

BDC334

Biogeography & Global Ecology

Topic 4

The Multivariate Nature of Ecological Data

Diversity can consider either,

- whether species are present or absent; this kind of data is called **presence-absence** data
 - this kind of data is binary (i.e. a species is there, or it is not there), or
- it can include aspects of how much (biomass, abundance, % cover) of each of the species that is present
 - we will call this kind of data **abundance** data.

convert to presence-absence

| site | sp_A | sp_B | sp_C | sp_D | sp_E | sp_F |
|--------|------|------|------|------|------|------|
| site_A | 1 | 1 | 1 | 2 | 1 | 10 |
| site_B | 1 | 2 | 1 | 1 | 2 | 1 |
| site_C | 4 | 4 | 5 | 4 | 5 | 4 |
| site_D | 10 | 11 | 10 | 10 | 10 | 11 |
| site_E | 0 | 0 | 0 | 0 | 1 | 1 |
| site_F | 0 | 0 | 0 | 0 | 1 | 10 |
| site_G | 1 | 1 | 1 | 1 | 1 | 1 |
| site_H | 10 | 10 | 10 | 10 | 10 | 10 |

| site | sp_A | sp_B | sp_C | sp_D | sp_E | sp_F |
|--------|------|------|------|------|------|------|
| site_A | 1 | 1 | 1 | 1 | 1 | 1 |
| site_B | 1 | 1 | 1 | 1 | 1 | 1 |
| site_C | 1 | 1 | 1 | 1 | 1 | 1 |
| site_D | 1 | 1 | 1 | 1 | 1 | 1 |
| site_E | 0 | 0 | 0 | 0 | 1 | 1 |
| site_F | 0 | 0 | 0 | 0 | 1 | 1 |
| site_G | 1 | 1 | 1 | 1 | 1 | 1 |
| site_H | 1 | 1 | 1 | 1 | 1 | 1 |

n = 7 sites
 p = 10 species
 q = 5 environmental variables

Environmental table
 (n × q)

| | var1 | var2 | var3 | var4 | var5 |
|-------|------|------|------|------|------|
| site1 | 23 | 455 | 1 | 6 | 10 |
| site2 | 25 | 345 | 2 | 5 | 11 |
| site3 | 19 | 421 | 1 | 3 | 13 |
| site4 | 13 | 329 | 2 | 6 | 9 |
| site5 | 21 | 401 | 1 | 7 | 10 |
| site6 | 23 | 367 | 1 | 5 | 11 |
| site7 | 31 | 399 | 1 | 6 | 12 |

Std. environmental table
 (n × q)

| | var1 | var2 | var3 | var4 | var5 |
|-------|------|------|------|------|------|
| site1 | 0 | 2 | -1 | 0 | -1 |
| site2 | 1 | -1 | 1 | -0 | 0 |
| site3 | -1 | 1 | -1 | -2 | 2 |
| site4 | -2 | -1 | 1 | 0 | -1 |
| site5 | -0 | 0 | -1 | 1 | -1 |
| site6 | 0 | -0 | -1 | -0 | 0 |
| site7 | 2 | 0 | -1 | 0 | 1 |

Correlation matrix
 (q × q)

| | var1 | var2 | var3 | var4 | var5 |
|------|------|------|------|------|------|
| var1 | 1 | ... | ... | ... | ... |
| var2 | ... | 1 | ... | ... | ... |
| var3 | ... | ... | 1 | ... | ... |
| var4 | ... | ... | ... | 1 | ... |
| var5 | ... | ... | ... | ... | 1 |

Dissimilarity matrix
 (n × n)

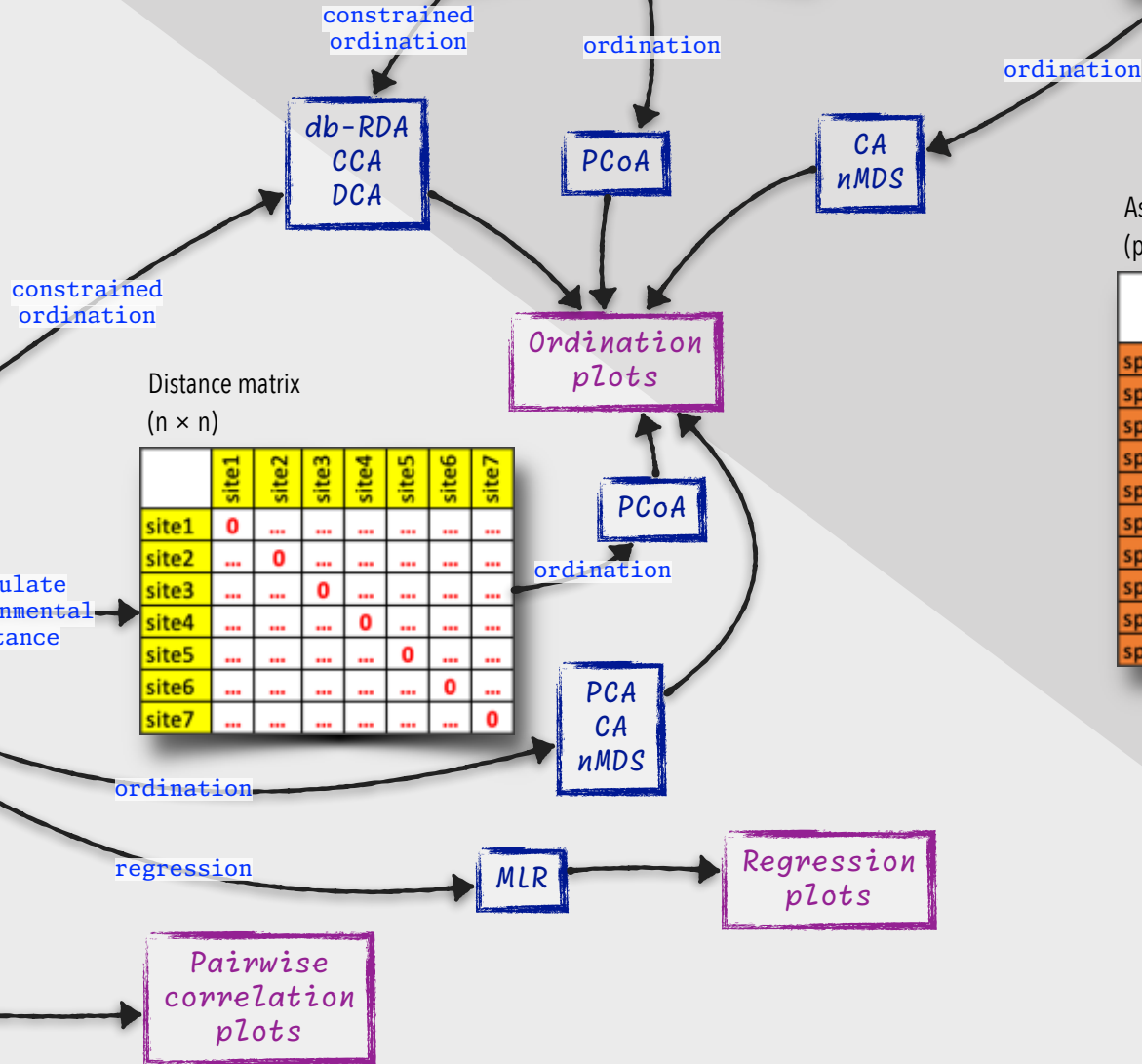
| | site1 | site2 | site3 | site4 | site5 | site6 | site7 |
|-------|-------|-------|-------|-------|-------|-------|-------|
| site1 | 0 | ... | ... | ... | ... | ... | ... |
| site2 | ... | 0 | ... | ... | ... | ... | ... |
| site3 | ... | ... | 0 | ... | ... | ... | ... |
| site4 | ... | ... | ... | 0 | ... | ... | ... |
| site5 | ... | ... | ... | ... | 0 | ... | ... |
| site6 | ... | ... | ... | ... | ... | 0 | ... |
| site7 | ... | ... | ... | ... | ... | ... | 0 |

Species table
 (n × p)

| | spp1 | spp2 | spp3 | spp4 | spp5 | spp6 | spp7 | spp8 | spp9 | spp10 |
|-------|------|------|------|------|------|------|------|------|------|-------|
| site1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 |
| site2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |
| site3 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| site4 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| site5 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |
| site6 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 |
| site7 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 |

Association matrix
 (p × p)

| | spp1 | spp2 | spp3 | spp4 | spp5 | spp6 | spp7 | spp8 | spp9 | spp10 |
|-------|------|------|------|------|------|------|------|------|------|-------|
| spp1 | 0 | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| spp2 | ... | 0 | ... | ... | ... | ... | ... | ... | ... | ... |
| spp3 | ... | ... | 0 | ... | ... | ... | ... | ... | ... | ... |
| spp4 | ... | ... | ... | 0 | ... | ... | ... | ... | ... | ... |
| spp5 | ... | ... | ... | ... | 0 | ... | ... | ... | ... | ... |
| spp6 | ... | ... | ... | ... | ... | 0 | ... | ... | ... | ... |
| spp7 | ... | ... | ... | ... | ... | ... | 0 | ... | ... | ... |
| spp8 | ... | ... | ... | ... | ... | ... | ... | 0 | ... | ... |
| spp9 | ... | ... | ... | ... | ... | ... | ... | ... | 0 | ... |
| spp10 | ... | ... | ... | ... | ... | ... | ... | ... | ... | 0 |



Distance matrices

- how similar sites (plot or quadrats or transects) are to each other is shown by **distance matrices**
- they are calculated from data tables (**species table** or **environment table**) by applying dissimilarity or distance calculations of some indices:
 - e.g. Euclidian distances for environmental data
- the result is a matrix of **pairwise differences (or distances) or similarities** in a metric that relates to the ecological distance between all sites, or the community composition (as synthesised by the chosen index)

Similarity and dissimilarity

- sites sharing a similar species composition are ecologically similar
 - 'composition' a function of species richness and abundance
 - *i.e.* high similarity / low dissimilarity
- how similar sites are depends on...
 - measurable environmental differences that influence species composition, or
 - it can be due to unmeasured influences, or
 - it can also simply be 'noise'
- it is the ecologist's role to figure out what influences the similarity / dissimilarity among sites
- they are grouped with a special class of matrix, *i.e.* the distance matrix

Distance matrix for environmental data

- **Euclidian distance** is “*the ‘ordinary’ straight-line distance between two points in Euclidean space*” (*i.e.* in its simplest form a planar area such as a graph with x - and y -axes)
- in 2D and 3D, gives **cartesian distance** between points on a plane (x, y), in a volume (x, y, z), or higher dimensions
- **conforms to our physical concept of distance**
 - *e.g.* short geographic distances between points on a map
 - (loses accuracy over large distances, as Earth’s surface is not on a plane but on a sphere... correct by using great circle distances, *e.g.* use the Haversine formula)
- calculated using the **Pythagorean theorem**
 - differences are squared, so single large differences become very important
 - this is **not useful for species data**

Distance matrices: properties

- the matrices are **square** and **symmetrical**
- **as many rows and columns as the number of sites** (*i.e.* rows) in the original species or environment table
- the diagonals are zero (a site is the same as itself, so it has zero dissimilarity), or one if it is a similarity matrix
- the table can be read directly, and each cell represents the **species or ecological difference between a pair of sites**
- all information of the species ID (and maybe also abundance) at a site is lost, as this info is condensed into one metric, the dissimilarity metric (or similarity metric)

**Distance matrices:
Euclidian distance with the
Pythagorean Theorem for
environmental data**

Two dimensions [\[edit \]](#)

In the [Euclidean plane](#), if $\mathbf{p} = (p_1, p_2)$ and $\mathbf{q} = (q_1, q_2)$ then the distance is given by

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2}.$$

This is equivalent to the [Pythagorean theorem](#).

Alternatively, it follows from (2) that if the [polar coordinates](#) of the point \mathbf{p} are (r_1, θ_1) and those of \mathbf{q} are (r_2, θ_2) , then the distance between the points is

$$\sqrt{r_1^2 + r_2^2 - 2r_1r_2 \cos(\theta_1 - \theta_2)}.$$

Three dimensions [\[edit \]](#)

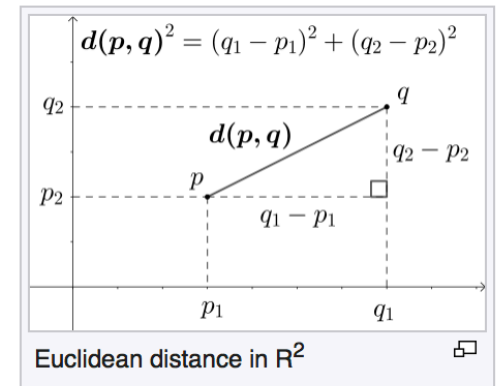
In three-dimensional Euclidean space, the distance is

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + (p_3 - q_3)^2}.$$

n dimensions [\[edit \]](#)

In general, for an n -dimensional space, the distance is

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_i - q_i)^2 + \cdots + (p_n - q_n)^2}.$$



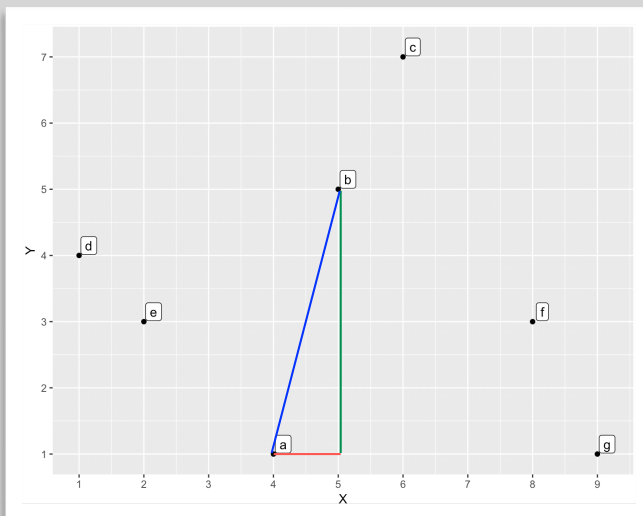
e.g. example with position (such as geographic) coordinates...

Raw data

| site | x | y |
|------|---|---|
| a | 4 | 1 |
| b | 5 | 5 |
| c | 6 | 6 |
| d | 1 | 4 |
| e | 2 | 3 |
| f | 8 | 3 |
| g | 9 | 1 |

Euclidian distances

| | a | b | c | d | e | f |
|---|----------|----------|----------|----------|----------|----------|
| b | 4.123106 | | | | | |
| c | 6.324555 | 2.236068 | | | | |
| d | 4.242641 | 4.123106 | 5.830952 | | | |
| e | 2.828427 | 3.605551 | 5.656854 | 1.414214 | | |
| f | 4.472136 | 3.605551 | 4.472136 | 7.071068 | 6.000000 | |
| g | 5.000000 | 5.656854 | 6.708204 | 8.544004 | 7.280110 | 2.236068 |



$$d(a, b) = \sqrt{(a_x - b_x)^2 + (a_y - b_y)^2}$$

e.g. example with 3D position coordinates (a.k.a. dimensions)...

Raw data

| site | x | y | z |
|------|---|---|---|
| a | 4 | 1 | 3 |
| b | 5 | 5 | 5 |
| c | 6 | 6 | 4 |
| d | 1 | 4 | 9 |
| e | 2 | 3 | 8 |
| f | 8 | 3 | 1 |
| g | 9 | 1 | 5 |

Euclidian distances

| | 1 | 2 | 3 | 4 | 5 | 6 |
|---|----------|----------|----------|-----------|----------|----------|
| 2 | 4.582576 | | | | | |
| 3 | 5.477226 | 1.732051 | | | | |
| 4 | 7.348469 | 5.744563 | 7.348469 | | | |
| 5 | 5.744563 | 4.690416 | 6.403124 | 1.732051 | | |
| 6 | 4.898979 | 5.385165 | 4.690416 | 10.677078 | 9.219544 | |
| 7 | 5.385165 | 5.656854 | 5.916080 | 9.433981 | 7.874008 | 4.582576 |

$$d(a, b) = \sqrt{(a_x - b_x)^2 + (a_y - b_y)^2 + (a_z - b_z)^2}$$

e.g. example with environmental 'dimensions'...

a dimensionless number

Raw data

| site | temperature | depth | light |
|------|-------------|-------|-------|
| a | 4 | 1 | 3 |
| b | 5 | 5 | 5 |
| c | 6 | 6 | 4 |
| d | 1 | 4 | 9 |
| e | 2 | 3 | 8 |
| f | 8 | 3 | 1 |
| g | 9 | 1 | 5 |

Euclidian distances

```
R> ex.xyz.euc <- vegdist(ex.xyz[,2:4], method = "euclidian")
R> ex.xyz.euc
      1      2      3      4      5      6
2  4.582576
3  5.477226  1.732051
4  7.348469  5.744563  7.348469
5  5.744563  4.690416  6.403124  1.732051
6  4.898979  5.385165  4.690416  10.677078  9.219544
7  5.385165  5.656854  5.916080  9.433981  7.874008  4.582576
```

$$d(a, b) = \sqrt{(a_{\text{temp}} - b_{\text{temp}})^2 + (a_{\text{depth}} - b_{\text{depth}})^2 + (a_{\text{light}} - b_{\text{light}})^2}$$

e.g. example with higher dimension environmental data...

Raw data

| | pH | O2 | temp | depth |
|---|-----|-----|------|-------|
| a | 7.1 | 6.5 | 12.1 | 1.1 |
| b | 7.5 | 5.5 | 12.3 | 1.3 |
| c | 7.6 | 5.7 | 11.9 | 1.5 |
| d | 7.0 | 5.4 | 11.8 | 1.6 |
| e | 7.1 | 6.3 | 12.0 | 1.8 |
| f | 7.2 | 6.3 | 12.1 | 1.9 |
| g | 6.9 | 6.1 | 12.2 | 2.2 |

(transformation)

Standardised data

| | pH | O2 | temp | depth |
|---|------------|------------|------------|-------------|
| a | -0.3872983 | 1.2156767 | 0.2494233 | -1.41749621 |
| b | 1.1618950 | -1.0842522 | 1.4133987 | -0.88114629 |
| c | 1.5491933 | -0.6242664 | -0.9145521 | -0.34479637 |
| d | -0.7745967 | -1.3142450 | -1.4965398 | -0.07662142 |
| e | -0.3872983 | 0.7556909 | -0.3325644 | 0.45972850 |
| f | 0.0000000 | 0.7556909 | 0.2494233 | 0.72790346 |
| g | -1.1618950 | 0.2957051 | 0.8314110 | 1.53242833 |

Euclidian distances

| | a | b | c | d | e | f |
|---|----------|----------|----------|----------|----------|----------|
| b | 4.123106 | | | | | |
| c | 6.324555 | 2.236068 | | | | |
| d | 4.242641 | 4.123106 | 5.830952 | | | |
| e | 2.828427 | 3.605551 | 5.656854 | 1.414214 | | |
| f | 4.472136 | 3.605551 | 4.472136 | 7.071068 | 6.000000 | |
| g | 5.000000 | 5.656854 | 6.708204 | 8.544004 | 7.280110 | 2.236068 |

Distance matrix for species data

- instead of using the Pythagorean Theorem to calculate 'distances' between species, we use
 - **Bray-Curtis** or **Jaccard** index for the case where data are abundances
 - Jaccard for presence-absence data — this is called the **Sørensen** dissimilarity index
- instead of having columns with measurements of environmental variables we have species abundance or presence-absence data
- Dissimilarity = 1 - Similarity
 - dissimilarity: the indices go from 0 (sites are identical) to 1 (sites are completely dissimilar)
 - similarity: the indices go from 0 (sites are completely dissimilar) to 1 (sites are identical)
- Qualitative indices (e.g. applied to presence-absence data) give more weight to rare species because the weights assigned to rare and common species are the same (1 in both instances).
- Quantitative indices give more weight to common species, which have more numerical variation between plots and these 'weights' feature more strongly in the calculation of indices.

**Distance matrices:
example with real **environmental**
data (Doubs River data)**

```

      dfs  alt  slo  flo  pH  har  pho  nit  amm  oxy  bod
      <dbl> <int> <dbl> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl>
1    0.3  934  48   0.84  7.9  45  0.01  0.2  0   12.2  2.7
2    2.2  932  3    1     8   40  0.02  0.2  0.1  10.3  1.9
3   10.2  914  3.7  1.8   8.3  52  0.05  0.22  0.05  10.5  3.5
4   18.5  854  3.2  2.53  8    72  0.1   0.21  0    11    1.3
5   21.5  849  2.3  2.64  8.1  84  0.38  0.52  0.2   8    6.2
6   32.4  846  3.2  2.86  7.9  60  0.2   0.15  0    10.2  5.3
7   36.8  841  6.6  4     8.1  88  0.07  0.15  0    11.1  2.2
8   70.5  752  1.2  4.8   8    90  0.3   0.82  0.12  7.2   5.2
9   99    617  9.9  10    7.7  82  0.06  0.75  0.01  10    4.3
10 123.   483  4.1  19.9  8.1  96  0.3   1.6   0    11.5  2.7
# ... with 19 more rows

```

```

      Cogo  Satr  Phph  Babl  Thth  Teso  Chna  Pato  Lele  Sqce  Baba  Albi  Gogo  Eslu  Pefl  Rham  Legi  Scer  Cyca
      <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int>
1      0    3    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
2      0    5    4    3    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
3      0    5    5    5    0    0    0    0    0    0    0    0    0    1    0    0    0    0    0
4      0    4    5    5    0    0    0    0    0    1    0    0    1    2    2    0    0    0    0
5      0    2    3    2    0    0    0    0    5    2    0    0    2    4    4    0    0    2    0
6      0    3    4    5    0    0    0    0    1    2    0    0    1    1    1    0    0    0    0
7      0    5    4    5    0    0    0    0    1    1    0    0    0    0    0    0    0    0    0
8      0    0    1    3    0    0    0    0    0    5    0    0    0    0    0    0    0    0    0
9      0    1    4    4    0    0    0    0    2    2    0    0    1    0    0    0    0    0    0
10     1    3    4    1    1    0    0    0    0    1    0    0    0    0    0    0    0    0    0
# ... with 19 more rows, and 8 more variables: Titi <int>, Abbr <int>, Icme <int>, Gyce <int>, Ruru <int>,
#   Blbj <int>, Alal <int>, Anan <int>

```


Raw data

```
  dfs  alt  slo  flo  pH  har  pho  nit  amm  oxy  bod
<dbl> <int> <dbl> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <dbl> <dbl>
1  0.3  934  48  0.84  7.9  45  0.01  0.2  0  12.2  2.7
2  2.2  932  3  1  8  40  0.02  0.2  0.1  10.3  1.9
3  10.2  914  3.7  1.8  8.3  52  0.05  0.22  0.05  10.5  3.5
4  18.5  854  3.2  2.53  8  72  0.1  0.21  0  11  1.3
5  21.5  849  2.3  2.64  8.1  84  0.38  0.52  0.2  8  6.2
6  32.4  846  3.2  2.86  7.9  60  0.2  0.15  0  10.2  5.3
7  36.8  841  6.6  4  8.1  88  0.07  0.15  0  11.1  2.2
8  70.5  752  1.2  4.8  8  90  0.3  0.82  0.12  7.2  5.2
9  99  617  9.9  10  7.7  82  0.06  0.75  0.01  10  4.3
10 123.  483  4.1  19.9  8.1  96  0.3  1.6  0  11.5  2.7
# ... with 19 more rows
```

(transformation)

Standardised data

```
  dfs  alt  slo  flo  pH  har  pho  nit  amm  oxy  bod
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 -1.38  1.72  5.05 -1.23 -0.84 -2.39 -0.63 -1.06 -0.55  1.24 -0.59
2 -1.37  1.71 -0.06 -1.22 -0.27 -2.68 -0.62 -1.06 -0.290  0.37 -0.8
3 -1.31  1.64  0.02 -1.17  1.43 -1.98 -0.580 -1.04 -0.42  0.47 -0.39
4 -1.25  1.42 -0.04 -1.13 -0.27 -0.81 -0.53 -1.05 -0.55  0.69 -0.95
5 -1.23  1.4  -0.14 -1.13  0.290 -0.11 -0.21 -0.83 -0.03 -0.67  0.3
6 -1.15  1.39 -0.04 -1.12 -0.84 -1.51 -0.42 -1.09 -0.55  0.33  0.07
7 -1.12  1.37  0.35 -1.05  0.290  0.13 -0.56 -1.09 -0.55  0.74 -0.72
8 -0.88  1.04 -0.26 -1.01 -0.27  0.24 -0.3  -0.62 -0.24 -1.03  0.05
9 -0.68  0.54  0.72 -0.72 -1.97 -0.22 -0.570 -0.67 -0.53  0.24 -0.18
10 -0.5  0.05  0.06 -0.17  0.290  0.59 -0.3  -0.07 -0.55  0.92 -0.59
# ... with 19 more rows
```

Euclidian distances

```
  `1`  `2`  `3`  `4`  `5`  `6`  `7`  `8`  `9`  `10`  `11`  `12`  `13`  `14`  `15`  `16`
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1  0  0.01  0.08  0.3  0.32  0.33  0.35  0.68  1.18  1.67  1.7  1.8  1.86  1.93  2.08  2.17
2  0.01  0  0.07  0.290  0.31  0.32  0.34  0.67  1.17  1.66  1.69  1.79  1.85  1.92  2.07  2.16
3  0.08  0.07  0  0.22  0.24  0.25  0.27  0.6  1.1  1.59  1.62  1.72  1.78  1.85  2  2.09
4  0.3  0.290  0.22  0  0.02  0.03  0.05  0.38  0.88  1.37  1.4  1.5  1.56  1.63  1.78  1.87
5  0.32  0.31  0.24  0.02  0  0.01  0.03  0.36  0.86  1.35  1.38  1.48  1.54  1.61  1.76  1.85
6  0.33  0.32  0.25  0.03  0.01  0  0.02  0.35  0.85  1.34  1.37  1.47  1.53  1.6  1.75  1.84
7  0.35  0.34  0.27  0.05  0.03  0.02  0  0.33  0.83  1.32  1.35  1.45  1.51  1.58  1.73  1.82
8  0.68  0.67  0.6  0.38  0.36  0.35  0.33  0  0.5  0.99  1.02  1.12  1.18  1.25  1.4  1.49
9  1.18  1.17  1.1  0.88  0.86  0.85  0.83  0.5  0  0.49  0.52  0.62  0.68  0.75  0.9  0.99
10 1.67  1.66  1.59  1.37  1.35  1.34  1.32  0.99  0.49  0  0.03  0.13  0.19  0.26  0.41  0.5
# ... with 19 more rows, and 13 more variables: `17` <dbl>, `18` <dbl>, `19` <dbl>, `20` <dbl>,
# `21` <dbl>, `22` <dbl>, `23` <dbl>, `24` <dbl>, `25` <dbl>, `26` <dbl>, `27` <dbl>, `28` <dbl>,
# `29` <dbl>
```

The full matrix

| ▲ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 |
|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| 1 | 0 | 2 | 20 | 80 | 85 | 88 | 93 | 142 | 182 | 317 | 451 | 457 | 484 | 500 | 519 | 559 | 585 | 601 | 624 | 648 | 672 | 680 | 688 | 693 | 703 | 720 | 728 | 739 | 751 | 762 |
| 2 | 2 | 0 | 18 | 78 | 83 | 86 | 91 | 140 | 180 | 315 | 449 | 455 | 482 | 498 | 517 | 557 | 583 | 599 | 622 | 646 | 670 | 678 | 686 | 691 | 701 | 718 | 726 | 737 | 749 | 760 |
| 3 | 20 | 18 | 0 | 60 | 65 | 68 | 73 | 122 | 162 | 297 | 431 | 437 | 464 | 480 | 499 | 539 | 565 | 581 | 604 | 628 | 652 | 660 | 668 | 673 | 683 | 700 | 708 | 719 | 731 | 742 |
| 4 | 80 | 78 | 60 | 0 | 5 | 8 | 13 | 62 | 102 | 237 | 371 | 377 | 404 | 420 | 439 | 479 | 505 | 521 | 544 | 568 | 592 | 600 | 608 | 613 | 623 | 640 | 648 | 659 | 671 | 682 |
| 5 | 85 | 83 | 65 | 5 | 0 | 3 | 8 | 57 | 97 | 232 | 366 | 372 | 399 | 415 | 434 | 474 | 500 | 516 | 539 | 563 | 587 | 595 | 603 | 608 | 618 | 635 | 643 | 654 | 666 | 677 |
| 6 | 88 | 86 | 68 | 8 | 3 | 0 | 5 | 54 | 94 | 229 | 363 | 369 | 396 | 412 | 431 | 471 | 497 | 513 | 536 | 560 | 584 | 592 | 600 | 605 | 615 | 632 | 640 | 651 | 663 | 674 |
| 7 | 93 | 91 | 73 | 13 | 8 | 5 | 0 | 49 | 89 | 224 | 358 | 364 | 391 | 407 | 426 | 466 | 492 | 508 | 531 | 555 | 579 | 587 | 595 | 600 | 610 | 627 | 635 | 646 | 658 | 669 |
| 8 | 142 | 140 | 122 | 62 | 57 | 54 | 49 | 0 | 40 | 175 | 309 | 315 | 342 | 358 | 377 | 417 | 443 | 459 | 482 | 506 | 530 | 538 | 546 | 551 | 561 | 578 | 586 | 597 | 609 | 620 |
| 9 | 182 | 180 | 162 | 102 | 97 | 94 | 89 | 40 | 0 | 135 | 269 | 275 | 302 | 318 | 337 | 377 | 403 | 419 | 442 | 466 | 490 | 498 | 506 | 511 | 521 | 538 | 546 | 557 | 569 | 580 |
| 10 | 317 | 315 | 297 | 237 | 232 | 229 | 224 | 175 | 135 | 0 | 134 | 140 | 167 | 183 | 202 | 242 | 268 | 284 | 307 | 331 | 355 | 363 | 371 | 376 | 386 | 403 | 411 | 422 | 434 | 445 |
| 11 | 451 | 449 | 431 | 371 | 366 | 363 | 358 | 309 | 269 | 134 | 0 | 6 | 33 | 49 | 68 | 108 | 134 | 150 | 173 | 197 | 221 | 229 | 237 | 242 | 252 | 269 | 277 | 288 | 300 | 311 |
| 12 | 457 | 455 | 437 | 377 | 372 | 369 | 364 | 315 | 275 | 140 | 6 | 0 | 27 | 43 | 62 | 102 | 128 | 144 | 167 | 191 | 215 | 223 | 231 | 236 | 246 | 263 | 271 | 282 | 294 | 305 |
| 13 | 484 | 482 | 464 | 404 | 399 | 396 | 391 | 342 | 302 | 167 | 33 | 27 | 0 | 16 | 35 | 75 | 101 | 117 | 140 | 164 | 188 | 196 | 204 | 209 | 219 | 236 | 244 | 255 | 267 | 278 |
| 14 | 500 | 498 | 480 | 420 | 415 | 412 | 407 | 358 | 318 | 183 | 49 | 43 | 16 | 0 | 19 | 59 | 85 | 101 | 124 | 148 | 172 | 180 | 188 | 193 | 203 | 220 | 228 | 239 | 251 | 262 |
| 15 | 519 | 517 | 499 | 439 | 434 | 431 | 426 | 377 | 337 | 202 | 68 | 62 | 35 | 19 | 0 | 40 | 66 | 82 | 105 | 129 | 153 | 161 | 169 | 174 | 184 | 201 | 209 | 220 | 232 | 243 |
| 16 | 559 | 557 | 539 | 479 | 474 | 471 | 466 | 417 | 377 | 242 | 108 | 102 | 75 | 59 | 40 | 0 | 26 | 42 | 65 | 89 | 113 | 121 | 129 | 134 | 144 | 161 | 169 | 180 | 192 | 203 |
| 17 | 585 | 583 | 565 | 505 | 500 | 497 | 492 | 443 | 403 | 268 | 134 | 128 | 101 | 85 | 66 | 26 | 0 | 16 | 39 | 63 | 87 | 95 | 103 | 108 | 118 | 135 | 143 | 154 | 166 | 177 |
| 18 | 601 | 599 | 581 | 521 | 516 | 513 | 508 | 459 | 419 | 284 | 150 | 144 | 117 | 101 | 82 | 42 | 16 | 0 | 23 | 47 | 71 | 79 | 87 | 92 | 102 | 119 | 127 | 138 | 150 | 161 |
| 19 | 624 | 622 | 604 | 544 | 539 | 536 | 531 | 482 | 442 | 307 | 173 | 167 | 140 | 124 | 105 | 65 | 39 | 23 | 0 | 24 | 48 | 56 | 64 | 69 | 79 | 96 | 104 | 115 | 127 | 138 |
| 20 | 648 | 646 | 628 | 568 | 563 | 560 | 555 | 506 | 466 | 331 | 197 | 191 | 164 | 148 | 129 | 89 | 63 | 47 | 24 | 0 | 24 | 32 | 40 | 45 | 55 | 72 | 80 | 91 | 103 | 114 |
| 21 | 672 | 670 | 652 | 592 | 587 | 584 | 579 | 530 | 490 | 355 | 221 | 215 | 188 | 172 | 153 | 113 | 87 | 71 | 48 | 24 | 0 | 8 | 16 | 21 | 31 | 48 | 56 | 67 | 79 | 90 |
| 22 | 680 | 678 | 660 | 600 | 595 | 592 | 587 | 538 | 498 | 363 | 229 | 223 | 196 | 180 | 161 | 121 | 95 | 79 | 56 | 32 | 8 | 0 | 8 | 13 | 23 | 40 | 48 | 59 | 71 | 82 |
| 23 | 688 | 686 | 668 | 608 | 603 | 600 | 595 | 546 | 506 | 371 | 237 | 231 | 204 | 188 | 169 | 129 | 103 | 87 | 64 | 40 | 16 | 8 | 0 | 5 | 15 | 32 | 40 | 51 | 63 | 74 |
| 24 | 693 | 691 | 673 | 613 | 608 | 605 | 600 | 551 | 511 | 376 | 242 | 236 | 209 | 193 | 174 | 134 | 108 | 92 | 69 | 45 | 21 | 13 | 5 | 0 | 10 | 27 | 35 | 46 | 58 | 69 |
| 25 | 703 | 701 | 683 | 623 | 618 | 615 | 610 | 561 | 521 | 386 | 252 | 246 | 219 | 203 | 184 | 144 | 118 | 102 | 79 | 55 | 31 | 23 | 15 | 10 | 0 | 17 | 25 | 36 | 48 | 59 |
| 26 | 720 | 718 | 700 | 640 | 635 | 632 | 627 | 578 | 538 | 403 | 269 | 263 | 236 | 220 | 201 | 161 | 135 | 119 | 96 | 72 | 48 | 40 | 32 | 27 | 17 | 0 | 8 | 19 | 31 | 42 |
| 27 | 728 | 726 | 708 | 648 | 643 | 640 | 635 | 586 | 546 | 411 | 277 | 271 | 244 | 228 | 209 | 169 | 143 | 127 | 104 | 80 | 56 | 48 | 40 | 35 | 25 | 8 | 0 | 11 | 23 | 34 |
| 28 | 739 | 737 | 719 | 659 | 654 | 651 | 646 | 597 | 557 | 422 | 288 | 282 | 255 | 239 | 220 | 180 | 154 | 138 | 115 | 91 | 67 | 59 | 51 | 46 | 36 | 19 | 11 | 0 | 12 | 23 |
| 29 | 751 | 749 | 731 | 671 | 666 | 663 | 658 | 609 | 569 | 434 | 300 | 294 | 267 | 251 | 232 | 192 | 166 | 150 | 127 | 103 | 79 | 71 | 63 | 58 | 48 | 31 | 23 | 12 | 0 | 11 |
| 30 | 762 | 760 | 742 | 682 | 677 | 674 | 669 | 620 | 580 | 445 | 311 | 305 | 278 | 262 | 243 | 203 | 177 | 161 | 138 | 114 | 90 | 82 | 74 | 69 | 59 | 42 | 34 | 23 | 11 | 0 |

Distance matrices: example with real **species** data (Doubs River data)

- use Bray-Curtis for the case where data are abundances
- use Jaccard (with `binary = TRUE`) for presence/absence data
- many more in `vegan`; see `?vegdist`

Raw data

```
> spe
# A tibble: 29 x 27
  Cogo Satr Phph Babl Thth Teso Chna Pato Lele Sqce Baba Albi
<int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int> <int>
1     0     3     0     0     0     0     0     0     0     0     0     0
2     0     5     4     3     0     0     0     0     0     0     0     0
3     0     5     5     5     0     0     0     0     0     0     0     0
4     0     4     5     5     0     0     0     0     0     1     0     0
5     0     2     3     2     0     0     0     0     5     2     0     0
6     0     3     4     5     0     0     0     0     1     2     0     0
7     0     5     4     5     0     0     0     0     1     1     0     0
8     0     0     1     3     0     0     0     0     0     5     0     0
9     0     1     4     4     0     0     0     0     2     2     0     0
10    1     3     4     1     1     0     0     0     0     1     0     0
# ... with 19 more rows, and 15 more variables: Gogo <int>, Eslu <int>,
# Pefl <int>, Rham <int>, Legi <int>, Scer <int>, Cyca <int>,
# Titi <int>, Abbr <int>, Icme <int>, Gyce <int>, Ruru <int>,
# Blbj <int>, Alal <int>, Anan <int>
```

Bray Curtis dissimilarities

```
> spe_dist <- round(vegdist(spe, method = "bray", diag = TRUE, upper = TRUE), 2)
> as.tibble(as.matrix(env_dist))
# A tibble: 29 x 29
  `1` `2` `3` `4` `5` `6` `7` `8` `9` `10` `11` `12`
<dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 0 0.01 0.08 0.3 0.32 0.33 0.35 0.68 1.18 1.67 1.7 1.8
2 0.01 0 0.07 0.290 0.31 0.32 0.34 0.67 1.17 1.66 1.69 1.79
3 0.08 0.07 0 0.22 0.24 0.25 0.27 0.6 1.1 1.59 1.62 1.72
4 0.3 0.290 0.22 0 0.02 0.03 0.05 0.38 0.88 1.37 1.4 1.5
5 0.32 0.31 0.24 0.02 0 0.01 0.03 0.36 0.86 1.35 1.38 1.48
6 0.33 0.32 0.25 0.03 0.01 0 0.02 0.35 0.85 1.34 1.37 1.47
7 0.35 0.34 0.27 0.05 0.03 0.02 0 0.33 0.83 1.32 1.35 1.45
8 0.68 0.67 0.6 0.38 0.36 0.35 0.33 0 0.5 0.99 1.02 1.12
9 1.18 1.17 1.1 0.88 0.86 0.85 0.83 0.5 0 0.49 0.52 0.62
10 1.67 1.66 1.59 1.37 1.35 1.34 1.32 0.99 0.49 0 0.03 0.13
# ... with 19 more rows, and 17 more variables: `13` <dbl>, `14` <dbl>,
# `15` <dbl>, `16` <dbl>, `17` <dbl>, `18` <dbl>, `19` <dbl>,
# `20` <dbl>, `21` <dbl>, `22` <dbl>, `23` <dbl>, `24` <dbl>,
# `25` <dbl>, `26` <dbl>, `27` <dbl>, `28` <dbl>, `29` <dbl>
```

**Association matrices:
example with species presence-
absence**

Associations: species presence-absence

Species table

```
> spe[1:10, 1:10]
# A tibble: 10 x 10
  Cogo Satr Phph Babl Thth Teso Chna Pato Lele Sqce
<int> <int> <int> <int> <int> <int> <int> <int> <int> <int>
1     0     3     0     0     0     0     0     0     0     0
2     0     5     4     3     0     0     0     0     0     0
3     0     5     5     5     0     0     0     0     0     0
4     0     4     5     5     0     0     0     0     0     1
5     0     2     3     2     0     0     0     0     5     2
6     0     3     4     5     0     0     0     0     1     2
7     0     5     4     5     0     0     0     0     1     1
8     0     0     1     3     0     0     0     0     0     5
9     0     1     4     4     0     0     0     0     2     2
10    1     3     4     1     1     0     0     0     0     1
```

Transposed

```
> spe.t <- t(spe)
> spe.t[1:10, 1:10]
      [,1] [,2] [,3] [,4] [,5] [,6] [,7] [,8] [,9] [,10]
Cogo    0    0    0    0    0    0    0    0    0    1
Satr    3    5    5    4    2    3    5    0    1    3
Phph    0    4    5    5    3    4    4    1    4    4
Babl    0    3    5    5    2    5    5    3    4    1
Thth    0    0    0    0    0    0    0    0    0    1
Teso    0    0    0    0    0    0    0    0    0    0
Chna    0    0    0    0    0    0    0    0    0    0
Pato    0    0    0    0    0    0    0    0    0    0
Lele    0    0    0    0    5    1    1    0    2    0
Sqce    0    0    0    1    2    2    1    5    2    1
```

Jaccard coefficient

```
> spe.t.S7 <- vegdist(spe.t, "jaccard", binary = TRUE)
> round(as.matrix(spe.t.S7)[1:10, 1:10], 2)
      Cogo Satr Phph Babl Thth Teso Chna Pato Lele Sqce
Cogo 0.00 0.53 0.60 0.67 0.22 0.40 0.89 0.81 0.82 0.73
Satr 0.53 0.00 0.24 0.36 0.53 0.61 0.88 0.83 0.65 0.55
Phph 0.60 0.24 0.00 0.17 0.60 0.60 0.77 0.71 0.54 0.39
Babl 0.67 0.36 0.17 0.00 0.67 0.67 0.62 0.60 0.38 0.25
Thth 0.22 0.53 0.60 0.67 0.00 0.40 0.82 0.81 0.82 0.73
Teso 0.40 0.61 0.60 0.67 0.40 0.00 0.75 0.64 0.70 0.73
Chna 0.89 0.88 0.77 0.62 0.82 0.75 0.00 0.23 0.42 0.52
Pato 0.81 0.83 0.71 0.60 0.81 0.64 0.23 0.00 0.39 0.56
Lele 0.82 0.65 0.54 0.38 0.82 0.70 0.42 0.39 0.00 0.28
Sqce 0.73 0.55 0.39 0.25 0.73 0.73 0.52 0.56 0.28 0.00
```

Interpretation

0—always associated with...

1—never associated with...