

Population Graphs

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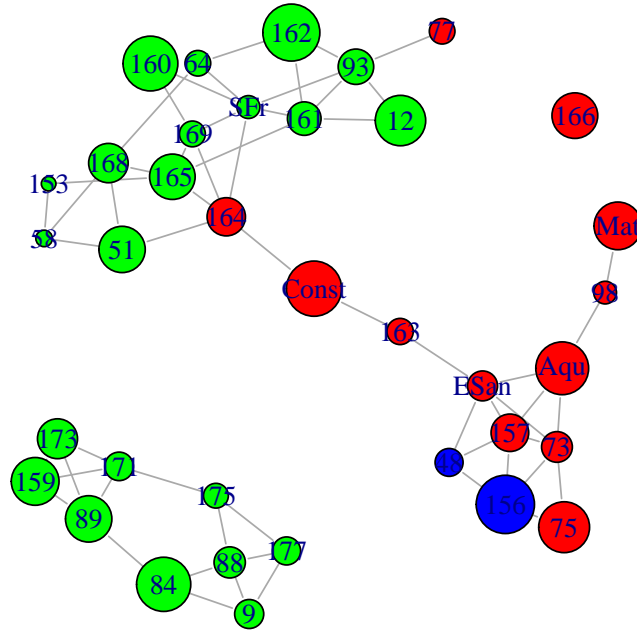
Synopsis

A population graph is a topological representation of within and among population genetic variance first introduced by Dyer & Nason (2004). It is particularly well suited to characterizing how spatial genetic variation is distributed among sites.

```
> require(gstudio)
> data(araptus_attenuatus)
> baja <- araptus_attenuatus[araptus_attenuatus$Species != "CladeB",
+ ]
```

Simple Population Graphs

```
> graph <- population.graph(baja, "Pop")
transforming data... done
Rotating mv genos and partitioning... done
Estimating conditional genetic covariance... done
Making graph... done
> summary(graph)
Vertices: 36
Edges: 59
Directed: FALSE
No graph attributes.
Vertex attributes: name, size, color.
Edge attributes: weight.
> l <- layout.fruchterman.reingold(graph)
> plot(graph, layout = l, vertex.label = V(graph)$name)
```

So if we only use the samples from CladeC we may be actually analyzing the data in a way that makes sense. Do this by:

1. Use only the CladeC individuals
2. Get rid of the populations with say $N < 5$ individuals
3. Make graph and examine the topology

```
> baja.cladeC <- baja[baja$Species == "CladeC", ]
> inds.per.pop <- lapply(partition(baja.cladeC, "Pop"), function(x) dim(x)[1])
> smPops <- c("Const", "ESan", "157", "73", "Aqu", "Mat", "98",
+           "75")
> baja.cladeC <- baja.cladeC[!(baja.cladeC$Pop %in% smPops), ]
> graph.cladeC <- population.graph(baja.cladeC, "Pop")
```

```
transforming data... done
Rotating mv genos and partitioning... done
Estimating conditional genetic covariance... done
Making graph... done
```

```
> summary(graph.cladeC)
```

```
Vertices: 26
```

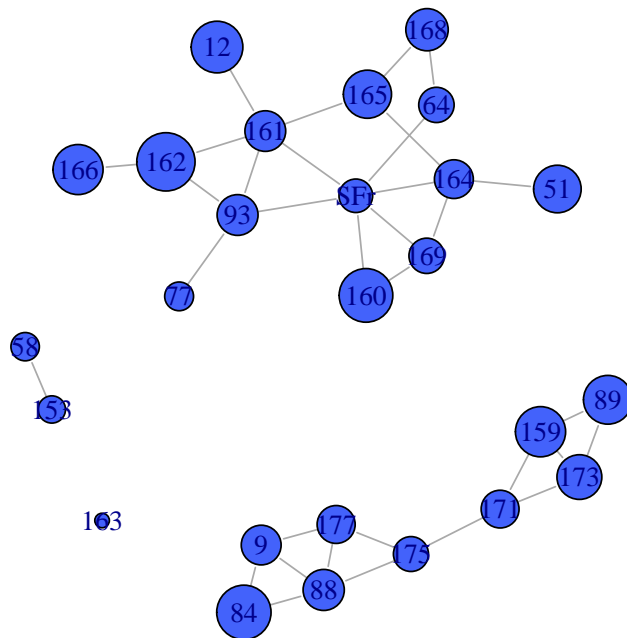
```
Edges: 33
```

```

Directed: FALSE
No graph attributes.
Vertex attributes: name, size, color.
Edge attributes: weight.

> l <- layout.fruchterman.reingold(graph.cladeC)
> plot(graph.cladeC, layout = l, vertex.label = V(graph.cladeC)$name)

```



From this plot, you can see even when we only focus on the true **CladeC** individuals, there is still partitioning of genetic covariance!

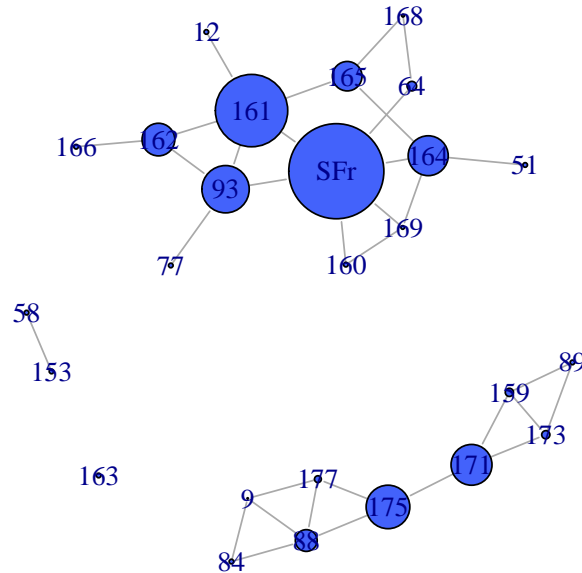
Node Position

Both node and edge position in the topology can easily be determined using common network analysis tools. The **igraph** package has some as does the most excellent **sna** package. Here is a quick example where the size of the node is depicting the node's betweenness (e.g., the number of shortest paths that go through that node).

```

> pop.betweenness <- betweenness(graph.cladeC, directed = F)
> plot(graph.cladeC, layout = l, vertex.label = V(graph.cladeC)$name,
+      vertex.size = pop.betweenness)

```



Which is rather interesting since betweenness can be used to classify relative population importance. Presently, it is common to use genetic diversity as a surrogate to identify populations of high conservation importance, but betweenness relates to the connectivity of the gene flow topology on the landscape and is not necessarily correlated with genetic diversity.

```
> cor.test(V(graph.cladeC)$size, pop.betweenness, method = "spearman")
```

Spearman's rank correlation rho

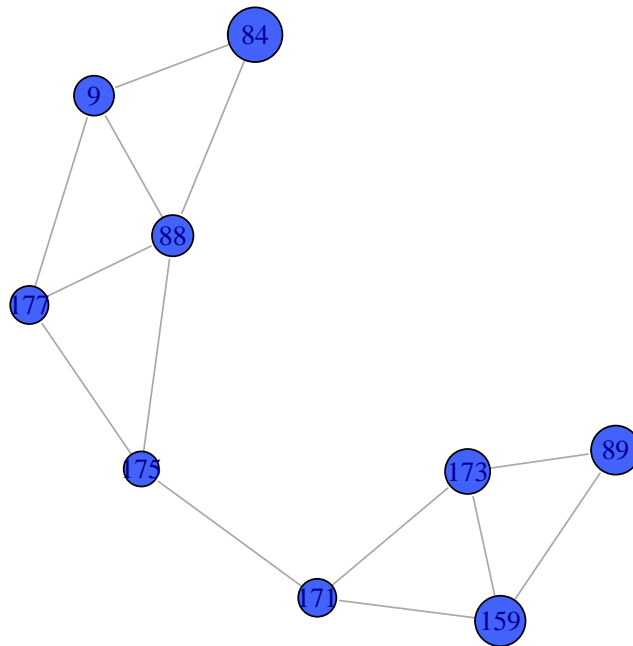
```
data: V(graph.cladeC)$size and pop.betweenness
S = 3259.634, p-value = 0.5779
alternative hypothesis: true rho is not equal to 0
sample estimates:
rho
-0.1144049
```

Conditional Genetic Distance

In Dyer *et al.* (2010) we showed that graph distance (e.g., the shortest path connecting points in the topology) was more powerful than pair-wise structure and distance approaches. We denoted the among population distance as *cGD* for conditional graph distance.

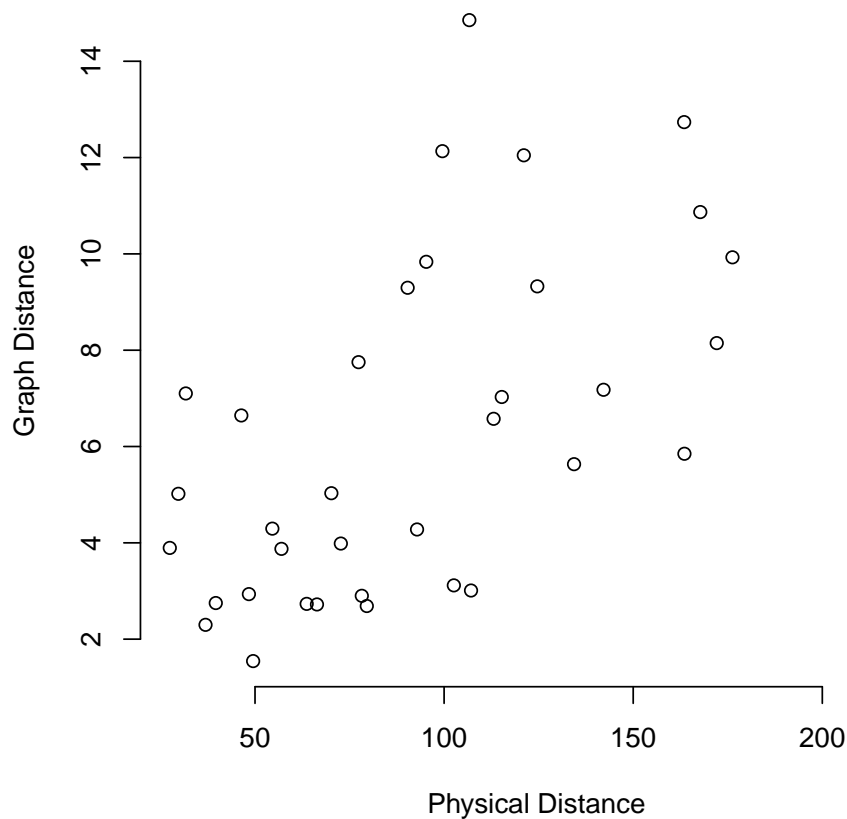
Since this topology is disconnected, we'll just focus on the medium sized component, the one with 84 in it.

```
> connected.to.84 <- subcomponent(graph.cladeC, v = "84")
> med.graph <- subgraph(graph.cladeC, v = connected.to.84)
> med.layout <- layout.fruchterman.reingold(med.graph)
> plot(med.graph, layout = med.layout, vertex.label = V(med.graph)$name)
> D <- shortest.paths(med.graph)
```



As discussed previously, we can also get the pair-wise physical distance and then examine "Isolation by Graph Distance" (IBGD), which has some nice properties that make it perhaps more precise than IBD based upon pair-wise structure estimates.

```
> pops <- V(med.graph)$name
> P <- stratum.distance(baja.cladeC, "Pop", lat = "Lat", lon = "Long",
+   subset = pops)
> plot(D[lower.tri(D)] ~ P[lower.tri(P)], bty = "n", xlab = "Physical Distance",
+   ylab = "Graph Distance")
```



We can use a Mantel test to see if there is a correlation between graph and physical distance for this subcomponent.

```
> require(ecodist, quietly = T)
> mantel(as.dist(D) ~ as.dist(P))
```

mantelr	pval1	pval2	pval3	l1im.2.5%	ulim.97.5%
0.5687480	0.0070000	0.9940000	0.0070000	0.4809887	0.7023255

The pval3 is the probability of $H_0 : Mantel\rho = 0$.

Graph Partitions

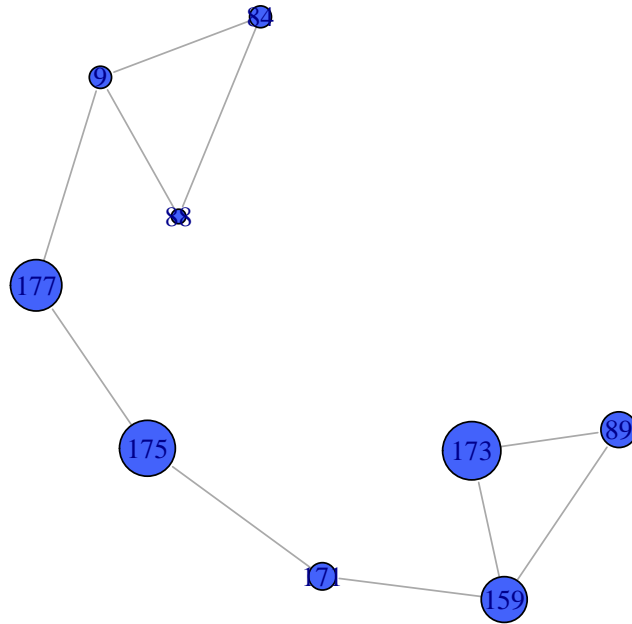
A very important point needs to be made here regarding subgraphs and partitions of the whole data set. The disconnected subgraph in the previous section is not necessarily the same graph you would get if you partitioned the genotypes into only those populations and then make the graph. Compare the previous network topology to this one.

```
> tmp.pop <- baja[baja$Pop %in% c("9", "84", "88", "89", "159",
+   "171", "173", "175", "177")]
> tmp.graph <- population.graph(tmp.pop, "Pop")
```

```

transforming data... done
Rotating mv genos and partitioning... done
Estimating conditional genetic covariance... done
Making graph... done
> plot(tmp.graph, layout = med.layout, vertex.label = V(tmp.graph)$name)

```



This is because Population Graphs are constructed using *Conditional Genetic Covariance*. The genetic covariance between populations 173 & 171 is conditional on their covariance with all the other data in the data set. In the first graph this includes the populations in this subgraph as well as the populations outside the subgraph.