The Southern Ocean Food Web

```
## Loading required package: knitr
```

Load required libraries:

```
require(igraph)
require(NetIndices)
require(reshape2)
require(ggplot2)
require(devtools)
require(vegan)
```

```
Warning: there is no package called 'vegan'
```

```
require(data.table)
```

Source code for functions to describe web properties

```
url <- "https://raw.githubusercontent.com/jjborrelli/Ecological-Networks/master/FoodWebs/Rscripts/web_fu
source_url(url)
```

Load in the data

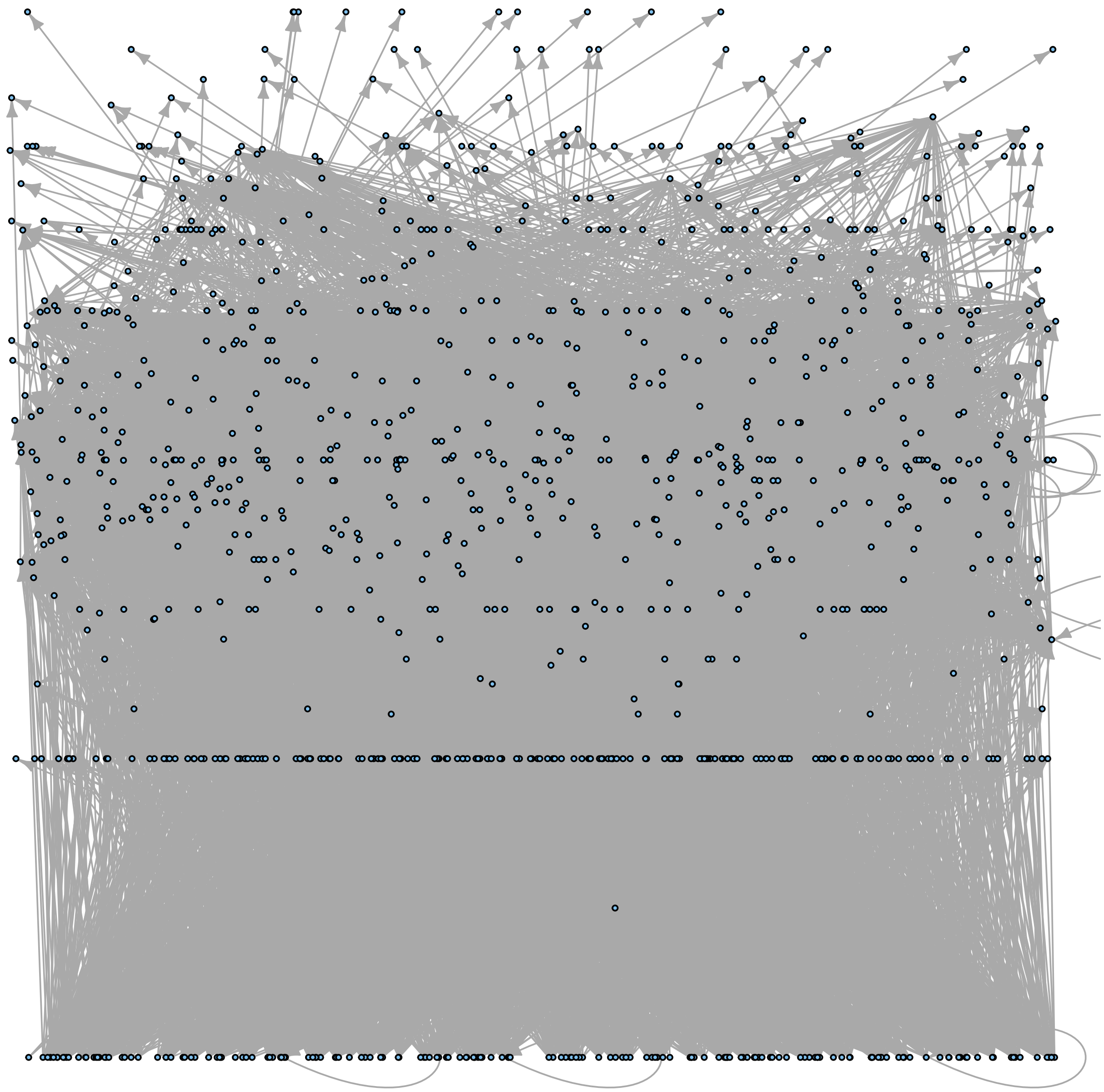
```
s.ocean <- read.csv("http://esapubs.org/archive/ecol/E092/097/diet.csv")
#s.ocean <- read.csv("~/Downloads/diet.csv")
```

Whole Southern Ocean

```
el.df <- data.frame(pred = s.ocean$PREDATOR_NAME, prey = s.ocean$PREY_NAME)

SOgraph <- graph.edgelist(unique(as.matrix(el.df[,1:2])))

SOadjacency <- get.adjacency(SOgraph, sparse = F)
```

First take a quick look at what the food web looks like. Here I plot the web by trophic level by setting the layout (code shown below). Nodes are plotted with trophic position along the y-axis and plotted along the x-axis according to a random uniform distribution (`runif(x, 0, 1)`).

```
par(mar = c(0,0,0,0))
layouts <- matrix(c(runif(gind$N), tind$TL), ncol = 2)
plot.igraph(SOgraph, layout = layouts, vertex.label = NA, edge.arrow.size = .5,
            vertex.size = 1)
```



The plot of the web is not very helpful because there are so many species and far too many interactions. So looking at some of the whole web statistical properties and node properties may be more useful than just plotting the web.

The `NetIndices` and `igraph` packages have functions to calculate a number of commonly used food web indices. The function `GenInd` from the `NetIndices` library easily calculates the number of nodes (N), total number of links (L), link density ($\frac{L}{N} = LD$), and connectance (along with some other indices that are not relevant to this dataset). Connectance in this case is calculated as:

$$C = \frac{L}{N * (N - 1)}$$

The `diameter` is the single longest path between two nodes. The `average.path.length` is the mean number of links between any two nodes in the web. The clustering coefficient (or `transitivity`) is the probability that the nearest neighbors of a given vertex are themselves connected. A high clustering coefficient is an indication that a network has "small world" properties. The sum of the diagonal elements of the adjacency matrix gives the number of species that are cannibalistic, with links that loop back to themselves.

Species in a food web may be either basal, intermediate, or top. These positions may be determined simply by examining the degree of each node. The number of links pointing towards a node is its in-degree and the number of links pointing away from a node is the out-degree. In-degree is therefore a measure of how many species the node of interest preys upon (generality) while out-degree is the number of predators a given node has (vulnerability). Basal nodes will have an in-degree of 0, and likewise top species will have an out-degree of 0. Once the number of basal and top species are found, the number of intermediate species is simply the remainder.

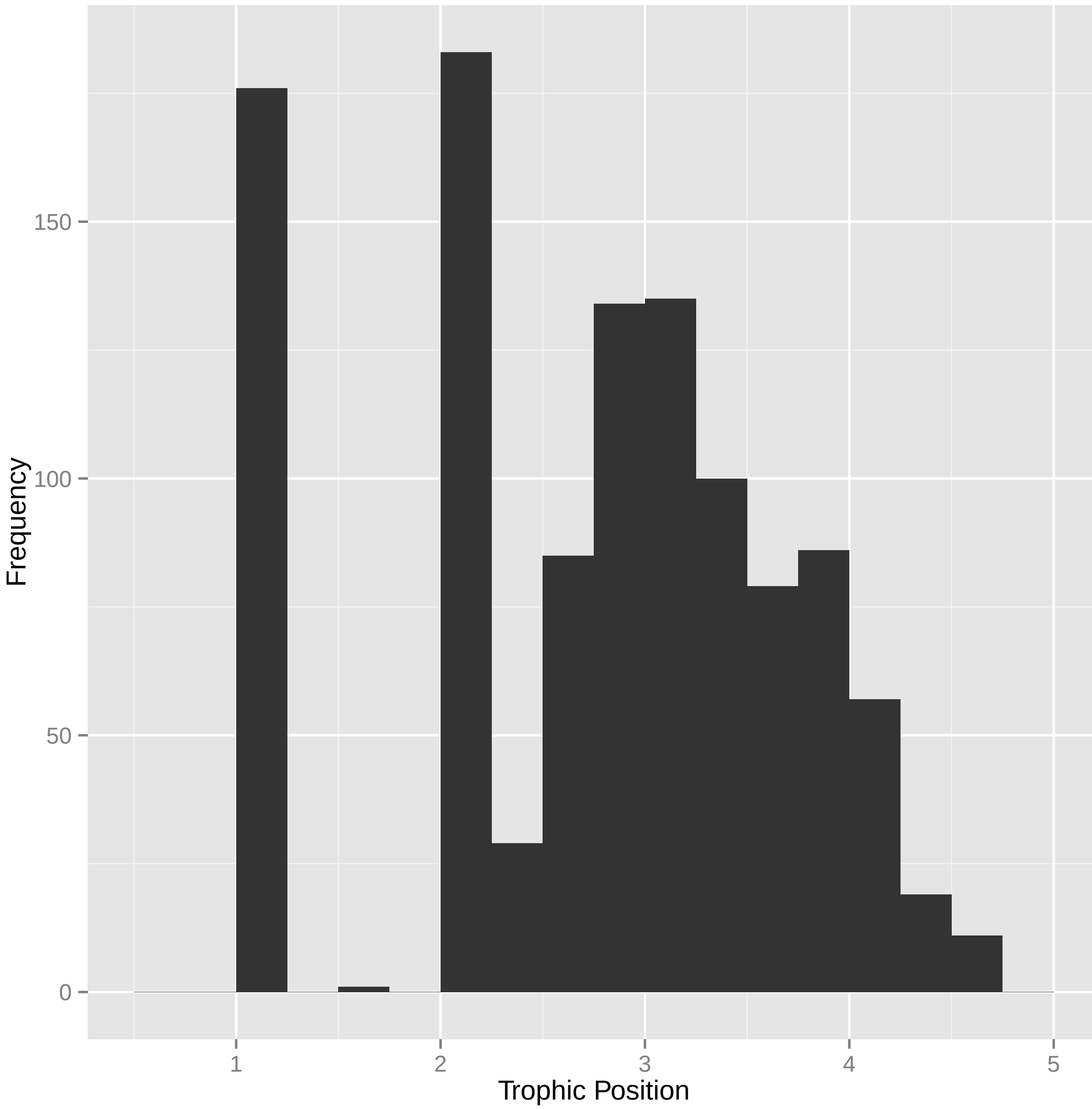
```
gind <- GenInd(SOadjacency)
diam <- diameter(SOgraph)
avpath <- average.path.length(SOgraph)
cluster <- transitivity(SOgraph)
cannibals <- sum(diag(SOadjacency))

degrees <- degree(SOgraph, mode = "all")
indegrees <- degree(SOgraph, mode = "in")
outdegrees <- degree(SOgraph, mode = "out")

numBas <- length(indegrees[which(indegrees == 0)])
numTop <- length(outdegrees[which(outdegrees == 0)])
basal <- (numBas/gind$N) * 100
top <- (numTop/gind$N) * 100
int <- ((gind$N - (numBas + numTop))/gind$N) * 100

web.props <- data.frame(N = gind$N, L = gind$Ltot, LD = gind$LD, C = gind$C, D = diam,
           AvgPath = avpath, ClCoef = cluster, Can = cannibals, Bas = basal, Top = top, Int = int)
```

```
     N     L    LD        C D AvgPath ClCoef Can  Bas   Top   Int
1 1095 10395 9.493 0.008677 6   2.114 0.1941  30 15.8 69.68 14.52
```

There are a total of 1095 species with 10395 interactions among them. The longest chain described in this food web is 6 but the average chain is 2.1144.

The short average path length in the food web is made clearer by looking at the distribution of trophic positions in the Southern Ocean Food Web.

```
qplot(tind$TL, binwidth = .25, geom = "histogram",
      xlab = "Trophic Position", ylab = "Frequency")
```

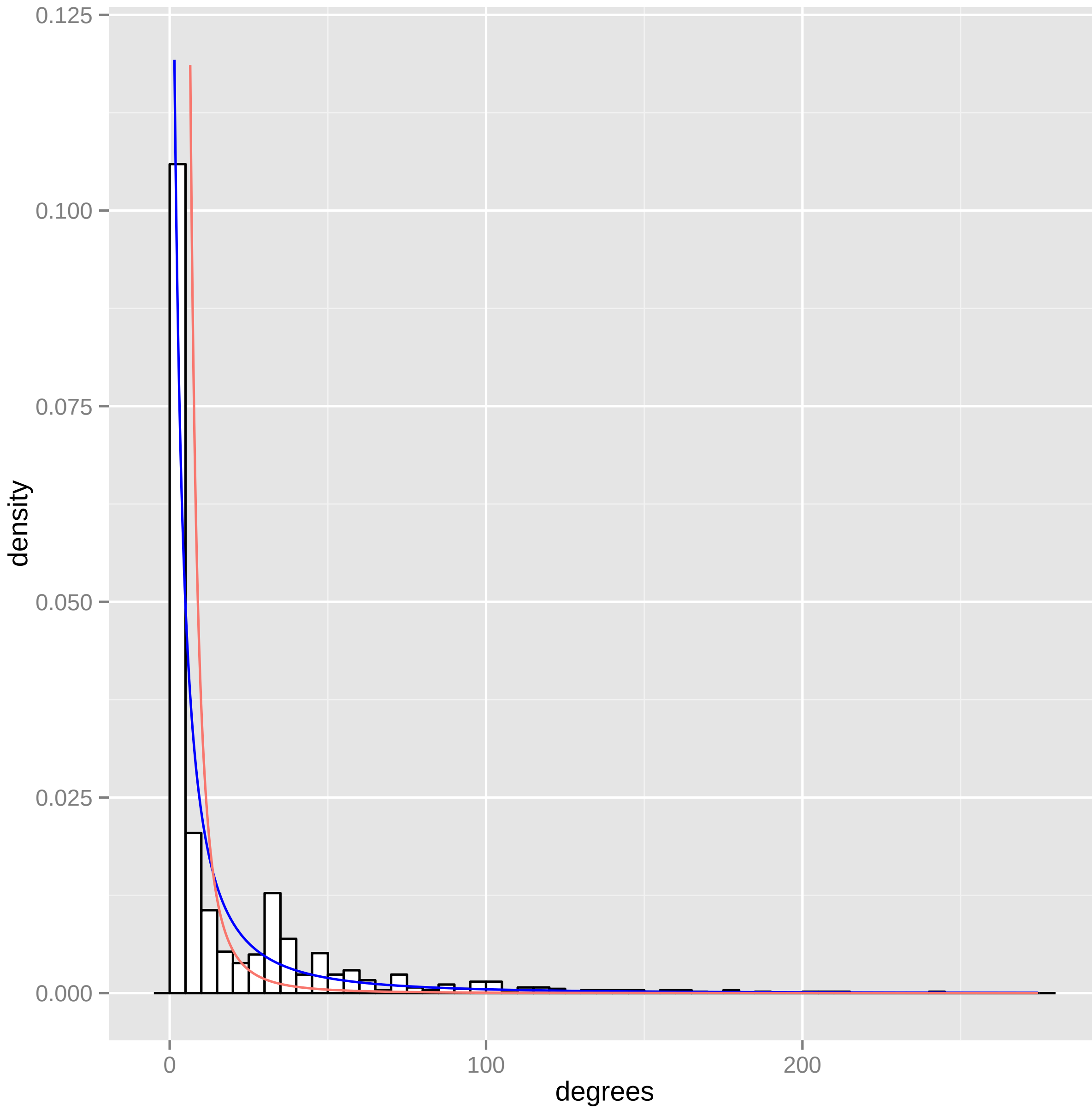


There is a tall bar at trophic level 1 and 2 representing plants and herbivores. There is a single organism, *Chionodraco hamatus*, with a trophic level between 1 and 2, suggesting that it consumes both plant and animals (a true omnivore). I am unconvinced, however, that the dataset includes a fully sampled food web and that some of those organisms described as basal are not plants, but are crustaceans, or other small organisms.

Most of the species in the food web are "top" predators with 70% of sampled species having no predators themselves. Plants ("basal species") make up 16% of the web, and the remaining 15% are "intermediate". The disproportionately large proportion of "top" species is unusual compared to other empirically described food webs and may be the result of sampling methods. The connectance of the Southern Ocean Food Web is relatively low at 0.0087, but that is expected with such a large number of species.

The degree distribution of a food web is often described as being power-law distributed, with most nodes having few links, and few nodes having many links. The degree distribution may be plotted as a histogram. Rather than fitting a power law to the distribution I have fit a lognormal distribution to the data, as it appears to be the better fit. In the following plot I have included a line fit to a lognormal (blue) and power law (green) distributions. The lognormal distribution appears to be a better fit to the degree distribution.

```
degdisfit <- fitdistr(degrees, "lognormal")
degdispow <- power.law.fit(degrees, force.continuous = T)

dd <- ggplot(data.frame(degrees = degrees), aes(x = degrees))
dd <- dd + geom_histogram(aes(y=..density..), binwidth = 5, colour = "black", fill = "white")

sequ <- seq(1, 300, .25)

dd <- dd + geom_line(aes(x = sequ[1:1095],
                         y = dlnorm(sequ[1:1095], degdisfit[[1]][1], degdisfit[[1]][2])),
                     colour = "blue")
dd <- dd + geom_line(aes(x = sequ[1:1095], y = 20 * sequ[1:1095] ^ -degdispow$alpha, colour = "green"))
dd + scale_y_continuous(limits = c(0, 0.12)) + theme(legend.position = "none")
```




```
motif_counter(list(SOgraph), webs = "Southern Ocean")
```

```
             web    s1    s2 s3     s4     s5   d1   d2   d3   d4 d5  d6
1 Southern Ocean 66406 40066  0 301234 208502 2167 4193 1557 2470  1 129
  d7 d8
1 30 13
```

By location

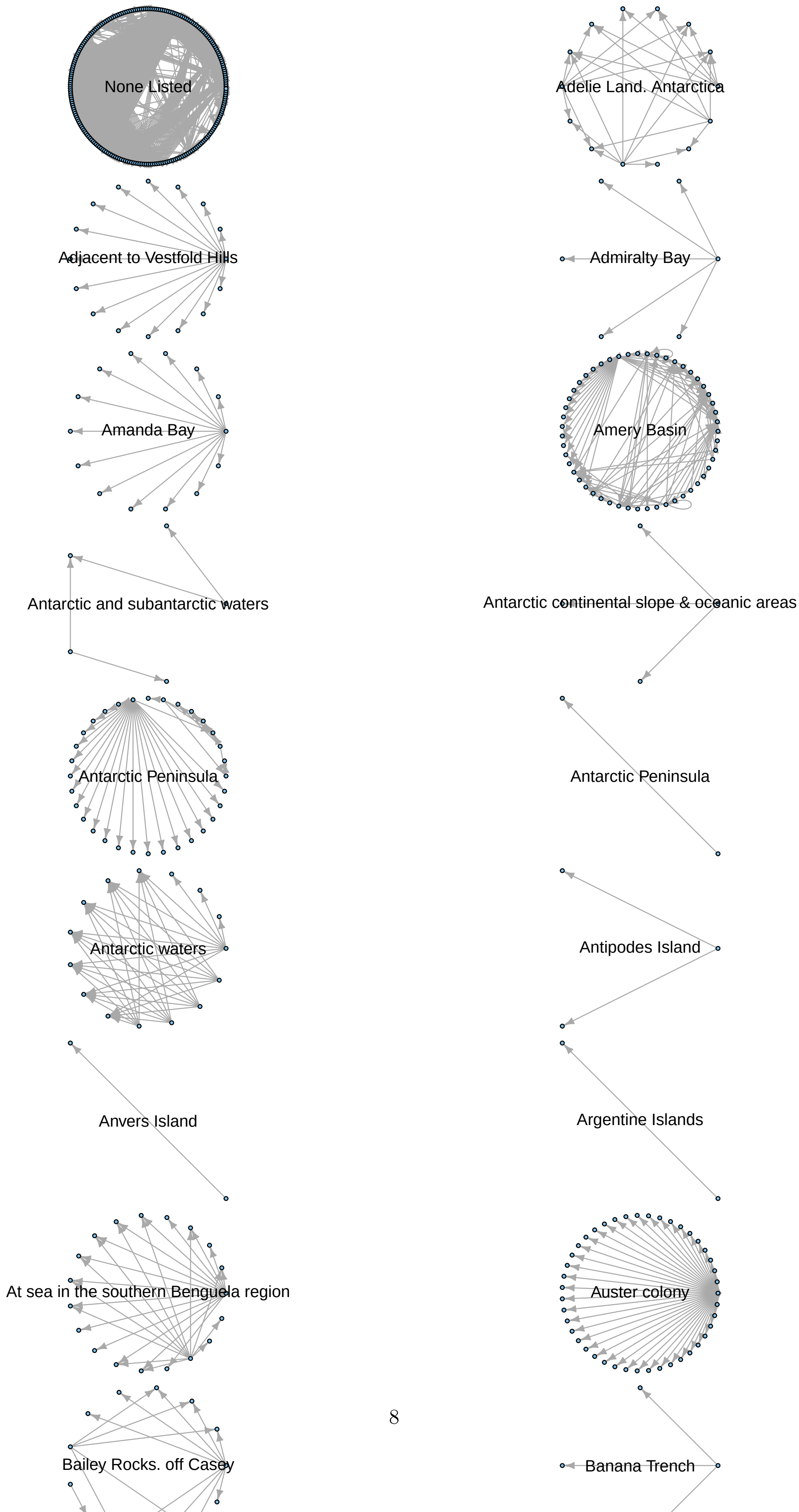
The following code splits up the dataframe by the location column. The resulting 228 graph objects get stored in `location.g`. *NOTE: the first location is a blank (" ") indicating that there are some rows without* *a location*

```
places <- read.csv("C:/Users/jjborrelli/Desktop/GitHub/Ecological-Networks/SouthernOcean/locationLEVELS
placesC <- c()
for(i in 1:228){
  placesC[i] <- as.character(places[[1]][i])
}

m <- split(s.ocean, f = s.ocean$LOCATION)
location.g <- list()
for (i in 1:length(levels(s.ocean$LOCATION))){

  el.df <- data.frame(pred = m[[i]]$PREDATOR_NAME, prey = m[[i]]$PREY_NAME)

  g <- graph.edgelist(unique(as.matrix(el.df[,1:2])))

  location.g[[i]] <- g

}
```

Plotting webs by location provides some idea about what trophic information was obtained from different sampling locations in the Southern Ocean.

```
par(mfrow = c(114, 2), mar = c(.01,.01,.01,.01))
for (i in 1:228){
  plot.igraph(location.g[[i]], layout = layout.circle, edge.arrow.size = .5, vertex.label = NA,
              vertex.size = 5)
  text(0, 0, label = placesC[i], cex = 1.5)
}
```

```
Warning: font width unknown for character 0x8f
Warning: font metrics unknown for character 0x8f
```


None Listed
Adelie Land. Antarctica
Adjacent to Vestfold Hills
Admiralty Bay
Amanda Bay
Amery Basin
Antarctic and subantarctic waters
Antarctic continental slope & oceanic areas
Antarctic Peninsula
Antarctic Peninsula
Antarctic waters
Antipodes Island
Anvers Island
Argentine Islands
At sea in the southern Benguela region
Auster colony
Bailey Rocks. off Casey
Banana Trench

It is readily apparent from the food web plots that some sampling locations (e.g., **Bay of Morbihan. Kerguelen Islands**; **Iles Crozets**; **Seal Island**; etc.) included only a single predator with a portion of its prey. Others, like **Amanda Bay** and **Rampen**, included a single prey with some of its predators. A few locations, however, have enough species and interactions to be conisdered a near complete food web themselves (e.g., **Croker Passage**; **Scotia Sea. Weddell Sea**). Most webs have a small number of predators and prey and a few interactions. It is also worth noting that there appears to be several repeat locations in the data, such as **Kerguelen Island, Kerguelen Island1, Kerguelen Islands, Kerguelen Islands1, Kerguelen waters**. It may be best to merge webs with locations that are approximately the same. This might reduce the number of webs with only a handful of species.

Like the whole food web properties calculated above, indices can be calculated for each of the location subwebs.

```
web.props1 <- data.frame()
for (i in 1:228){
  gind <- GenInd(get.adjacency(location.g[[i]], sparse = F))
  diam <- diameter(location.g[[i]])
  avpath <- average.path.length(location.g[[i]])
  cluster <- transitivity(location.g[[i]])
  cannibals <- sum(diag(get.adjacency(location.g[[i]], sparse = F)))

  degrees <- degree(location.g[[i]], mode = "all")
  indegrees <- degree(location.g[[i]], mode = "in")
  outdegrees <- degree(location.g[[i]], mode = "out")

  numBas <- length(indegrees[which(indegrees == 0)])
  numTop <- length(outdegrees[which(outdegrees == 0)])
  basal <- (numBas/gind$N) * 100
  top <- (numTop/gind$N) * 100
  int <- ((gind$N - (numBas + numTop))/gind$N) * 100

  web.props <- data.frame(N = gind$N, L = gind$Ltot, LD = gind$LD, C = gind$C, D = diam,
                          AvgPath = avpath, ClCoef = cluster, Can = cannibals, Bas = basal,
                          Top = top, Int = int)
  web.props1 <- rbind(web.props1, web.props)
}

print(web.props1)
```

```
      N    L      LD       C D AvgPath   ClCoef Can    Bas    Top   Int
1   232 2158  9.3017 0.04027 4   1.261 0.020466   1 25.431 65.086 9.483
2    14   27  1.9286 0.14835 1   1.000 0.000000   0 28.571 71.429 0.000
3    16   15  0.9375 0.06250 1   1.000 0.000000   0  6.250 93.750 0.000
4     6    5  0.8333 0.16667 1   1.000 0.000000   0 16.667 83.333 0.000
5    14   13  0.9286 0.07143 1   1.000 0.000000   0  7.143 92.857 0.000
6    51   98  1.9216 0.03843 3   1.203 0.060484   2 29.412 62.745 7.843
7     5    4  0.8000 0.20000 1   1.000 0.000000   0 40.000 60.000 0.000
8     4    3  0.7500 0.25000 1   1.000 0.000000   0 25.000 75.000 0.000
9    32   33  1.0312 0.03327 2   1.057 0.000000   0  9.375 87.500 3.125
10    2    1  0.5000 0.50000 1   1.000      NaN   0 50.000 50.000 0.000
11   15   38  2.5333 0.18095 1   1.000 0.000000   0 33.333 66.667 0.000
12    3    2  0.6667 0.33333 1   1.000 0.000000   0 33.333 66.667 0.000
13    2    1  0.5000 0.50000 1   1.000      NaN   0 50.000 50.000 0.000
14    2    1  0.5000 0.50000 1   1.000      NaN   0 50.000 50.000 0.000
```

15	19	27	1.4211	0.07895	1	1.000	0.000000	0	10.526	89.474	0.000
16	43	42	0.9767	0.02326	1	1.000	0.000000	0	2.326	97.674	0.000
17	13	15	1.1538	0.09615	1	1.000	0.000000	0	23.077	76.923	0.000
18	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
19	17	16	0.9412	0.05882	1	1.000	0.000000	0	5.882	94.118	0.000
20	3	2	0.6667	0.33333	1	1.000	0.000000	0	66.667	33.333	0.000
21	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
22	167	337	2.0180	0.01216	2	1.259	0.003253	0	4.192	92.216	3.593
23	141	274	1.9433	0.01388	1	1.000	0.000000	0	8.511	91.489	0.000
24	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
25	39	38	0.9744	0.02564	1	1.000	0.000000	0	2.564	97.436	0.000
26	17	22	1.2941	0.08088	1	1.000	0.000000	0	23.529	76.471	0.000
27	6	5	0.8333	0.16667	1	1.000	0.000000	0	16.667	83.333	0.000
28	24	23	0.9583	0.04167	1	1.000	0.000000	0	4.167	95.833	0.000
29	23	43	1.8696	0.08498	1	1.000	0.000000	0	26.087	73.913	0.000
30	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
31	61	60	0.9836	0.01639	1	1.000	0.000000	0	1.639	98.361	0.000
32	49	48	0.9796	0.02041	1	1.000	0.000000	0	2.041	97.959	0.000
33	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
34	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
35	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
36	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
37	23	22	0.9565	0.04348	1	1.000	0.000000	0	4.348	95.652	0.000
38	30	29	0.9667	0.03333	1	1.000	0.000000	0	3.333	96.667	0.000
39	16	15	0.9375	0.06250	1	1.000	0.000000	0	6.250	93.750	0.000
40	18	17	0.9444	0.05556	1	1.000	0.000000	0	5.556	94.444	0.000
41	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
42	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
43	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
44	27	36	1.3333	0.05128	1	1.000	0.000000	0	11.111	88.889	0.000
45	26	25	0.9615	0.03846	1	1.000	0.000000	0	3.846	96.154	0.000
46	10	9	0.9000	0.10000	1	1.000	0.000000	0	10.000	90.000	0.000
47	9	14	1.5556	0.19444	1	1.000	0.000000	0	22.222	77.778	0.000
48	24	23	0.9583	0.04167	1	1.000	0.000000	0	8.333	91.667	0.000
49	47	69	1.4681	0.03191	1	1.000	0.000000	0	6.383	93.617	0.000
50	25	24	0.9600	0.04000	1	1.000	0.000000	0	4.000	96.000	0.000
51	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
52	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
53	113	2852	25.2389	0.22535	2	1.058	0.356413	10	69.912	21.239	8.850
54	32	50	1.5625	0.05040	1	1.000	0.000000	1	12.500	84.375	3.125
55	10	13	1.3000	0.14444	1	1.000	0.000000	0	30.000	70.000	0.000
56	31	30	0.9677	0.03226	1	1.000	0.000000	0	3.226	96.774	0.000
57	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
58	113	225	1.9912	0.01778	2	1.277	0.006606	0	7.965	90.265	1.770
59	38	37	0.9737	0.02632	1	1.000	0.000000	0	2.632	97.368	0.000
60	27	52	1.9259	0.07407	2	1.136	0.025140	1	7.407	85.185	7.407
61	33	32	0.9697	0.03030	1	1.000	0.000000	0	3.030	96.970	0.000
62	10	9	0.9000	0.10000	1	1.000	0.000000	0	10.000	90.000	0.000
63	40	39	0.9750	0.02500	1	1.000	0.000000	0	2.500	97.500	0.000
64	17	16	0.9412	0.05882	1	1.000	0.000000	0	5.882	94.118	0.000
65	16	15	0.9375	0.06250	1	1.000	0.000000	0	6.250	93.750	0.000
66	10	9	0.9000	0.10000	1	1.000	0.000000	0	10.000	90.000	0.000
67	28	45	1.6071	0.05952	1	1.000	0.000000	0	25.000	75.000	0.000
68	41	40	0.9756	0.02439	1	1.000	0.000000	0	2.439	97.561	0.000

69	27	43	1.5926	0.06125	1	1.000	0.000000	0	29.630	70.370	0.000
70	24	33	1.3750	0.05978	2	1.158	0.101887	1	0.000	91.667	8.333
71	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
72	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
73	22	21	0.9545	0.04545	1	1.000	0.000000	0	4.545	95.455	0.000
74	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
75	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
76	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
77	7	10	1.4286	0.23810	1	1.000	0.000000	0	28.571	71.429	0.000
78	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
79	22	23	1.0455	0.04978	1	1.000	0.000000	0	9.091	90.909	0.000
80	15	16	1.0667	0.07619	2	1.158	0.083333	0	6.667	86.667	6.667
81	84	151	1.7976	0.02166	1	1.000	0.000000	0	8.333	91.667	0.000
82	25	24	0.9600	0.04000	1	1.000	0.000000	0	4.000	96.000	0.000
83	12	12	1.0000	0.09091	1	1.000	0.000000	0	16.667	83.333	0.000
84	5	3	0.6000	0.15000	1	1.000	0.000000	0	60.000	40.000	0.000
85	7	11	1.5714	0.26190	1	1.000	0.000000	0	42.857	57.143	0.000
86	33	32	0.9697	0.03030	1	1.000	0.000000	0	3.030	96.970	0.000
87	16	15	0.9375	0.06250	1	1.000	0.000000	0	6.250	93.750	0.000
88	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
89	8	7	0.8750	0.12500	1	1.000	0.000000	0	12.500	87.500	0.000
90	6	6	1.0000	0.20000	1	1.000	0.000000	0	33.333	66.667	0.000
91	72	77	1.0694	0.01506	1	1.000	0.000000	0	5.556	94.444	0.000
92	8	7	0.8750	0.12500	1	1.000	0.000000	0	12.500	87.500	0.000
93	22	21	0.9545	0.04545	1	1.000	0.000000	0	9.091	90.909	0.000
94	12	28	2.3333	0.21212	1	1.000	0.000000	0	58.333	41.667	0.000
95	13	12	0.9231	0.07692	1	1.000	0.000000	0	92.308	7.692	0.000
96	56	96	1.7143	0.03117	1	1.000	0.000000	0	5.357	94.643	0.000
97	67	115	1.7164	0.02601	1	1.000	0.000000	0	13.433	86.567	0.000
98	7	6	0.8571	0.14286	1	1.000	0.000000	0	14.286	85.714	0.000
99	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
100	42	42	1.0000	0.02439	1	1.000	0.000000	0	4.762	95.238	0.000
101	31	54	1.7419	0.05806	2	1.054	0.034722	1	9.677	87.097	3.226
102	4	2	0.5000	0.16667	1	1.000	NaN	0	50.000	50.000	0.000
103	29	27	0.9310	0.03325	1	1.000	0.000000	0	10.345	89.655	0.000
104	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
105	29	38	1.3103	0.04680	1	1.000	0.000000	0	10.345	89.655	0.000
106	50	165	3.3000	0.06735	2	1.125	0.306778	4	4.000	88.000	8.000
107	6	5	0.8333	0.16667	1	1.000	0.000000	0	16.667	83.333	0.000
108	9	8	0.8889	0.11111	1	1.000	0.000000	0	11.111	88.889	0.000
109	32	33	1.0312	0.03327	2	1.418	0.009119	1	0.000	93.750	6.250
110	48	67	1.3958	0.02970	1	1.000	0.000000	0	6.250	93.750	0.000
111	10	9	0.9000	0.10000	1	1.000	0.000000	0	10.000	90.000	0.000
112	35	37	1.0571	0.03109	1	1.000	0.000000	0	5.714	94.286	0.000
113	50	59	1.1800	0.02408	2	1.033	0.005515	1	8.000	88.000	4.000
114	23	42	1.8261	0.08300	1	1.000	0.000000	0	8.696	91.304	0.000
115	10	16	1.6000	0.17778	1	1.000	0.000000	0	20.000	80.000	0.000
116	35	34	0.9714	0.02857	1	1.000	0.000000	0	2.857	97.143	0.000
117	103	205	1.9903	0.01951	1	1.000	0.000000	0	10.680	89.320	0.000
118	10	9	0.9000	0.10000	1	1.000	0.000000	0	10.000	90.000	0.000
119	32	31	0.9688	0.03125	1	1.000	0.000000	0	3.125	96.875	0.000
120	13	12	0.9231	0.07692	1	1.000	0.000000	0	7.692	92.308	0.000
121	22	28	1.2727	0.06061	1	1.000	0.000000	0	13.636	86.364	0.000
122	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000

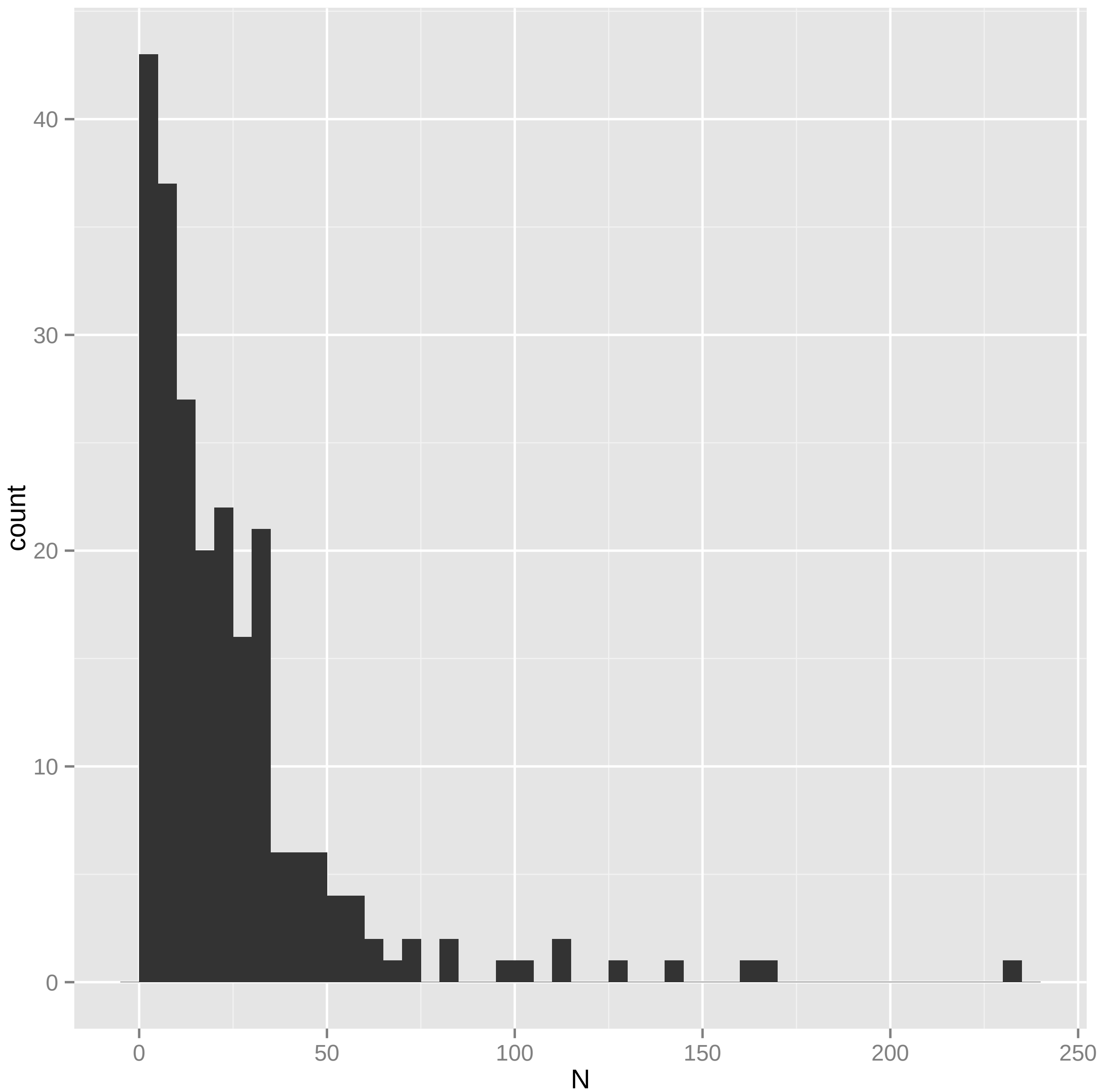
123	12	16	1.3333	0.12121	1	1.000	0.000000	0	75.000	25.000	0.000
124	52	51	0.9808	0.01923	1	1.000	0.000000	0	1.923	98.077	0.000
125	37	40	1.0811	0.03003	2	1.375	0.007874	0	5.405	91.892	2.703
126	25	46	1.8400	0.07667	1	1.000	0.000000	0	8.000	92.000	0.000
127	125	967	7.7360	0.06239	3	1.074	0.311741	4	36.800	56.000	7.200
128	30	29	0.9667	0.03333	1	1.000	0.000000	0	3.333	96.667	0.000
129	31	67	2.1613	0.07204	1	1.000	0.000000	0	25.806	74.194	0.000
130	13	12	0.9231	0.07692	1	1.000	0.000000	0	7.692	92.308	0.000
131	30	30	1.0000	0.03448	1	1.000	0.000000	1	0.000	96.667	3.333
132	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
133	11	10	0.9091	0.09091	1	1.000	0.000000	0	9.091	90.909	0.000
134	30	29	0.9667	0.03333	1	1.000	0.000000	0	3.333	96.667	0.000
135	6	5	0.8333	0.16667	1	1.000	0.000000	0	16.667	83.333	0.000
136	19	27	1.4211	0.07895	1	1.000	0.000000	0	21.053	78.947	0.000
137	21	27	1.2857	0.06429	1	1.000	0.000000	0	19.048	80.952	0.000
138	7	6	0.8571	0.14286	1	1.000	0.000000	0	28.571	71.429	0.000
139	18	17	0.9444	0.05556	1	1.000	0.000000	0	5.556	94.444	0.000
140	29	49	1.6897	0.06034	1	1.000	0.000000	0	27.586	72.414	0.000
141	4	3	0.7500	0.25000	1	1.000	0.000000	0	50.000	50.000	0.000
142	6	8	1.3333	0.26667	1	1.000	0.000000	0	33.333	66.667	0.000
143	22	51	2.3182	0.11039	1	1.000	0.000000	0	31.818	68.182	0.000
144	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
145	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
146	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
147	22	22	1.0000	0.04762	1	1.000	0.000000	1	0.000	95.455	4.545
148	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
149	27	26	0.9630	0.03704	1	1.000	0.000000	0	3.704	96.296	0.000
150	9	8	0.8889	0.11111	1	1.000	0.000000	0	11.111	88.889	0.000
151	8	7	0.8750	0.12500	1	1.000	0.000000	0	12.500	87.500	0.000
152	9	8	0.8889	0.11111	1	1.000	0.000000	0	22.222	77.778	0.000
153	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
154	6	5	0.8333	0.16667	1	1.000	0.000000	0	16.667	83.333	0.000
155	8	12	1.5000	0.21429	1	1.000	0.000000	0	37.500	62.500	0.000
156	48	47	0.9792	0.02083	1	1.000	0.000000	0	2.083	97.917	0.000
157	32	31	0.9688	0.03125	1	1.000	0.000000	0	3.125	96.875	0.000
158	33	32	0.9697	0.03030	1	1.000	0.000000	0	3.030	96.970	0.000
159	30	29	0.9667	0.03333	1	1.000	0.000000	0	3.333	96.667	0.000
160	11	10	0.9091	0.09091	1	1.000	0.000000	0	9.091	90.909	0.000
161	22	21	0.9545	0.04545	2	1.764	0.000000	0	18.182	77.273	4.545
162	25	34	1.3600	0.05667	2	1.029	0.061644	0	24.000	72.000	4.000
163	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
164	30	29	0.9667	0.03333	1	1.000	0.000000	0	3.333	96.667	0.000
165	14	13	0.9286	0.07143	1	1.000	0.000000	0	7.143	92.857	0.000
166	14	13	0.9286	0.07143	1	1.000	0.000000	0	7.143	92.857	0.000
167	72	75	1.0417	0.01467	2	1.051	0.000000	1	5.556	91.667	2.778
168	56	62	1.1071	0.02013	1	1.000	0.000000	0	3.571	96.429	0.000
169	55	756	13.7455	0.25455	1	1.000	0.000000	0	50.909	49.091	0.000
170	24	52	2.1667	0.09420	1	1.000	0.000000	0	33.333	66.667	0.000
171	46	201	4.3696	0.09710	1	1.000	0.000000	0	19.565	80.435	0.000
172	41	378	9.2195	0.23049	1	1.000	0.000000	0	34.146	65.854	0.000
173	5	5	1.0000	0.25000	1	1.000	0.000000	0	40.000	60.000	0.000
174	7	6	0.8571	0.14286	1	1.000	0.000000	0	14.286	85.714	0.000
175	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
176	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000

177	58	65	1.1207	0.01966	2	1.030	0.013663	1	1.724	96.552	1.724
178	95	114	1.2000	0.01277	2	1.333	0.015446	2	0.000	97.895	2.105
179	16	20	1.2500	0.08333	1	1.000	0.000000	0	12.500	87.500	0.000
180	29	50	1.7241	0.06158	1	1.000	0.000000	0	31.034	68.966	0.000
181	34	73	2.1471	0.06506	1	1.000	0.000000	0	20.588	79.412	0.000
182	12	20	1.6667	0.15152	1	1.000	0.000000	0	16.667	83.333	0.000
183	8	9	1.1250	0.16071	1	1.000	0.000000	0	25.000	75.000	0.000
184	6	4	0.6667	0.13333	1	1.000	0.000000	0	33.333	66.667	0.000
185	160	527	3.2938	0.02072	2	1.165	0.069385	2	16.875	75.000	8.125
186	34	34	1.0000	0.03030	1	1.000	0.000000	1	0.000	97.059	2.941
187	46	67	1.4565	0.03237	1	1.000	0.000000	0	17.391	82.609	0.000
188	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
189	10	12	1.2000	0.13333	1	1.000	0.000000	0	20.000	80.000	0.000
190	19	51	2.6842	0.14912	1	1.000	0.000000	0	73.684	26.316	0.000
191	15	14	0.9333	0.06667	1	1.000	0.000000	0	6.667	93.333	0.000
192	27	46	1.7037	0.06553	2	1.098	0.000000	0	22.222	74.074	3.704
193	24	35	1.4583	0.06341	1	1.000	0.000000	0	16.667	83.333	0.000
194	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
195	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
196	15	17	1.1333	0.08095	1	1.000	0.000000	0	46.667	53.333	0.000
197	63	84	1.3333	0.02151	1	1.000	0.000000	0	6.349	93.651	0.000
198	12	11	0.9167	0.08333	1	1.000	0.000000	0	8.333	91.667	0.000
199	41	40	0.9756	0.02439	1	1.000	0.000000	0	2.439	97.561	0.000
200	5	4	0.8000	0.20000	1	1.000	0.000000	0	20.000	80.000	0.000
201	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
202	24	23	0.9583	0.04167	1	1.000	0.000000	0	4.167	95.833	0.000
203	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
204	23	22	0.9565	0.04348	1	1.000	0.000000	0	4.348	95.652	0.000
205	4	3	0.7500	0.25000	1	1.000	0.000000	0	25.000	75.000	0.000
206	2	1	0.5000	0.50000	1	1.000	NaN	0	50.000	50.000	0.000
207	14	13	0.9286	0.07143	1	1.000	0.000000	0	7.143	92.857	0.000
208	11	10	0.9091	0.09091	1	1.000	0.000000	0	9.091	90.909	0.000
209	23	21	0.9130	0.04150	1	1.000	0.000000	0	8.696	91.304	0.000
210	38	37	0.9737	0.02632	1	1.000	0.000000	0	2.632	97.368	0.000
211	8	7	0.8750	0.12500	1	1.000	0.000000	0	12.500	87.500	0.000
212	83	81	0.9759	0.01190	2	1.036	0.000000	0	2.410	96.386	1.205
213	7	6	0.8571	0.14286	1	1.000	0.000000	0	14.286	85.714	0.000
214	5	4	0.8000	0.20000	1	1.000	0.000000	0	40.000	60.000	0.000
215	27	34	1.2593	0.04843	1	1.000	0.000000	0	11.111	88.889	0.000
216	32	196	6.1250	0.19758	1	1.000	0.339161	3	12.500	78.125	9.375
217	8	7	0.8750	0.12500	1	1.000	0.000000	0	12.500	87.500	0.000
218	3	2	0.6667	0.33333	1	1.000	0.000000	0	33.333	66.667	0.000
219	22	21	0.9545	0.04545	1	1.000	0.000000	0	4.545	95.455	0.000
220	24	23	0.9583	0.04167	1	1.000	0.000000	0	4.167	95.833	0.000
221	33	32	0.9697	0.03030	1	1.000	0.000000	0	3.030	96.970	0.000
222	15	16	1.0667	0.07619	1	1.000	0.000000	0	26.667	73.333	0.000
223	11	10	0.9091	0.09091	1	1.000	0.000000	0	9.091	90.909	0.000
224	18	28	1.5556	0.09150	1	1.000	0.000000	0	27.778	72.222	0.000
225	18	25	1.3889	0.08170	1	1.000	0.000000	0	22.222	77.778	0.000
226	20	26	1.3000	0.06842	1	1.000	0.000000	0	30.000	70.000	0.000
227	12	18	1.5000	0.13636	1	1.000	0.000000	0	25.000	75.000	0.000
228	9	7	0.7778	0.09722	1	1.000	0.000000	0	22.222	77.778	0.000

Because there are so many different locations (228) the dataframe of web properties becomes a bit unwieldy.

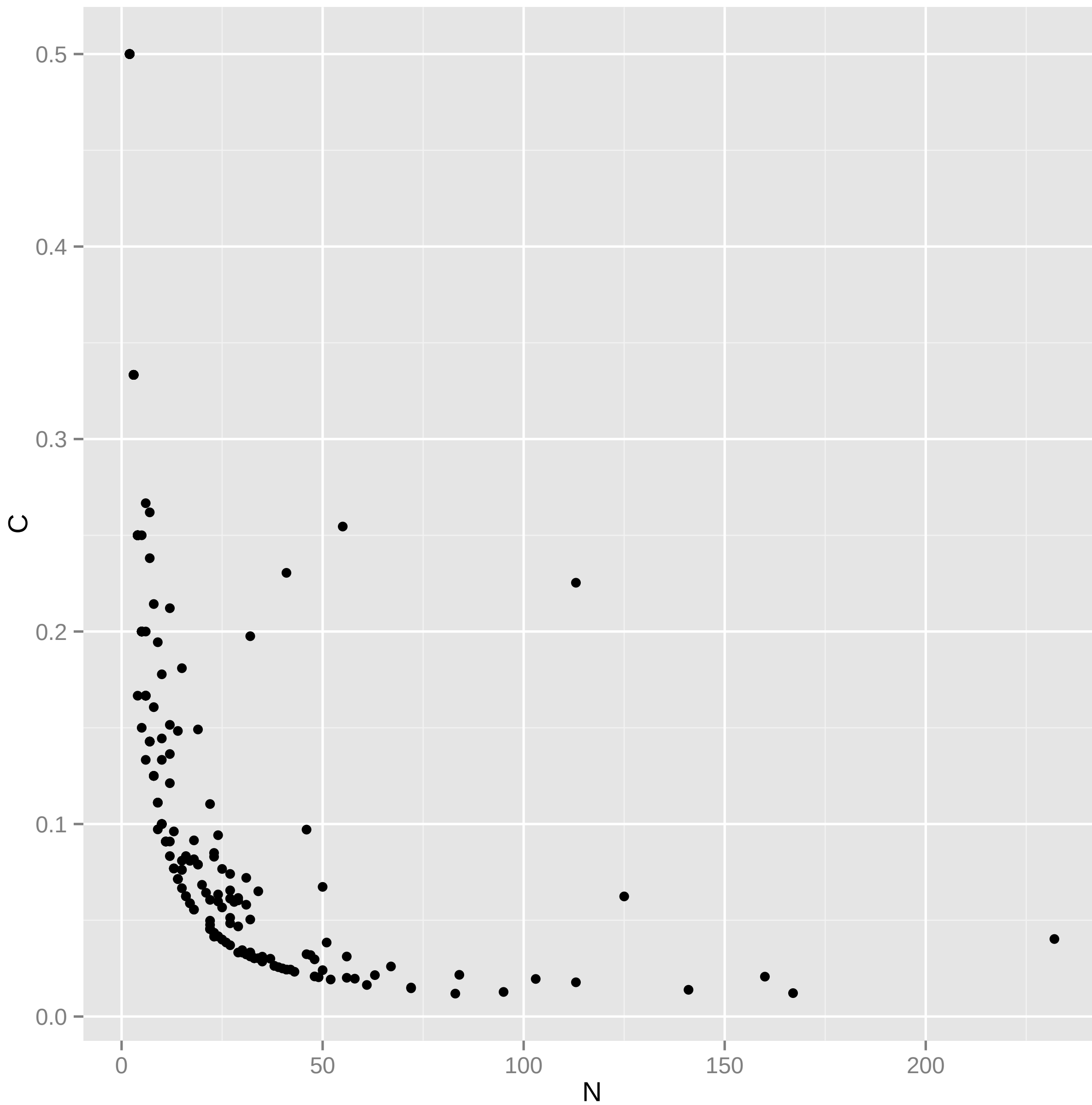
Plotting the different indices is a useful way to examine some of the properties of the different locations' food webs. First, a histogram of the number of nodes (N) in each web shows that most of the webs invovle less than 50 species, but a few are greater than 150 species.

```
ggplot(web.props1) + geom_histogram(aes(x = N), binwidth = 5)
```

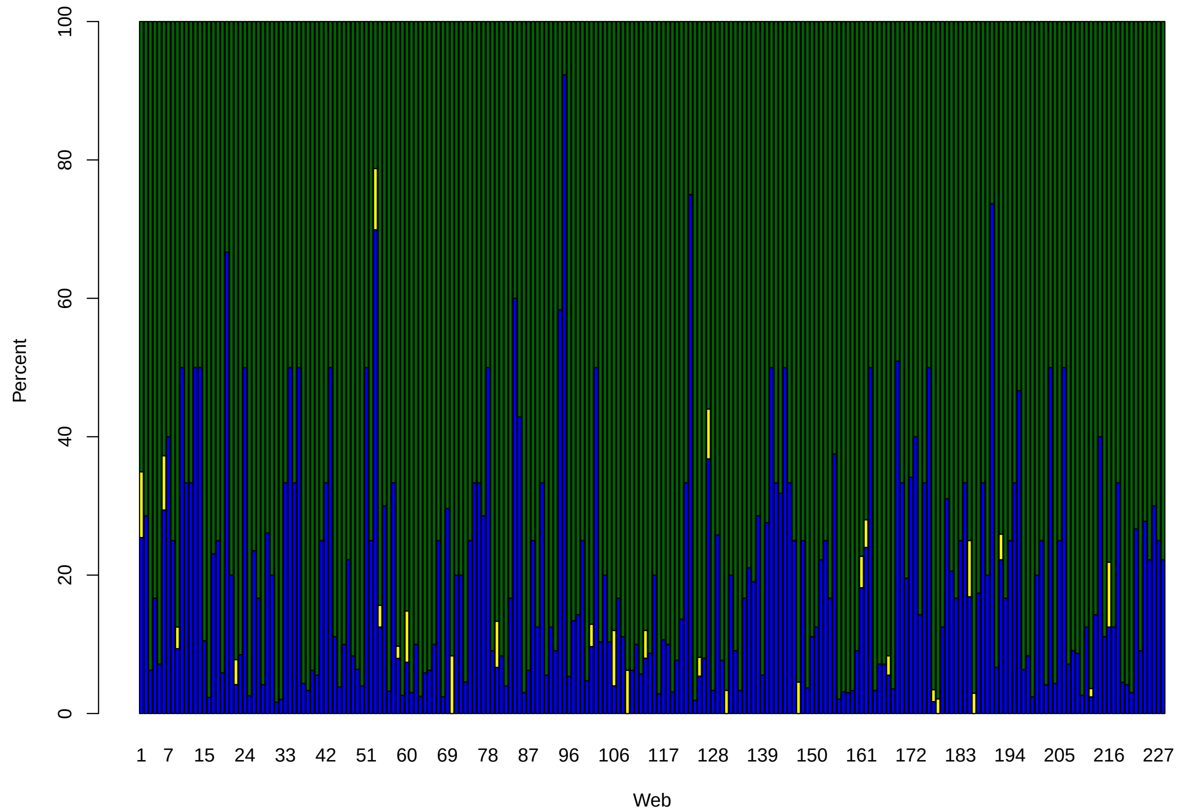


A plot of connectance (C) against size (N) shows the expected relationship of a decline in connectance with size. It is also evident that most of the food webs in this study have a connectance less than 0.1. A number of webs have a connectance of 0.5, but those represent the locations with webs that are only two species with one interaction.

```
ggplot(web.props1) + geom_point(aes(x = N, y = C))
```




```
nn<- matrix(c(web.props1$Bas, web.props1$Int, web.props1$Top), nrow = 3, ncol = 228, byrow = T)
colnames(nn) <- as.character(1:228)

barplot(nn, col = c("blue", "yellow", "darkgreen"), xlab = "Web", ylab = "Percent")
```

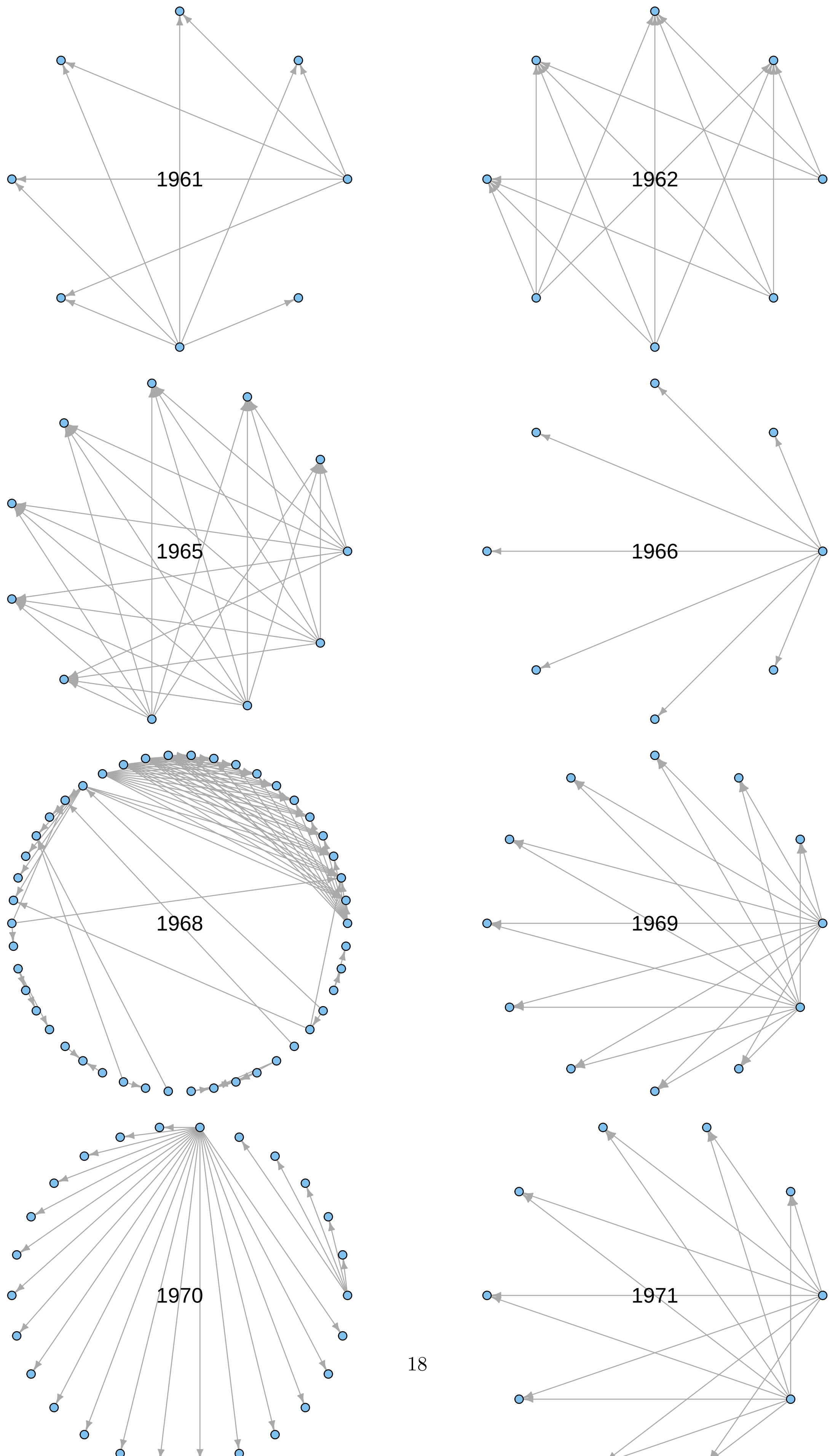


By year

```
so.ode <- as.character(s.ocean$OBSERVATION_DATE_END)
so.ode.split <- strsplit(so.ode, split = "/")

year <- c()
for(i in 1:length(so.ode.split)){
  year[i] <- so.ode.split[[i]][3]
}
s.ocean2 <- cbind(s.ocean, year)

m2 <- split(s.ocean2, f = s.ocean2$year)
year.g <- list()
for (i in 1:length(levels(s.ocean2$year))){

  el.df <- data.frame(pred = m2[[i]]$PREDATOR_NAME, prey = m2[[i]]$PREY_NAME)

  g <- graph.edgelist(unique(as.matrix(el.df[,1:2])))

  year.g[[i]] <- g
}
```

Plot webs by year

```
par(mfrow = c(23, 2), mar = c(.01,.01,.01,.01))
for (i in 1:45){
  plot.igraph(year.g[[i]], layout = layout.circle, edge.arrow.size = .5, vertex.label = NA,
              vertex.size = 5)
  text(0, 0, label = levels(s.ocean2$year)[i], cex = 2)
}
```


1961
1962
1965
1966
1968
1969
1970
1971

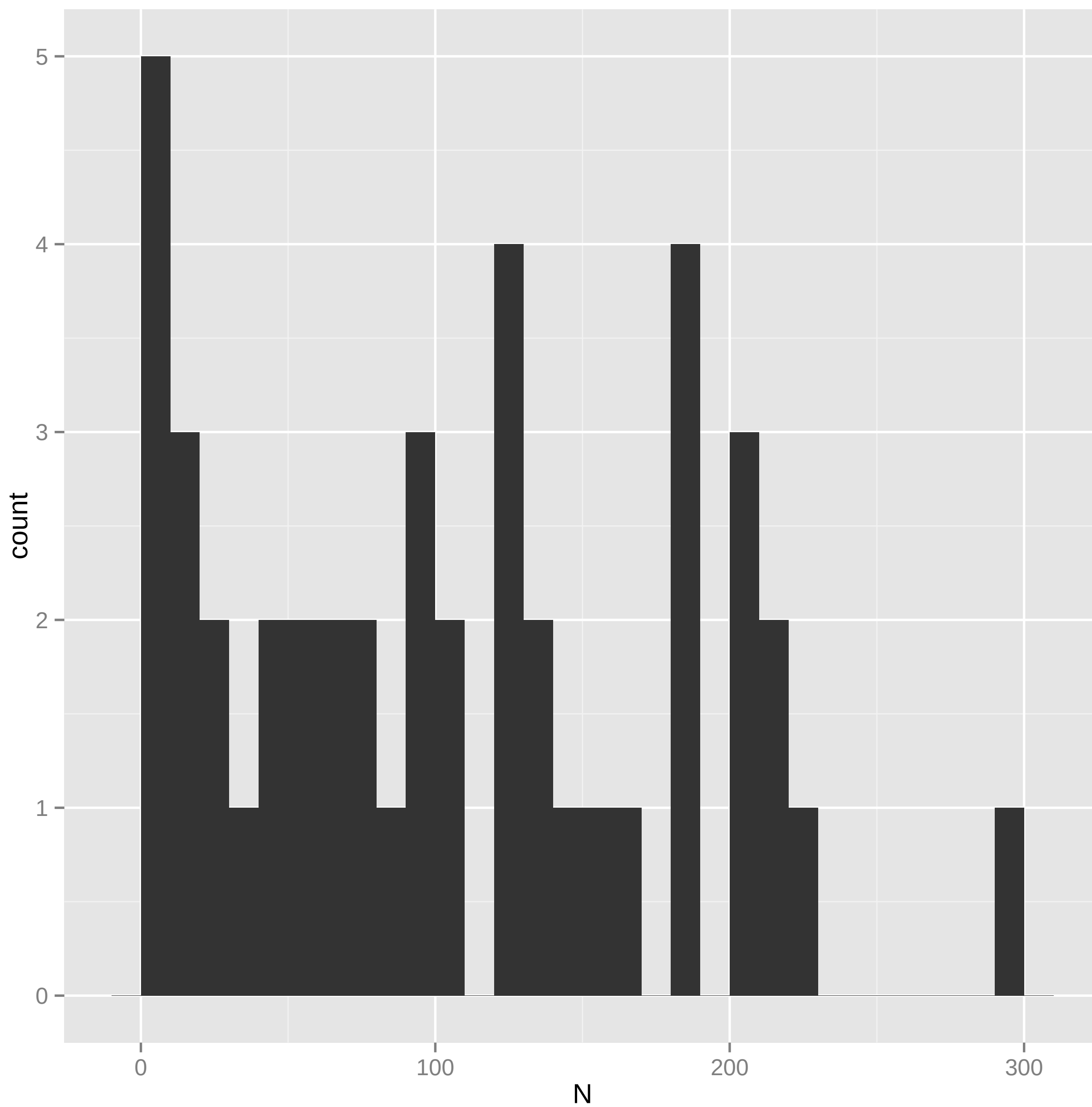
```r
web.props2 <- data.frame()
for (i in 1:45){
  gind <- GenInd(get.adjacency(year.g[[i]], sparse = F))
  diam <- diameter(year.g[[i]])
  avpath <- average.path.length(year.g[[i]])
  cluster <- transitivity(year.g[[i]])
  cannibals <- sum(diag(get.adjacency(year.g[[i]], sparse = F)))

  degrees <- degree(year.g[[i]], mode = "all")
  indegrees <- degree(year.g[[i]], mode = "in")
  outdegrees <- degree(year.g[[i]], mode = "out")

  numBas <- length(indegrees[which(indegrees == 0)])
  numTop <- length(outdegrees[which(outdegrees == 0)])
  basal <- (numBas/gind$N) * 100
  top <- (numTop/gind$N) * 100
  int <- ((gind$N - (numBas + numTop))/gind$N) * 100

  web.props <- data.frame(Year = levels(s.ocean2$year)[i], N = gind$N, L = gind$Ltot,
                          LD = gind$LD, C = gind$C, D = diam,
                          AvgPath = avpath, ClCoef = cluster, Can = cannibals, Bas = basal,
                          Top = top, Int = int)
  web.props2 <- rbind(web.props2, web.props)
}

print(web.props2)
```

```
   Year   N    L      LD        C D AvgPath    ClCoef Can    Bas   Top
1  1961   8   11  1.3750 0.196429 1   1.000 0.0000000   0 25.000 75.00
2  1962   8   16  2.0000 0.285714 1   1.000 0.0000000   0 50.000 50.00
3  1965  11   28  2.5455 0.254545 1   1.000 0.0000000   0 36.364 63.64
4  1966   8    7  0.8750 0.125000 1   1.000 0.0000000   0 12.500 87.50
5  1968  46   88  1.9130 0.042512 2   1.093 0.0000000   0 36.957 58.70
6  1969  12   20  1.6667 0.151515 1   1.000 0.0000000   0 16.667 83.33
7  1970  26   24  0.9231 0.036923 1   1.000 0.0000000   0  7.692 92.31
8  1971  10   16  1.6000 0.177778 1   1.000 0.0000000   0 20.000 80.00
9  1973   9    9  1.0000 0.125000 1   1.000 0.0000000   0 33.333 66.67
10 1974  49   58  1.1837 0.024660 1   1.000 0.0000000   0  6.122 93.88
11 1975  70   83  1.1857 0.017184 1   1.000 0.0000000   0  4.286 95.71
12 1976  28   38  1.3571 0.050265 1   1.000 0.0000000   0 14.286 85.71
13 1977  31   34  1.0968 0.036559 1   1.000 0.0000000   0 16.129 83.87
14 1979  95  157  1.6526 0.017581 1   1.000 0.0000000   0 14.737 85.26
15 1980  90  299  3.3222 0.037328 2   1.010 0.2691166   4 14.444 81.11
16 1981  94  139  1.4787 0.015900 2   1.042 0.0115607   1 11.702 86.17
17 1982 208  433  2.0817 0.010057 2   1.207 0.0101225   1 12.981 82.69
18 1983 299 4257 14.2375 0.047777 3   1.420 0.3121464  13 31.104 60.54
19 1984 109  163  1.4954 0.013846 2   1.190 0.0085511   1  9.174 87.16
20 1985 125  207  1.6560 0.013355 2   1.205 0.0144695   1 14.400 82.40
21 1986 120  219  1.8250 0.015336 1   1.000 0.0000000   0 10.833 89.17
22 1987 104  202  1.9423 0.018857 2   1.151 0.0000000   0  8.654 90.38
23 1988 155  825  5.3226 0.034562 3   1.119 0.0086548   0 21.290 70.97
24 1989  53   65  1.2264 0.023585 2   1.133 0.0164835   0 11.321 84.91
25 1990 129  224  1.7364 0.013566 2   1.189 0.0024430   1  6.977 89.15
```

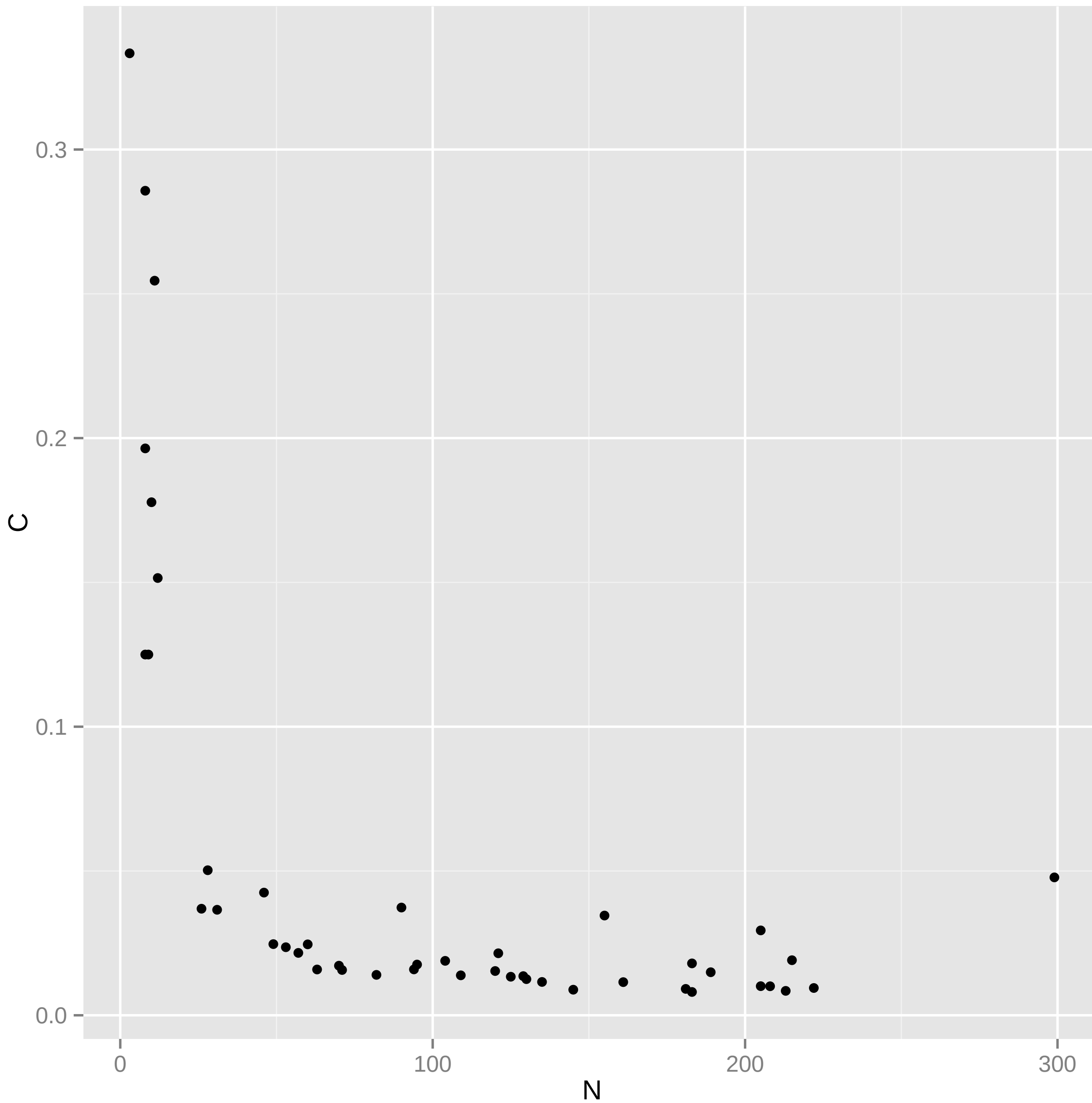
```
26 1991 145  185  1.2759 0.008860 3   1.464 0.0132890   2  9.655 85.52
27 1992 130  210  1.6154 0.012522 3   1.290 0.0186722   1 10.769 86.92
28 1993 205 1230  6.0000 0.029412 4   1.336 0.0006669   1 14.634 81.95
29 1994 215  878  4.0837 0.019083 3   1.421 0.0179806   0  9.767 86.98
30 1995 213  382  1.7934 0.008460 3   1.799 0.0149495   1  5.164 90.61
31 1996 189  530  2.8042 0.014916 4   1.656 0.1237898   5 12.698 80.95
32 1997 205  422  2.0585 0.010091 3   1.099 0.0032805   1 11.707 85.37
33 1998 181  298  1.6464 0.009147 3   1.107 0.0050220   0  9.392 88.95
34 1999 183  599  3.2732 0.017985 3   1.290 0.0505352   1 10.929 78.69
35 2000 222  464  2.0901 0.009457 2   1.241 0.0189959   1  6.306 92.34
36 2001 161  296  1.8385 0.011491 3   1.317 0.0184049   1  6.832 89.44
37 2002 135  209  1.5481 0.011553 3   1.256 0.0156018   1  5.926 91.85
38 2003  60   87  1.4500 0.024576 3   1.442 0.0403769   1  6.667 88.33
39 2004 121  312  2.5785 0.021488 3   1.539 0.0496710   2  9.917 80.99
40 2005  57   69  1.2105 0.021617 2   1.374 0.0299700   2  1.754 94.74
41 2006 183  269  1.4699 0.008077 3   1.708 0.0408666   3  3.279 93.44
42 2007  63   62  0.9841 0.015873 1   1.000 0.0000000   0  1.587 98.41
43 2008  82   93  1.1341 0.014002 1   1.000 0.0000000   0  7.317 92.68
44 2009  71   78  1.0986 0.015694 1   1.000 0.0000000   0  4.225 95.77
45 2010   3    2  0.6667 0.333333 1   1.000 0.0000000   0 33.333 66.67
       Int
1   0.0000
2   0.0000
3   0.0000
4   0.0000
5   4.3478
6   0.0000
7   0.0000
8   0.0000
9   0.0000
10  0.0000
11  0.0000
12  0.0000
13  0.0000
14  0.0000
15  4.4444
16  2.1277
17  4.3269
18  8.3612
19  3.6697
20  3.2000
21  0.0000
22  0.9615
23  7.7419
24  3.7736
25  3.8760
26  4.8276
27  2.3077
28  3.4146
29  3.2558
30  4.2254
31  6.3492
32  2.9268
33  1.6575
```

```
34 10.3825
35  1.3514
36  3.7267
37  2.2222
38  5.0000
39  9.0909
40  3.5088
41  3.2787
42  0.0000
43  0.0000
44  0.0000
45  0.0000
```

```r
ggplot(web.props2) + geom_histogram(aes(x = N), binwidth = 10)
```

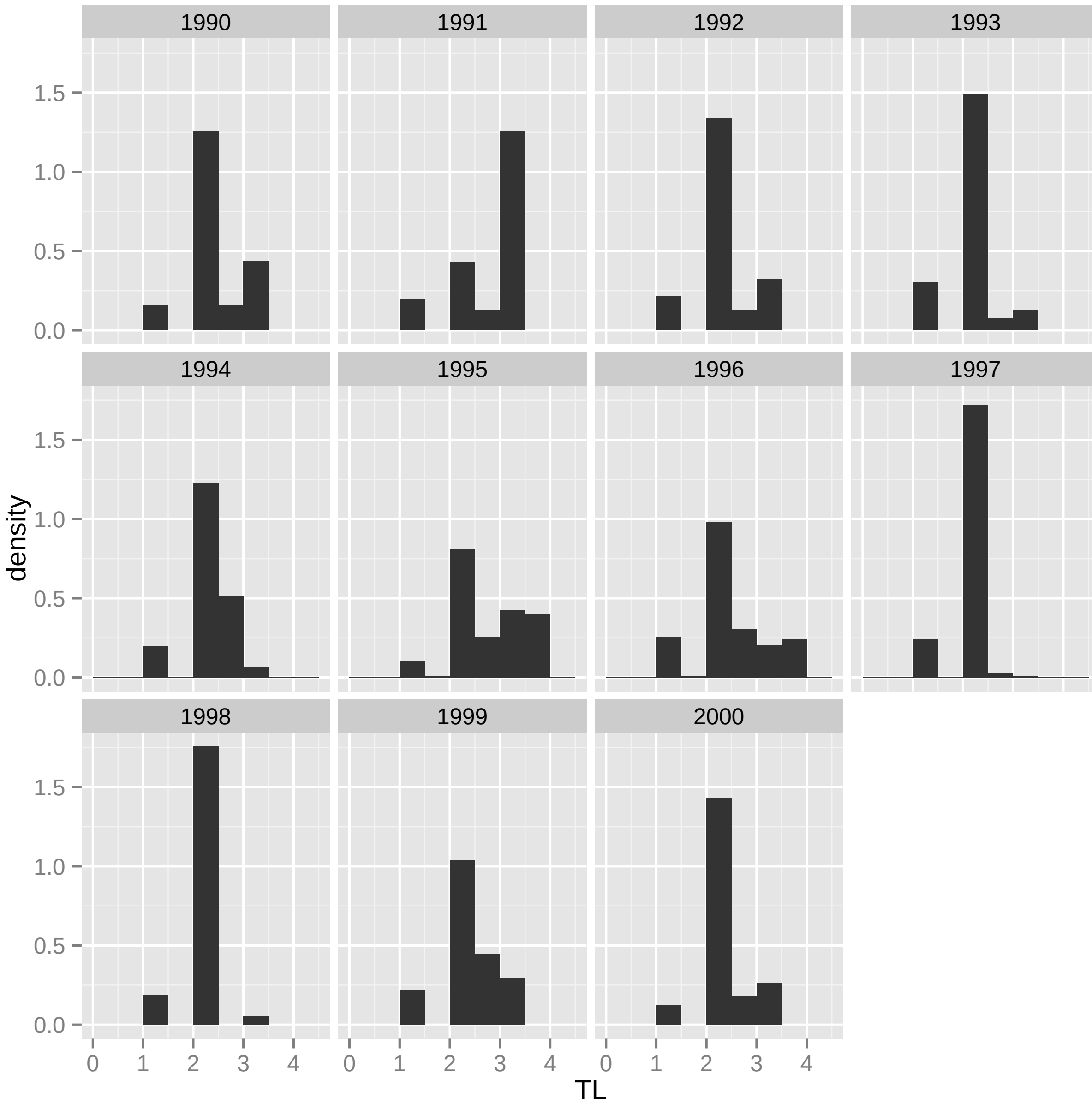


```
ggplot(web.props2) + geom_point(aes(x = N, y = C))
```



Variation: 1990-2000

```
wp2 <- web.props2[25:35,]
ytind <- lapply(year.g[25:35], get.adjacency, sparse = F)
ytind <- lapply(ytind, TrophInd)
dtind <- cbind(rep(wp2$Year, sapply(ytind, nrow)), rbindlist(ytind))
ggplot(dtind, aes(x = TL, y = ..density..)) + geom_histogram(binwidth = .5) + facet_wrap(~V1)
```


1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
density
0.0
0.5
1.0
1.5
0
1
2
3
4
TL