Finding Groups

- *Objectives:*

Discuss the nature of community composition data

Introduce community analysis with Multi-Variate Statistics

Community Analysis - Introduction

- Community data (species counts in time / space) are multi-variate because each sample unit characterized by:

  - the occurrence (presence / absence) or abundance (counts) of number of co-occurring species

  - a set of (cross-correlated) environmental factors affecting species distributions

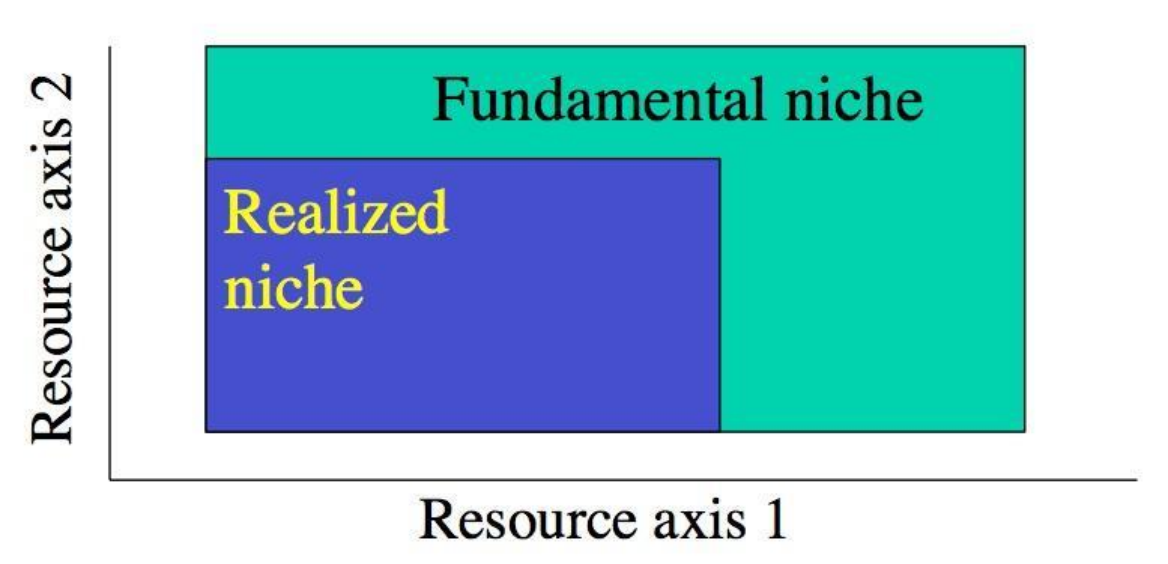
  - a set of temporal (e.g., absolute time, relative time) and spatial attributes (e.g., lat / long, habitat type)

(James & McCulloch 1990)

Community Analysis - Introduction

- Community ecologists analyze effects of multiple environmental factors on large numbers of co-occurring species and deal with statistical errors (measurement / structural)

- Why are species data not independent ?



Species on Environmental Gradients - Ideal

Robert H. Whittaker (Ed), *Classification of Plant Communities, 1978 (Handbook of Vegetation Science)*, Kluwer Academic Publishers

➢ Ideal species distributions across environmental gradients:

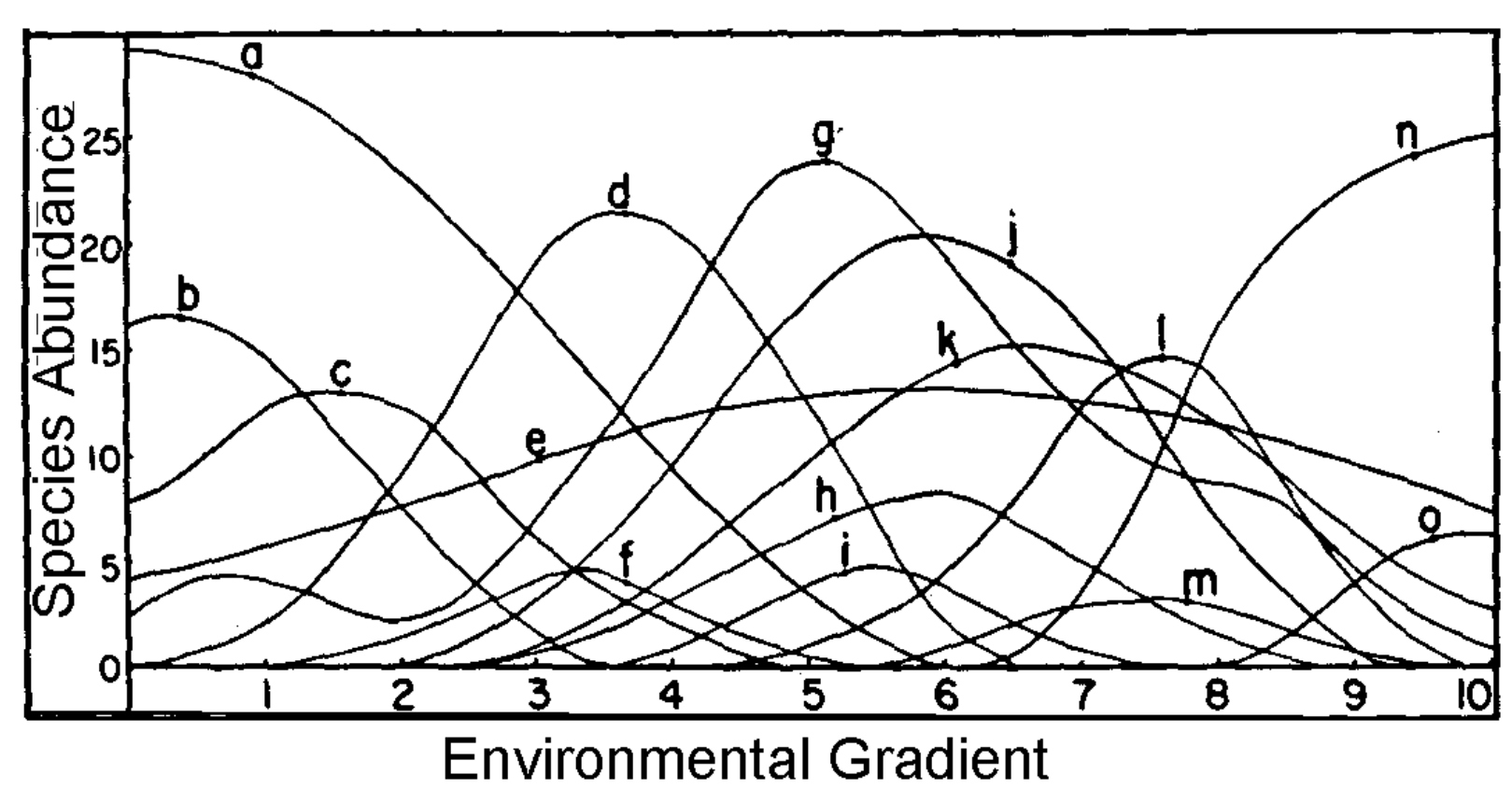
- Gaussian Response: Smooth normal curves

  Characterized by: mean ± SD, mode

- Linear Response: Smooth straight lines

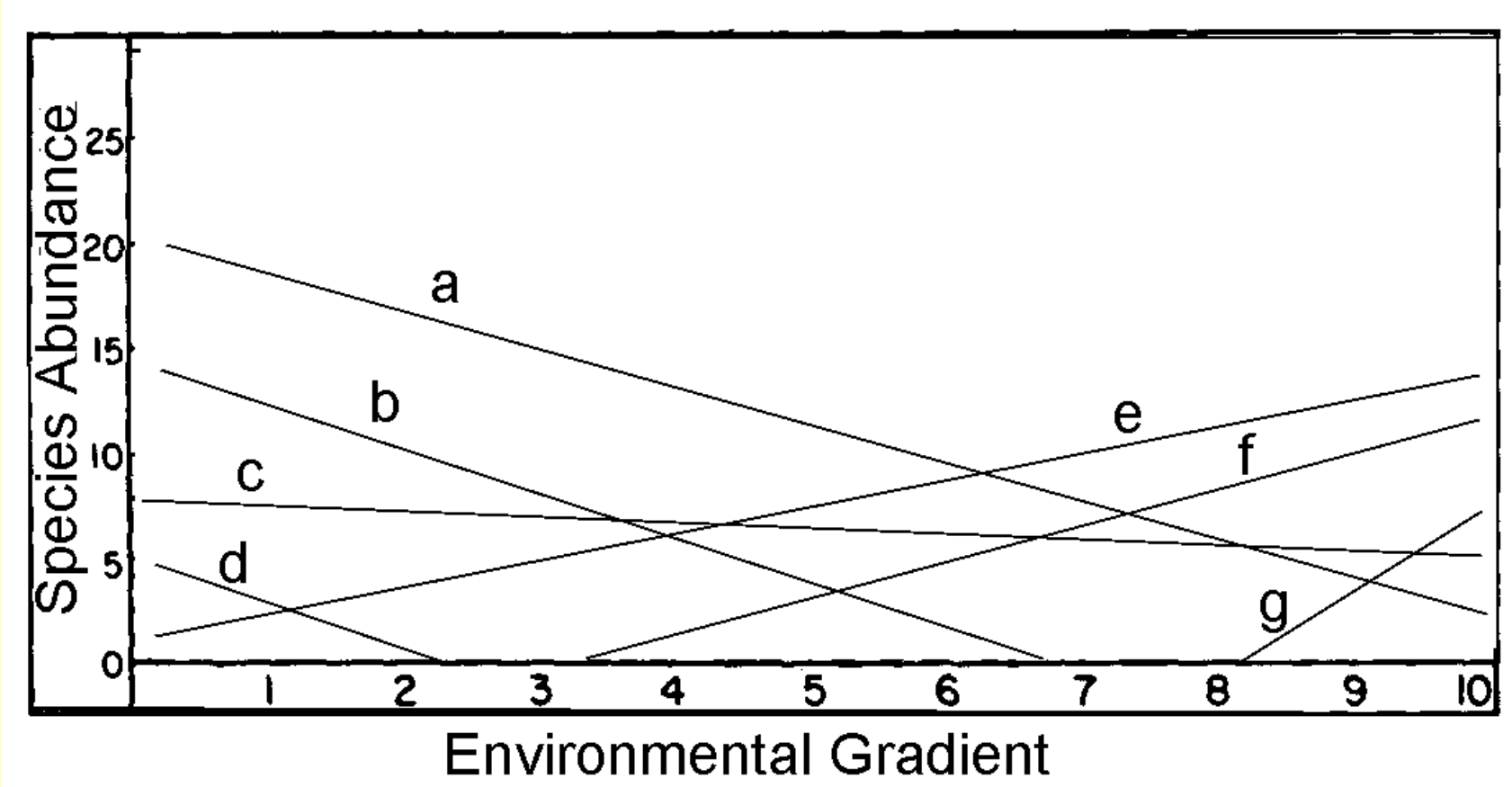
  Characterized by: range, slope

Gaussian (Normal) Distribution



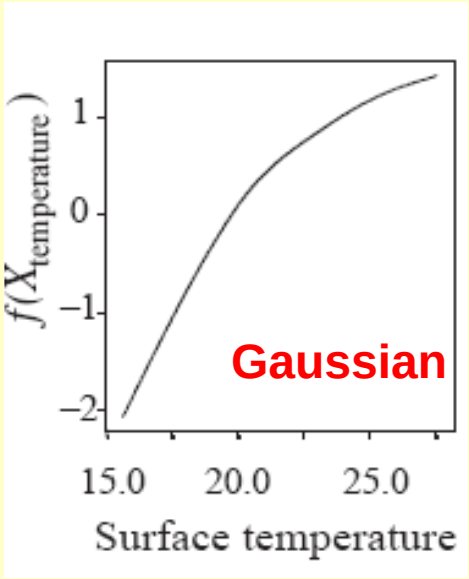
Hypothetical species abundance in response to an environmental gradient. Lettered curves represent different species. From Whittaker (1954).

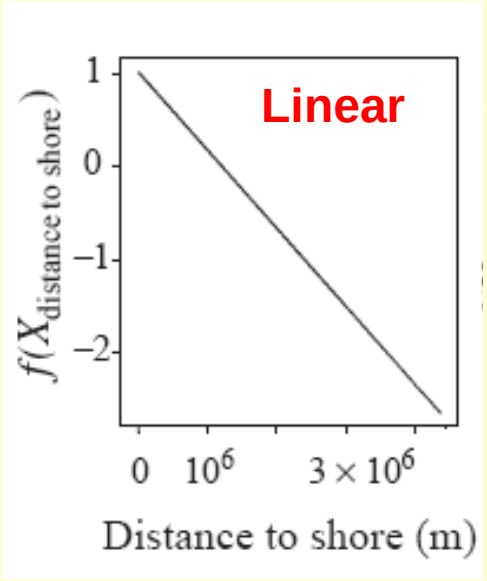
Linear Distribution

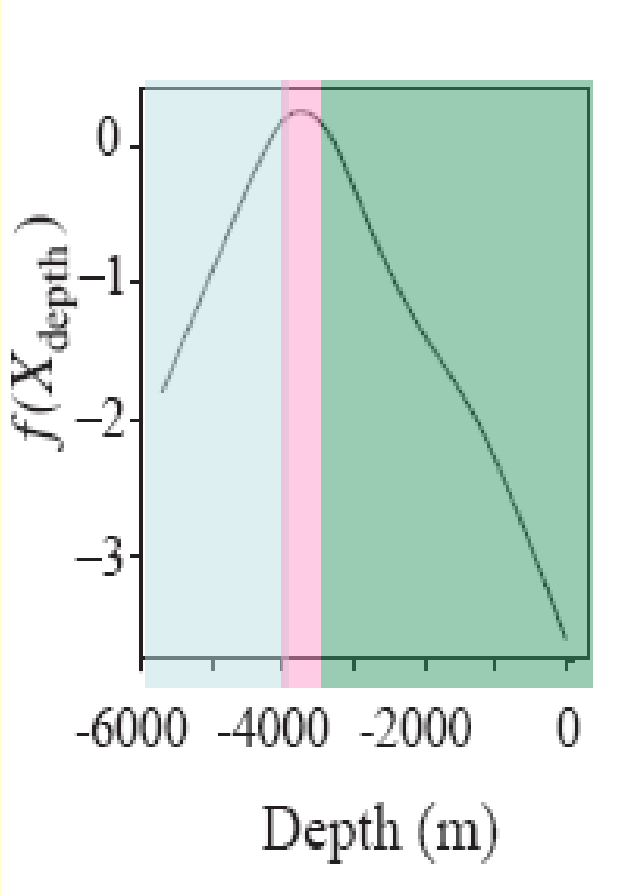


Hypothetical linear responses of species abundance to an environmental gradient. Lettered lines represent different species. From Whittaker (1954).

Species on Environmental Gradients - Real







Study 1:
(4 - 6 km depth):
Species prefers shallow habitat

Study 3:
(3.5 - 4 km depth):
Species shows no preference

Study 2:
(0 - 3.5 km depth):
Species prefers deep habitat

Some times the answer is scale-dependent

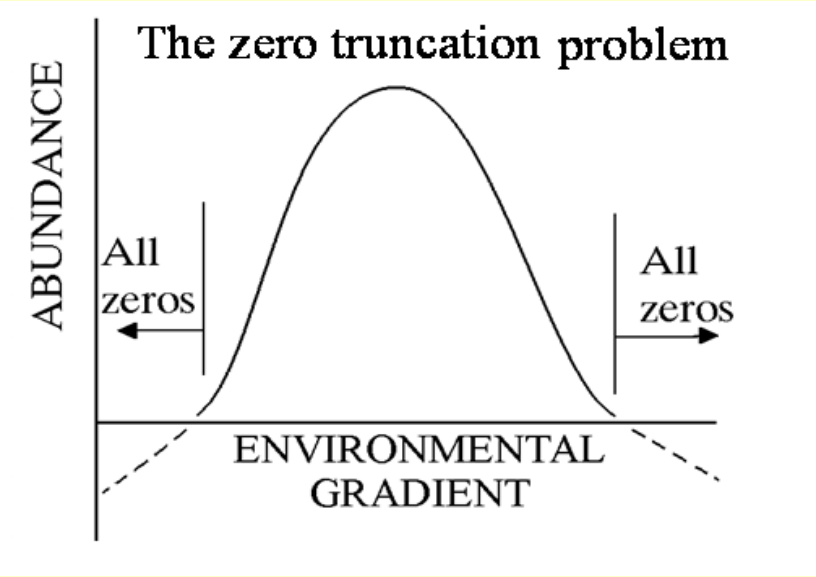
Species on Environmental Gradients - Real

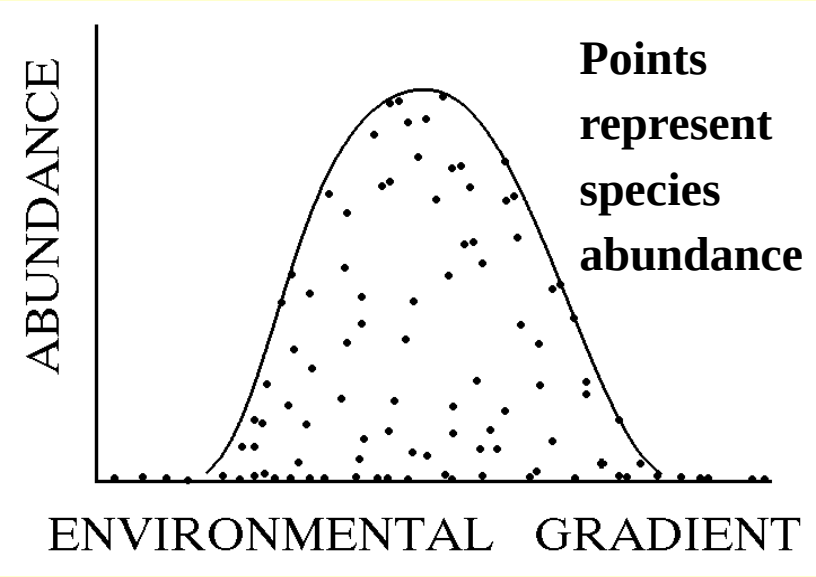
- 3 important issues to consider:
  - Zero-truncation Problem:
  - Solid Curves:
  - Complex Curves:

Observation: Species are often below their "optimal abundance", given the driving environmental factor. Why?

Other limiting factors

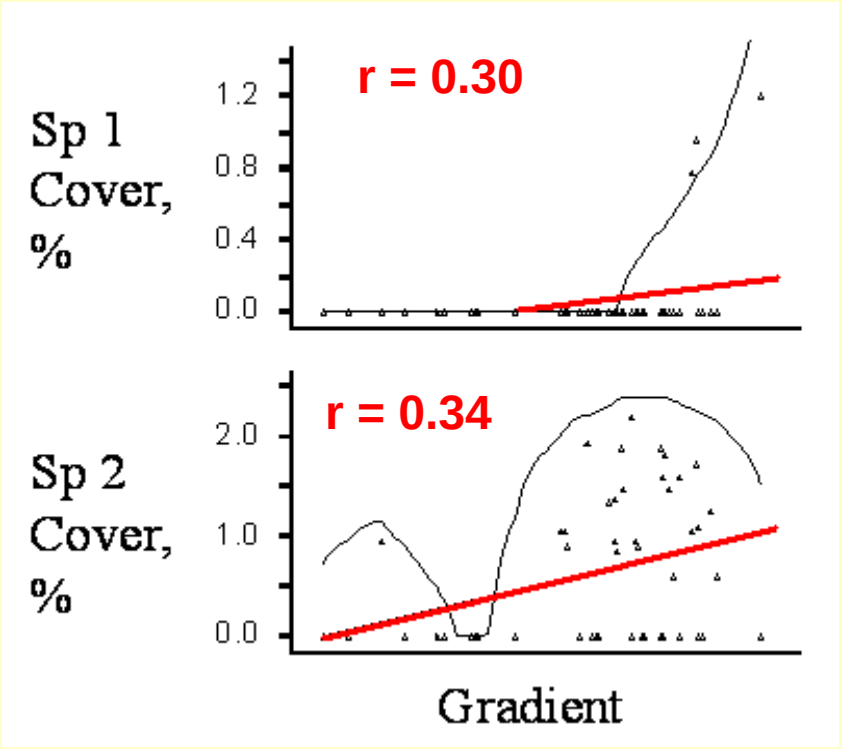
(e.g., Other environmental factors, other species, life-history, chance)

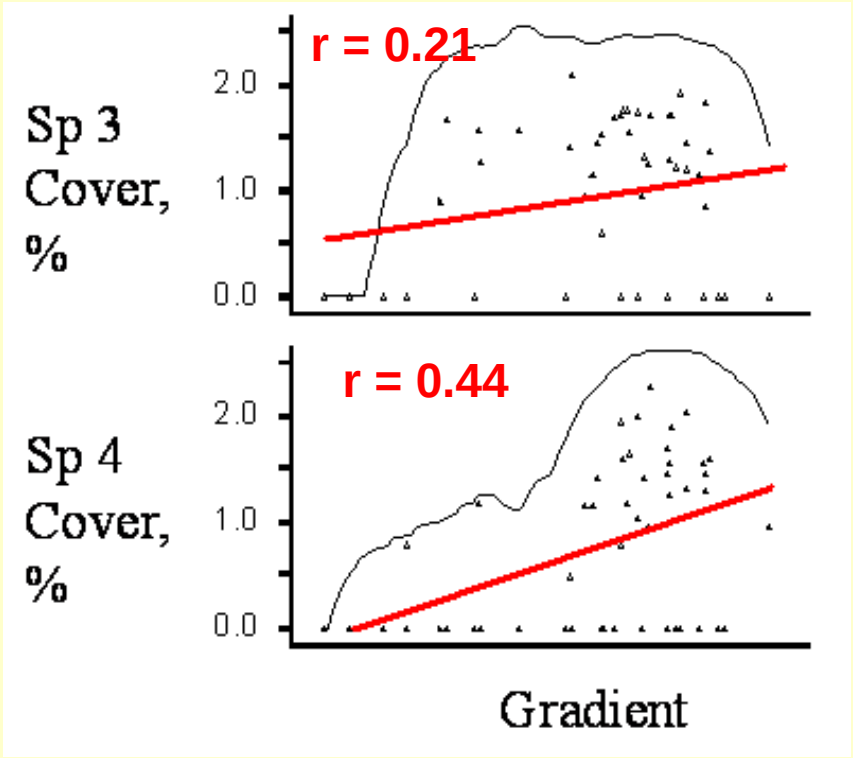




Species on Environmental Gradients - Real

Linear Regression — Fitted Envelope





Abrupt Ranges (Boundaries)

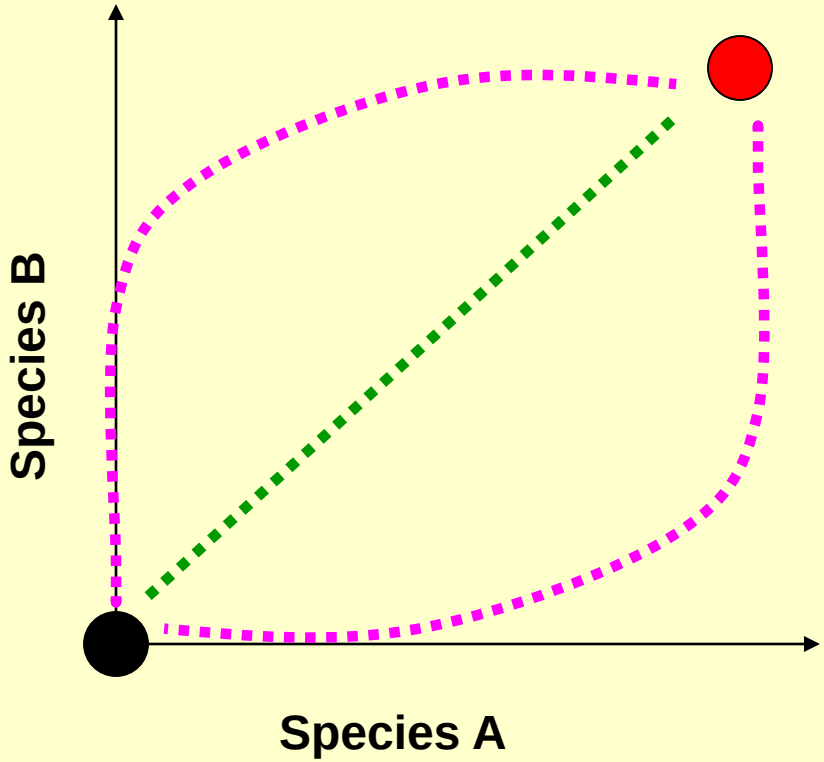
Multiple Modes

Linear Responses

Peaks (Optima)

Community Analysis – Bivariate Plots

More fruitful to explore how pairs of species abundances are related with “bivariate plots”.

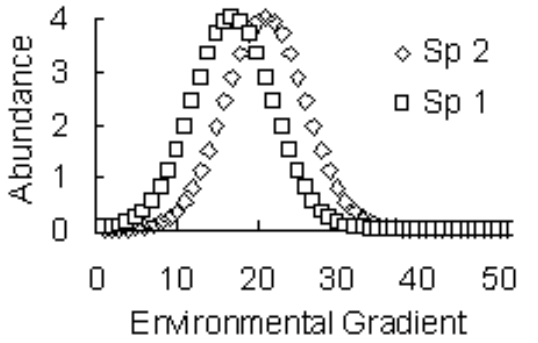


- Joint Absences (0,0)
- Joint Occurrences (lots, lots)
- Perfect correlation
- Weak correlation

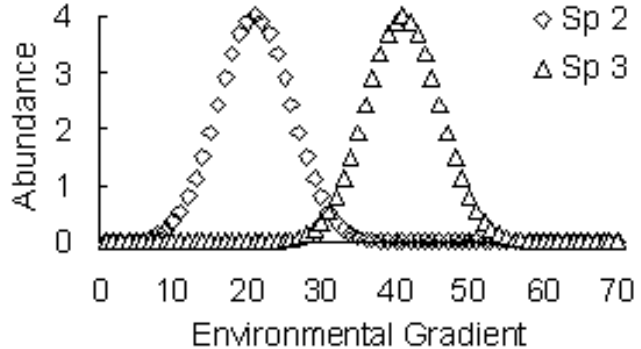
Community Analysis – Bivariate Plots

Bivariate plots from pairs of species responses to the same environmental gradients

positively associated



negatively associated

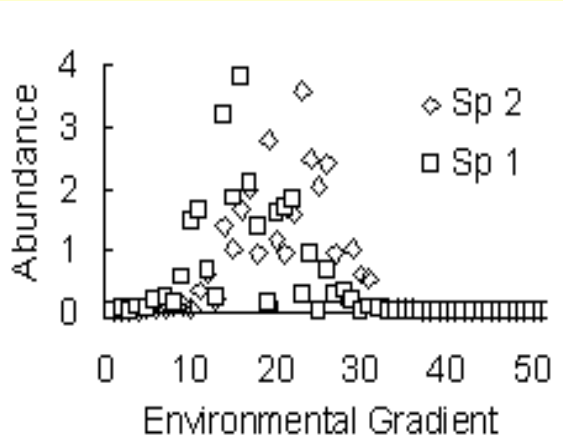


- Both have joint absence (0, 0) data

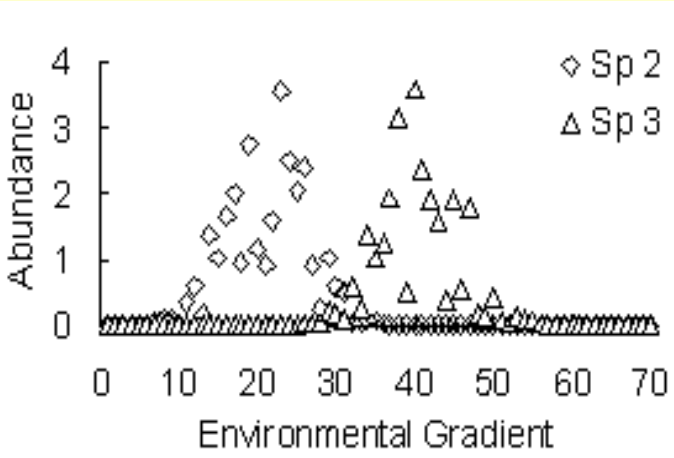
- Joint occurrence versus single occurrence

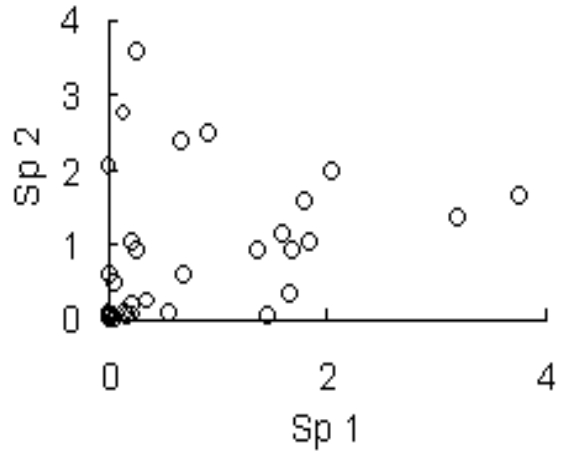
Community Analysis – Bivariate Plots

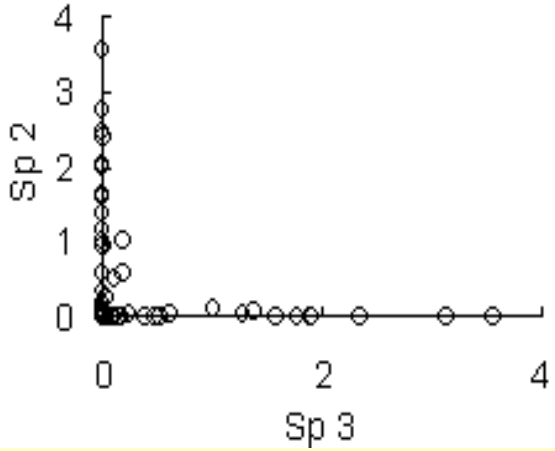
positively associated



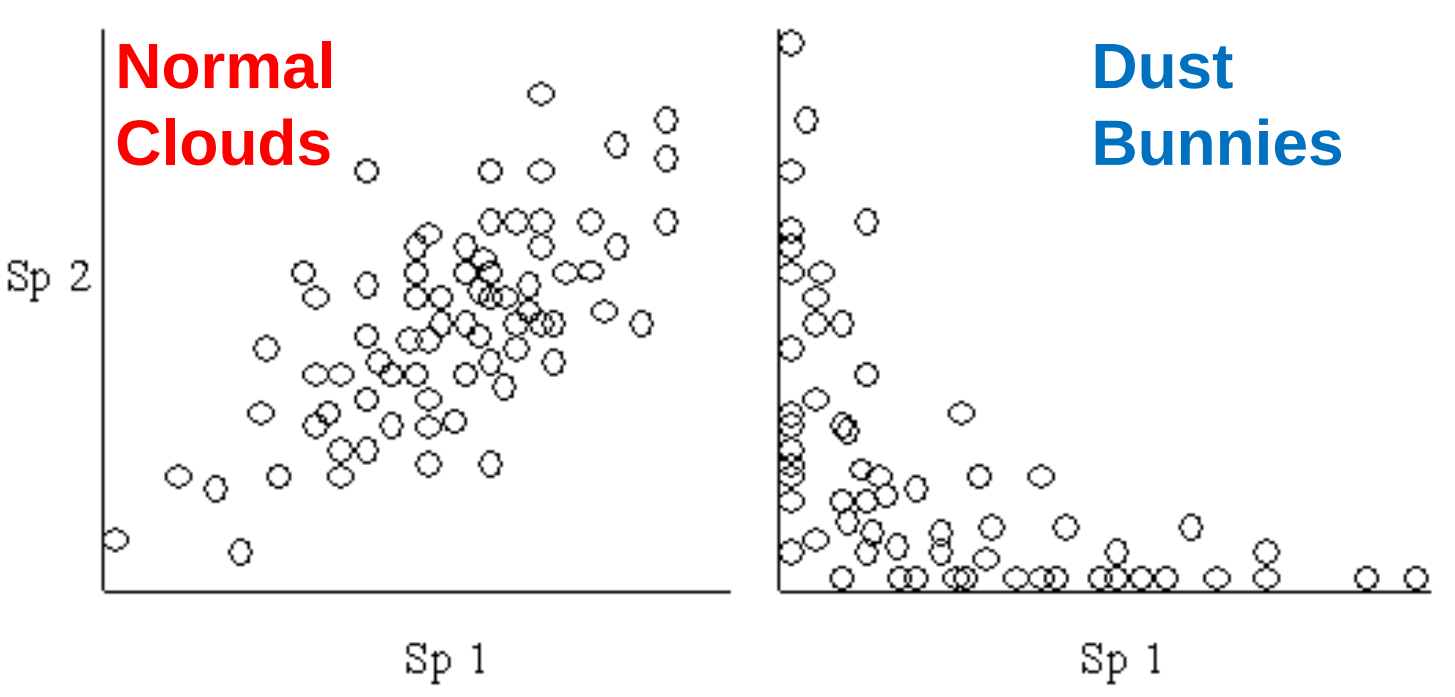
negatively associated







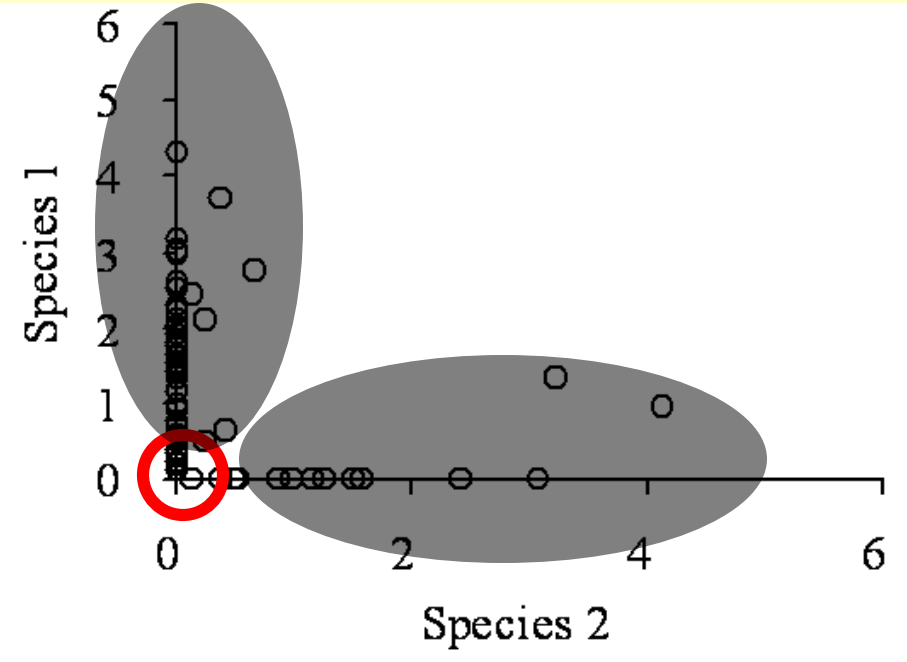
Community Analysis – Correlations

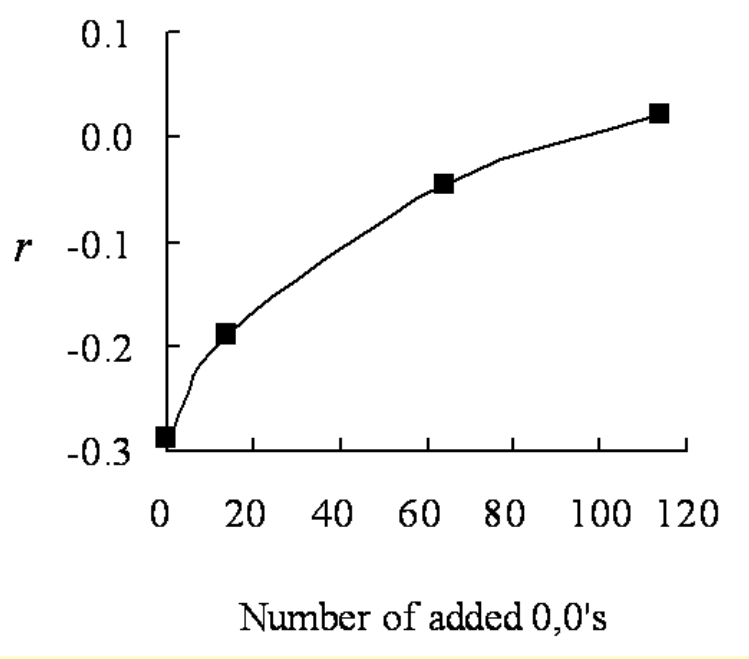


r is positive

r is negative

Community Analysis – Correlations





Consider two species with different habitat responses

(a negative association)

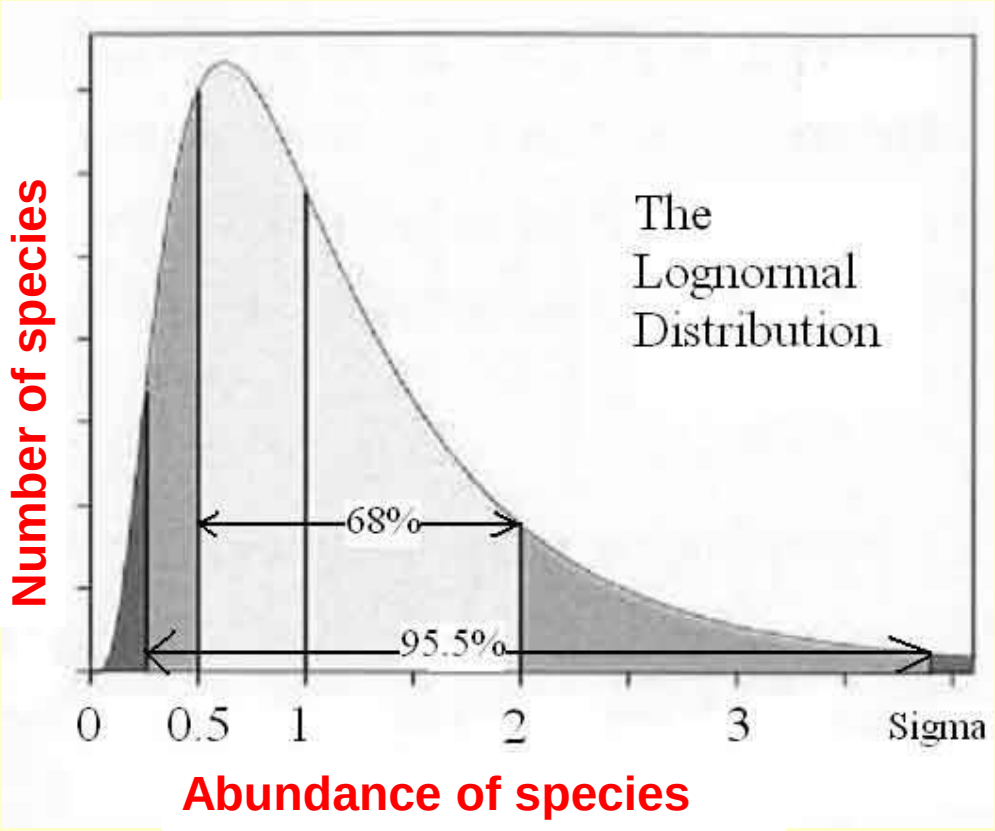
Beware:

As we sample beyond their habitats, we record more and more joint absences…

Summary: Sampling Communities

Species Abundance Data

- Large proportion of species absent
- Some species numerically dominant
- Most species infrequent



So What ?

Carefully consider sampling design (how big a sample ?) and the analysis, starting from choice of similarity measure

Summary: Sampling Communities

- Plots of species responses (abundance) to single environmental variables are informative:
  - unimodal – multimodal
  - linear / normal
  - peak(s) reveals optimums
- Bivariate plots (sp1 vs sp2) more informative: compare responses of pair of species to all environmental variables (at once)
- Typical responses:

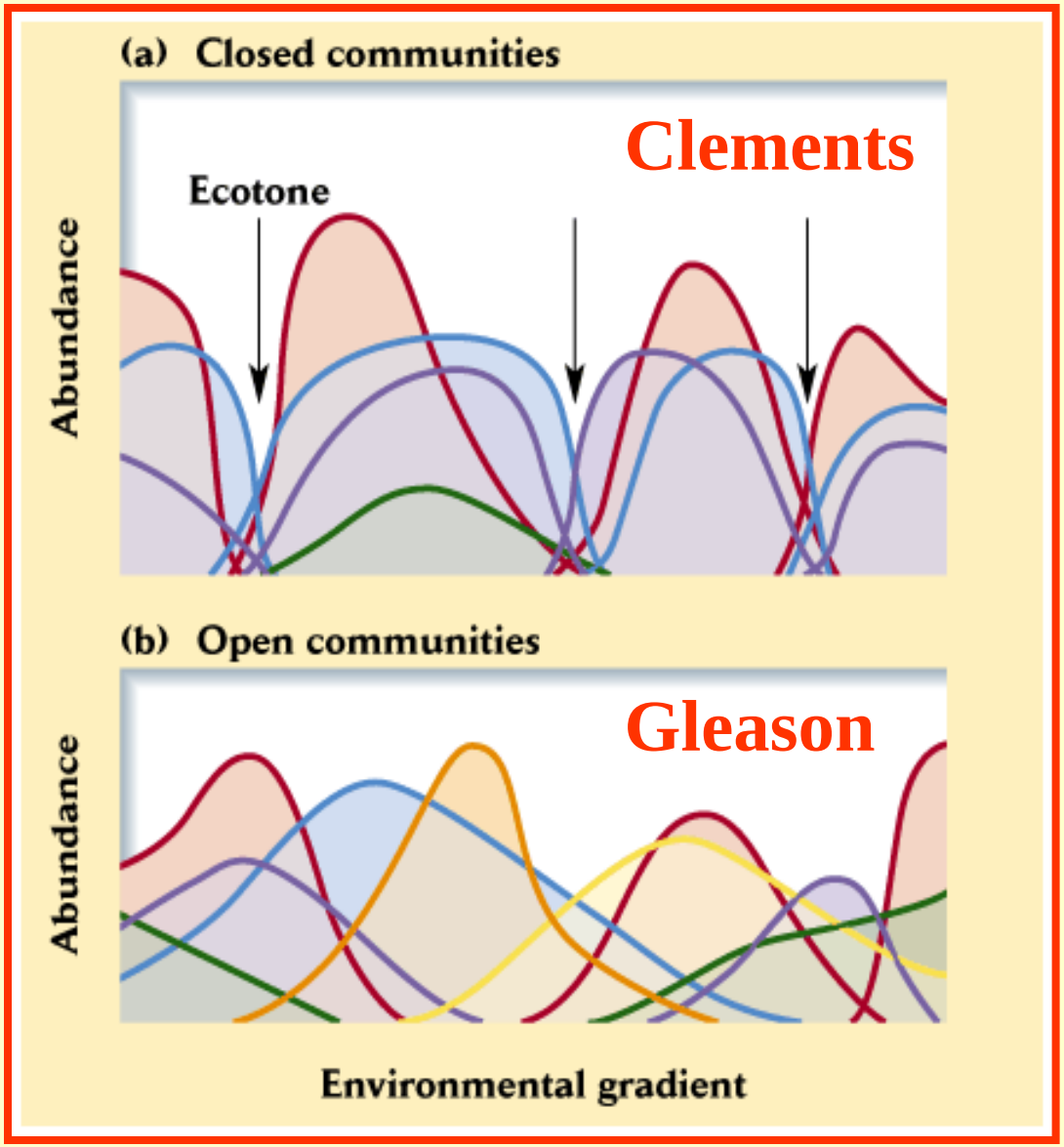
  “normal cloud” and “dust bunnies”

What is an Ecological Community ?

➢ Two views have dominated the debate over the nature of ecological communities since the 1920's:

- Clements' discrete unit

- Gleason's loose assemblage of species



What is an Ecological Community ?

➢ Clements' Perspective:

- Discrete entities with recognizable boundaries
- The community fully integrated functionally
- Species have coevolved, enhancing their interdependence

➢ Gleason's Perspective:

- Community is a chance association of species with similar adaptations and ecological requirements
- No distinct boundaries where communities meets

Community Analysis - Introduction

Community analysis techniques fall into two groups:

classification and ordination

- Classification is the placement of species and / or sample units into (discrete) groups

- Ordination is the arrangement or ‘ordering’ of species and / or sample units along gradients

Classification - Objectives

- Objectives and Limitations (James & McCulloch 1990)

Objectives:

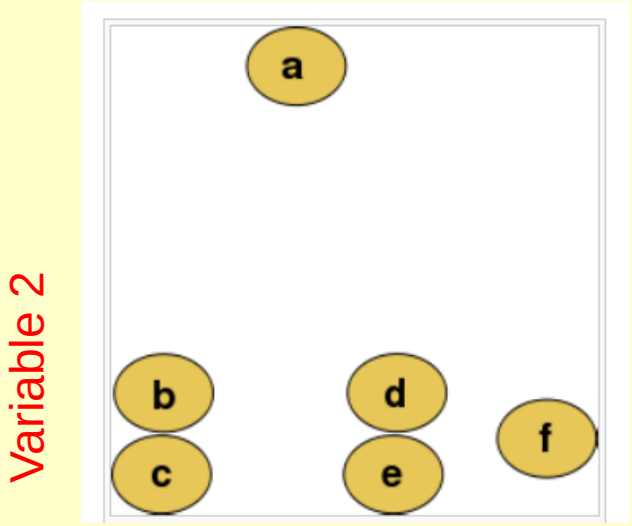
1. To classify groups of objects judged to be similar according to distance or similarity measure
2. To reduce consideration of n objects to g (g less than n) group of objects

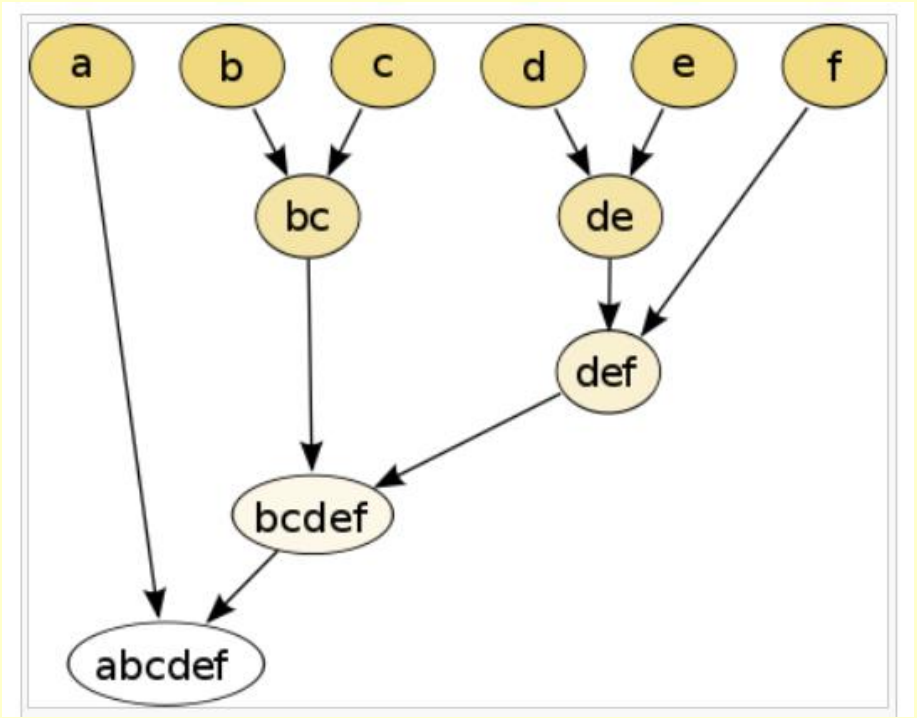
Limitations:

1. Results depend on the distance measure chosen.
2. Results depend on the algorithm chosen for forming clusters

Clustering - Introduction

- Approach: Objects placed in groups according to a similarity measure and a grouping algorithm.





Clustering - Introduction

1. Start with pairwise similarity matrix among objects (individuals, sites, populations, taxa).

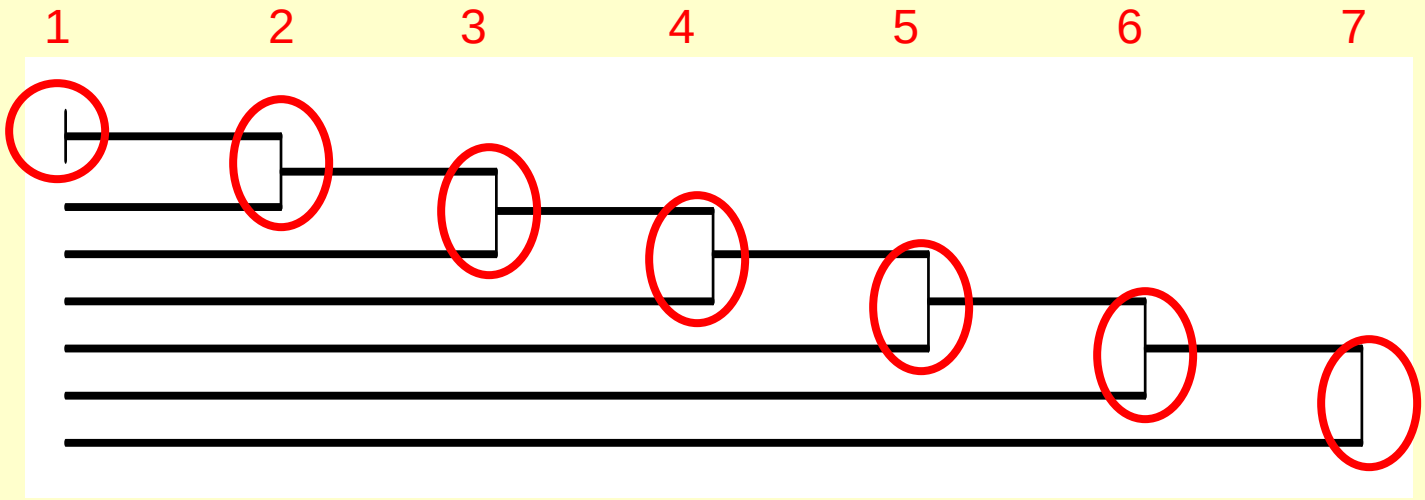
2. Two most similar objects are joined into a group, and the similarities of this group to all other units are calculated.

3. Repeatedly the two closest groups are combined until only a single group remains.

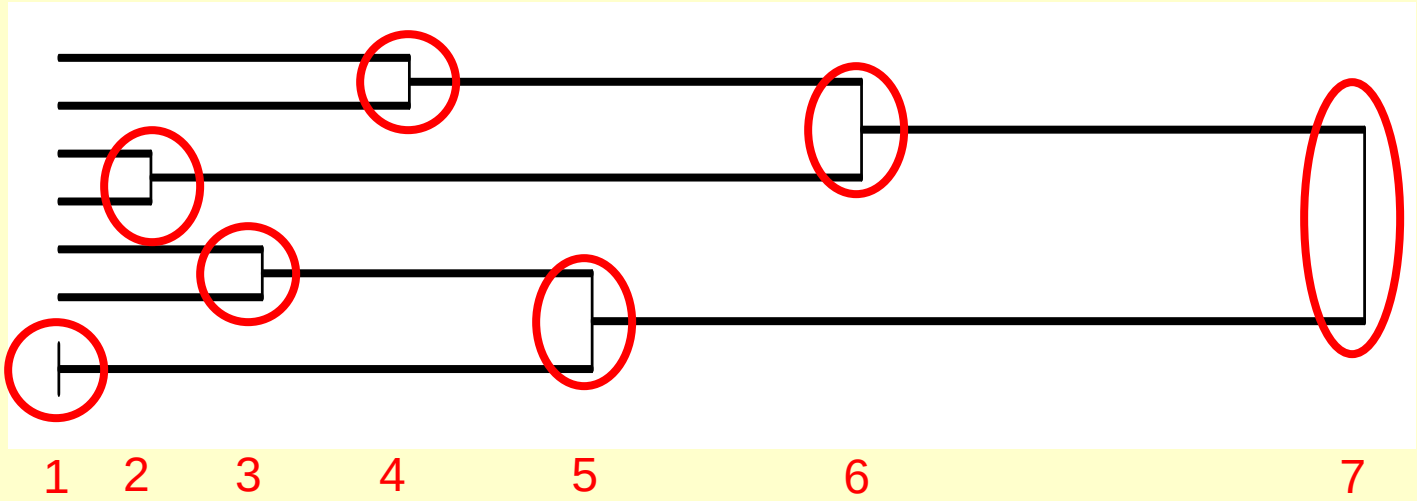
4. Results usually expressed in the form of a dendrogram, a two-dimensional hierarchical tree diagram representing the complex multi-variate relationships among the objects.

Clustering - Introduction

Two ways to sort eight samples (multiple species) into groups

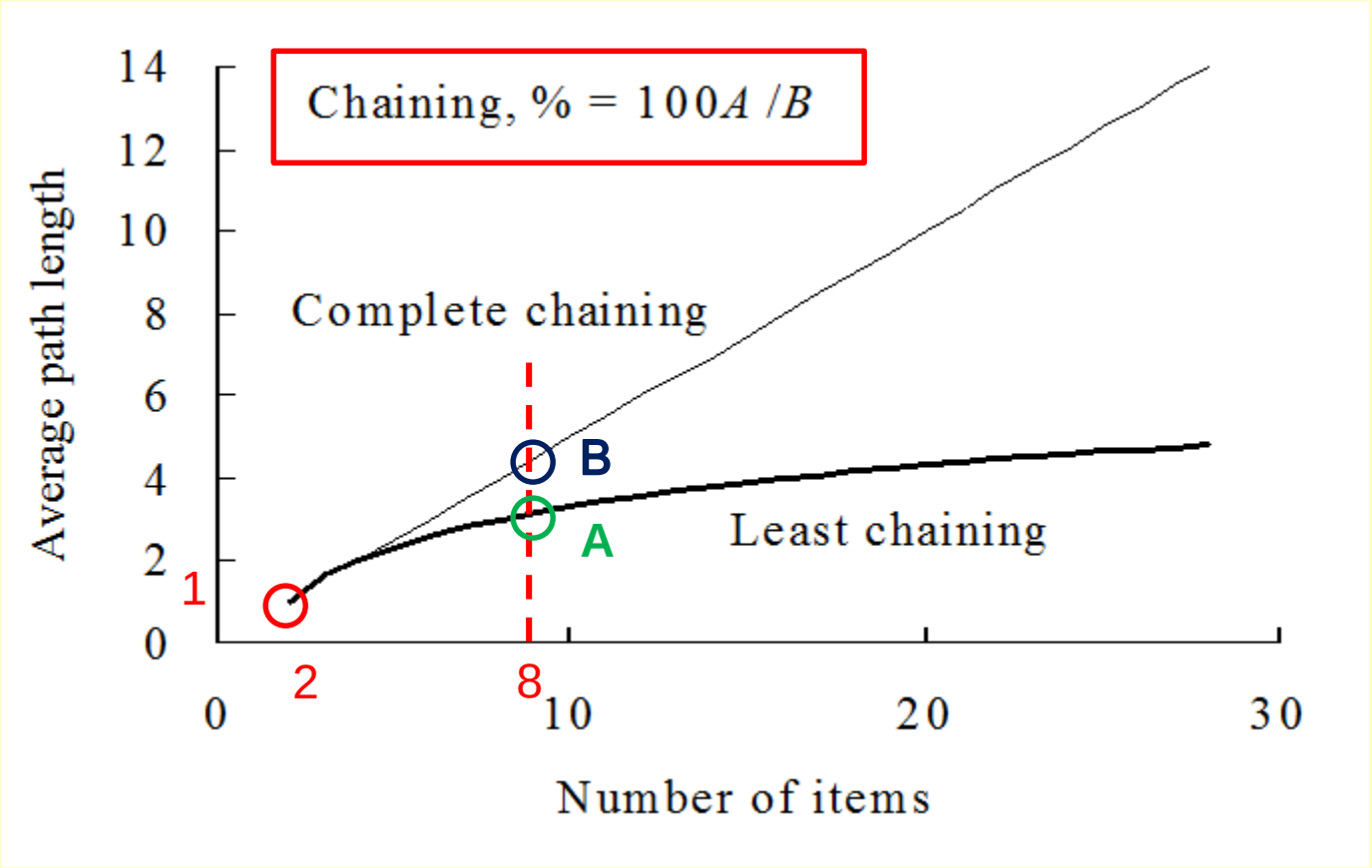


Complete chaining (1 group)



No chaining (2 groups)

Clustering - Introduction



Example with 2 items?

- Two paths
- One node in each
- Avg. Path Length = 1

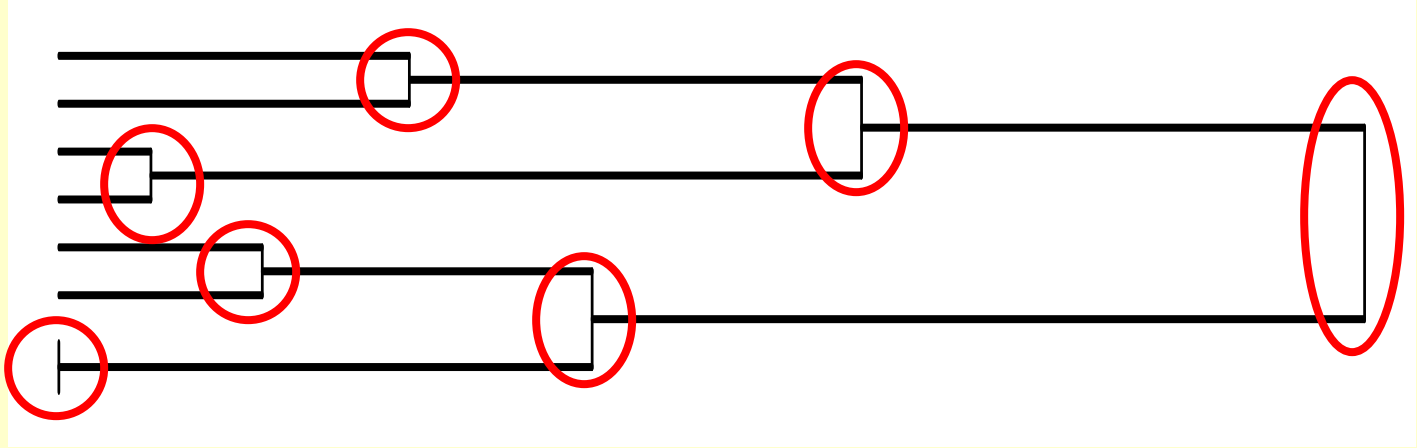
Average path length used to measure percent chaining in cluster analysis. Path length is the number of nodes between tip of a branch and trunk.

Clustering - Introduction

Two ways to sort eight samples (multiple species) into groups

A) No chaining:

1 2 3 4 5 6 7



Number of paths = 8

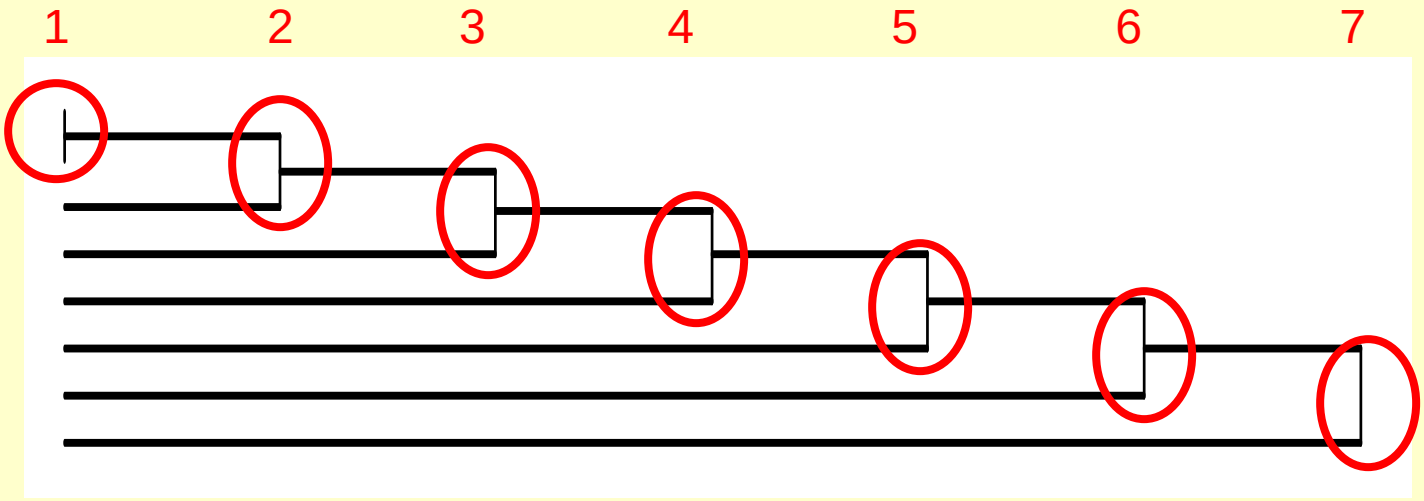
Sum of nodes = 3 3 3 3 3 3 3 3 = 24

Avg. path length = 24 / 8 = 3.00

Clustering - Introduction

Two ways to sort eight samples (multiple species) into groups

B) Complete chaining:

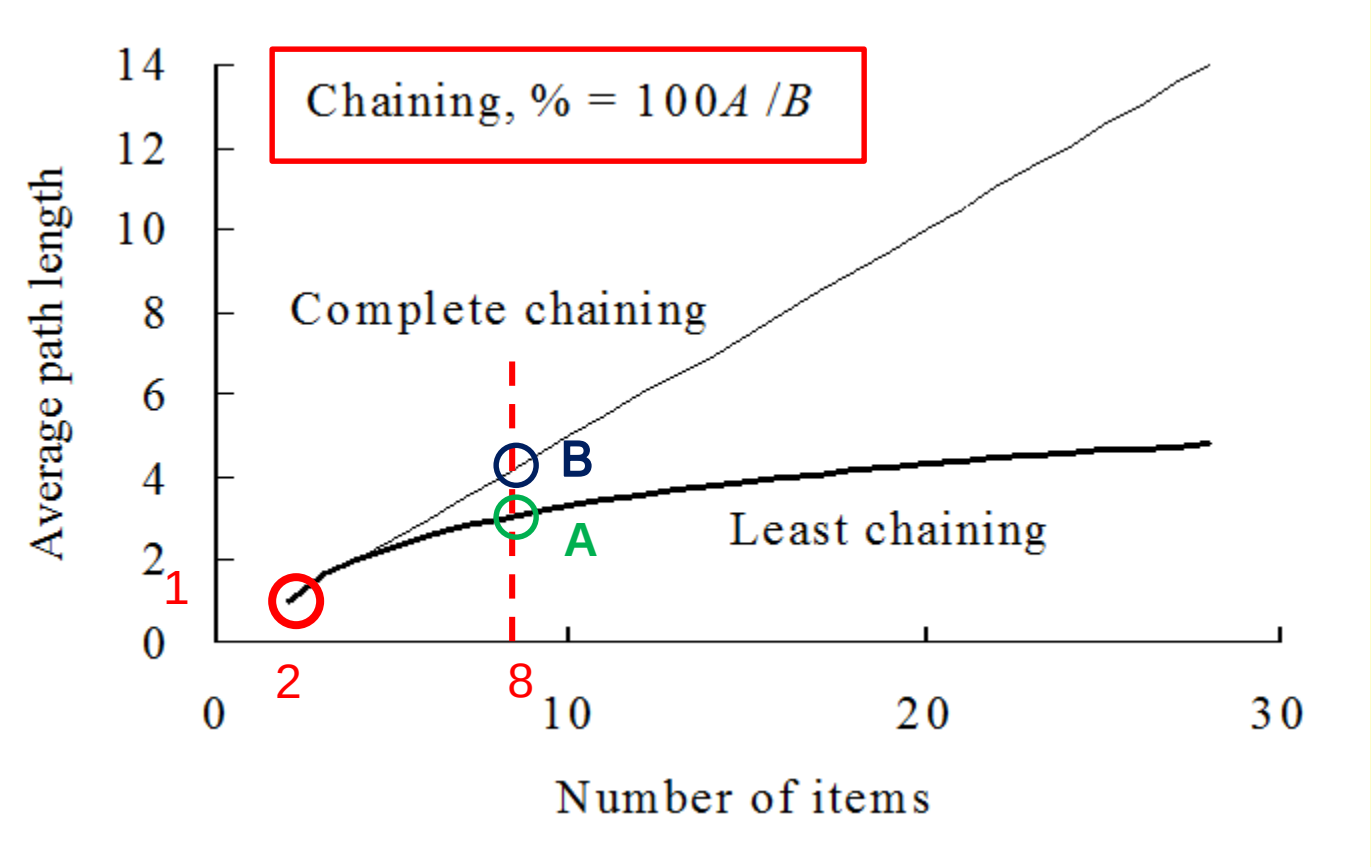


Number of paths = 8

Sum of nodes = 7 7 6 5 4 3 2 1 = 35

Avg. path length = 35 / 8 = 4.375

Clustering - Introduction



NOTE: Chaining can be calculated for any given clustering pattern

Chaining (A) = 100 * (A / complete-chain) = 100 * (3 / 4.375) = 68.57 %

Chaining (B) = 100 * (B / complete-chain) = 100 * (4.375 / 4.375) = 100%

Clustering – How it Works

A dissimilarity matrix of order $n \times n$ (n = number of entities) is calculated and each of the elements is squared. The algorithm then performs n-1 loops (clustering cycles) in which the following steps are done:

1. The smallest element (d_{pq}^2) in dissimilarity matrix sought (groups associated with this element are S_p and S_q).

2. The objective function E_n (the amount of information lost by linking to cycle n) is incremented according to the rule.

3. Group S_p is replaced by $S_p \cup S_q$ by recalculating the dissimilarity between the new group and all other groups (this requires calculating new dissimilarities).

4. Group S_q is inactive and its elements are assigned to new group $S_p \cup S_q$. After joining all items, procedure is complete.

Clustering – How it Works

The **objective function (E)** is the sum of the error sum of squares from each centroid to the items in that group.

Where :

t indexes the T clusters

E_t is the error sum of squares for cluster t

$$E = \sum_{t=1}^{T} E_t$$

And each E_t is found by:

$$E_t = \sum_{i=1}^{k_t} \sum_{j=1}^{p} (x_{ijt} - \bar{x}_{jt})^2$$

x_{ijt} is the value of the:

jth variable for the

ith point of cluster t

(which contains k_t points)

$\bar{x}$ is the mean of the jth variable for cluster t.

Clustering – How it Works

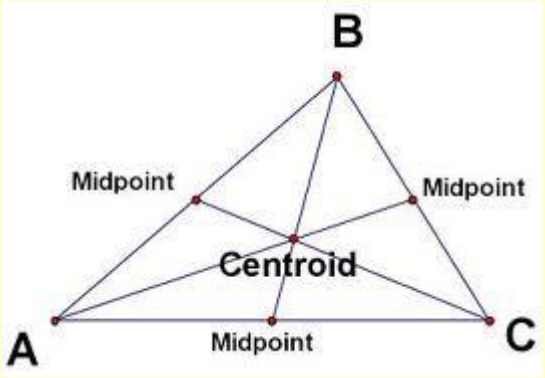
Calculate E for each cluster, separately and sum up (Note: there are T clusters):

$$E = \sum_{t=1}^{T} E_t$$

Calculate E by summing the deviations between all points and centroid, for all variables:

$$E_t = \sum_{i=1}^{k_t} \sum_{j=1}^{p} (x_{ijt} - \bar{x}_{jt})^2$$

What is $\bar{X}$?



A cluster of 3 points, plotted in 2 dimensions

Clustering – How it Works

We need a rule to progressively combine the elements, as we go through the cycles and the groups become larger.

The basic combinatorial equation is:

$$d_{ir}^2 = \alpha_p d_{ip}^2 + \alpha_q d_{iq}^2 + \beta d_{pq}^2 + \gamma |d_{ip}^2 - d_{iq}^2|$$

where values of α_p, α_q, β, and γ determine the type of sorting strategy (See Table below).

Why Are there Different Linkage Methods?

Use different coefficients in the basic combinatorial equation.

	Coefficient			
Linkage method	α_p	α_q	β	γ
Nearest neighbor	0.5	0.5	0	-0.5
Farthest neighbor	0.5	0.5	0	0.5
Median	0.5	0.5	-0.25	0
Group average	n_p / n_r	n_q / n_r	0	0
Centroid	n_p / n_r	n_q / n_r	$-\alpha_p\ \alpha_p$	0
Ward's method	$\frac{n_i + n_p}{n_i + n_r}$	$\frac{n_i + n_q}{n_i + n_r}$	$\frac{-n_i}{n_i + n_r}$	0
Flexible beta	$(1 - \beta)/2$	$(1 - \beta)/2$	β	0
McQuitty's method	0.5	0.5	0	0

n_p = number of elements in S_p $\quad$ n_q = number of elements in S_q

n_r = number of elements in $S_r = S_p \cup S_q$

n_i = number of elements in S_i $\quad$ $i = 1, n$ $\quad$ except $i \neq p$ and $i \neq q$

Defining Groups (clusters)

The properties of linkage methods (“sorting strategies”) depend on type of dissimilarity measure used.

We consider two generic classes of dissimilarity measures:

Euclidean (absolute, relative)
Proportional (Sorensen, Jaccard)

We consider eight linkage methods:

Nearest neighbor	Farthest neighbor
Median	Group average
Centroid	Ward's method
Flexible beta	McQuitty's method

Homework #2 – Due Feb 22

- **The objectives of this homework are:**

A) To review and practice data transformations.
B) To calculate dissimilarities for a data matrix.
C) To perform a clustering analysis.
D) To practice reporting the results of clustering analyses.

To complete this homework, you will need:

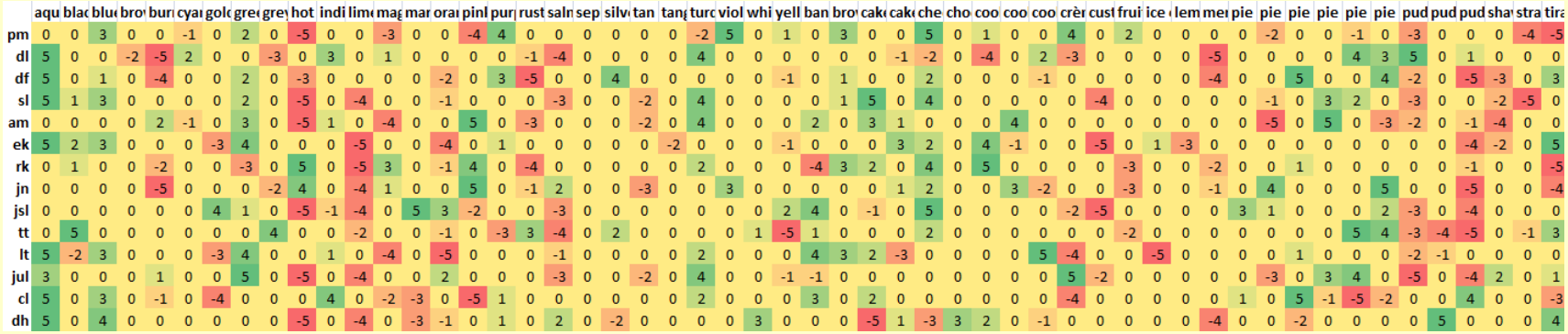
Instruction file: "BIOL6090_hw2.doc" – edit and turn in

"desserts colors.xls" data file: (open with excel) – do not turn in

"aMoss1M.WK1" data file: (open with PC-ORD) – do not turn in

Similarity & Dissimilarity

- Raw data = expressed in terms of individual variables



	aqu	blac	blu	bro	bur	cya	gol	gre	grey	hot	indi	lim	mag	mar	ora	pinl	pur	rust	saln	sep	silv	tan	tan	turc	viol	whi	yell	ban	bro	cak	cak	che	cho	coo	coo	coo	crèr	cust	frui	ice	lem	mer	pie	pie	pie	pie	pie	pie	pud	pud	pud	sha	stra	tira
pm	0	0	3	0	0	-1	0	2	0	-5	0	0	-3	0	0	-4	4	0	0	0	0	0	0	-2	5	0	1	0	3	0	0	5	0	1	0	0	4	0	2	0	0	0	0	-2	0	0	-1	0	-3	0	0	0	-4	-5
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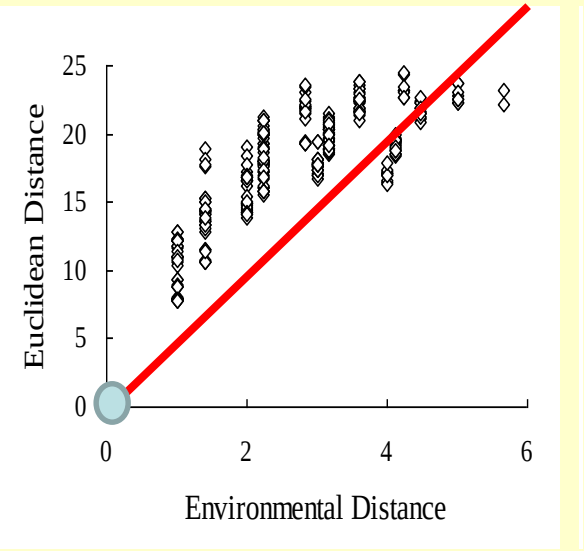
ek	5	2	3	0	0	0	-3	4	0	0	0	-5	0	0	-4	0	1	0	0	0	0	0	-2	0	0	0	-1	0	0	0	3	2	0	4	-1	0	0	-5	0	1	-3	0	0	0	0	0	0	0	0	-4	-2	0	5
rk	0	1	0	0	-2	0	0	-3	0	5	0	-5	3	0	-1	4	0	-4	0	0	0	0	0	2	0	0	0	-4	3	2	0	4	0	5	0	0	0	0	-3	0	0	-2	0	0	1	0	0	0	0	0	-1	0	0	-5
jn	0	0	0	0	-5	0	0	0	-2	4	0	-4	1	0	0	5	0	-1	2	0	0	-3	0	0	3	0	0	0	0	0	1	2	0	0	3	-2	0	0	-3	0	0	-1	0	4	0	0	0	5	0	0	-5	0	0	-4
jsl	0	0	0	0	0	0	4	1	0	-5	-1	-4	0	5	3	-2	0	0	-3	0	0	0	0	0	0	0	2	4	0	-1	0	5	0	0	0	0	-2	-5	0	0	0	0	3	1	0	0	0	2	-3	0	-4	0	0	0
tt	0	5	0	0	0	0	0	0	4	0	0	-2	0	0	-1	0	-3	3	-4	0	2	0	0	0	0	1	-5	1	0	0	0	2	0	0	0	0	0	0	-2	0	0	0	0	0	0	0	5	4	-3	-4	-5	0	-1	3
lt	5	-2	3	0	0	0	-3	4	0	0	1	0	-4	0	-5	0	0	0	-1	0	0	0	0	2	0	0	0	4	3	2	-3	0	0	0	0	5	-4	0	0	-5	0	0	0	0	1	0	0	0	-2	-1	0	0	0	0
jul	3	0	0	0	1	0	0	5	0	-5	0	-4	0	0	2	0	0	0	-3	0	0	-2	0	4	0	0	-1	-1	0	0	0	0	0	0	0	0	5	-2	0	0	0	0	0	-3	0	3	4	0	-5	0	-4	2	0	1
cl	5	0	3	0	-1	0	-4	0	0	0	4	0	-2	-3	0	-5	1	0	0	0	0	0	0	2	0	0	0	3	0	2	0	0	0	0	0	0	-4	0	0	0	0	0	1	0	5	-1	-5	-2	0	0	4	0	0	-3
dh	5	0	4	0	0	0	0	0	0	-5	0	-4	0	-3	-1	0	1	0	2	0	-2	0	0	0	0	3	0	0	0	-5	1	-3	3	2	0	-1	0	0	0	0	0	0	-4	0	0	-2	0	0	0	0	5	0	0	0	4

- Similarity (S) = expressed in terms of all of the variables

14	samples														
14	samples														
	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q
	pm	dl	df	sl	am	ek	rk	jn	jsl	tt	lt	jul	cl	dh	
pm	1	-0.26364	0.168182	0.372727	0.145455	0.040909	-0.03182	-0.05455	0.277273	-0.08182	0.109091	0.263636	0.177273	0.036364	
dl	-0.26364	1	0.277273	0.172727	-0.06818	-0.00909	0.027273	0.140909	-0.03636	0.040909	0.231818	0.045455	0.172727	0.145455	
df	0.168182	0.277273	1	0.318182	0.168182	0.422727	0.104545	0.254545	0.240909	0.231818	0.240909	0.272727	0.104545	0.245455	
sl	0.372727	0.172727	0.318182	1	0.454545	0.454545	0.127273	0	0.418182	0.263636	0.340909	0.6	0.177273	0.163636	
am	0.145455	-0.06818	0.168182	0.454545	1	0.104545	-0.05	-0.07727	0.095455	-0.03636	0.236364	0.436364	0.009091	0.05	
ek	0.040909	-0.00909	0.422727	0.454545	0.104545	1	0.118182	0.109091	0.222727	0.295455	0.277273	0.340909	0.072727	0.395455	
rk	-0.03182	0.027273	0.104545	0.127273	-0.05	0.118182	1	0.55	-0.05909	0.018182	-0.08636	-0.05909	-0.05455	-0.13636	
jn	-0.05455	0.140909	0.254545	0	-0.07727	0.109091	0.55	1	0.109091	0.145455	-0.08636	-0.02273	-0.18182	-0.06818	
jsl	0.277273	-0.03636	0.240909	0.418182	0.095455	0.222727	-0.05909	0.109091	1	0.263636	0.031818	0.377273	-0.10909	0.031818	
tt	-0.08182	0.040909	0.231818	0.263636	-0.03636	0.295455	0.018182	0.145455	0.263636	1	0.059091	0.363636	-0.28182	-0.07727	
lt	0.109091	0.231818	0.240909	0.340909	0.236364	0.277273	-0.08636	-0.08636	0.031818	0.059091	1	0.1	0.45	0.068182	
jul	0.263636	0.045455	0.272727	0.6	0.436364	0.340909	-0.05909	-0.02273	0.377273	0.363636	0.1	1	-0.19545	0.236364	
cl	0.177273	0.172727	0.104545	0.177273	0.009091	0.072727	-0.05455	-0.18182	-0.10909	-0.28182	0.45	-0.19545	1	0.068182	
dh	0.036364	0.145455	0.245455	0.163636	0.05	0.395455	-0.13636	-0.06818	0.031818	-0.07727	0.068182	0.236364	0.068182	1	

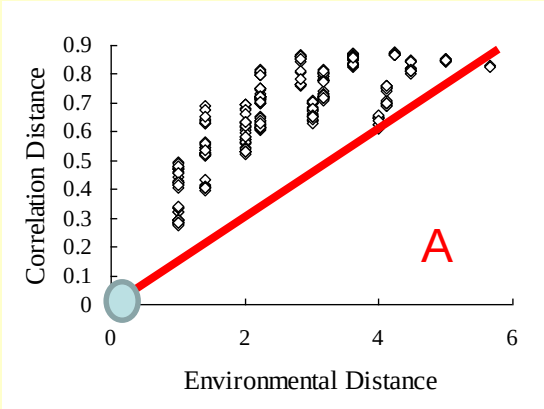
14	samples													
14	samples													
	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q	Q
	pm	dl	df	sl	am	ek	rk	jn	jsl	tt	lt	jul	cl	dh
pm	0	23.57965	19.13113	16.61325	19.39072	20.54264	21.30728	21.54066	17.83255	21.81742	19.79899	18	19.0263	20.59126
dl	23.57965	0	17.83255	19.07878	21.67948	21.07131	20.68816	19.44222	21.35416	20.54264	18.38478	20.4939	19.07878	19.39072
df	19.13113	17.83255	0	17.32051	19.13113	15.93738	19.84943	18.11077	18.27567	18.38478	18.27567	17.88854	19.84943	18.22087
sl	16.61325	19.07878	17.32051	0	15.49193	15.49193	19.59592	20.97618	16	18	17.02939	13.2665	19.0263	19.18333
am	19.39072	21.67948	19.13113	15.49193	0	19.84943	21.49418	21.77154	19.94994	21.35416	18.3303	15.74802	20.88061	20.44505
ek	20.54264	21.07131	15.93738	15.49193	19.84943	0	19.69772	19.79899	18.49324	17.60682	17.83255	17.02939	20.19901	16.30951
rk	21.30728	20.68816	19.84943	19.59592	21.49418	19.69772	0	14.07125	21.58703	20.78461	21.86321	21.58703	21.54066	22.36068
jn	21.54066	19.44222	18.11077	20.97618	21.77154	19.79899	14.07125	0	19.79899	19.39072	21.86321	21.2132	22.80351	21.67948
jsl	17.83255	21.35416	18.27567	16	19.94994	18.49324	21.58703	19.79899	0	18	20.63977	16.55295	22.09072	20.63977
tt	21.81742	20.54264	18.38478	18	21.35416	17.60682	20.78461	19.39072	18	0	20.34699	16.7332	23.74868	21.77154
lt	19.79899	18.38478	18.27567	17.02939	18.3303	17.83255	21.86321	21.86321	20.63977	20.34699	0	19.89975	15.55635	20.24846
jul	18	20.4939	17.88854	13.2665	15.74802	17.02939	21.58703	21.2132	16.55295	16.7332	19.89975	0	22.93469	18.3303
cl	19.0263	19.07878	19.84943	19.0263	20.88061	20.19901	21.54066	22.80351	22.09072	23.74868	15.55635	22.93469	0	20.24846
dh	20.59126	19.39072	18.22087	19.18333	20.44505	16.30951	22.36068	21.67948	20.63977	21.77154	20.24846	18.3303	20.24846	0

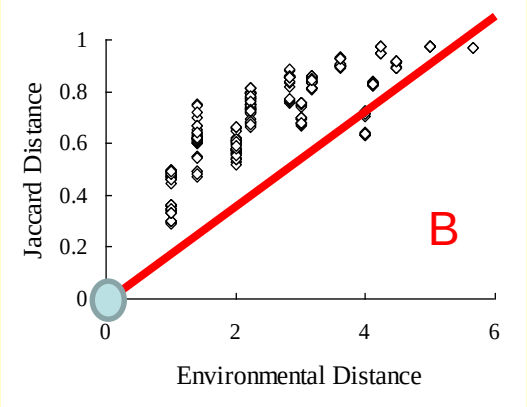
Distance Measures – Recommendations

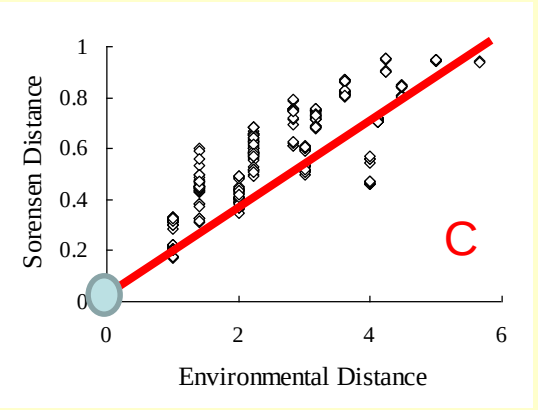


Is the distance metric bounded ?

Is the distance metric monotonic ?







NOTE: use linear regression “anchored” at origin (0,0)

Homework #2 – Readings

- Critically reading of journal articles

ELSEVIER

Fisheries Research 31 (1997) 147–158

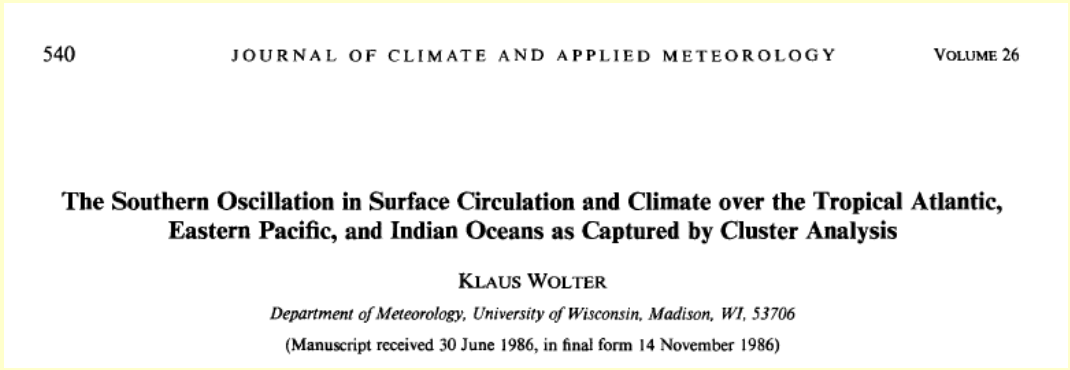
FISHERIES RESEARCH

Cluster analysis of longline sets and fishing strategies within the Hawaii-based fishery

Xi He [a,*], Keith A. Bigelow [a], Christofer H. Boggs [b]

[a] *Pelagic Fisheries Research Program, Joint Institute for Marine and Atmospheric Research, School of Ocean and Earth Science and Technology, University of Hawaii, 2570 Dole Street, Honolulu, HI 96822, USA*

[b] *Honolulu Laboratory, Southwest Fisheries Science Center, National Marine Fisheries Service, NOAA, 2570 Dole Street, Honolulu, HI 96822, USA*

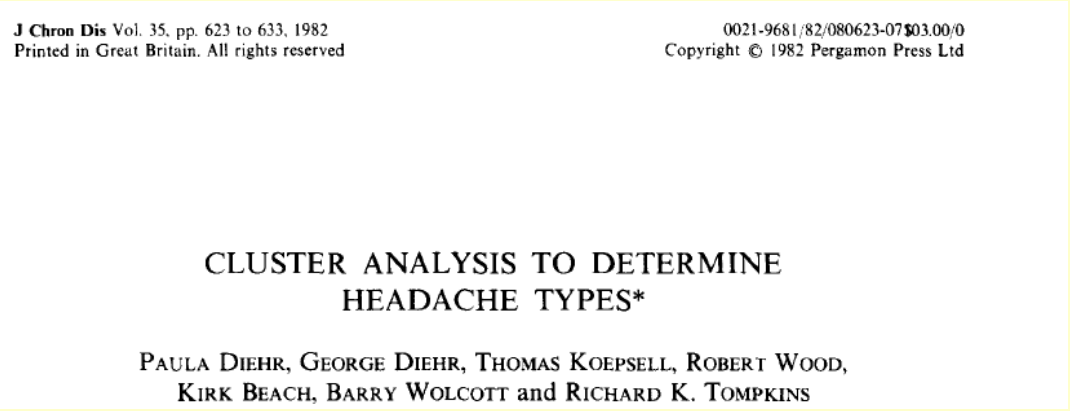


The Southern Oscillation in Surface Circulation and Climate over the Tropical Atlantic, Eastern Pacific, and Indian Oceans as Captured by Cluster Analysis

KLAUS WOLTER

Department of Meteorology, University of Wisconsin, Madison, WI, 53706

(Manuscript received 30 June 1986, in final form 14 November 1986)



J Chron Dis Vol. 35, pp. 623 to 633, 1982
Printed in Great Britain.

0021-9681/82/080623-07$03.00/0

CLUSTER ANALYSIS TO DETERMINE HEADACHE TYPES*

PAULA DIEHR, GEORGE DIEHR, THOMAS KOEPSELL, ROBERT WOOD, KIRK BEACH, BARRY WOLCOTT and RICHARD K. TOMPKINS