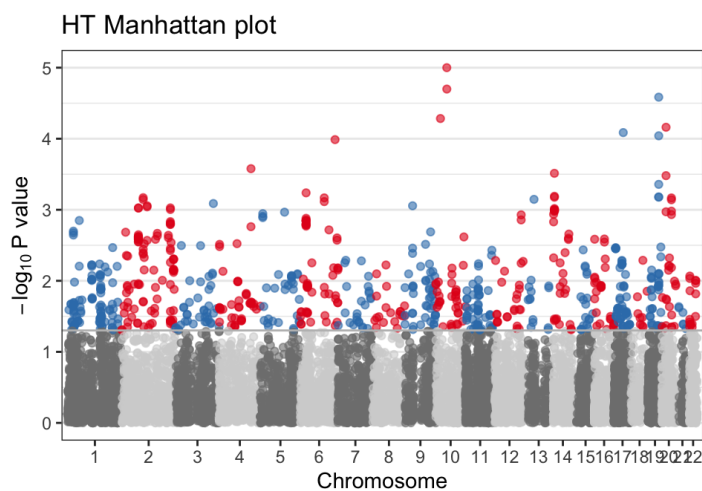
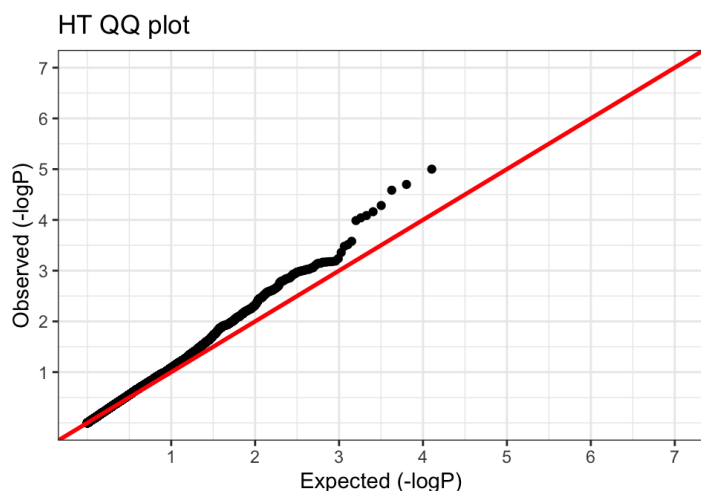
Q1: After exploring the Manhattan plots, and qq-plots from each GWAS, what can you tell about the power of each study?

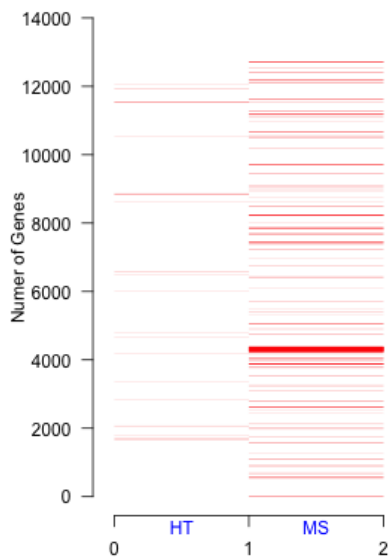
ANS: The MS GWAS has a higher power than the HT study. This can be seen by the flat line in the Q-Q plot of the latter. Advanced comment: The early departure from the diagonal in the MS study, might suggest genomic inflation, but its power is clearly superior.

```
g1 <- sergio_qqplot(read.table("MS.pvals.out", header=T))
g2 <- sergio_manhattan(read.table("MS.pvals.out", header=T, as.is=T))

g3 <- sergio_qqplot(read.table("HT.pvals.out", header=T))
g4 <- sergio_manhattan(read.table("HT.pvals.out", header=T, as.is=T))

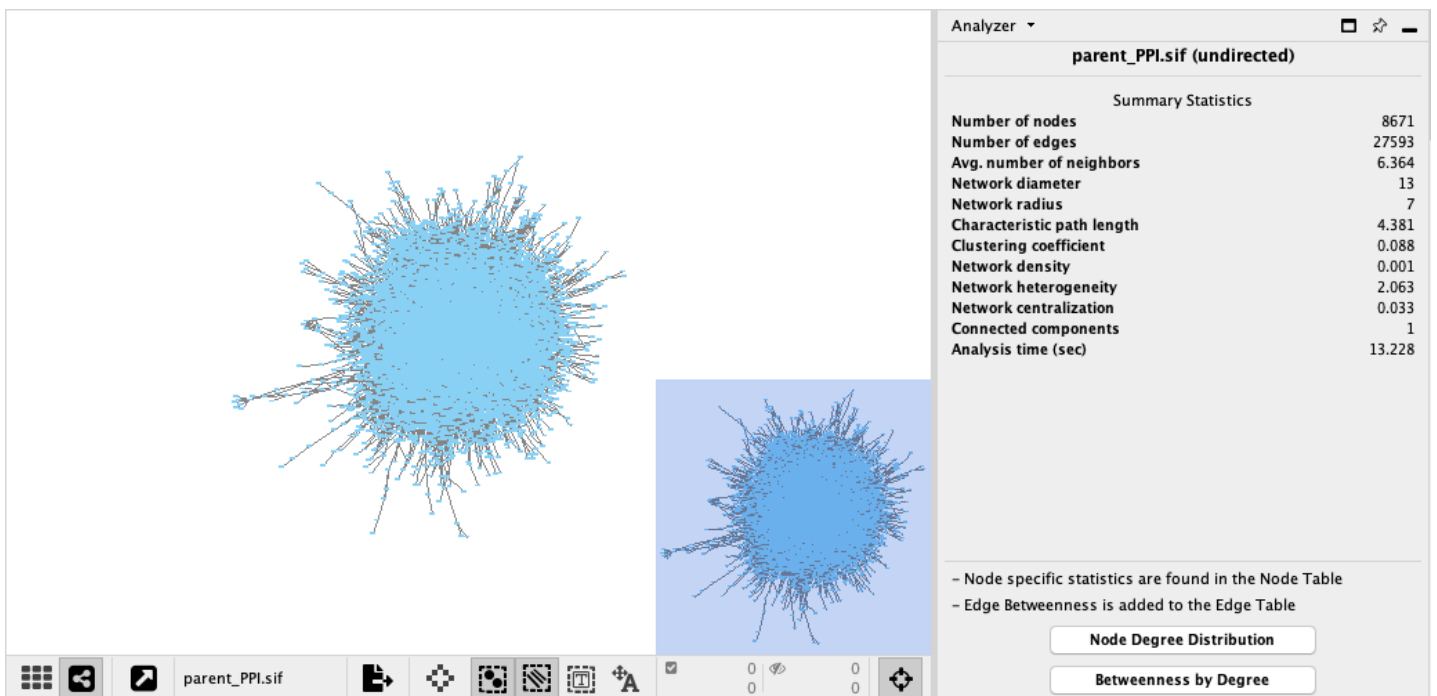
grid.arrange(g3+ggtitle("HT QQ plot"), g4+ggtitle("HT Manhattan plot"),
             g1+ggtitle("MS QQ plot"), g2+ggtitle("MS Manhattan plot"),
             ncol=2)
```

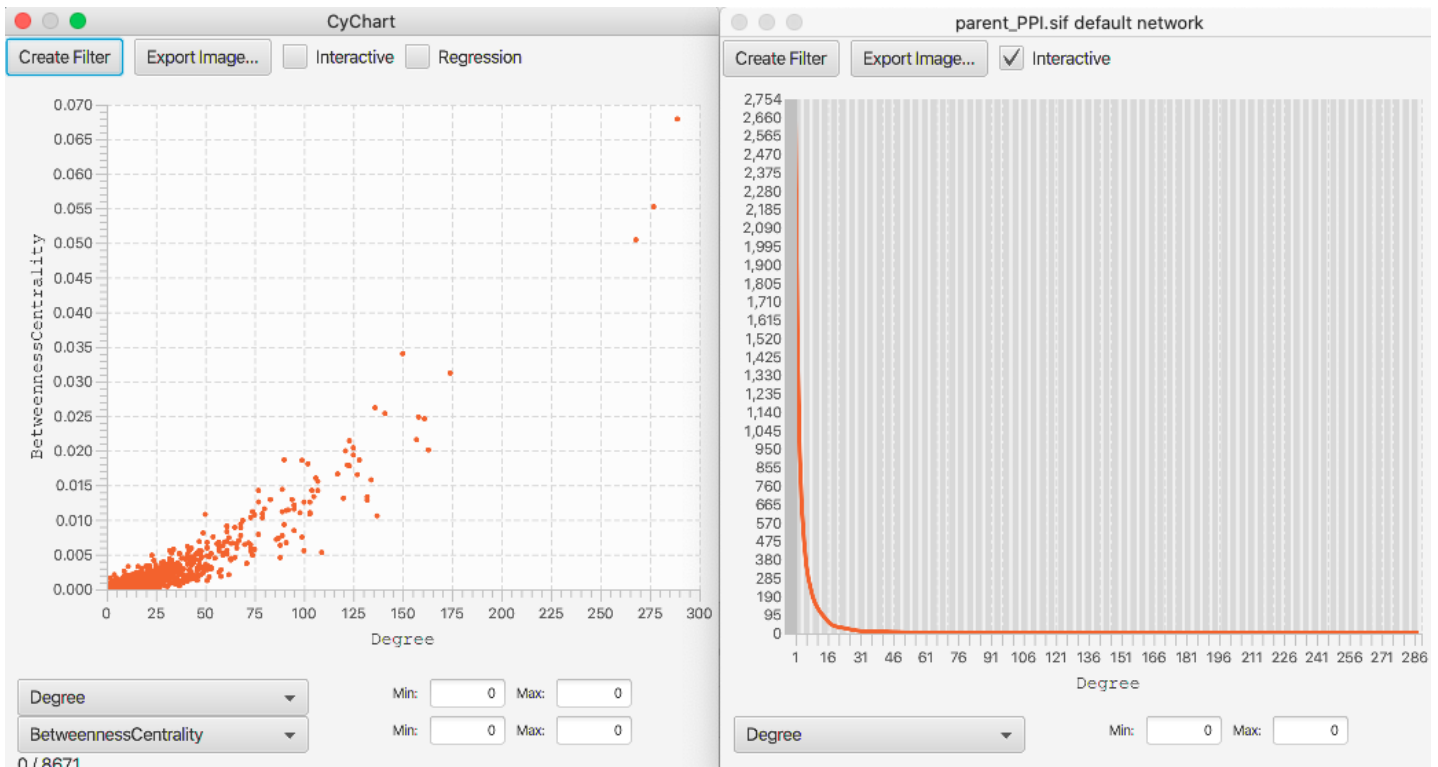




Q2: Using Cytoscape, analyze the PPI and describe its main network properties (this may take 20-40 min! do at home)

ANS: There are ~8K nodes (proteins) and ~27K edges (protein interaction/binding). The network is scale-free. Answers could also describe the clustering coefficient, and closeness metrics.





Q3: Using Cytoscape, find the first order networks ($p < 0.05$) for each GWAS

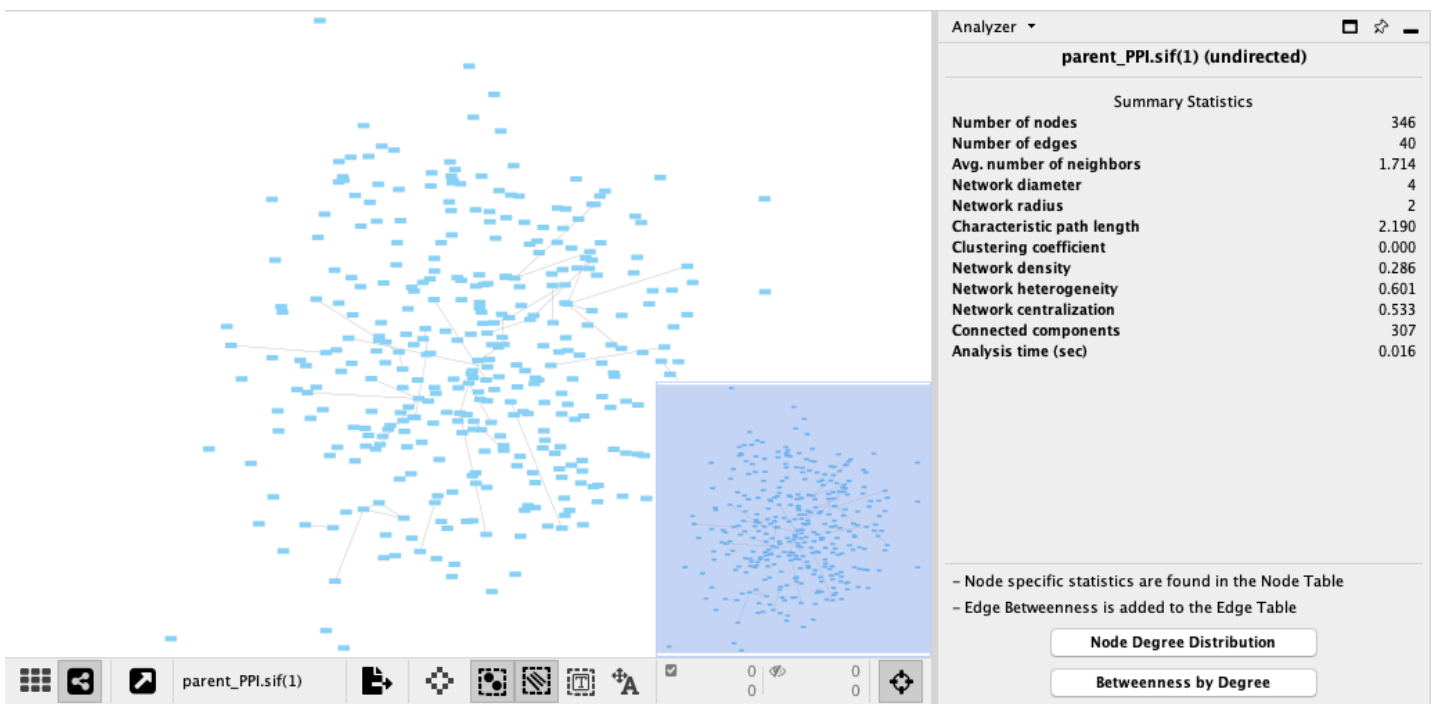
ANS:

Filter > + > Node:Pvalue between 0 and 0.05 inclusive (N=346 for HT, N=667 for MS)

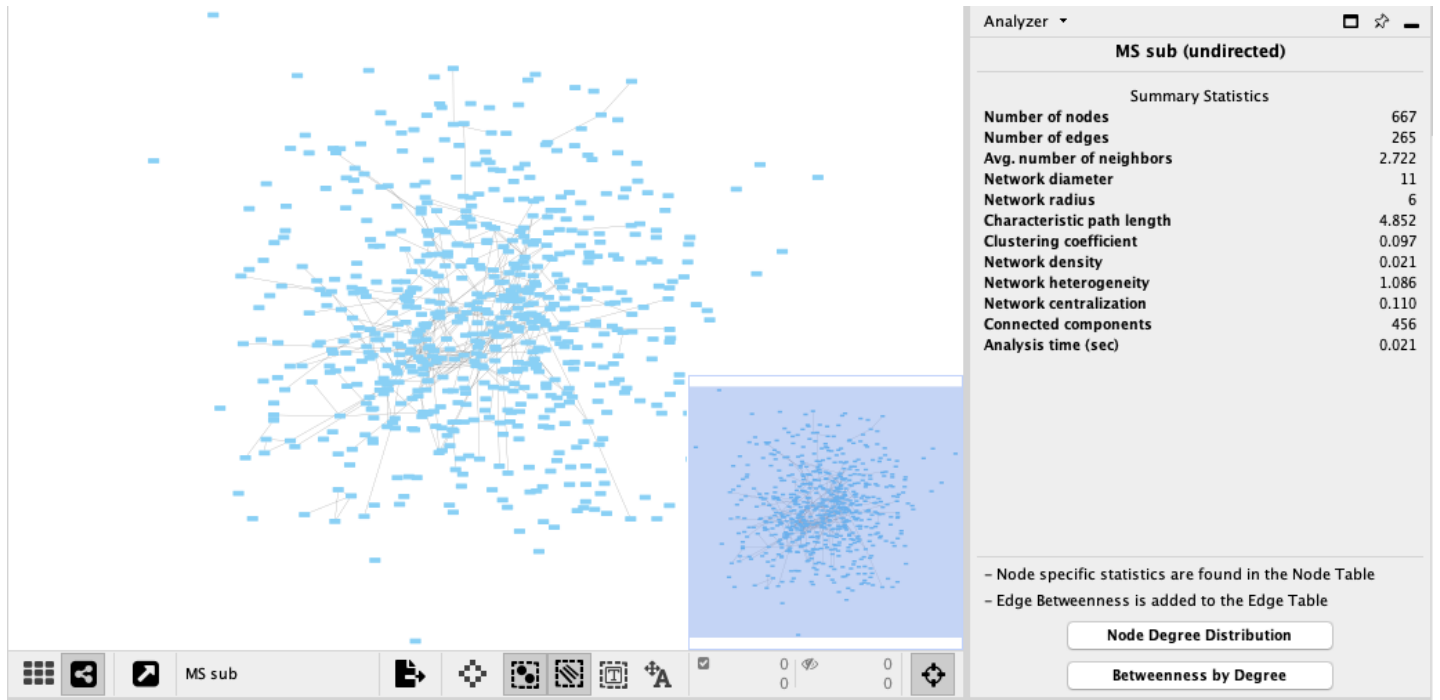
File > New Network > From selected nodes, all edges

Tools > Analyze Network

The HT first order network contains 346 nodes and 40 edges.



The MS first order network contains 667 nodes and 265 edges. In contrast to the HT subnetwork, this network has metrics reflecting it is fairly connected and may contain more hub genes (via network heterogeneity).

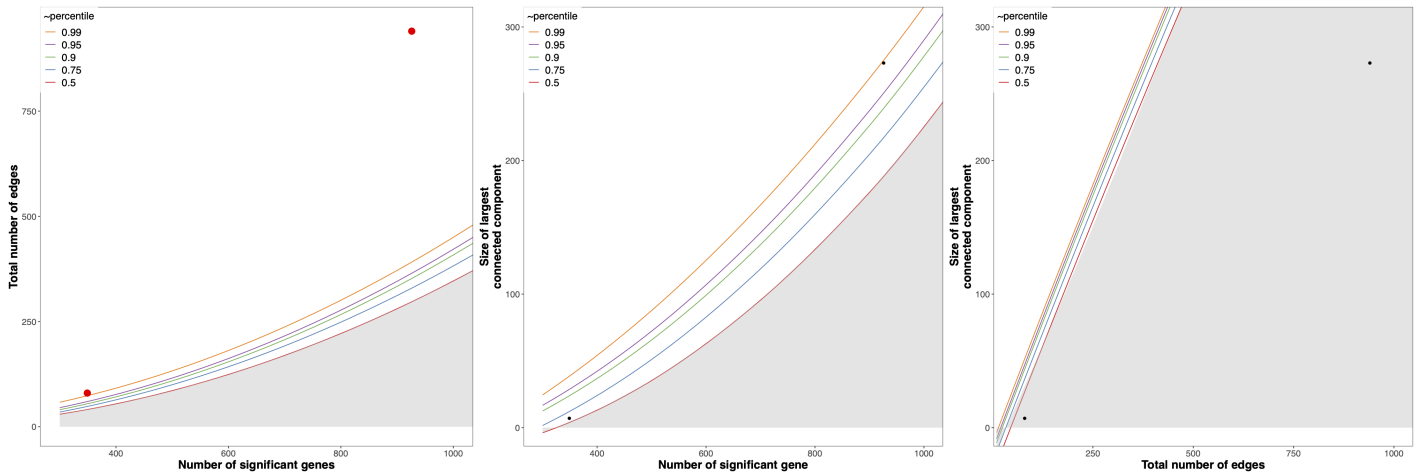


Q4: Source "Pathway_permutation.r". Are the first order networks from both GWAS more connected than expected? What does this mean?

ANS: The sub-network of MS is more connected than expected (way above the 99th percentile) The sub-network of HT is not.

```
source("Pathway_permutation.r")
```

	Region	Extracted_nodes	Edges	largest_nodes
1	HT	349	80	7
2	MS	926	940	273



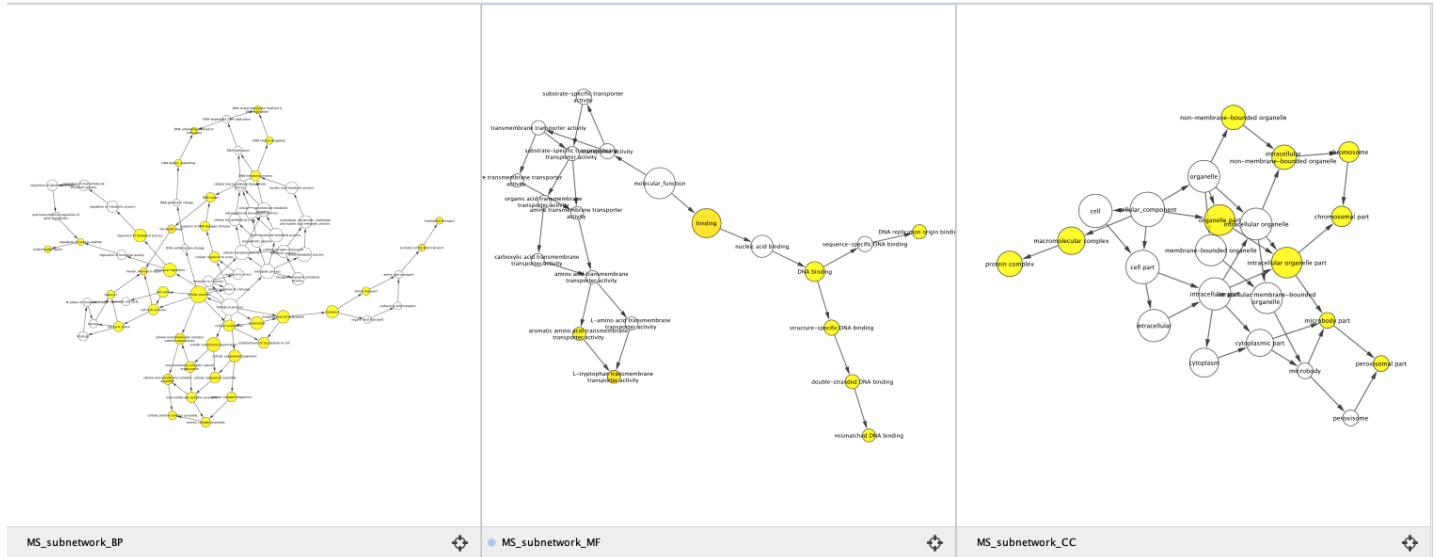
Q5: Run BINGO App on all nodes from largest connected component. What biological processes emerge from the first order networks?

ANS: There should be several immune-related GO significantly enriched in the MS network. Not much (if anything) in the HT net.

ANS: In the total PPI network the top overrepresented GO terms are: cellular process (BP), cellular macromolecule metabolic process (BP), general RNA polymerase II transcription factor activity (MF), macromolecular complex (CC), and protein complex (CC). Overall not particularly informative.



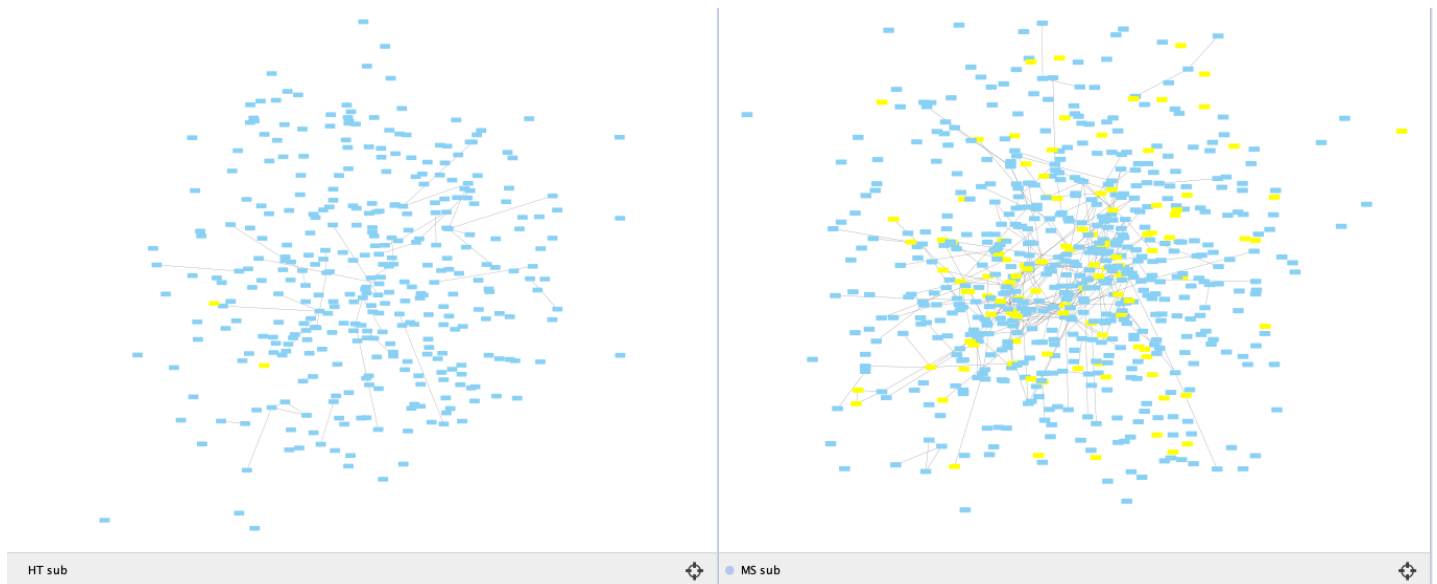
The first order network for the MS dataset shows enrichment for mismatch repair (BP), binding (MF), organelle part (CC) and quite a few terms about aromatic or tryptophan activity but this is mainly driven by the two genes “TAP2|TAP1”.



The first order network for the HT dataset returned no significantly enriched GO terms.

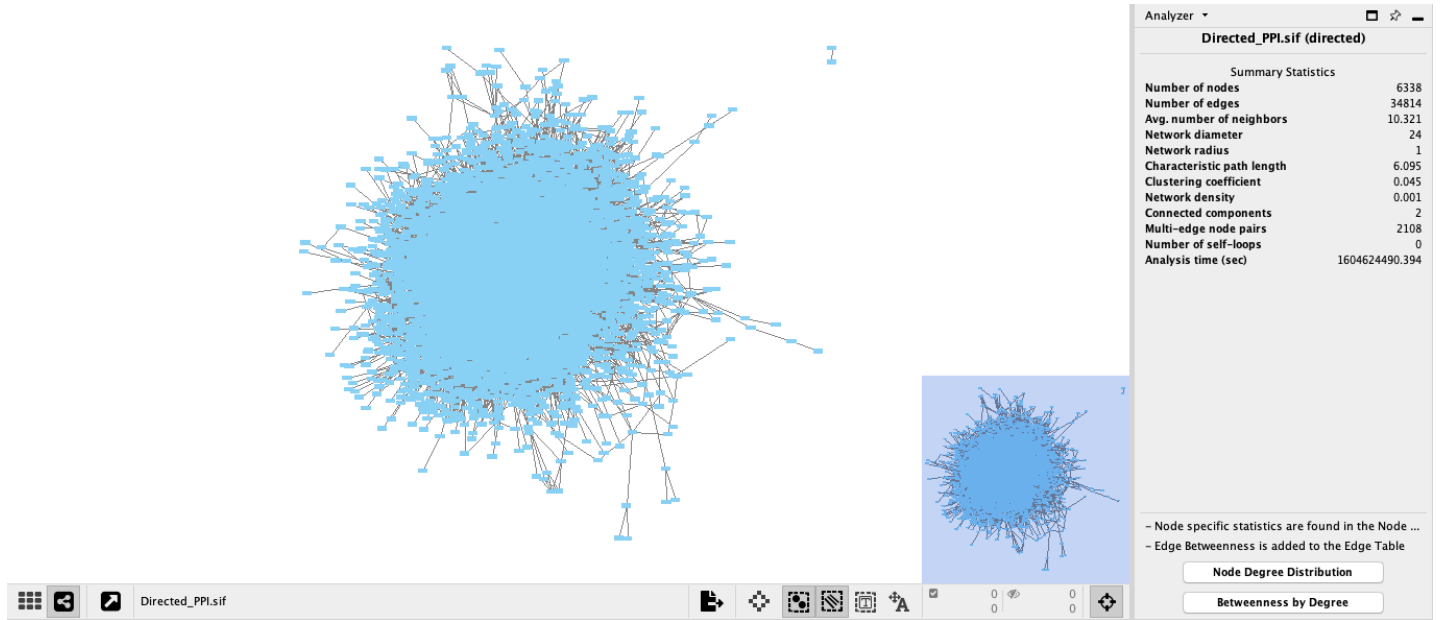
Q6: Map and color known MS and HT genes onto their respective first order nets. Interpret results.

ANS: The MS net contains more known genes. Perhaps the HT GWAS has a high false negative rate due to low power.

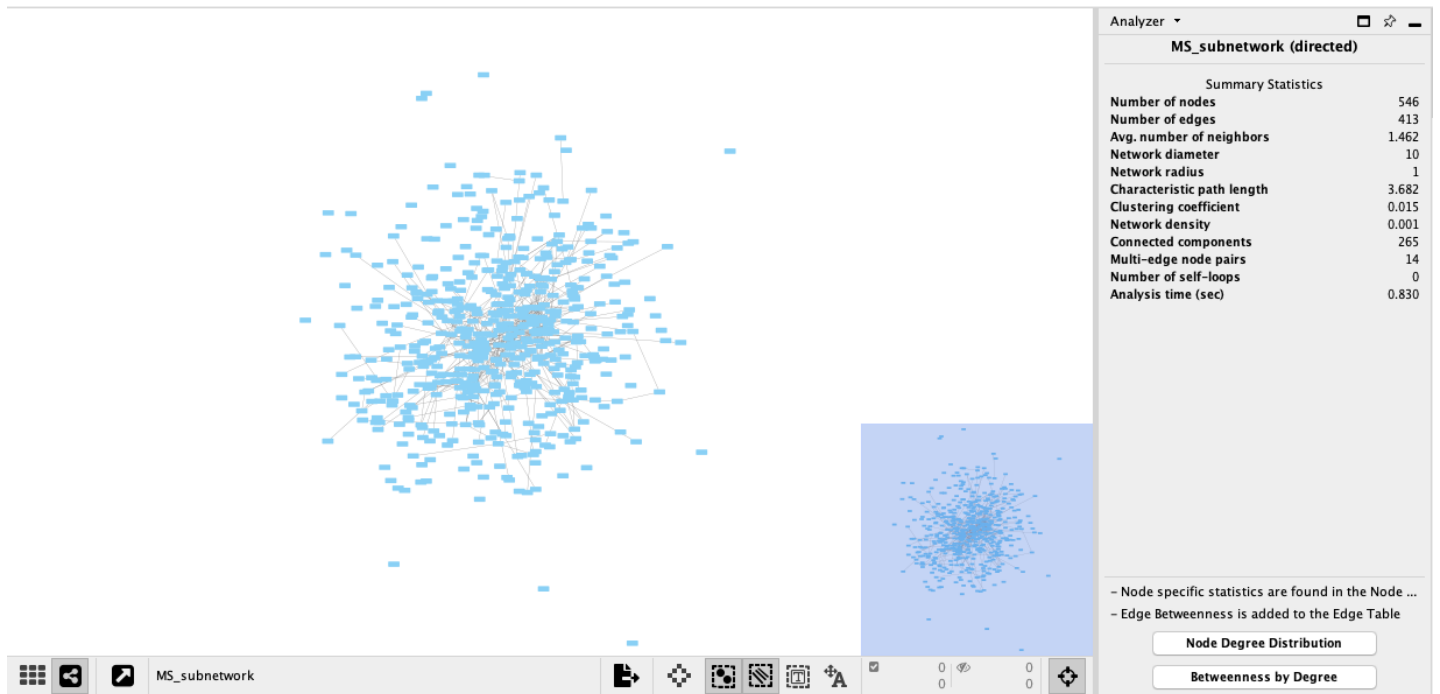


Q7: Repeat steps 3 and 4 with directed protein network from PNAS paper.

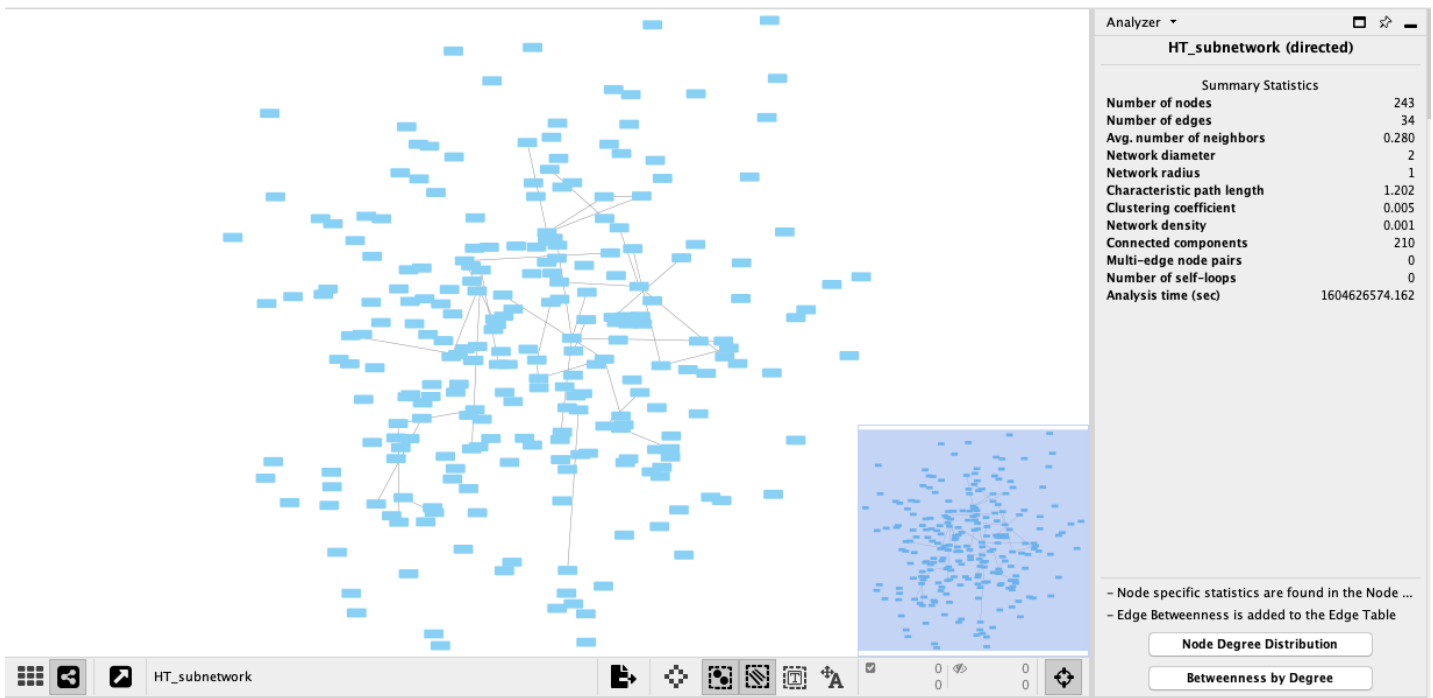
ANS: Compared to the HT first order network, the MS first order network is much more connected with a large connected component that exceeds what is expected by chance using a permutation null distribution.



The MS first order network contains 546 nodes and 413 edges.



The HT first order network contains 243 nodes and 34 edges. This is much fewer edges than expected leaving quite a few orphan nodes. This is reflected in the large reduction in the average number of neighbors (0.28)



Compared to the undirected network, all numbers for the HT network are reduced. Possibly because the lack of connectivity. For the MS-directed first order network, we see an increase in the number of edges and largest node.

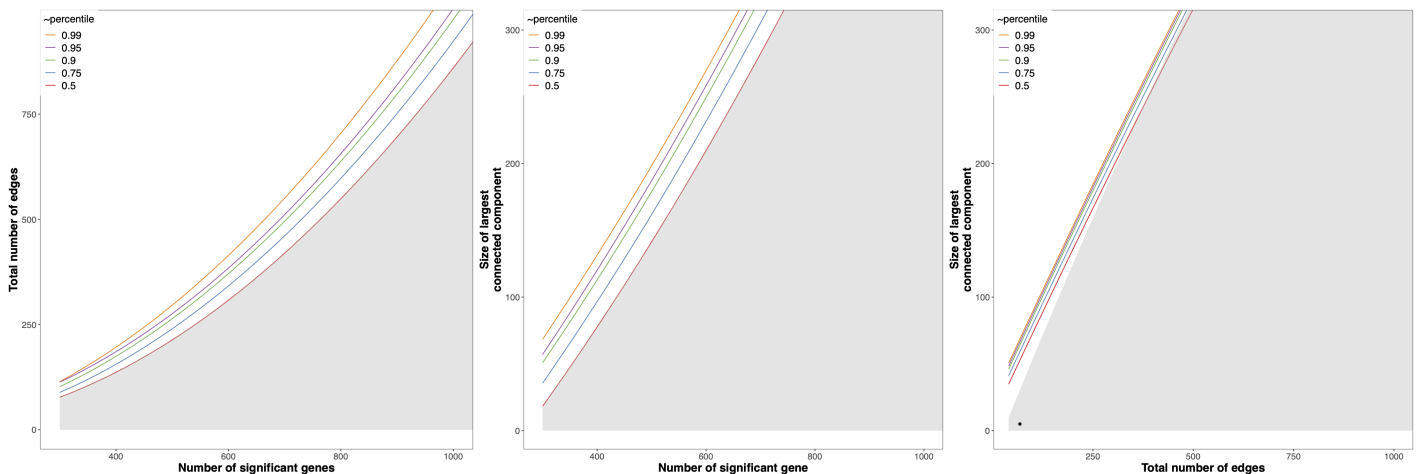
```
source("Pathway_permutation.r")

UNDIRECTED
  Region Extracted_nodes Edges largest_nodes
1      HT              349    80             7
2      MS              926   940            273

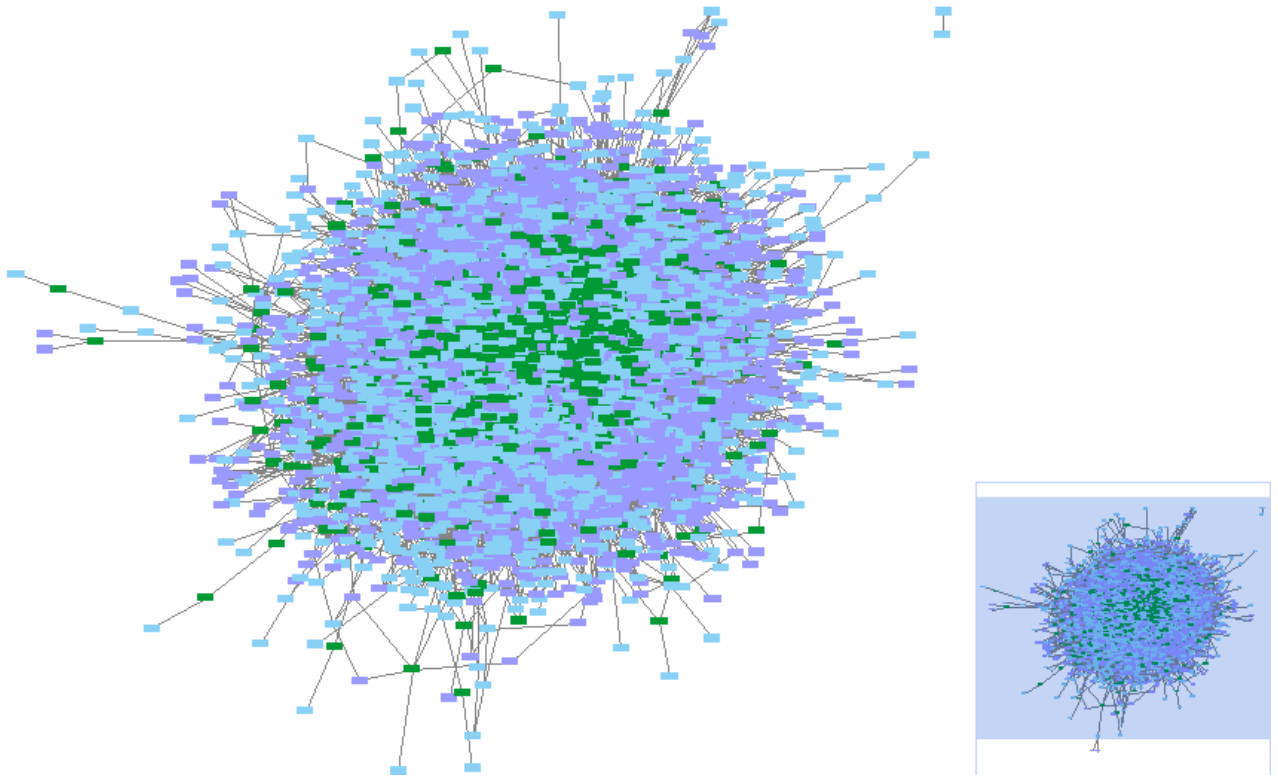
VS

DIRECTED
  Region Extracted_nodes Edges largest_nodes
1      HT              243    68             5
2      MS              742  1354            379
```

Similar to before we see that the MS-directed first order network is more connected than our permuted distribution whereas the HT falls well within the bounds.



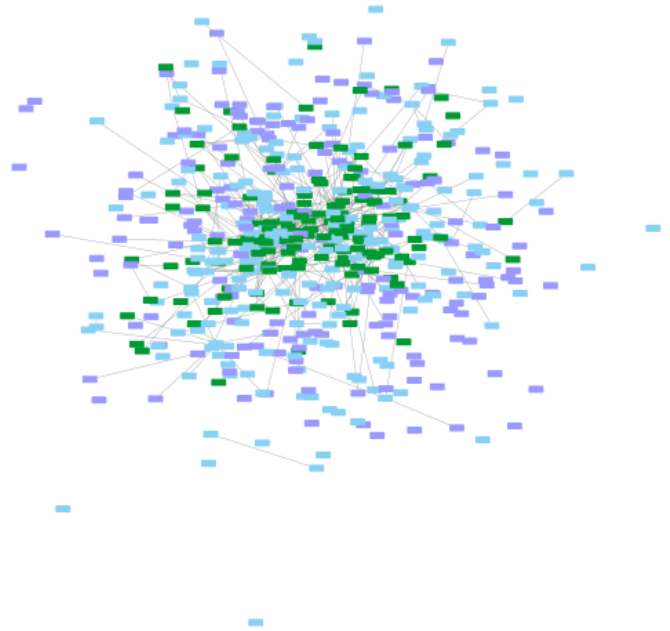
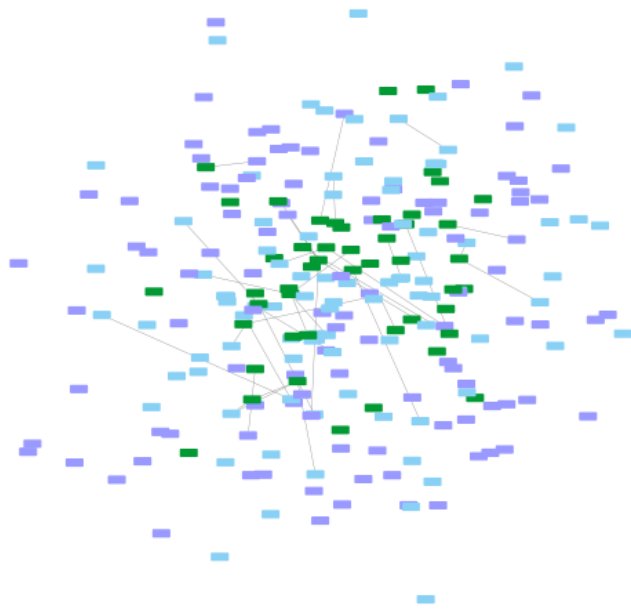
Q8: Color nodes by controllability category (dispensable, indispensable, neutral).



Q9: Repeat step 6. Are MS-associated genes more enriched in any controllability category? Interpret.

ANS: There is no significant enrichment of MS (or HT) associated genes in any controllability category. This is in line with Fig. 2B in the controllability paper (PMID: 27091990).

further: For the nodes in the directed MS network with a $pval < 0.05$, 229/546 are Neutral, 175/546 are Dispensable, and 142/546 are Indispensable. Via hypergeometric test comparing the amount of total proteins in each controllability group versus the MS subnetwork, we see there is enrichment for both "Indispensable" and "Neutral" proteins but not "Dispensable". One way this could be biologically explained is if the MS GWAS picked up on highly critical genes (as expected) as well as their more neutral interactors. Dispensable genes were not picked up through the GWAS as these may be more likely to vary in the "control" population as well.



HT_sub

MS_sub

```
#phyper(neutral in subnet, subnet_size, total_size-subnet size, total neutral genes)  
#Note: I removed the 8 genes with missing controllability categories
```

```
#Test for over-representation
```

```
phyper(229, 546, 6330-546, 2261, lower.tail = F) #Neutral
```

```
## [1] 0.0007079792
```

```
phyper(175, 546, 6330-546, 2343, lower.tail = F) #Dispensable
```

```
## [1] 0.9935267
```

```
phyper(142, 546, 6330-546, 1326, lower.tail = F) #Indispensable
```

```
## [1] 0.001234459
```

```
knitr::knit_exit()
```