

Statistical Analysis for Story Telling

Recall what we have seen at Feature Extraction:

```
setwd("D:/STOR893-Zhang/vessel-network/feature_extraction/feature")

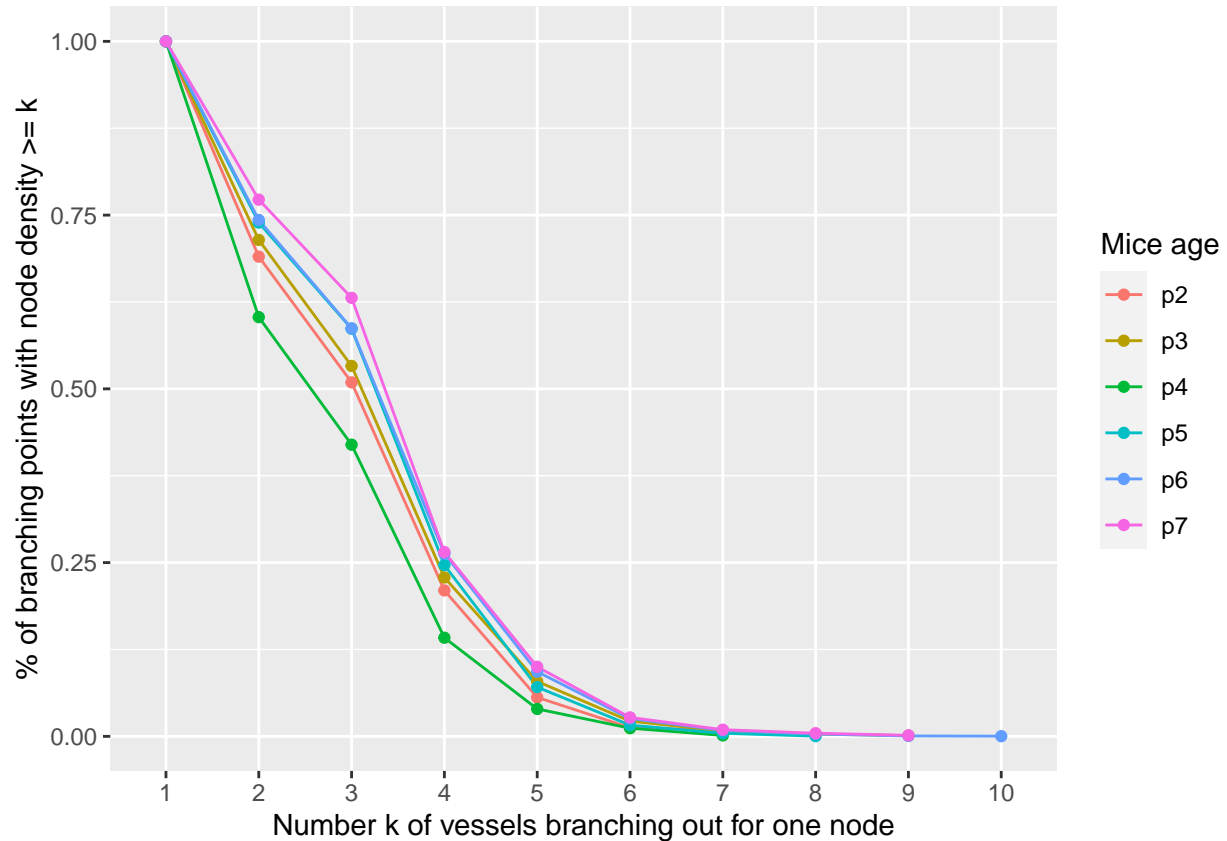
deg.dat.p2 = read_excel("p2-fro_degreedata.xlsx")
deg.dat.p3 = read_excel("p3-fro_degreedata.xlsx")
deg.dat.p4 = read_excel("p4-fro_degreedata.xlsx")
deg.dat.p5 = read_excel("p5-fro_degreedata.xlsx")
deg.dat.p6 = read_excel("p6-fro_degreedata.xlsx")
deg.dat.p7 = read_excel("p7-fro_degreedata.xlsx")

deg_density = function(x,i){
  degree = x$degree
  deg_density = table(degree)[max(degree):1] %>%
    prop.table() %>%
    cumsum() %>%
    rev()
  dt.frame = data.frame(miceage = rep(paste0("p",i,sep=""),max(degree)),
                        degree = 1:max(degree),
                        density = deg_density)

  return(dt.frame)
}

deg.density.p2 = deg_density(deg.dat.p2,2)
deg.density.p3 = deg_density(deg.dat.p3,3)
deg.density.p4 = deg_density(deg.dat.p4,4)
deg.density.p5 = deg_density(deg.dat.p5,5)
deg.density.p6 = deg_density(deg.dat.p6,6)
deg.density.p7 = deg_density(deg.dat.p7,7)
deg_spatial_density = rbind(deg.density.p2,
                             deg.density.p3,
                             deg.density.p4,
                             deg.density.p5,
                             deg.density.p6,
                             deg.density.p7)

deg_spatial_density$miceage = as.factor(deg_spatial_density$miceage)
deg_spatial_density$degree = as.factor(deg_spatial_density$degree)
ggplot(deg_spatial_density, aes(x = degree, y = density, color = miceage, group = miceage)) +
  geom_line() +
  geom_point() +
  labs(x = "Number k of vessels branching out for one node",
       y = "% of branching points with node density >= k") +
  scale_color_discrete("Mice age")
```



The question is why the degree of spatial density at P4 is lower than the others. We can make a conjecture that at postnatal day 4, there is something happen at the retina of the small mouse.

First, define the function to construct adjacency matrices of P2 through P7: This work is time consuming. Just call the data set that I stored in advance.

```
load("D:/STOR893-Zhang/vessel-network/network_graph/Data.basic.network.RData")
```

By changing eval=FALSE to eval=TRUE, you can run the function.

```
Adj_mat_generate = function(x){

  data.tmp = x

  identified_nodes_key = sort(unique(rbind(data.tmp$node1,data.tmp$node2)[2,]),decreasing=TRUE)
  node1 = sort(x$node1,decreasing=TRUE)
  node2 = sort(x$node2,decreasing=TRUE)

  d = length(identified_nodes_key)
  Adj_mat = matrix(NA,nrow=d,ncol=d)
  rownames(Adj_mat) = identified_nodes_key
  colnames(Adj_mat) = identified_nodes_key

  for (i in 1:d){
    j = 1;
    while ( j <= i ){
      if (i == j){
        Adj_mat[i,j] = 0
      }
    }
  }
}
```

```

    }
    else{

        key.from = identified_nodes_key[i]
        key.to = identified_nodes_key[j]
    }
    j = j+1
}
# Ticker: can be commentized
print(i)
}

return(list(Adj_mat,weight_line,weight_length,weight_width,weight_tortuosity))
}

p2.clean = Adj_mat_generate(all.dat.p2)
p3.clean = Adj_mat_generate(all.dat.p3)
p4.clean = Adj_mat_generate(all.dat.p4)
p5.clean = Adj_mat_generate(all.dat.p5)
p6.clean = Adj_mat_generate(all.dat.p6)
p7.clean = Adj_mat_generate(all.dat.p7)

```

Next, construct the graphs by:

```

G2 = graph_from_adjacency_matrix(p2.clean[[1]],mode="undirected")
G3 = graph_from_adjacency_matrix(p3.clean[[1]],mode="undirected")
G4 = graph_from_adjacency_matrix(p4.clean[[1]],mode="undirected")
G5 = graph_from_adjacency_matrix(p5.clean[[1]],mode="undirected")
G6 = graph_from_adjacency_matrix(p6.clean[[1]],mode="undirected")
G7 = graph_from_adjacency_matrix(p7.clean[[1]],mode="undirected")

```

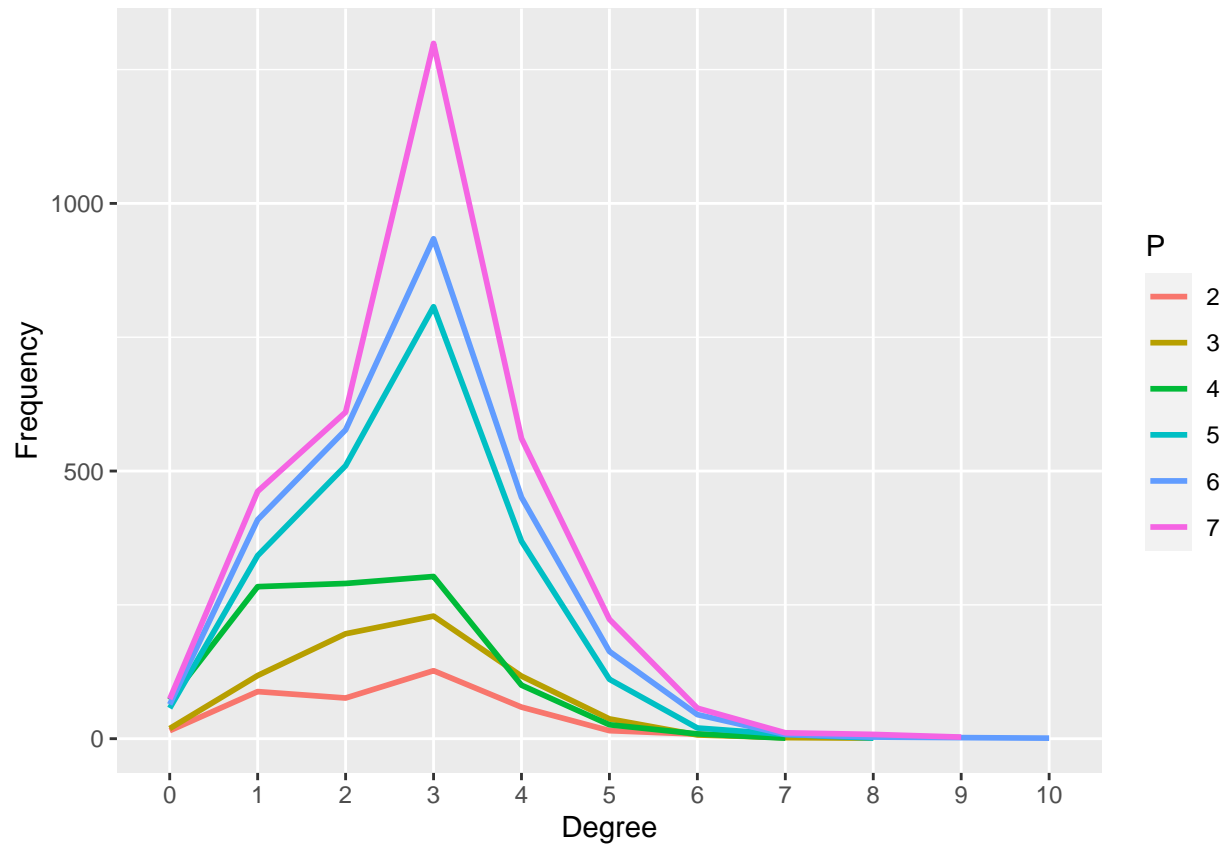
Note that the plot below has the same information but is drawn in different way.

```

dt.degree.p2 = data.frame(as.data.frame(table(degree(G2))), P=rep(2,length(table(degree(G2)))))
dt.degree.p3 = data.frame(as.data.frame(table(degree(G3))), P=rep(3,length(table(degree(G3)))))
dt.degree.p4 = data.frame(as.data.frame(table(degree(G4))), P=rep(4,length(table(degree(G4)))))
dt.degree.p5 = data.frame(as.data.frame(table(degree(G5))), P=rep(5,length(table(degree(G5)))))
dt.degree.p6 = data.frame(as.data.frame(table(degree(G6))), P=rep(6,length(table(degree(G6)))))
dt.degree.p7 = data.frame(as.data.frame(table(degree(G7))), P=rep(7,length(table(degree(G7)))))
dt.degree = rbind(dt.degree.p2,dt.degree.p3,dt.degree.p4,dt.degree.p5,dt.degree.p6,dt.degree.p7)
names(dt.degree) = c("Deg","Freq","P")

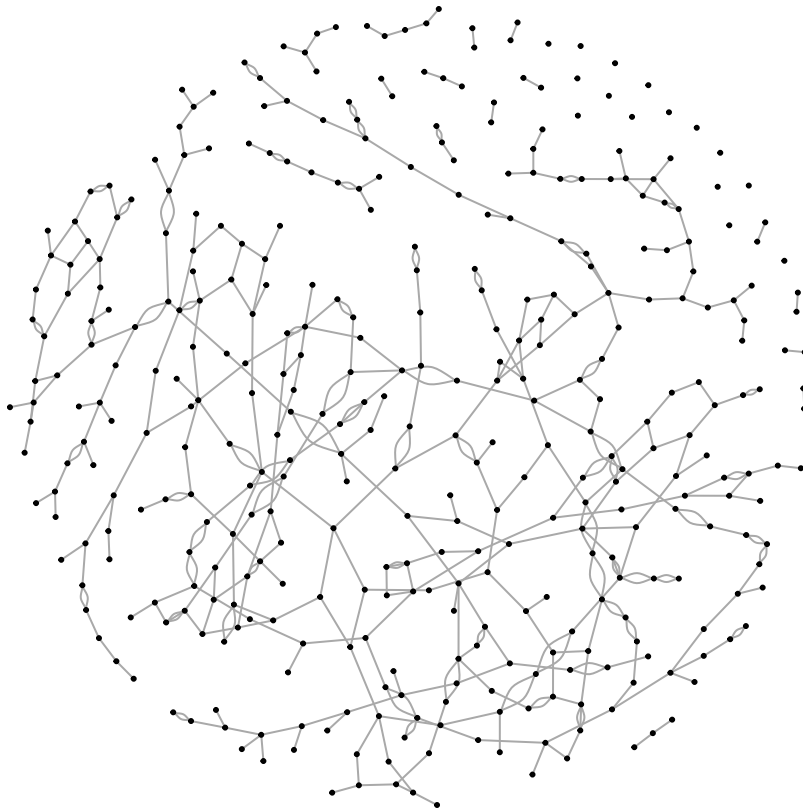
G.deg = ggplot(dt.degree, aes(y=Freq,x=factor(Deg),color=factor(P),group=factor(P))) +
  ylab("Frequency") +
  scale_x_discrete(name = "Degree", limits=c("0","1","2","3","4","5","6","7","8","9","10")) +
  scale_color_discrete(name="P") +
  geom_line(cex=1)
G.deg

```

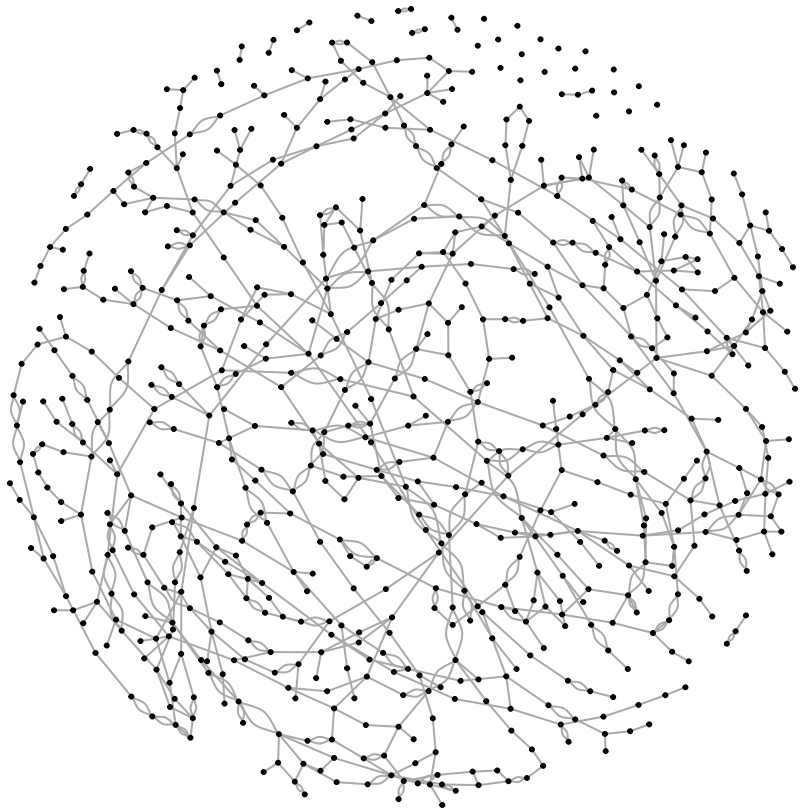


Here are the graph plots before clustering. From P4, we can see the shape of graph does change a lot.

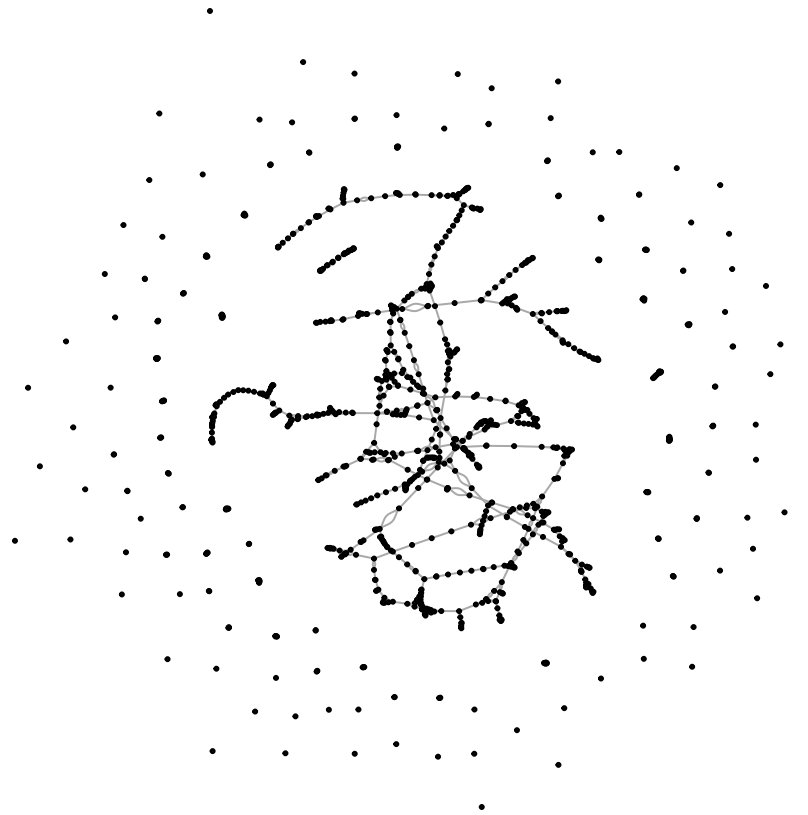
```
par(mar=c(0,0,0,0))
plot(G2,vertex.label=NA,vertex.size=1,vertex.color="grey2")
```



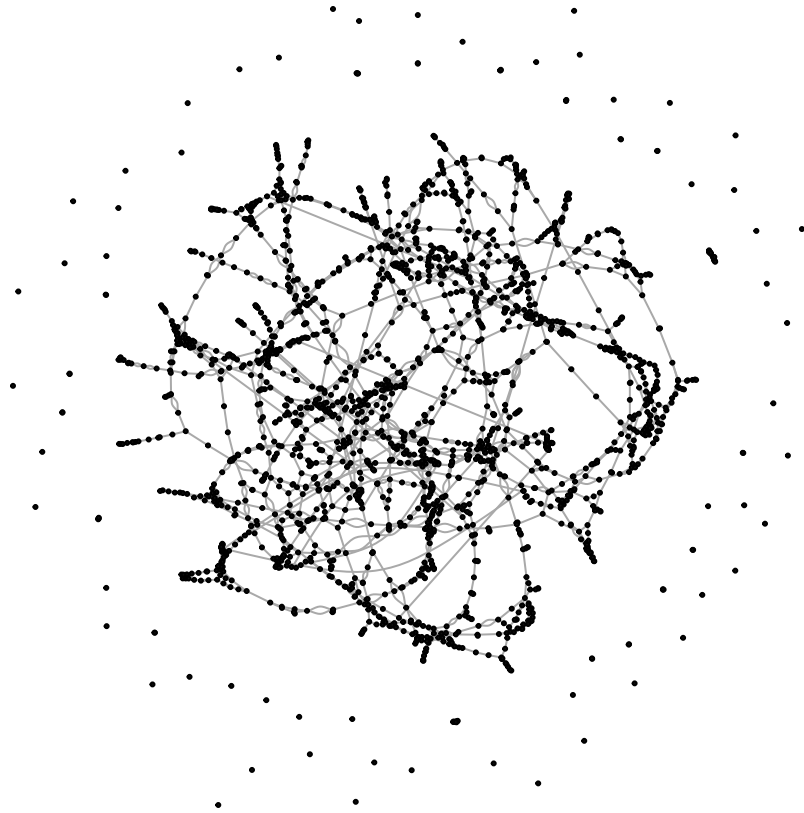
```
plot(G3,vertex.label=NA,vertex.size=1,vertex.color="grey3")
```



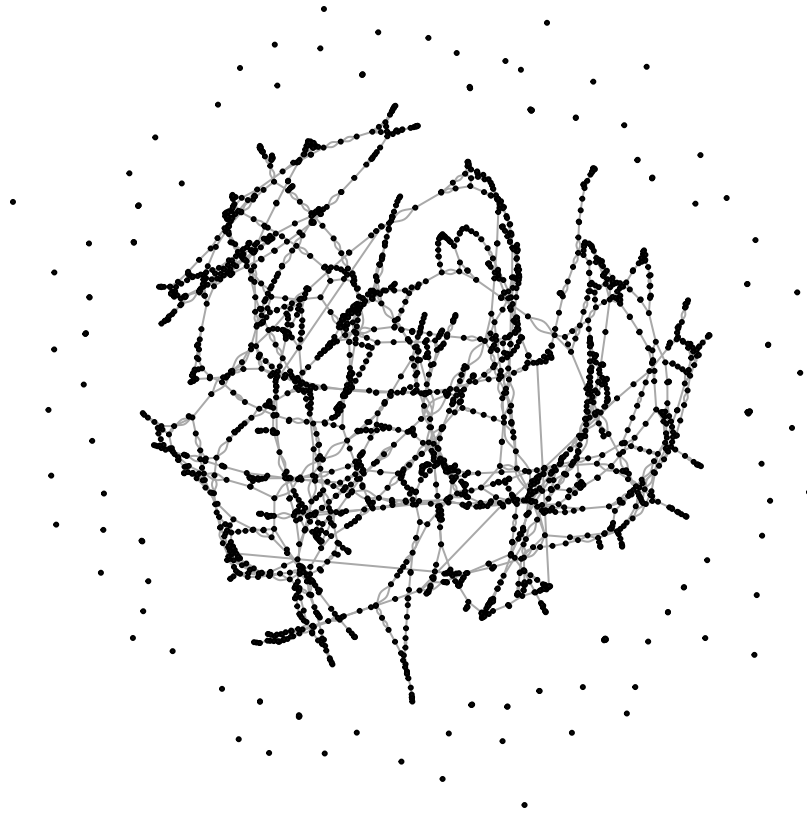
```
plot(G4,vertex.label=NA,vertex.size=1,vertex.color="grey4")
```



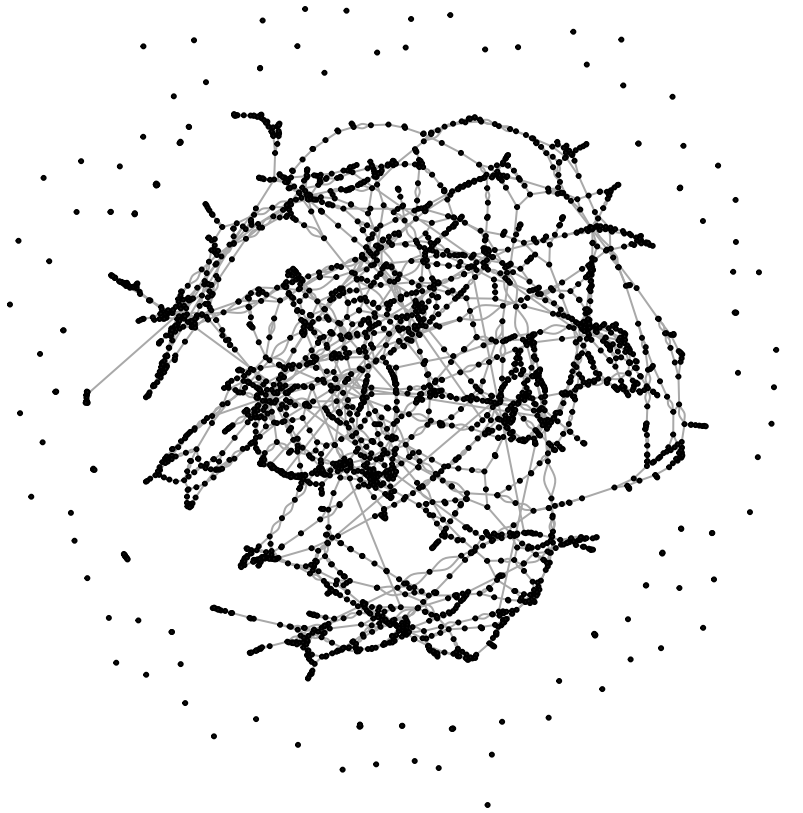
```
plot(G5,vertex.label=NA,vertex.size=1,vertex.color="grey5")
```



```
plot(G6,vertex.label=NA,vertex.size=1,vertex.color="grey6")
```

```
plot(G7,vertex.label=NA,vertex.size=1,vertex.color="grey7")
```



We run clustering by using edge betweenness. As we can see, at P4, there are explosively many groups appearing.

```
Cl.betw.2 = cluster_edge_betweenness(graph=G2)
Cl.betw.3 = cluster_edge_betweenness(graph=G3)
Cl.betw.4 = cluster_edge_betweenness(graph=G4)
Cl.betw.5 = cluster_edge_betweenness(graph=G5)
Cl.betw.6 = cluster_edge_betweenness(graph=G6)
Cl.betw.7 = cluster_edge_betweenness(graph=G7)
```

```
length(sort(unique(Cl.betw.2$membership),decreasing=FALSE))
```

```
## [1] 49
```

```
length(sort(unique(Cl.betw.3$membership),decreasing=FALSE))
```

```
## [1] 54
```

```
length(sort(unique(Cl.betw.4$membership),decreasing=FALSE))
```

```
## [1] 151
```

```
length(sort(unique(Cl.betw.5$membership),decreasing=FALSE))
```

```
## [1] 110
```

```
length(sort(unique(Cl.betw.6$membership),decreasing=FALSE))
```

```
## [1] 127
```

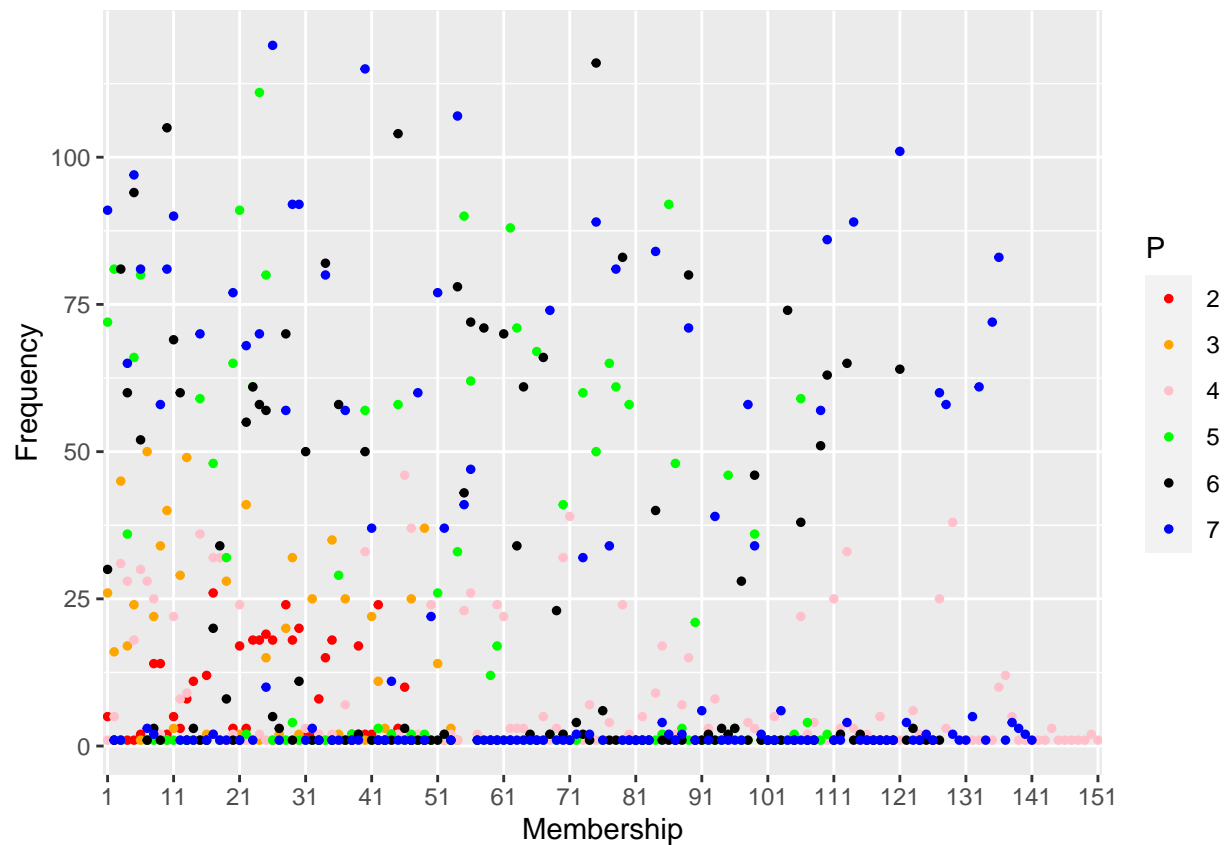
```
length(sort(unique(Cl.betw.7$membership),decreasing=FALSE))
```

```
## [1] 141
```

We can check that for each P , how many members are joining into a single membership. We can observe that the membership status are similar between $P2, P3$ and $P4$ while $P5, P6$, and $P7$ have similarity by themselves but show difference from the previous ones.

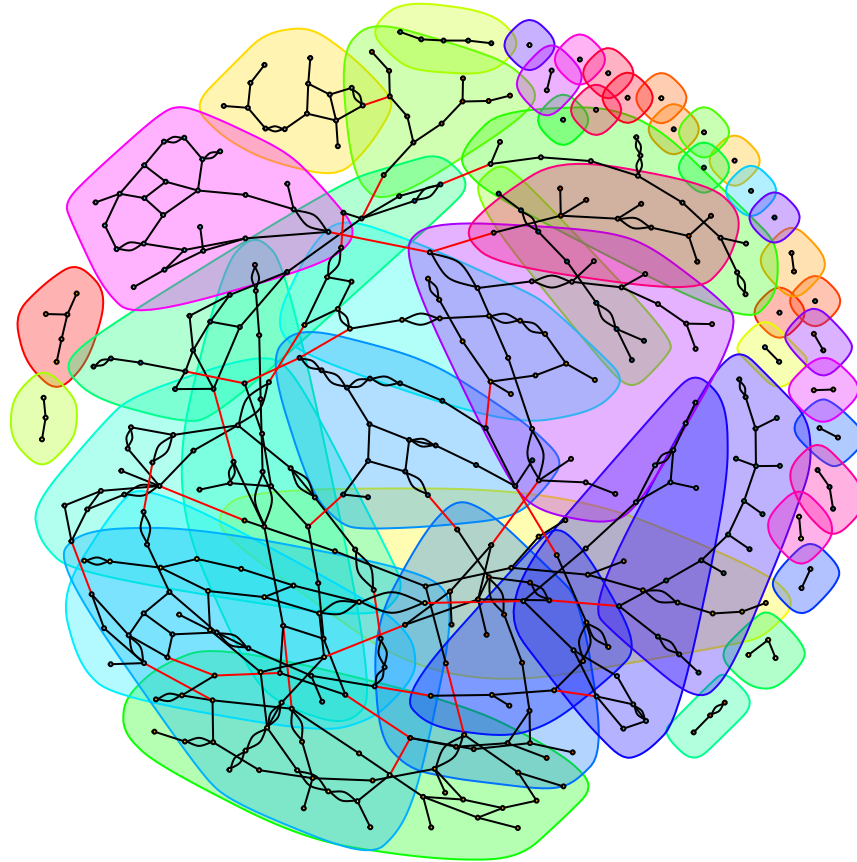
```
dt.membership.p2 = data.frame(as.data.frame(table(Cl.betw.2$membership)),
                              P=rep(2,length(table(Cl.betw.2$membership))))
dt.membership.p3 = data.frame(as.data.frame(table(Cl.betw.3$membership)),
                              P=rep(3,length(table(Cl.betw.3$membership))))
dt.membership.p4 = data.frame(as.data.frame(table(Cl.betw.4$membership)),
                              P=rep(4,length(table(Cl.betw.4$membership))))
dt.membership.p5 = data.frame(as.data.frame(table(Cl.betw.5$membership)),
                              P=rep(5,length(table(Cl.betw.5$membership))))
dt.membership.p6 = data.frame(as.data.frame(table(Cl.betw.6$membership)),
                              P=rep(6,length(table(Cl.betw.6$membership))))
dt.membership.p7 = data.frame(as.data.frame(table(Cl.betw.7$membership)),
                              P=rep(7,length(table(Cl.betw.7$membership))))
dt.membership = rbind(dt.membership.p2,
                      dt.membership.p3,
                      dt.membership.p4,
                      dt.membership.p5,
                      dt.membership.p6,
                      dt.membership.p7)
names(dt.membership) = c("Membership", "Freq", "P")

G.membership = ggplot(dt.membership, aes(y=Freq,x=factor(Membership),color=factor(P))) +
  scale_x_discrete(breaks=seq(1,190,10))+
  ylab("Frequency") +
  xlab("Membership") +
  scale_color_manual(name="P",values=c("red","orange","pink","green","black","blue")) +
  geom_point(cex=1)
G.membership
```

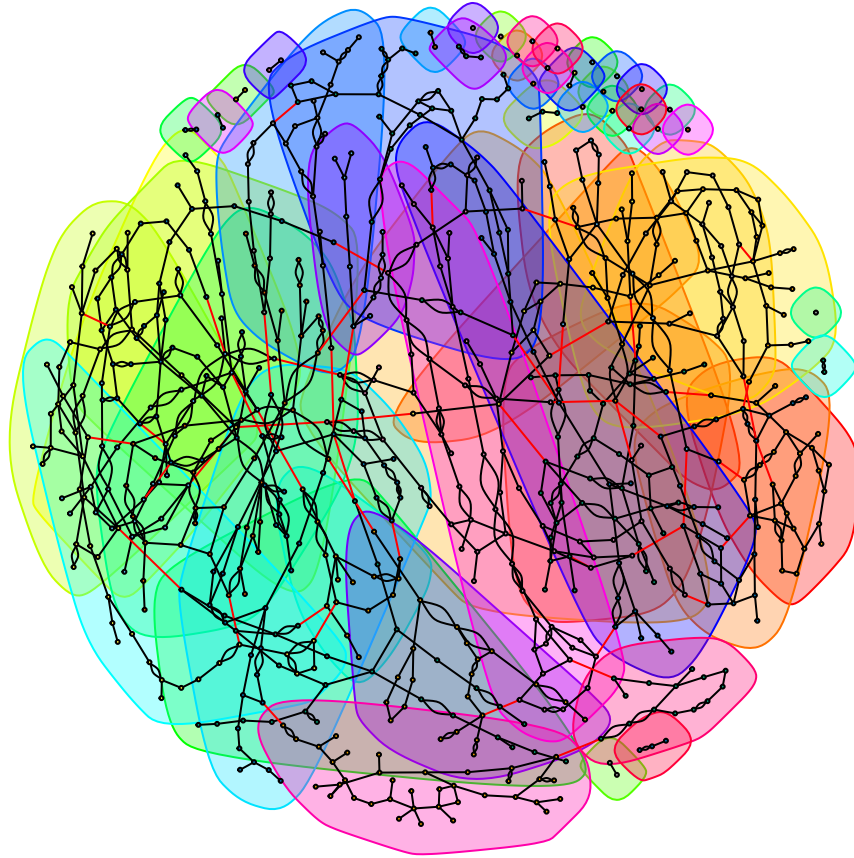


Here are the final plots after clustering. As we can see, from P4, we can see the dramatic change of the form of the plot.

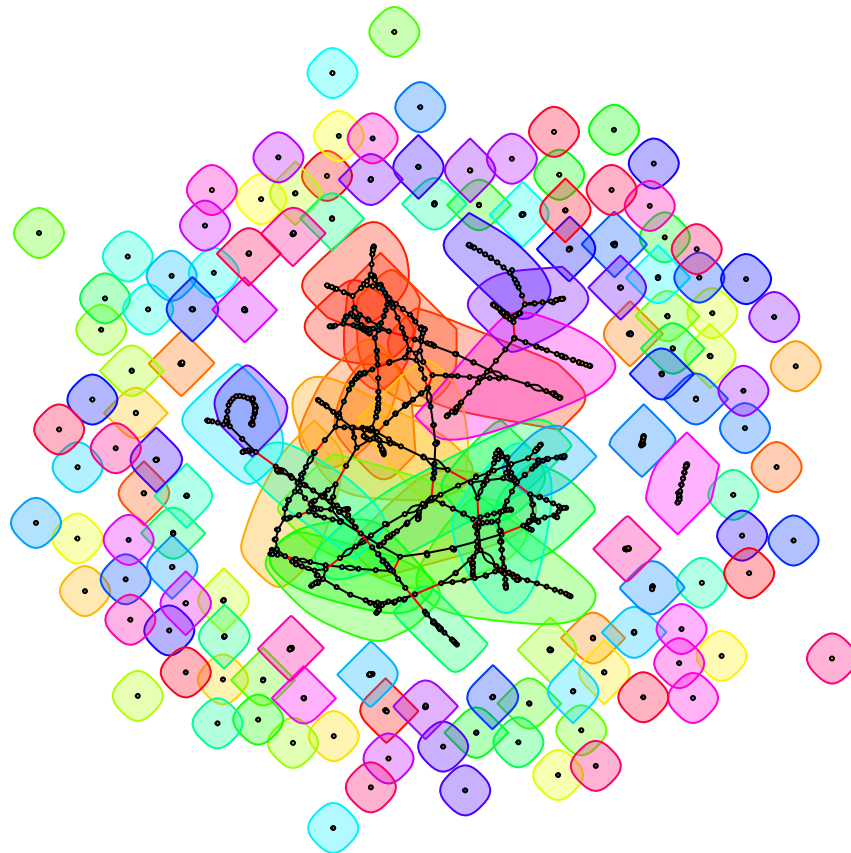
```
par(mar=c(0,0,0,0))
plot(C1.betw.2,G2,vertex.label=NA,vertex.size=1)
```



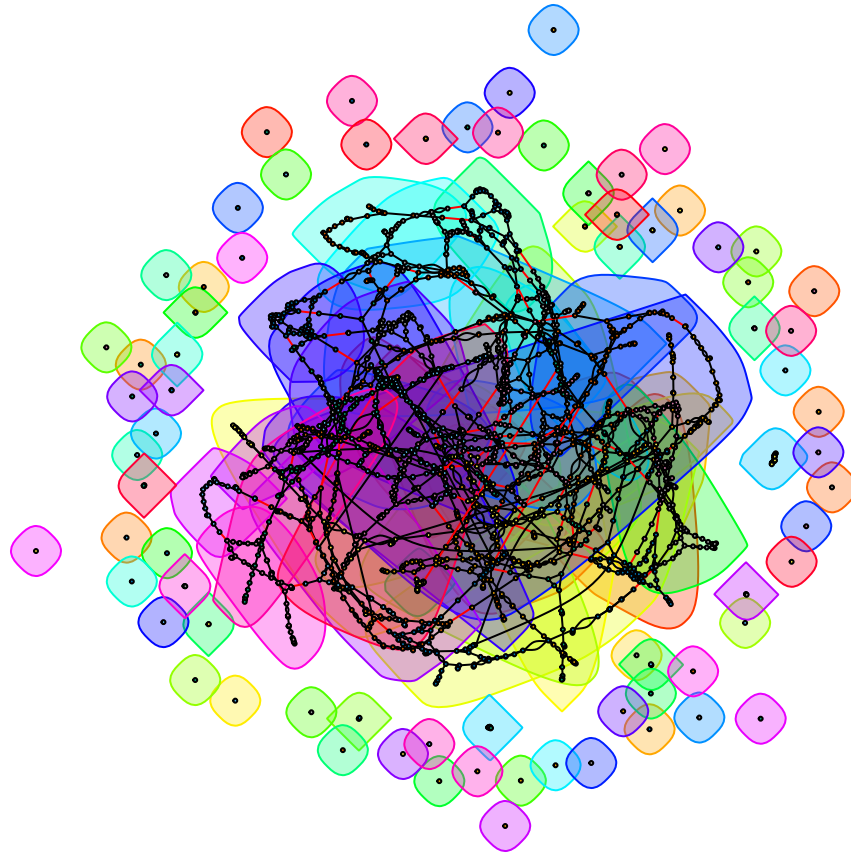
```
plot(C1.betw.3,G3,vertex.label=NA,vertex.size=1)
```



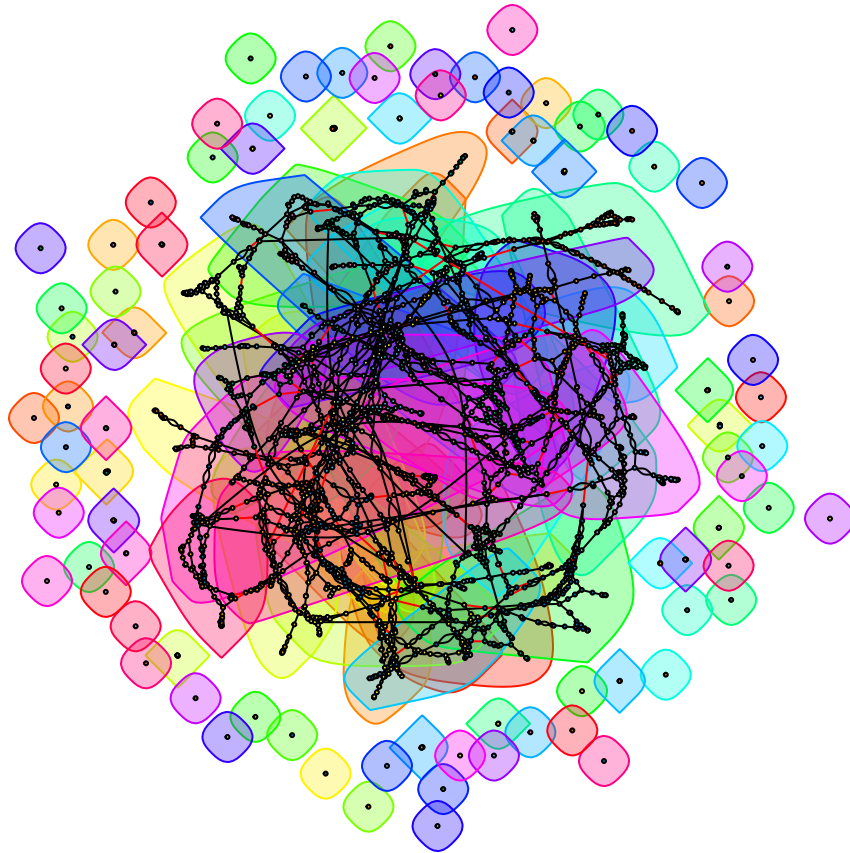
```
plot(C1.betw.4,G4,vertex.label=NA,vertex.size=1)
```



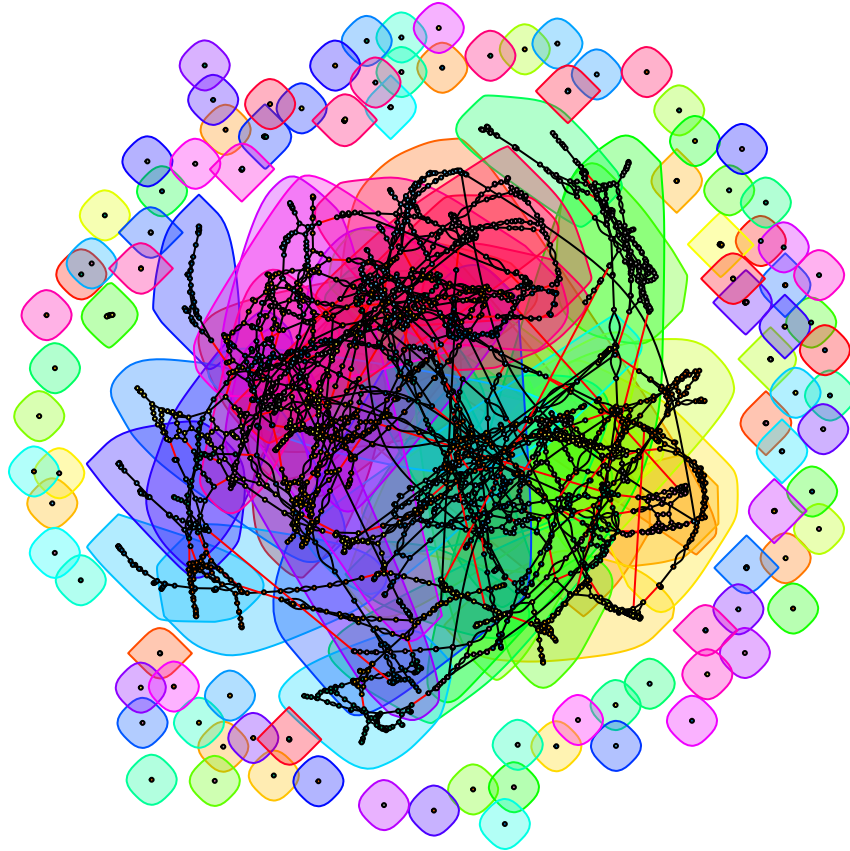
```
plot(C1.betw.5,G5,vertex.label=NA,vertex.size=1)
```



```
plot(C1.betw.6,G6,vertex.label=NA,vertex.size=1)
```

```
plot(C1.betw.7,G7,vertex.label=NA,vertex.size=1)
```



Hence, we can visually find the “change point”. Next question: how to find this by statistical hypothesis testing?