Analysis Of Behavioural Data

Ethogram Courtship Behavior
(Stickleback)

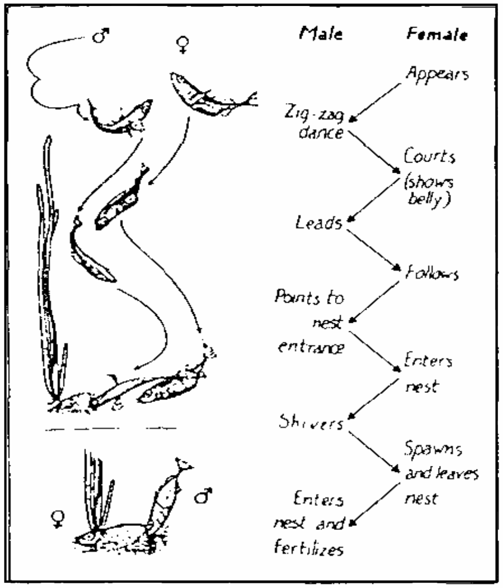
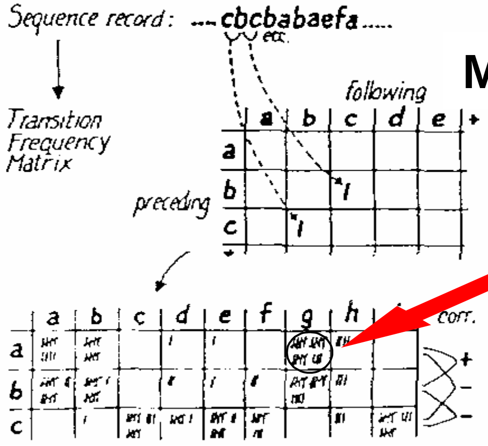


Figure 7.2. The classic example of a diagram of a typical interaction sequence is the one by Tinbergen (1951), showing the behaviors of a male three spined stickleback in a reproductive mood and of a "ripe" female visiting his nesting territory.



Schematic representation of the procedure of constructing a transition frequency matrix

Markov Modelling

Transition Rate

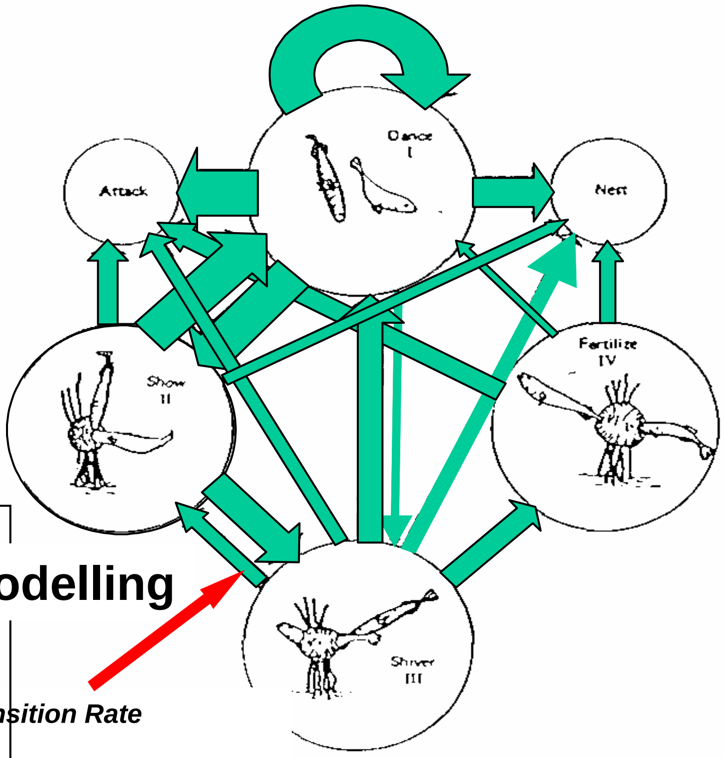


Figure 7.4. A kinematic graph of the sequence of activities shown by a male ten-spined stickleback in a reproductive mood (as shown by his black color) toward a female entering his territory. The width of an arrow represents the number of times a transition between two acts has been observed. Source: Marler and Hamilton, 1966, p. 191, based on data from Morris, 1958.

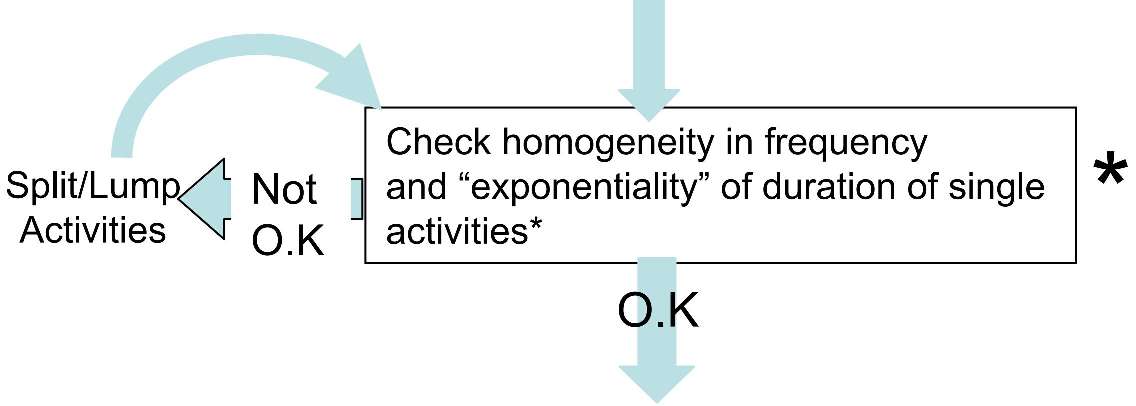
PCA or Factor Analysis

DIMENSION REDUCTION

Steps in the Analysis

1) <u>Inventory</u>: Decide upon behavioural elements (“Activities”):
= setting up an ***Ethogram***

2) <u>Recording</u>: Register the onset and termination timing of the activities.
Allows for the computation and assessment of *duration* and *sequence*.



3) <u>Summarizing</u>: Cast the ordering of the activities into a ***Transition Matrix***

4) [<u>Dimension Reduction</u>: Combine activities with similar *profiles* by means of ***Cluster Analysis***, ***Factor Analysis*** and/or ***Principal Component Analysis***]

5) <u>Sequential Analysis</u>: ***Markov Modelling***

*Only when modelling *Continuous Time Markov Chains*
See: P. Haccou & E. Meelis (1992): Statistical Analysis of Behaviour. Oxford University Press

This Course

- Ethogram
- Setting up Transition Matrices
- Simple Markov Model
- Dimension Reduction

Theory
(Lecture;
Background Reading)

Application
(Practical)

Theory

- Slides of Lectures

- Literature:

Boekhorst, I.J.A. te(2001). Freeing machines from Cartesian chains. In: “Cognitive Technology: Instruments of Mind” (eds. M. Beynon, C.L. Nehaniv & K. Dautenhahn). Proceedings of the 4th International Conference, CT2001, Coventry, UK. Pp. 95 – 108. Lecture Notes in Artificial Intelligence 2117. Springer, Berlin

Optional:

Bakeman, R. & Gottman, J. M. (1986). Observing Interaction. Cambridge University Press.

Haccou, P. & E. Meelis (1992): Statistical Analysis of Behaviour. Oxford University Press

Lehner, P. N. (1996). Handbook of Ethological Methods. Cambridge University Press.

Application

Material (Software):

- **seqdepnv**: Simple Excel Macro for analysing transition matrices (Markov modelling)
- **XLSTAT** (Cluster analysis, PCA)

Data:

- CD with LEGO robot experiments

How to characterize behavioural dynamics?

- Set up a list of behavioural activities (“ethogram”)
- For example: A = Attention

  B = Body Movement

  C = Contact
- Record the sequence of activities*

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*If the activity is measured as a *continuously changing variable*, its value a teach point in time should be recorded.
In this hand-out, however, behaviour is considered to be a sequence of *discrete activities*. What should be recorded therefore are the starting- and termination time of each activity. In case the activities are defined so as to be *mutually exclusive*, the termination of a foregoing activity implies the initiation of the next and an activity of a given type cannot be followed by itself.

Example 1. Recording of the Behaviour of a Mouse (Table I)

Activity $_t$
shake
walk
sit
walk
sit
walk
care
sit
walk
sit
walk
sit
walk
sit
rear
sit
walk
sit
walk
sit
rear
sit
rear
sit
walk
sit
shake
walk
sit
care
sit
walk
rear
sit
walk
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walk
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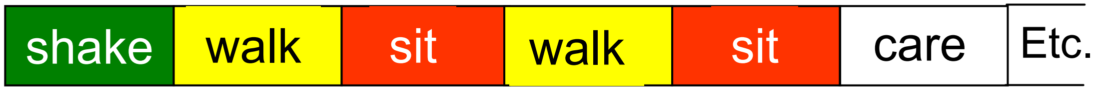
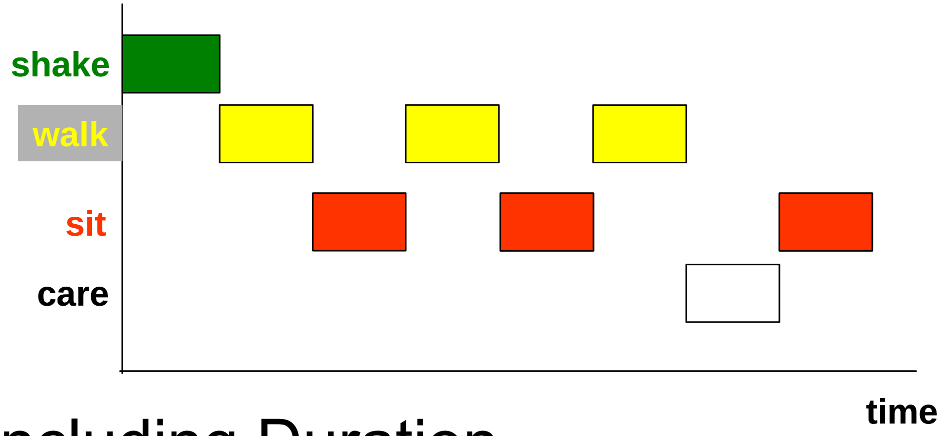
sit
rear
sit
care
shake
walk



Default dataset* analysed in seqdepnv (see also the ExampleDataAnalysis in the Programs-XLSTAT folder

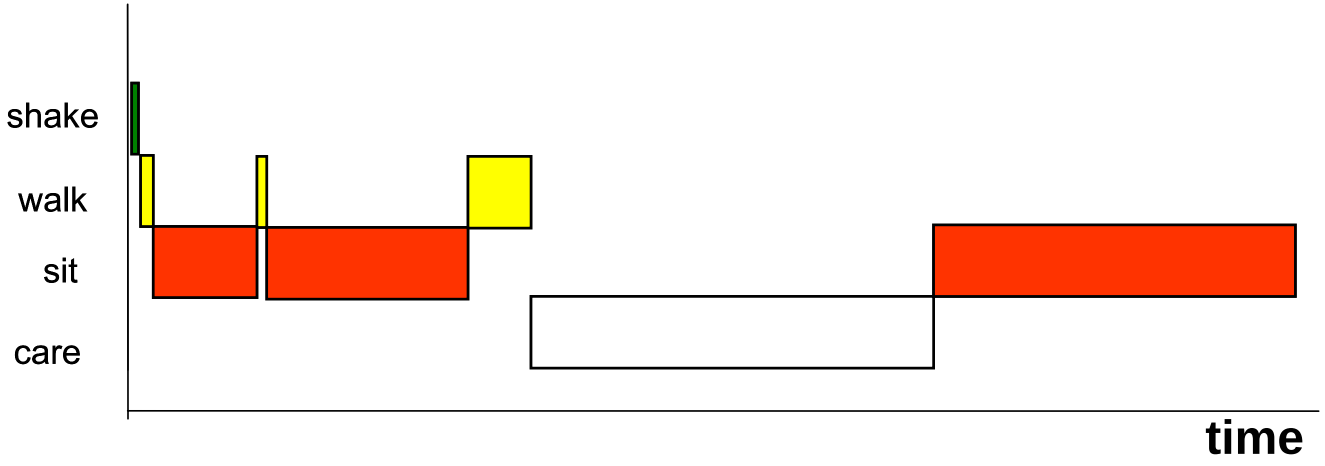
•From: Haccou, P. & E. Meelis (1992): Statistical Analysis of Behaviour. Oxford University Press

Example 1 ctd



Including Duration

ELEMENT	BEGIN	DURATION
shake	0	0.45
walk	0.45	0.59
sit	1.04	10.51
walk	11.55	0.89
sit	12.44	20.25
walk	32.69	6.19
care	38.88	40.29
sit	79.17	36.2
walk	115.37	6.25
sit	121.62	10.79



Inclusion of duration leads to more complete models (Continuous Time Markov Chains), but requires the testing of additional assumptions. For details: Haccou, P. & E. Meelis (1992): Statistical Analysis of Behaviour. Oxford University Press)

MARKOV MODELS

- Markov Property:

Probability of any future behaviour of the process

WHEN ITS PRESENT STATE IS KNOWN EXACTLY

is NOT altered by additional knowledge of its past

$$\mathbf{X_{n+1} = c_1X_n}$$

$$X_n = c_0 + c_1X_{n-1} + e_n$$

First order Markov process (-chain)

Current behaviour depends only on immediate past

$$\downarrow$$

$$\mathbf{X_n = c_0 + c_1X_{n-1} + c_2X_{n-2} + \ldots + e_n}$$

Second- and higher order Markov processes

$$X_n = \underset{\substack{\uparrow \\ \text{constant (mean)}}}{c_0} + \overset{\substack{\text{“noise” or “error”} \\ \downarrow}}{e_n}$$

Zero order Markov process (-chain)

Current behaviour has “no memory”

MARKOV MODELS

$$X_{n+1} = c_0 + c_1 X_n$$

X = nominal

Values ("States") are *categories*

p_{AB} = Pr{next state is B|process is in A}

DURATIONS:

Not Considered

Considered

Fixed

- (almost) zero: point-events
- constant

Continuous

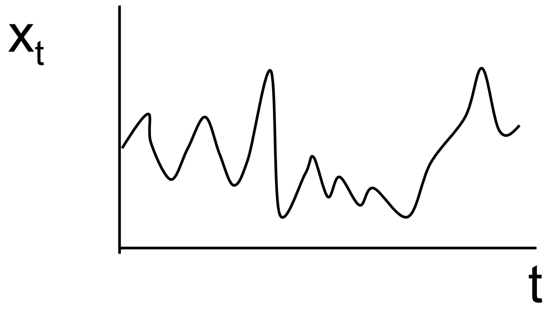
Discrete Markov Chains (this course)

Continuous Time Markov Chains

$X \geq$ ordinal

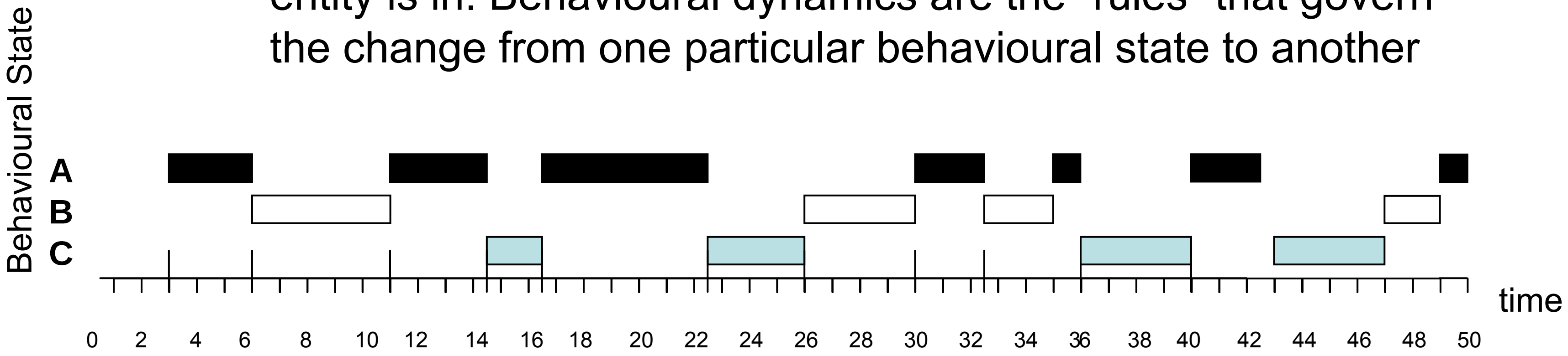
States are integers (ordinal) or reals (interval, ratio scale) measured at fixed time intervals

$$X_t = c_0 + c_1 X_{t-1} + e_t$$



Time Series Analysis

The activity displayed conveys the *behavioural state* the entity is in. Behavioural dynamics are the “rules” that govern the change from one particular behavioural state to another



time	Activity
3.0	A
6.0	B
11.0	A
14.5	C
16.5	A
22.5	C
26.0	B
30.0	A
32.5	B
35.0	A
36.0	C
40.0	A
43.0	C
47.0	B
49.0	A
50.0	End

From the time recording, the sequence of behavioural states can be distilled …

Sequence of Behavioural States:
A B A C A C B A B A C A C B A

Transition Matrix

State n+1 (next)

State n (preceding)

	A	B	C
A	-	II	IIII
B	IIII	-	
C	II	II	-

… and summarized in a *transition matrix*

Transition Matrix

Transition frequencies

State n+1 (next)

State n (preceding)	A	B	C	Σ_{rows}:
A	-	2 f_{AB}	4 f_{AC}	6
B	4 f_{BA}	-		4
C	2 ◂ f_{CA}	2 ◂ f_{CB}	-	4
$\Sigma_{columns}$:	6	4	4	14

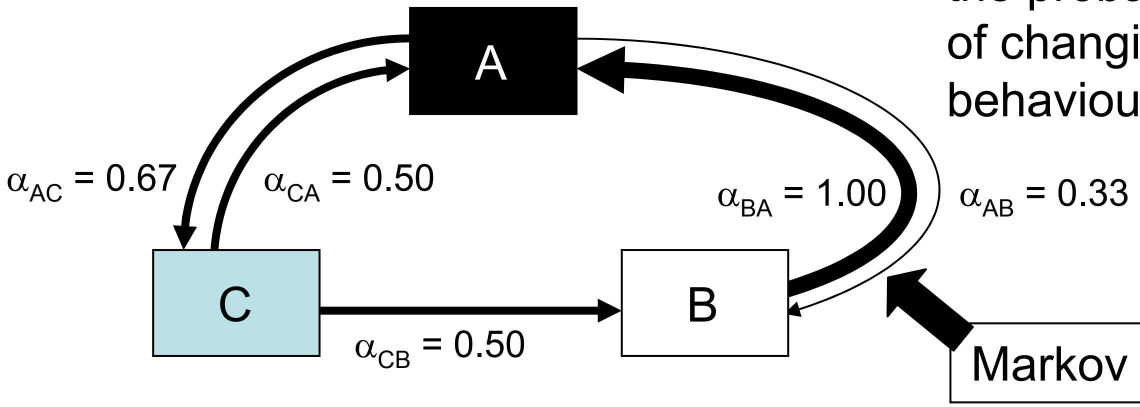
Transition rates

State n+1 (next)

State n (preceding)	A	B	C
A	-	2/6 = 0.33 α_{AB}	4/6 = 0.67 α_{AC}
B	4/4 = 1.00 α_{BA}	-	
C	2/4 = 0.50 α_{CA}	2/4 = 0.50 α_{CB}	-

The *transition rates* (α_{ij}) describe the probability per time interval of changing from one particular behavioural state (i) to another (j)

(First order) Markov Model



Markov State Space Diagram

Example. Transition Matrix of the Behaviour of a Mouse (Table I)

Transition frequencies

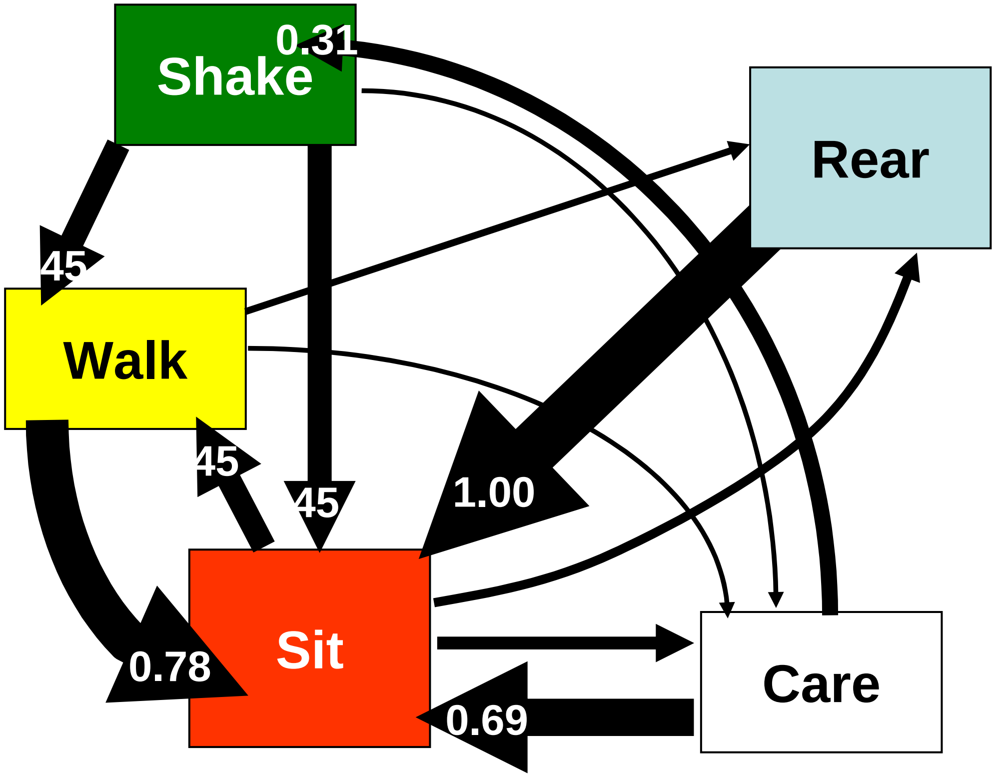
Count of Activityt	Activity(t+1)					
Activity(t)	care	rear	shake	sit	walk	Grand Total
care			4	9		13
rear				10		10
shake	1			5	5	11
sit	10	7	6		19	42
walk	2	3		18		23
Grand Total	13	10	10	42	24	99

Transition rates

Count of Activityt	Activity(t+1)					
Activity(t)	care	rear	shake	sit	walk	Grand Total
care	0.00%	0.00%	30.77%	69.23%	0.00%	100.00%
rear	0.00%	0.00%	0.00%	100.00%	0.00%	100.00%
shake	9.09%	0.00%	0.00%	45.45%	45.45%	100.00%
sit	23.81%	16.67%	14.29%	0.00%	45.24%	100.00%
walk	8.70%	13.04%	0.00%	78.26%	0.00%	100.00%
Grand Total	13.13%	10.10%	10.10%	42.42%	24.24%	100.00%

Example. Markov State Space Diagram of the Behaviour of a Mouse (based on transition rates)

Count of Activityt	Activity(t+1)					
Activity(t)	care	rear	shake	sit	walk	Grand Total
care	0.00%	0.00%	30.77%	69.23%	0.00%	100.00%
rear	0.00%	0.00%	0.00%	100.00%	0.00%	100.00%
shake	9.09%	0.00%	0.00%	45.45%	45.45%	100.00%
sit	23.81%	16.67%	14.29%	0.00%	45.24%	100.00%
walk	8.70%	13.04%	0.00%	78.26%	0.00%	100.00%
Grand Total	13.13%	10.10%	10.10%	42.42%	24.24%	100.00%



Definitions

$$\alpha_{AB} = \frac{\Pr\left[A \rightarrow B, in\ dt \middle| A(t)\right]}{dt}$$

Transition rate

$$\lambda_A = \frac{\Pr\left[A \rightarrow, in\ dt \middle| A(t)\right]}{dt}$$

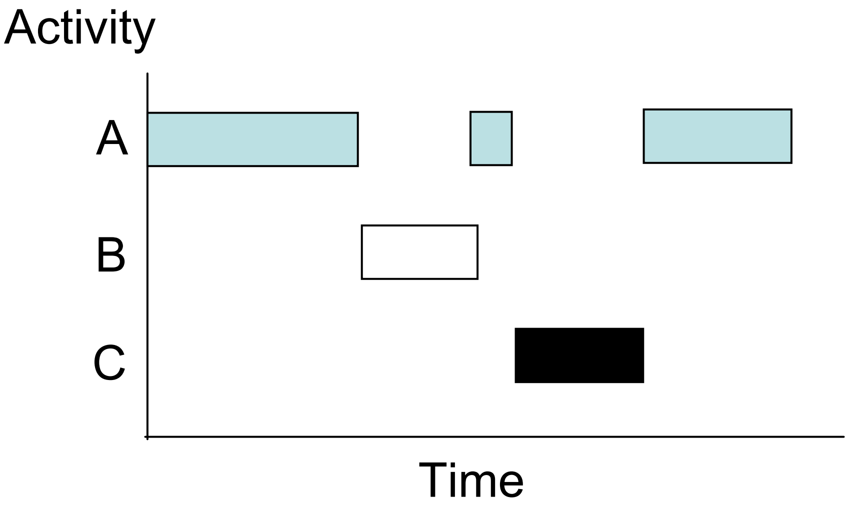
Termination rate

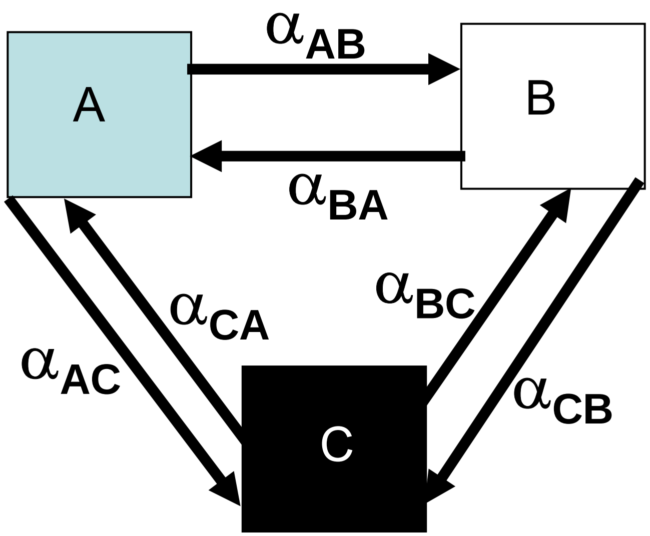
$$\alpha_{AB} \big/ \lambda_A = \frac{\Pr\left[A \rightarrow B, in\ dt \middle| A(t)\right]}{\Pr\left[A \rightarrow, in\ dt \middle| A(t)\right]} = \Pr\left[\rightarrow B, in\ dt \middle| A(t)\right]$$

$$= P_{AB}$$

Transition probability

Transition rates completely define the behavioural dynamics of a system





… given certain assumptions:

1. ERGODICITY: **All states** can eventually be reached from each other
2. STATIONARITY: a. Probability to change states is **constant**
   b. Transition rates are independent of "history"
   = independent of time already spent in current state
   = independent of identity of foregoing states

Violation of the requirement: ***Dependency*** between identities of behavioural state and ***next*** state

Check: χ^2 statistic

Measures deviations observed frequencies from expected frequencies

$$\chi^2 = \frac{\sum (\text{Obs - Exp})^2}{\text{Exp}}$$

Expected by *chance*

Large χ^2 = large deviation from chance = “Exceptional”

When the probability of finding an even larger χ^2 is very small (say, < 5%)

observed frequencies very much larger than expected by chance: indicates ***dependency***

Calculating the Degree of Association

Act	A	B	C	S rows
A	0	2	1	**3**
B	3	1	3	**7**
C	1	0	1	**2**
S columns	**4**	**3**	**5**	**12**

For each cell:
E = matching row total × column total
divided by grand total

1. From the observed (O) frequencies, calculate the *expected* (E) frequencies (by chance)

Act	A	B	C
A	***3·4)/12*** 1.0	***(3·3)/12*** 0.75	***(3·5)/12*** 1.25
B	***(7·4)/12*** 2.33	***(7·3)/12*** 1.75	***(7·5)/12*** 2.92
C	***(2·4)/12*** 0.66	***(2·3)/12*** 0.50	***(2·5)/12*** 0.83

2. For each cell compute: $(O-E)^2/E$

Act	A	B	C
A	$(0-1.0)^2/1$ *1*	$(2-0.75)^2/0.75$ *2.08*	$(1-1.25)^2/1.25$ *0.05*
B	$(3-2.33)^2/2.33$ *0.19*	$(1-1.75)^2/1.75$ *0.32*	$(3-2.92)^2/2.92$ *0.002*
A	$(1-0.66)^2 0.66$ *0.18*	$(0-0.50)^2/0.50$ *0.50*	$(1-0.83)^2/0.83$ *0. 21*

3. Add up = $\Sigma (O-E)^2/E = \chi^2$ ("Chi-square")
Here: $\chi^2 = 4.53$

For given degree of freedoms = (#columns-1) (#rows-1), the probability of $c^2_{obs} \geq c^2_{exp}$ can be looked up in tables

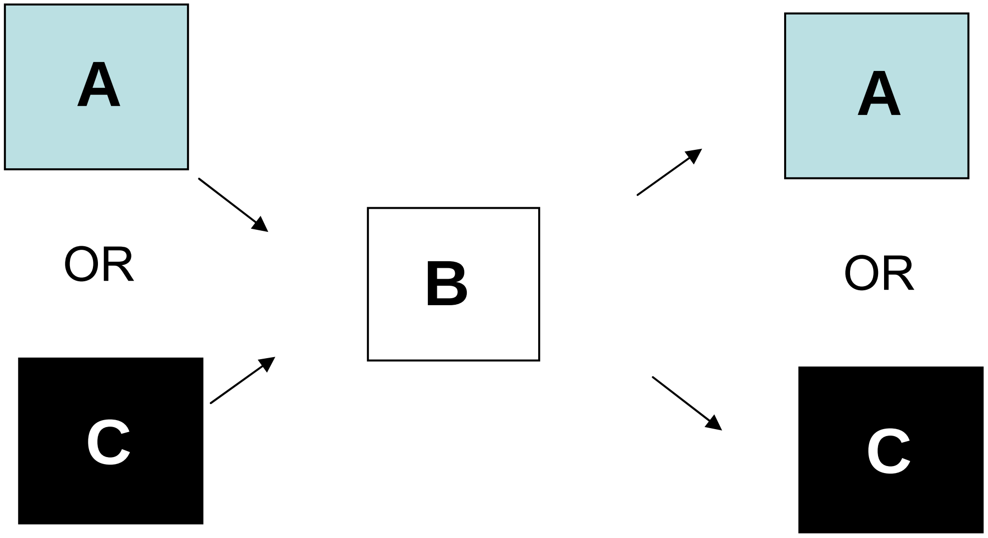
Here, df = 2 × 2 = 4, p = 0.34

A more exact hypothesis for behavioural data:

Identity of next behavioural state should be independent of the identity of the state preceding the current activity

Transition from state i → j should be independent from the transition h → i

What follows activity i should be independent of what brought it into state i



Preceding act (h) → Current (“Middle”) act (i) → Following act (j)

at t – 1 at t at t + 1

Unit of Analysis: triad

Preceding act (h) → Current (“Middle”) act (i) → Following act (j)

The sequence A,B,A,C,B,B,C,A,A,C,B,A consists of the triads:

	Preceding	**Middle (Current)**	**Next**
	(Act at t-1)	**(Act at t)**	**(Act at t+1)**
1.	**A**	**B**	**A**
2.	**B**	**A**	**C**
3.	**A**	**C**	**B**
4.	**C**	**B**	**B**
5.	**B**	**B**	**C**
6.	**B**	**C**	**A**
7.	**C**	**A**	**A**
8.	**A**	**A**	**C**
9.	**A**	**C**	**B**
10.	**C**	**B**	**A**
11.	**(B**	**A**	
12.	**A**		**)**

For each middle act a table is set up

Element B in example (last slide) occurs as middle act in the triads:

1. A B A
4. C B B
5. B B C
10.C B A

The table for B as middle act is:

Elements that follow “Middle” act i

Elements that precede “Middle” act i

B	**A**	**B**	**C**
A	1		
B			1
C		1	

For each element such a table is constructed and a χ^2 calculated
The sum of all the χ^2’s is the overall χ^2

Example Mouse Behaviour

Overall χ^2	**14.5525**
***DF =**	15
***P =**	0.48411

NOT significant:
No indications for a dependency between the identity of an act and that of a preceding act

If Markov models are set up for different external / experimental conditions, a comparison of the transition rates tells you about the effect of those treatments on the organisation of behaviour

EXAMPLE

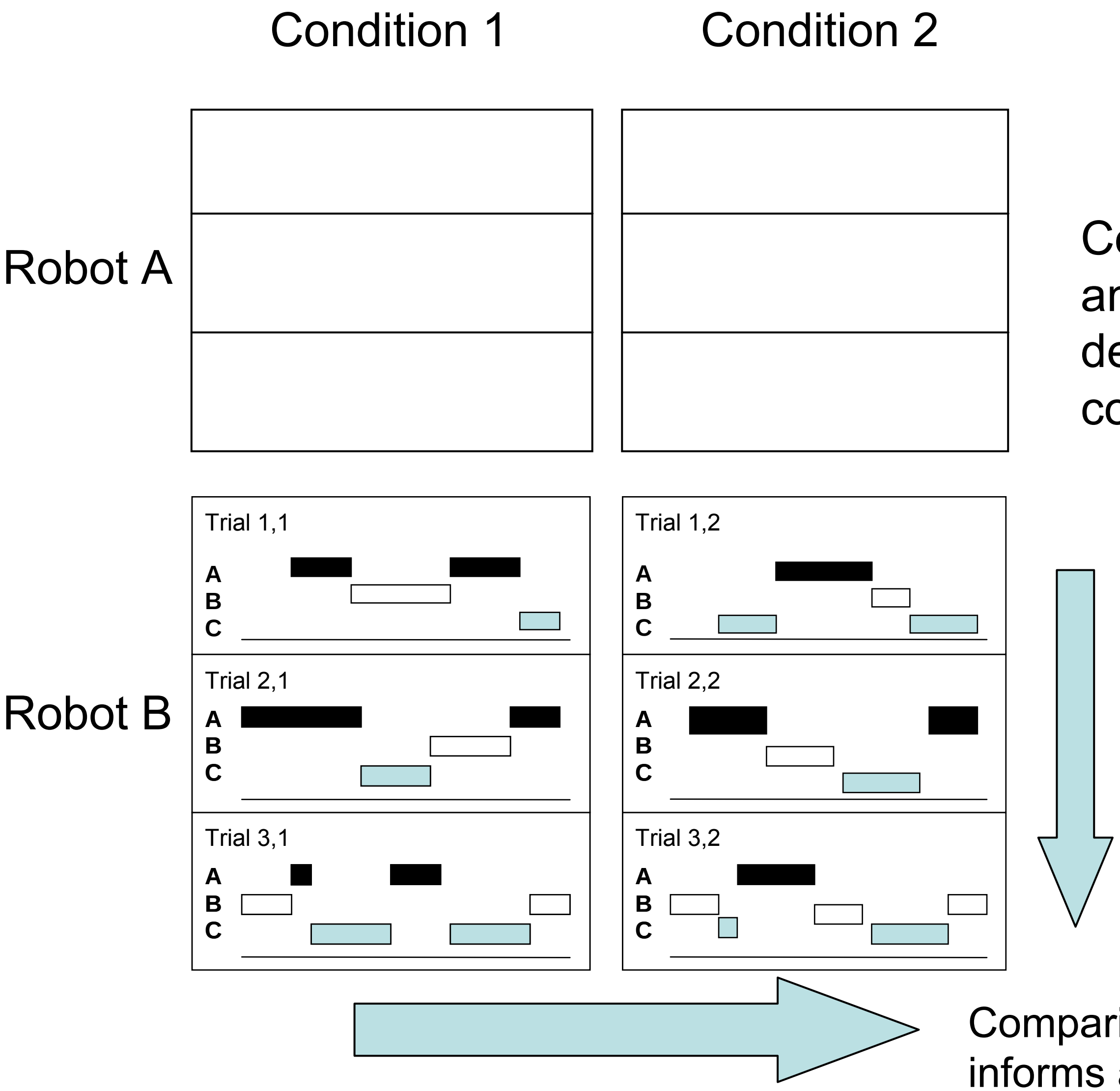
Behaviour of robots measured under *different conditions* …

Condition 1: robot in environment with cluttered objects
Condition 2: robot in environment with randomly distributed object

… and during *replicated trials*

Comparing the transition rates between the trials (within the same condition) informs about the changes of behaviour in time (“development”)

Comparing the transition rates between the conditions informs about the effects of the treatment



Comparing the $\alpha_{ij(1,\cdot)}$ with the $\alpha_{ij(2,\cdot)}$ and the $\alpha_{ij(3,\cdot)}$ informs about the development of behaviour within conditions ·

$\alpha_{AB(1,1)}$, $\alpha_{BA(1,1)}$,
$\alpha_{AC(1,1)}$, $\alpha_{CA(1,1)}$,
$\alpha_{BC(1,1)}$, $\alpha_{CB(1,1)}$

$\alpha_{AB(2,1)}$, $\alpha_{BA(2,1)}$,
$\alpha_{AC(2,1)}$, $\alpha_{CA(2,1)}$,
$\alpha_{BC(2,1)}$, $\alpha_{CB(2,1)}$

$\alpha_{AB(3,1)}$, $\alpha_{BA(3,1)}$,
$\alpha_{AC(3,1)}$, $\alpha_{CA(3,1)}$,
$\alpha_{BC(3,1)}$, $\alpha_{CB(3,1)}$

Comparing the $\alpha_{ij(\cdot,1)}$ with the $\alpha_{ij(\cdot,2)}$ informs about the effect of conditions 1 and 2

Effect of experimental conditions

$\alpha_{AB(\cdot,1)}$, $\alpha_{BA(\cdot,1)}$,
$\alpha_{AC(\cdot,1)}$, $\alpha_{CA(\cdot,1)}$,
$\alpha_{BC(\cdot,1)}$, $\alpha_{CB(\cdot,1)}$

$\alpha_{AB(\cdot,2)}$, $\alpha_{BA(\cdot,2)}$,
$\alpha_{AC(\cdot,2)}$, $\alpha_{CA(\cdot,2)}$,
$\alpha_{BC(\cdot,2)}$, $\alpha_{CB(\cdot,2)}$

Finally, the transition rates can be compared between robots

Dimension Reduction

WHY distinguishing several variables (activities) when they express the same thing?

… when , in some way, they are *similar*

Cluster Analysis

or, more specifically, when they are *correlated*?

Factor Analysis
Principal Component Analyse

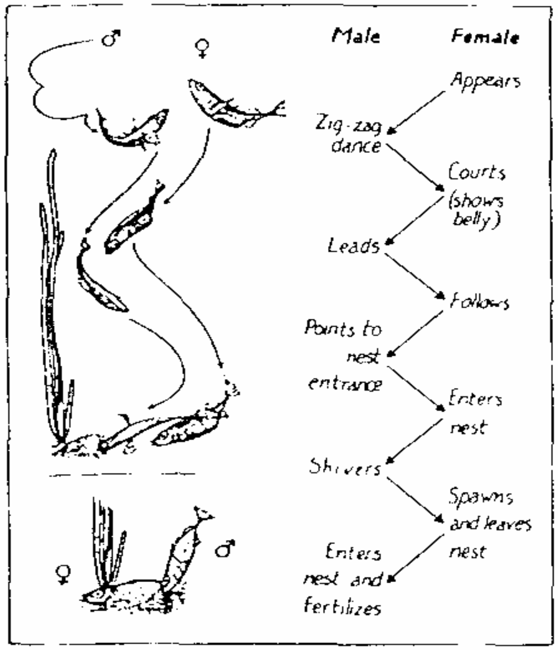


Figure 7.2. The classic example of a diagram of a typical interaction sequence is the one by Tinbergen (1951), showing the behaviors of a male three-spined stickleback in a reproductive mood and of a "ripe" female visiting his nesting territory.

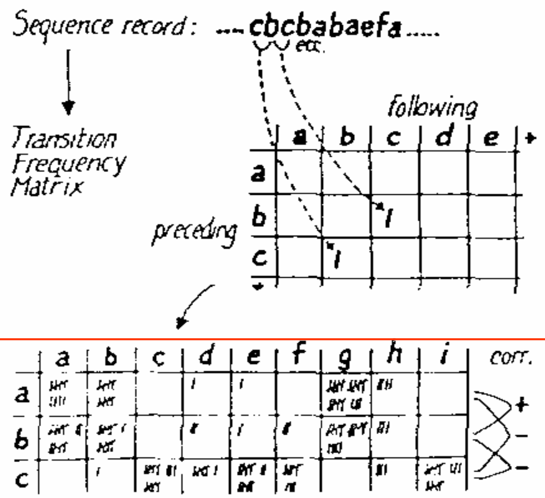


Figure 7.3. Schematic representation of the procedure of constructing a transition [illegible]

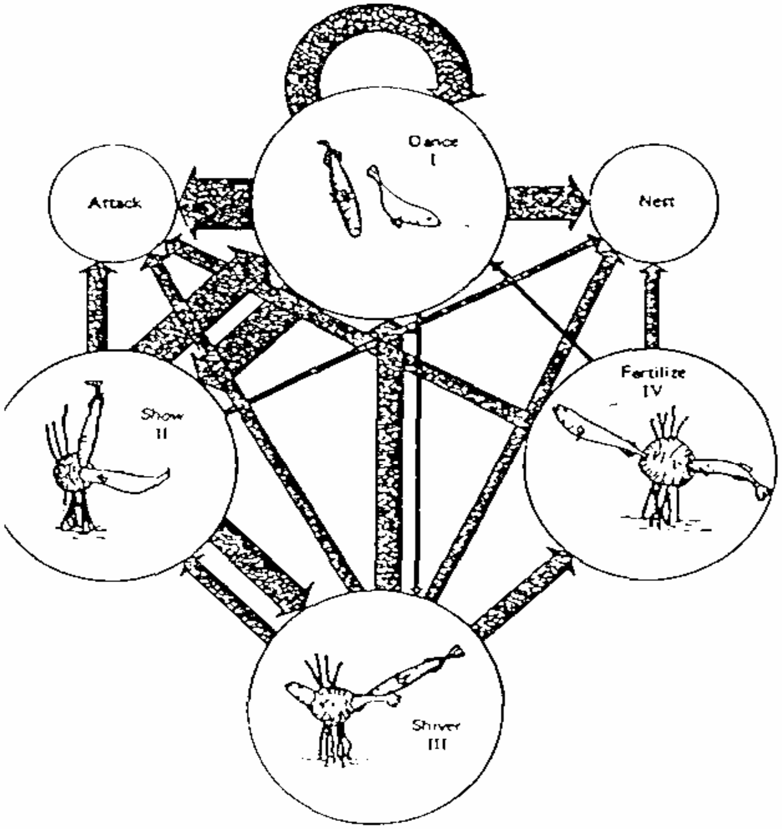


Figure 7.4. A kinematic graph of the sequence of activities shown by a male ten-spined stickleback in a reproductive mood (as shown by his black color) toward a female entering his territory. The width of an arrow represents the number of times a transition between two acts has been observed. Source: Marler and Hamilton, 1966, p. 191, based on data from Morris, 1958.

Cluster Analysis:

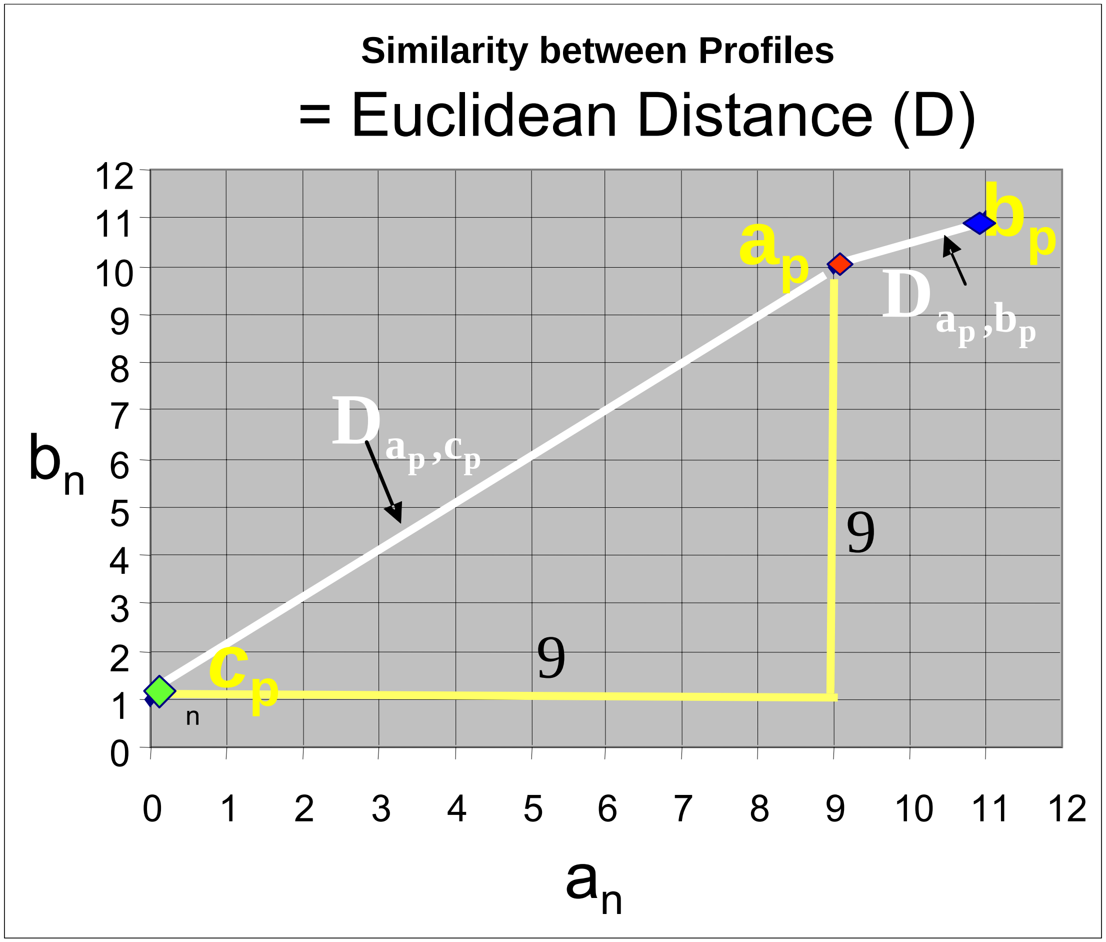
Comparing Activity Profiles

“characteristics”

nex previous	a_n	b_n	c_n	d_n	e_n	f_n	g_n	h_n	i_n
a_p	**9**	**10**	**0**	**1**	**1**	**0**	**18**	**4**	**0**
b_p	**11**	**11**	**0**	**2**	**1**	**2**	**14**	**3**	**0**
c_p	***0***	***1***	***13***	***6***	***12***	***8***	***0***	***4***	***7***
d_p	5	1	7	11	11	12	0	5	10
e_p	2	3	1	0	2	3	0	3	4
f_p	7	4	4	4	11	6	5	4	12
g_p	10	12	3	11	1	8	10	12	6
h_p	***1***	***2***	***10***	***7***	***11***	***9***	***2***	***2***	***4***
i_p	9	9	1	0	2	1	17	5	1

Take together those profiles that are most similar with respect to “characteristics”(i.e. frequency of subsequent activity)

next previous	a_n(“X”)	b_n(“Y”)
a_p	9	10
b_p	11	11
c_p	*0*	*1*



Similarity between Profiles

= Euclidean Distance (D)

next previous	a_n("X")	b_n("Y")
a_p	9	10
b_p	11	11
c_p	0	1

Euclidean Distance between a_p and b_p

$$D_{a_p,b_p} = \sqrt{[(a_p,a_n)-(b_p,a_n)]^2 + [(a_p,b_n)-(b_p,b_n)]^2}$$

$$= \sqrt{\quad [(9)-(11)]^2 \quad + \quad [(10)-(11)]^2 \quad} = \sqrt{5} = 2.24$$

Euclidean Distance between a_p and c_p

$$D_{a_p,c_p} = \sqrt{[(a_p,a_n)-(c_p,a_n)]^2 + [(a_p,b_n)-(c_p,b_n)]^2}$$

$$= \sqrt{\quad [9]^2 \quad + \quad [9]^2 \quad} = \sqrt{162} = 12.73$$

next previous	a_n(“X”)	b_n(“Y”)	c_n(“Z”)
a_p	**9**	**10**	**0**
b_p	**11**	**11**	**0**
c_p	***0***	***1***	***13***

Euclidean Distance between a_p and c_p based on **three** characteristics

$$D_{a_p,c_p} = \sqrt{[(a_p,a_n)-(c_p,a_n)]^2+[(a_p,b_n)-(c_p,b_n)]^2+[(a_p,c_n)-(c_p,c_n)]^2}$$

$$= \sqrt{\quad [9]^2 \quad + \quad [9]^2 \quad + \quad [13]^2}$$

$$= \sqrt{250} = 15.73$$

DISTANCE (DISSIMILARITY) MATRIX

Euclidean distances	a	b	c	d	**e**	**f**	**g**	**h**	**i**
a	0	**5.196152**	30.23243	30.24897	21.23676	22.67157	18.49324	26.85144	**2.828427**
b	5.196152	0	28.44292	27.6767	19.07878	20.66398	**16.15549**	24.81935	5.385165
c	30.23243	28.44292	0	10.63015	17.9722	14.07125	25.13961	**5.567764**	28.28427
d	30.24897	27.6767	10.63015	0	19.2873	**11.7047**	21.04757	**10**	28.44292
e	21.23676	19.07878	17.9722	19.2873	0	**15.19868**	21.93171	15.93738	19.77372
f	22.67157	20.66398	14.07125	11.7047	15.19868	0	18.76166	13.0767	20.63977
g	18.49324	16.15549	25.13961	21.04757	21.93171	18.76166	0	22.69361	17.54993
h	26.85144	24.81935	5.567764	10	15.93738	13.0767	22.69361	0	25.11971
i	2.828427	5.385165	28.28427	28.44292	19.77372	20.63977	17.54993	25.11971	0

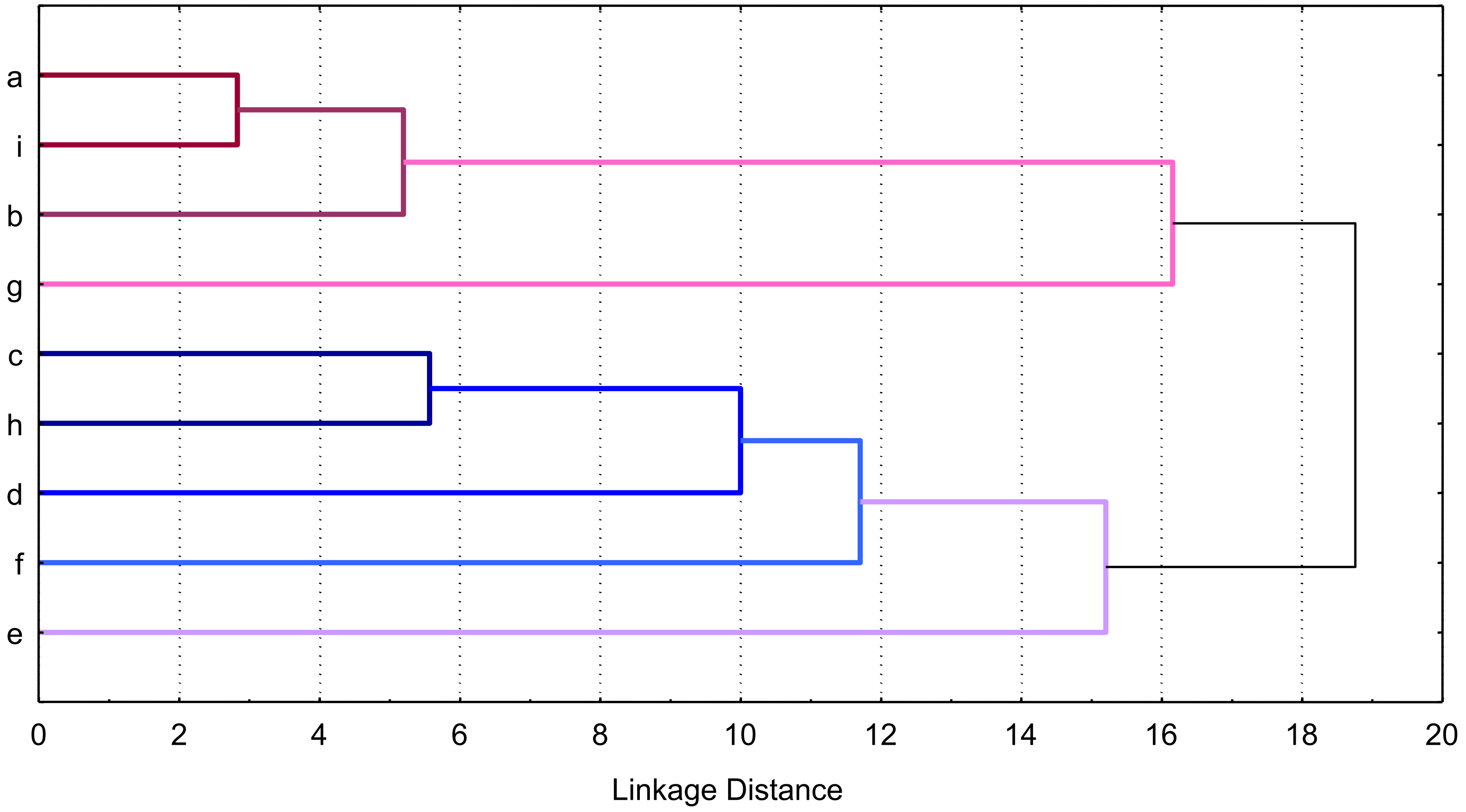
Amalgamation Schedule

Single Linkage

Euclidean
distances

	Obj. No.	Obj. No.	Obj. No.	Obj. No.	Obj. No.	Obj. No.	Obj. No.	Obj. No.	Obj. No.
	1	2	3	4	5	6	7	8	9
2.828427	**a**	**i**							
5.196152	**a**	**i**	**b**						
5.567764	**c**	**h**							
10.00000	**c**	**h**	**d**						
11.70470	**c**	**h**	**d**	**f**					
15.19868	**c**	**h**	**d**	**f**	**e**				
16.15549	**a**	**i**	**b**	**g**					
18.76166	**a**	**i**	**b**	**g**	**c**	**h**	**d**	**f**	**e**

Dendrogram



Tree Diagram for 9 Cases
Single Linkage
Euclidean distances

Types of Cluster Analysis

Similarity Criteria ("Neighbourhood Distances"):

- **Euclidean Distance**
- City Block Distance
- and many more …

Can give different results!

Cluster analysis is a ***heuristic***/ ***pattern recognizing*** technique

Cluster Criteria

- Single Linkage
- Complete Linkage
- Centroid
- **Ward's Average**
  minimizes within cluster variance
- and many more

TABLE I. Transition rates (from Table 3 in SeqDep)

Activity(t)	care	rear	shake	sit	walk
CARE	0.00%	0.00%	30.77%	69.23%	0.00%
REAR	0.00%	0.00%	0.00%	100.00%	0.00%
SHAKE	9.09%	0.00%	0.00%	45.45%	45.45%
SIT	23.81%	16.67%	14.29%	0.00%	45.24%
WALK	8.70%	13.04%	0.00%	78.26%	0.00%

xlSTAT - Classification 2

Data range : Workbook = Book1 / Sheet = Sheet1 / Range = $AM$10:$AR$15

TABLE II. Cluster Amalgation Schedule

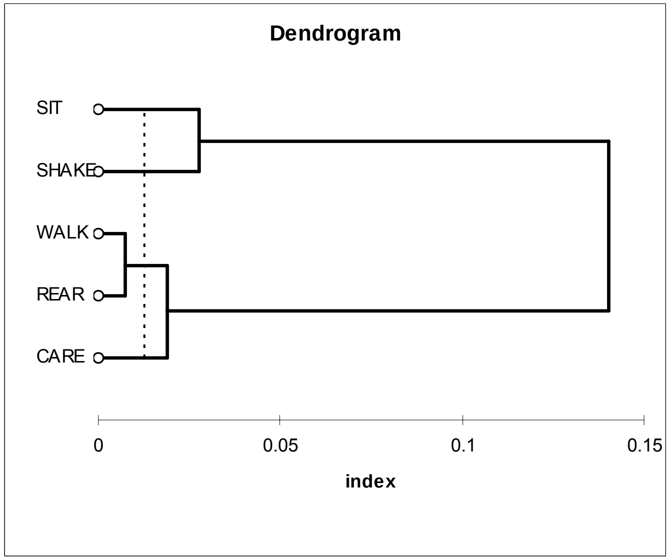
Time :
0h 0mn 0s

Observations	**Ordinate on dendrogram**
CARE	1
REAR	2
SHAKE	4
SIT	5
WALK	3

knots	**caption**	**weight**	**index**
1	REAR ~ WALK	2	0.0072
2	CARE ~ REAR ~ WALK	3	0.0187
3	SHAKE ~ SIT	2	0.0276
4	CARE ~ REAR ~ WALK ~ SHAKE ~ SIT	5	0.1401

A level index rupture has been detected between knots 1 and 2

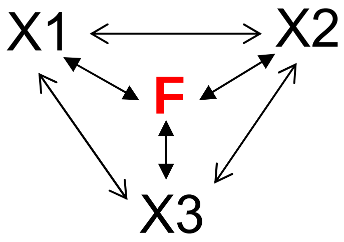
The best partition contains 4 groups



Factor Analysis

Combine those that are significantly correlated …

Rationale: set of variables are dependent because all of them are correlated with a common factor (F)



More specifically: … ***those whose mutual correlation disappear after partial correlation***

Cf. Spearman’s “G” factor
For general intelligence

Factor Analysis

Tool for ***variable reduction***

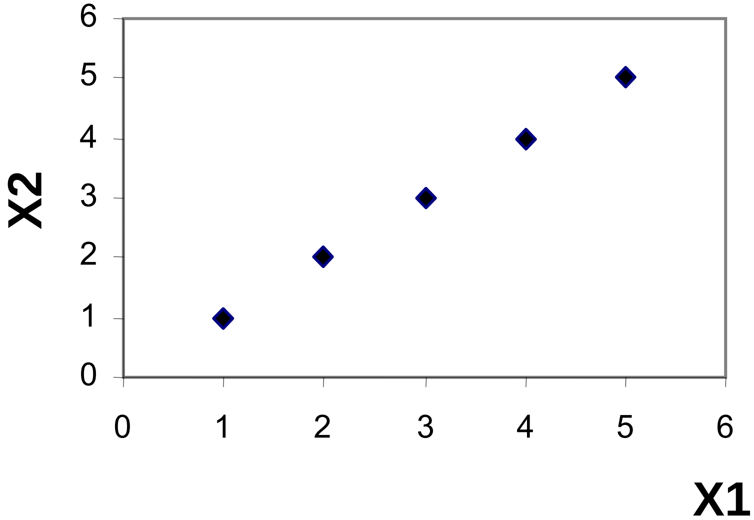
1. Use partial correlations to find out how STRONG they are correlated to the common factor

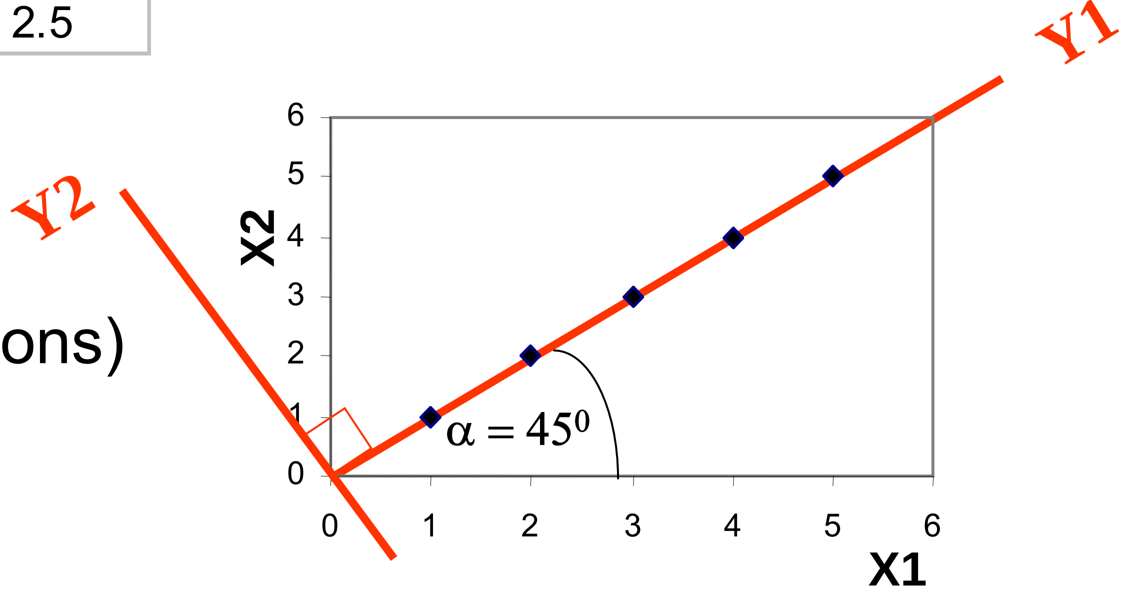
   (how strong each original variable “loads” on the factor)

2. Reconstruct the common factor by combining the values of the constituting variables.
   = average values over the variables (weighted to their contribution to the common factor)

Principal Component Analysis (PCA)

	X1	X2
	$x1_1 = 1$	$x2_1 = 1$
	$x1_2 = 2$	$x2_2 = 2$
	$x1_3 = 3$	$x2_3 = 3$
	$x1_4 = 4$	$x2_4 = 4$
	$x1_5 = 5$	$x2_5 = 5$
Mean	3	3
Variance	2.5	2.5





New axes (dimensions)
after rotation

Variable (Dimension) reduction:

Rotation of axes such that **first new axis explains maximal variance** (in example: all variance!) and **second new axis** (orthogonal to the first one) **explains the residual variance**

$\vec{Y1}\vec{Y2}^T$ = Variance Covariance Matrix of transformed values

Matrix with variances on the diagonal, covariances off diagonal

Because the new axes are orthogonal, they are un-orrelated, i.e. covariance is zero

Only diagonal elements (= “eigenvalues”) remain

Largest eigenvalue = amount of variance explained by first PC

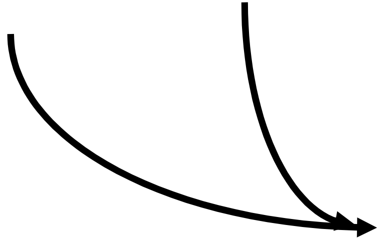
etc.

Eigenvalues can be calculated from the Var Covar matrix of the original data and rotation angle

Rotation is the **transformation**:

$$y1_r = (\cos \alpha) \cdot x1 + (\sin \alpha) \cdot x2$$

$$y2r = (\sin \alpha) \cdot x1 + (\cos \alpha) \cdot x2$$



“weights”

First new axis = sum of transformed (**weighted**) old axes

*First **Principal Component** = linear combination of the original variables and explains major part of the variance*

Subsequent PC’s are orthogonal to previous PC’s and explain residual variance

EXAMPLE (DEFAULT DATA IN SEQDEPNV)

TABLE I. Transition rates (from Table 3 in SeqDep)

Activity(t)	care	rear	shake	sit	walk
CARE	0.00%	0.00%	30.77%	69.23%	0.00%
REAR	0.00%	0.00%	0.00%	100.00%	0.00%
SHAKE	9.09%	0.00%	0.00%	45.45%	45.45%
SIT	23.81%	16.67%	14.29%	0.00%	45.24%
WALK	8.70%	13.04%	0.00%	78.26%	0.00%

TRANSPOSE MATRIX
(COLUMNS→ROWS)

TABLE III. Transposed matrix of transition rates

Activity(t)	CARE	REAR	SHAKE	SIT	WALK
care	0	0	0.090909	0.238095238	0.086957
rear	0	0	0	0.166666667	0.130435
shake	0.30769231	0	0	0.142857143	0
sit	0.69230769	1	0.454545	0	0.782609
walk	0	0	0.454545	0.452380952	0

TRANSPOSED MATRIX

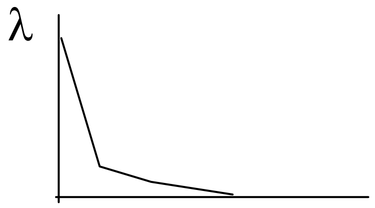
TABLE IV.
Correlations matrix:

	CARE	REAR	SHAKE	SIT	WALK
CARE	1	**0.9001**	*0.3985*	*-0.7710*	**0.8455**
REAR	0.9001	1	*0.6047*	*-0.6757*	**0.9853**
SHAKE	*0.3985*	*0.6047*	1	*0.1751*	*0.5259*
SIT	*-0.7710*	*-0.6757*	*0.1751*	1	*-0.7201*
WALK	0.8455	0.9853	*0.5259*	*-0.7201*	1

CORRELATION MATRIX

TABLE V.
Eigenvalues and eigenvectors :

Eigenvalue.	**1**	**2**	**3**	**4**	**5**
Value	3.6541	1.1908	0.1548	0.0004	0.0000
% of variability	***0.7308***	***0.2382***	0.0310	0.0001	0.0000
Cumulated %	0.7308	0.9690	0.9999	1.0000	1.0000



EIGENVALUES

TABLE VI.

Correlations between initial variables and principal factors (see Fig. 2):

	factor 1	factor 2	factor 3	factor 4	factor 5
CARE	0.9430	-0.1070	-0.3152	0.0017	0.0000
REAR	0.9906	0.1176	0.0682	0.0127	0.0000
SHAKE	0.5105	0.8593	-0.0288	-0.0099	0.0000
SIT	-0.7569	0.6522	-0.0396	0.0111	0.0000
WALK	0.9747	0.0404	0.2199	-0.0008	0.0000

CORRELATION MATRIX
(~ VARIANCE-COVARIANCE MATRIX)

Figure 2 **Circle of correlations : axis 1 and axis 2 (97%)**

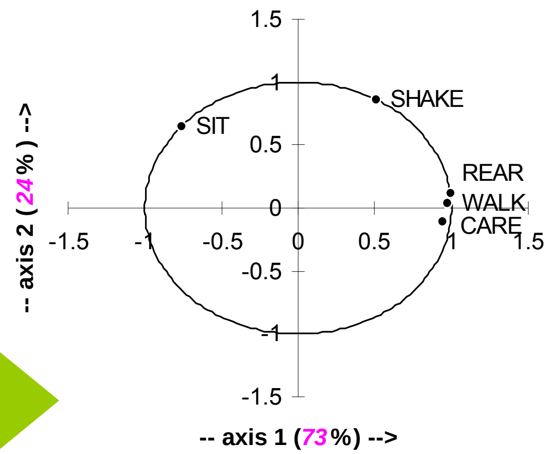


TABLE VII.

Data coordinates on new axes (principal components):

	axis 1	axis 2	axis 3	axis 4	axis 5
care	-1.0552	-0.2507	0.2975	0.0344	0.0000
rear	-0.9044	-0.8738	0.4600	-0.0261	0.0000
shake	-0.5107	-1.0966	-0.6718	-0.0010	0.000
sit	3.7873	0.2567	0.0537	0.0005	0.0000
walk	-1.3170	1.9644	-0.1394	-0.0078	0.0000

CONTRIBUTION (WEIGHTS) TO PRINCIPAL COMPONENTS

Figure 3 **Data on axis 1 and axis 2 (97%)**

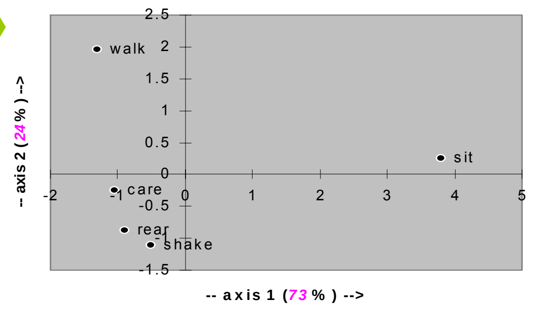
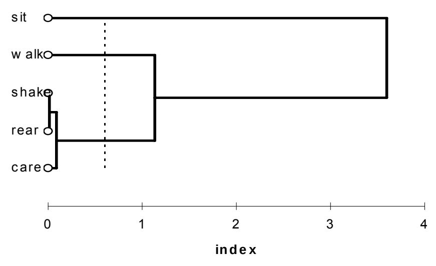


Figure 4 **Dendrogram**
(from a clusteranalysis on TABLE VII)



profiles that are similar with respect to preceding activities

Example: Analysis of Robot Behaviour*

Sample No	Activity	Description
1	av.o	avoid object
1	ta	turn around
1	av.o	
1	to.o	touch object
1	ta.o	turn around, ipo object
1	nb.o	nudge (behind) object
1	ta.o	
2	av.o	
2	av.o	
2	av.o	
2	to.o	
2	av.o	
3	wi	wiggle
3	ad.d	adjust ipo dida
3	wi.w	wiggle ifo wall
3	ta.o	turn around ifo wall
3	av.o	
3	av.o	
4	ta.o	
4	wi	
4	nb.o	
4	ad.o	adjust ipo object
4	ta.o	
4	ta.ow	turn around ifo object+wall
5	av.o	
5	to.o	

ETHOGRAM

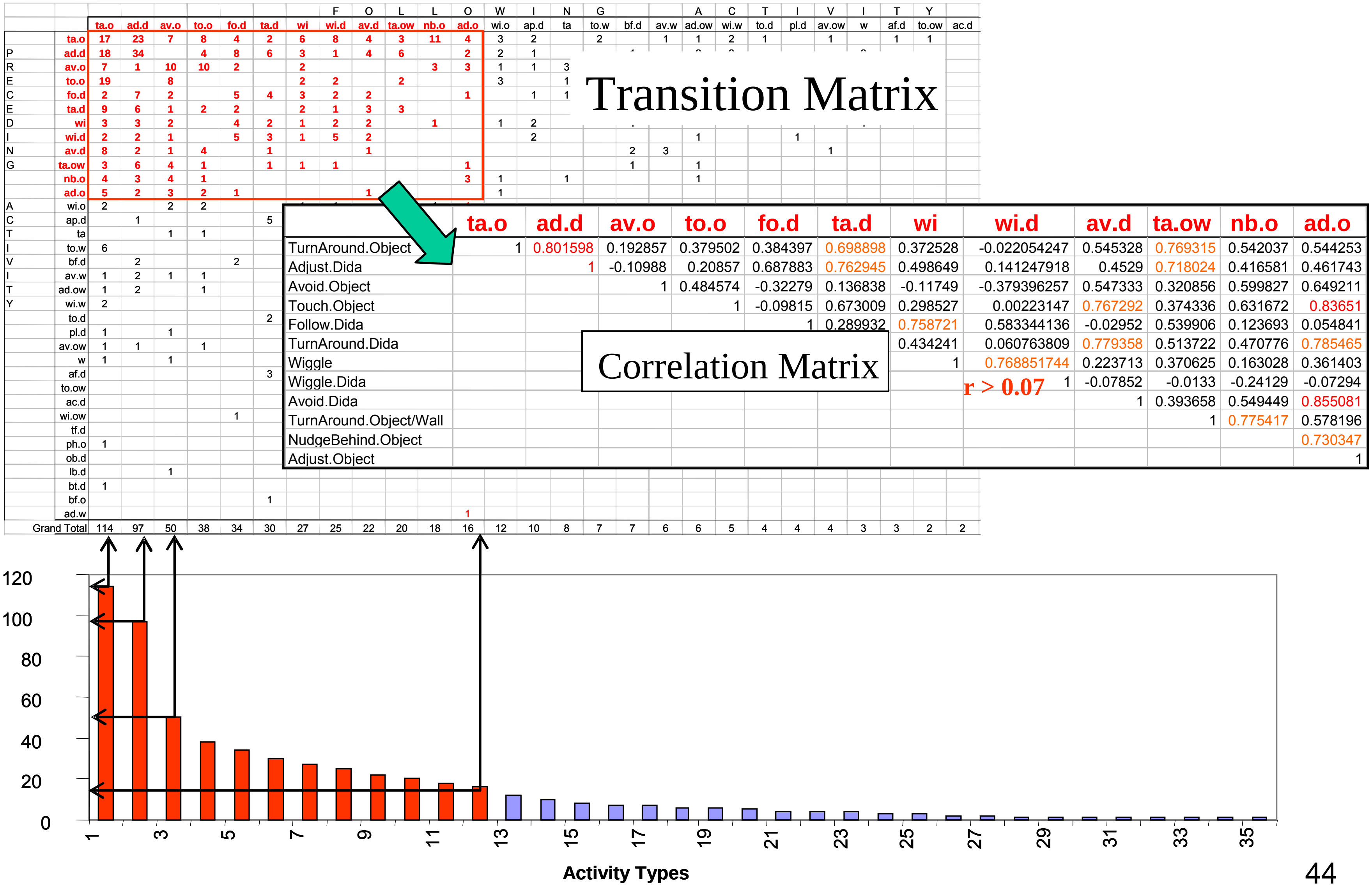
Object-Robot Behaviour

Robot - Robot Behaviour

For a worked out example showing the application of cluster analysis and PCA, see also the ExampleDataAnalysis file in the XLSTAT folder

* From: Boekhorst, I.J.A. te (2001). Freeing machines from Cartesian chains. In: “Cognitive Technology: Instruments of Mind” (eds. M. Beynon, C.L. Nehaniv & K. Dautenhahn). Proceedings of the 4th International Conference, CT2001, Coventry, UK Pp. 95 – 108. Lecture Notes in Artificial Intelligence 2117. Springer, Berlin

ETHOLOGICAL ANALYSIS DIDABOT BEHAVIOUR



Transition Matrix

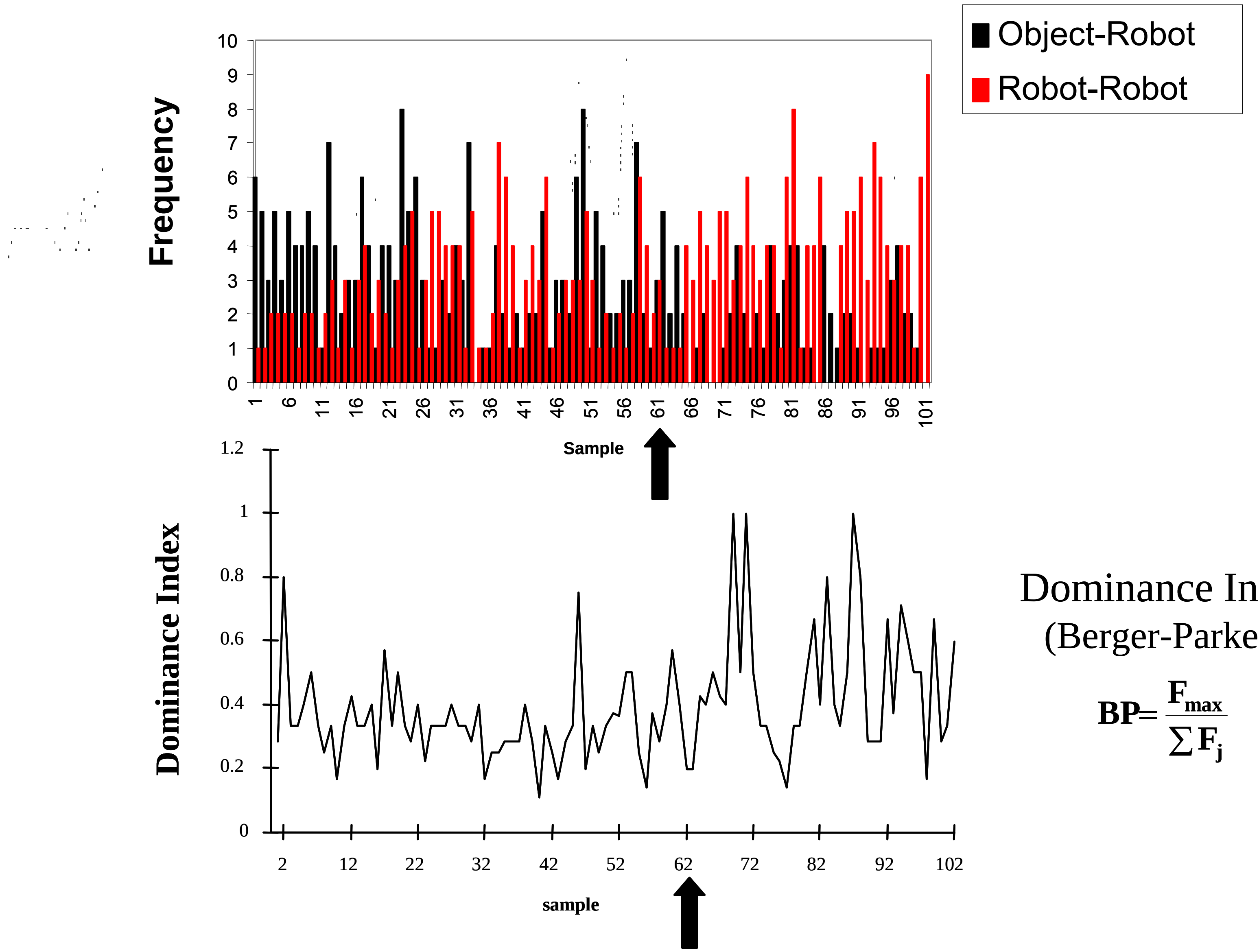
									F	O	L	L	O	W	I	N	G			A	C	T	I	V	I	T	Y	
		ta.o	ad.d	av.o	to.o	fo.d	ta.d	wi	wi.d	av.d	ta.ow	nb.o	ad.o	wi.o	ap.d	ta	to.w	bf.d	av.w	ad.ow	wi.w	to.d	pl.d	av.ow	w	af.d	to.ow	ac.d
	ta.o	17	23	7	8	4	2	6	8	4	3	11	4	3	2		2		1	1	2	1		1		1	1	
P	ad.d	18	34		4	8	6	3	1	4	6		2	2	1			[illegible]		[illegible]	[illegible]				[illegible]			
R	av.o	7	1	10	10	2		2				3	3	1	1	3												
E	to.o	19		8				2	2		2			3		1												
C	fo.d	2	7	2		5	4	3	2	2			1		1	1												
E	ta.d	9	6	1	2	2		2	1	3	3																	
D	wi	3	3	2		4	2	1	2	2		1		1	2			[illegible]							[illegible]			
I	wi.d	2	2	1		5	3	1	5	2					2					1			1					
N	av.d	8	2	1	4		1			1								2	3					1				
G	ta.ow	3	6	4	1		1	1	1				1					1		1								
	nb.o	4	3	4	1								3	1		1				1								
	ad.o	5	2	3	2	1				1				1														
A	wi.o	2		2	2			[illegible]	[illegible]			[illegible]	[illegible]															
C	ap.d		1				5																					
T	ta			1	1																							
I	to.w	6																										
V	bf.d		2			2																						
I	av.w	1	2	1	1																							
T	ad.ow	1	2		1																							
Y	wi.w	2																										
	to.d						2																					
	pl.d	1		1																								
	av.ow	1	1		1																							
	w	1		1																								
	af.d						3																					
	to.ow																											
	ac.d																											
	wi.ow					1																						
	tf.d																											
	ph.o	1																										
	ob.d																											
	lb.d			1																								
	bt.d	1																										
	bf.o						1																					
	ad.w												1															
Grand Total		114	97	50	38	34	30	27	25	22	20	18	16	12	10	8	7	7	6	6	5	4	4	4	3	3	2	2

Correlation Matrix

	ta.o	ad.d	av.o	to.o	fo.d	ta.d	wi	wi.d	av.d	ta.ow	nb.o	ad.o
TurnAround.Object	1	0.801598	0.192857	0.379502	0.384397	0.698898	0.372528	-0.022054247	0.545328	0.769315	0.542037	0.544253
Adjust.Dida		1	-0.10988	0.20857	0.687883	0.762945	0.498649	0.141247918	0.4529	0.718024	0.416581	0.461743
Avoid.Object			1	0.484574	-0.32279	0.136838	-0.11749	-0.379396257	0.547333	0.320856	0.599827	0.649211
Touch.Object				1	-0.09815	0.673009	0.298527	0.00223147	0.767292	0.374336	0.631672	0.83651
Follow.Dida					1	0.289932	0.758721	0.583344136	-0.02952	0.539906	0.123693	0.054841
TurnAround.Dida							0.434241	0.060763809	0.779358	0.513722	0.470776	0.785465
Wiggle							1	0.768851744	0.223713	0.370625	0.163028	0.361403
Wiggle.Dida								1	-0.07852	-0.0133	-0.24129	-0.07294
Avoid.Dida									1	0.393658	0.549449	0.855081
TurnAround.Object/Wall										1	0.775417	0.578196
NudgeBehind.Object												0.730347
Adjust.Object												1

r > 0.07

Measures of Didabot Behaviour

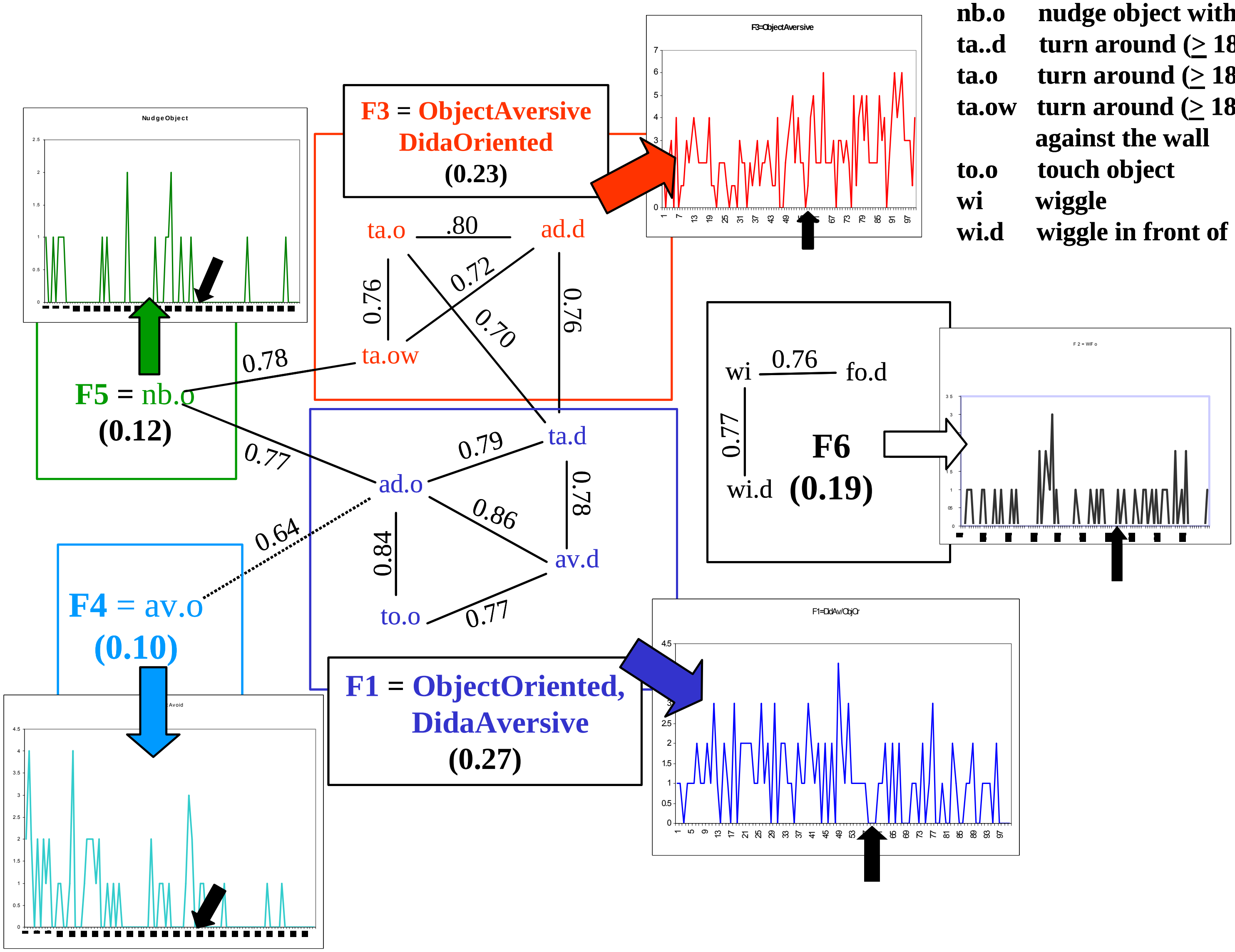


Dominance Index
(Berger-Parker):

$$\mathbf{BP} = \frac{\mathbf{F_{max}}}{\sum \mathbf{F_j}}$$

Factor Analysis

ad.d	**adjust in presence of didabot**
ad.o	**adjust in presence of object**
av.d	**avoid didabot**
fo.d	**follow didabot**
nb.o	**nudge object with backside**
ta..d	**turn around (≥ 180º) in presence of didabot**
ta.o	**turn around (≥ 180º) in presence of object**
ta.ow	**turn around (≥ 180º) before an object against the wall**
to.o	**touch object**
wi	**wiggle**
wi.d	**wiggle in front of didabot**



F3 = ObjectAversive DidaOriented
(0.23)

ta.o .80 ad.d
0.76
0.72
0.70
0.76
ta.ow

F5 = nb.o
(0.12)

0.78
0.77

ta.d
0.79
ad.o
0.78
0.86
0.84
av.d
to.o
0.77
0.64

F4 = av.o
(0.10)

F1 = ObjectOriented, DidaAversive
(0.27)

wi 0.76 fo.d
0.77
wi.d

F6
(0.19)

Markov Model

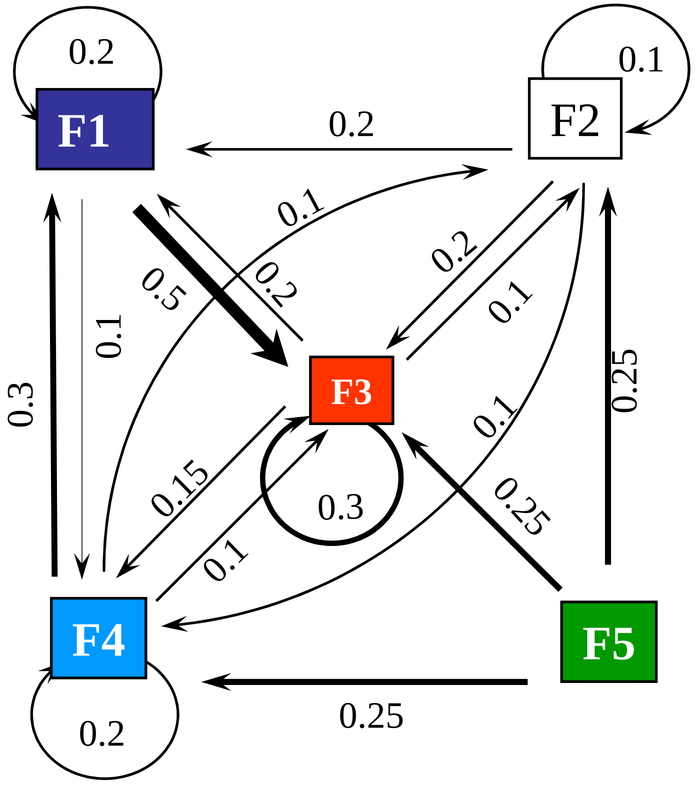
Sub Period I

(samples 12-41)

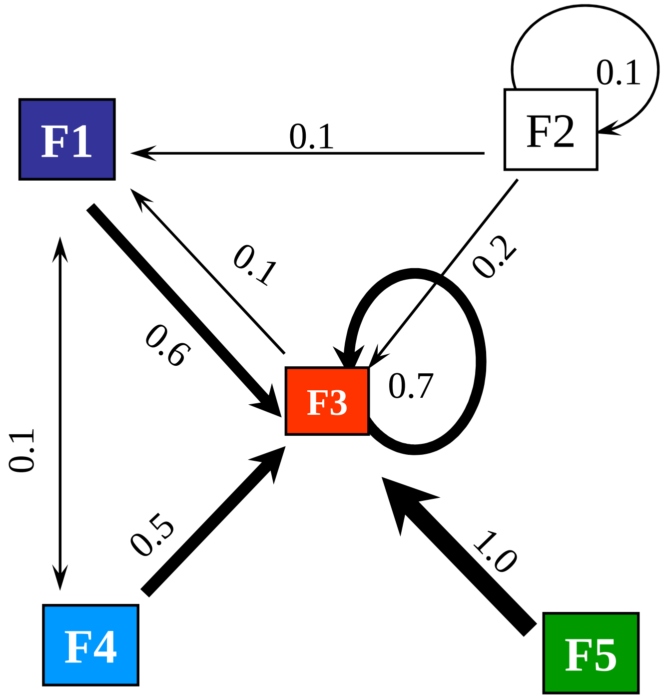
N = 174 activities

Sub Period II

(samples 72-102)



χ^2 = 124.5, df = 108, p = .132



χ^2 = 53.02, df = 43, p = .141