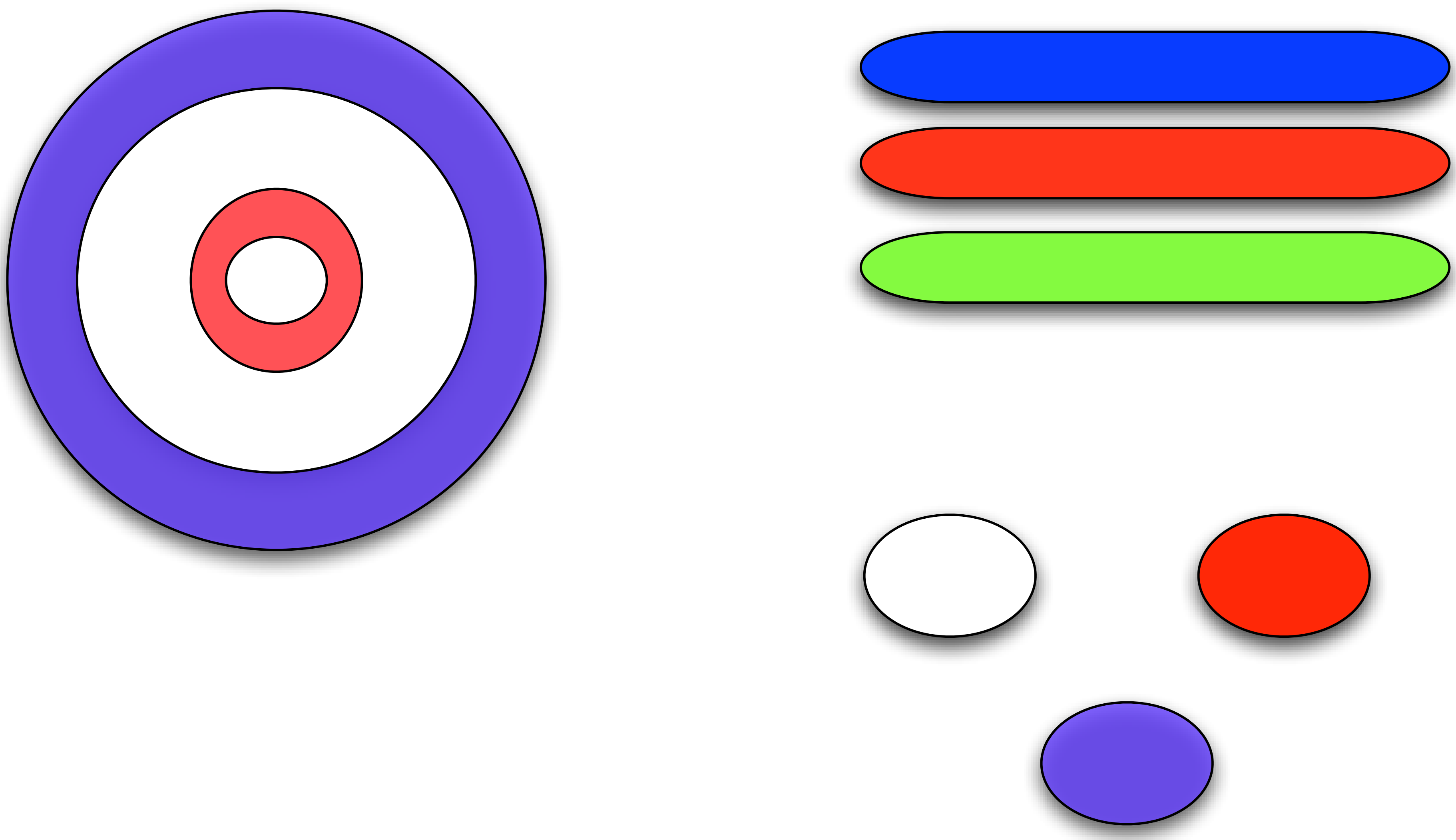
Psychometric Theory Further topics

June, 2020

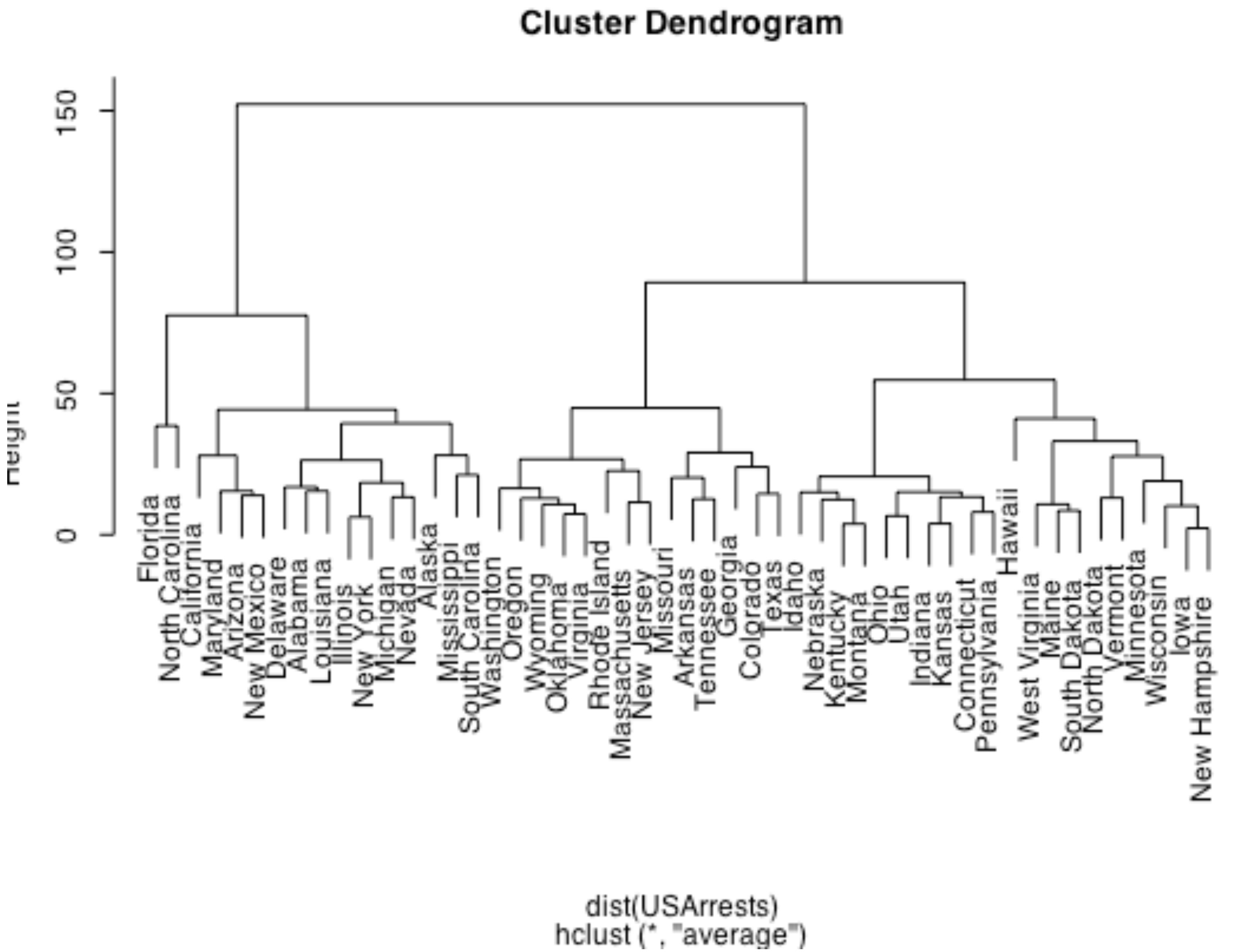
What is a cluster?



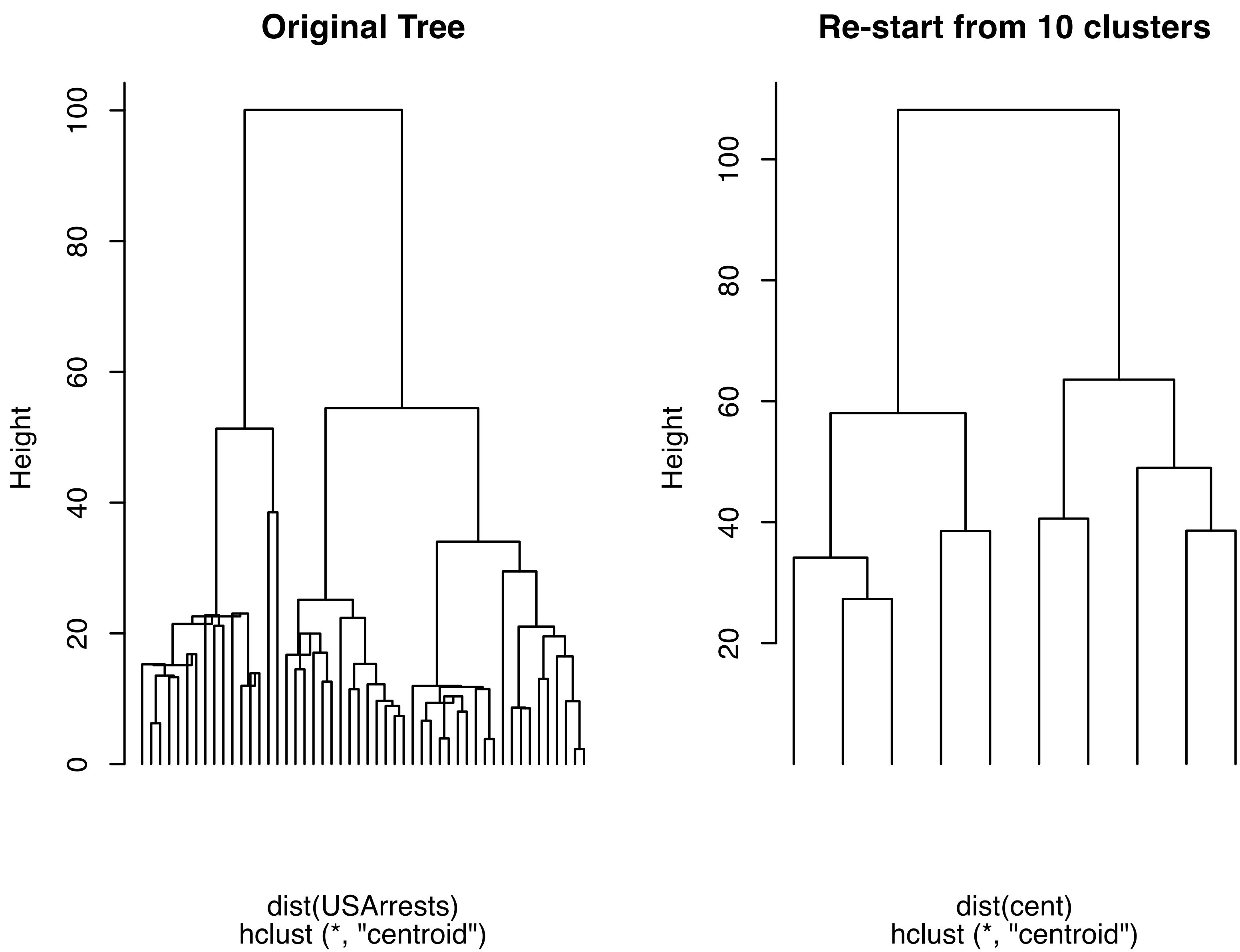
Clustering rules

- Distance:
  - Nearest neighbor
  - Farthest neighbor
  - Centroid distance
- Methods
  - Hierarchical
    - Agglomerative
    - Divisive
  - non-hierarchical

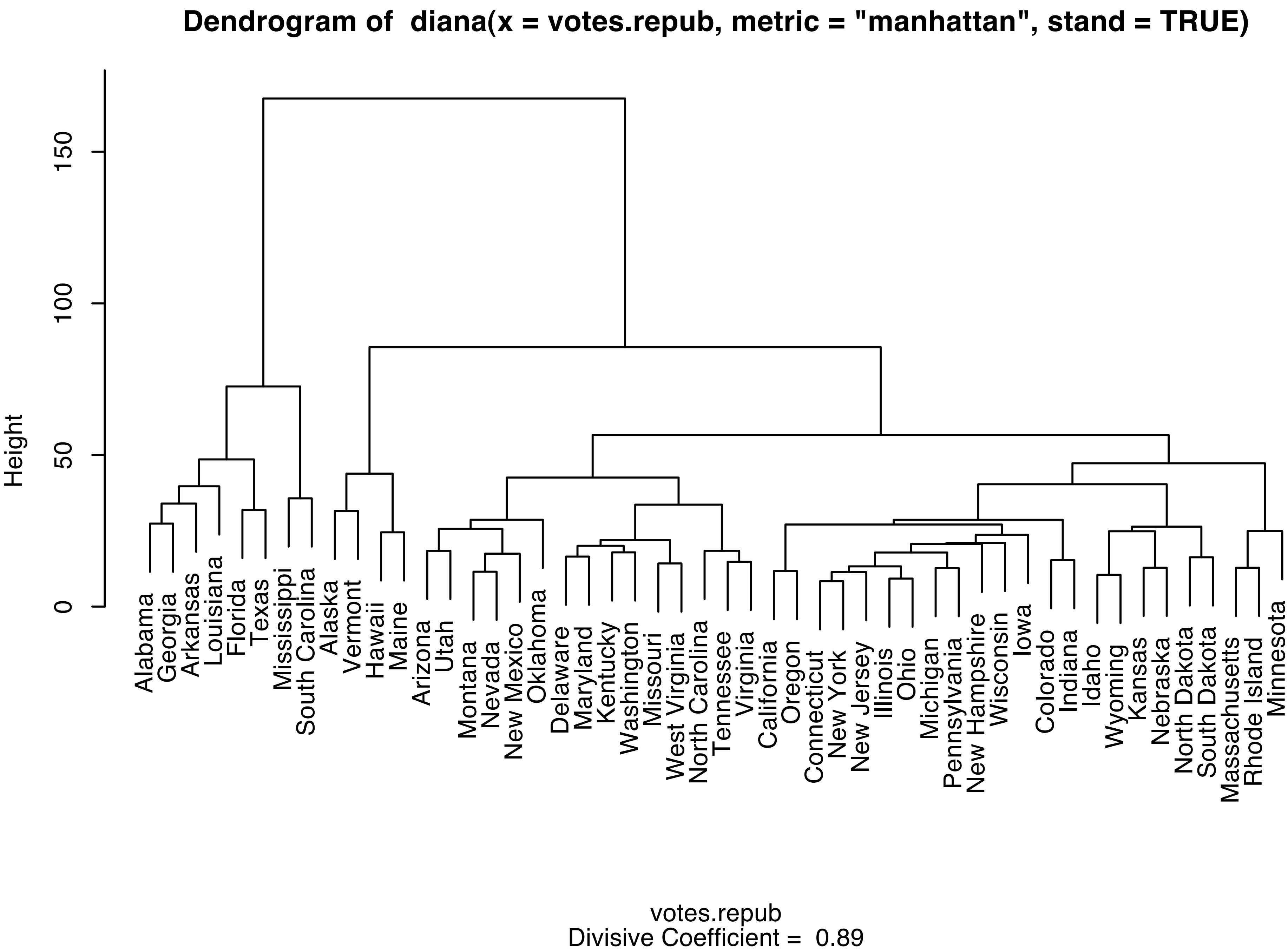
Hierarchical Clustering



More clustering

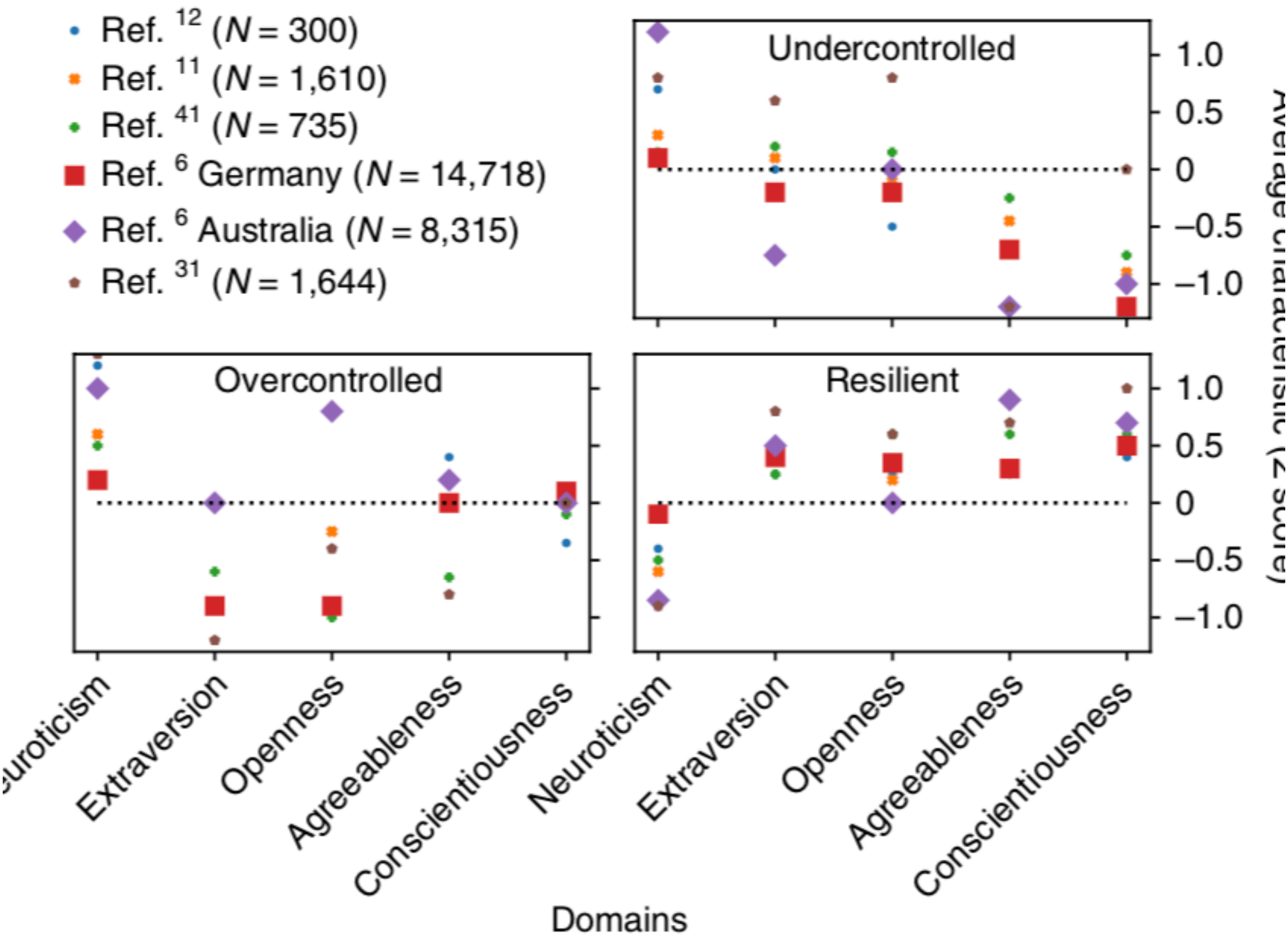


Clusters of voting behavior



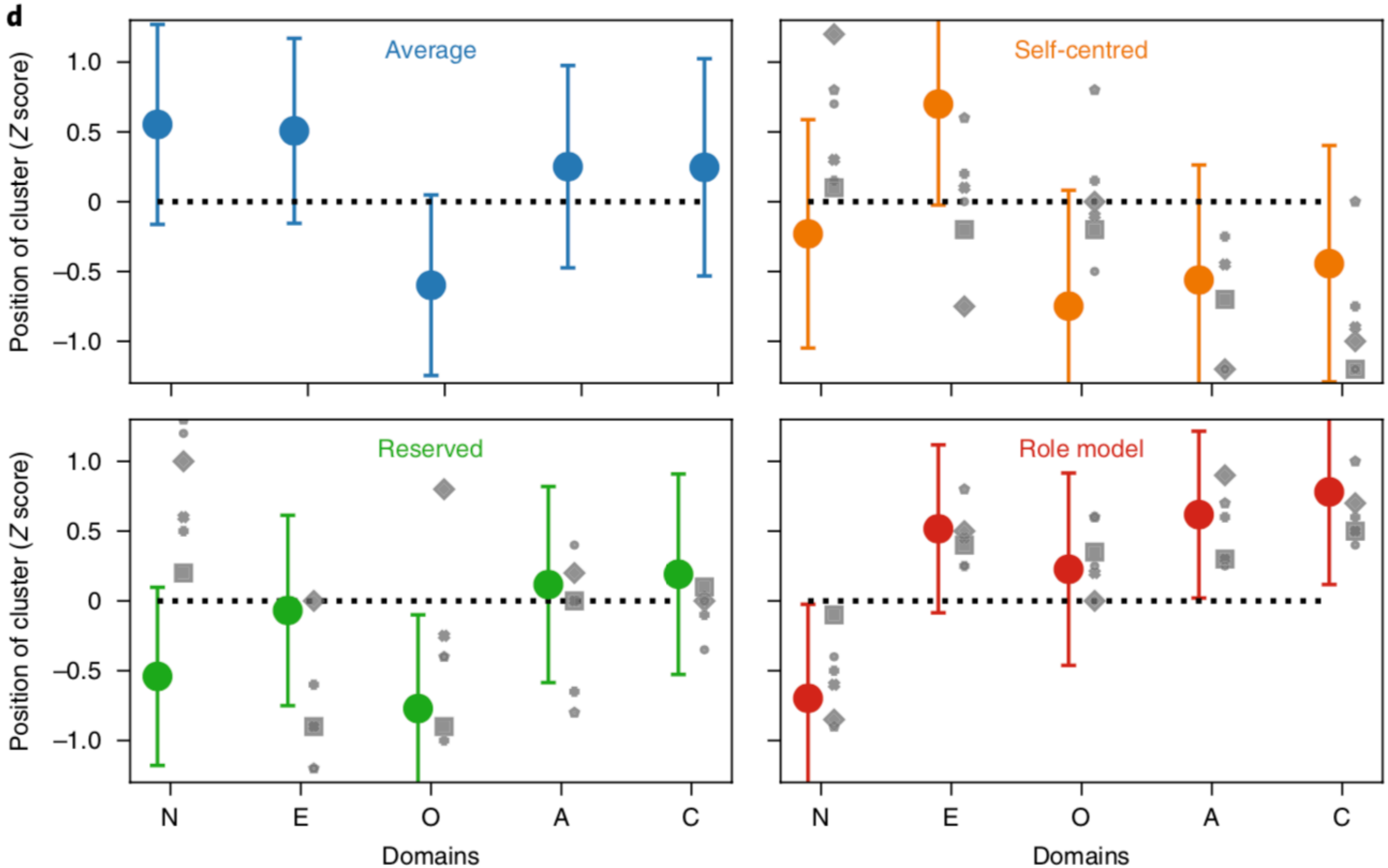
Clustering Issues

- Cluster Objects/people
  - similarities or distances?
    - what distance metric
  - can objects be reversed? (not usually)
- Cluster items (unusual, but see ICLUST)
  - items can be reversed (-happy)
  - results are similar to factor analysis
- Stopping rules for cluster
  - number of cluster problem



g. 1 | Uncertainty in the ARC-type classification. The location in the

Gerlach et al, 2018



Similarity and distance

Questions:

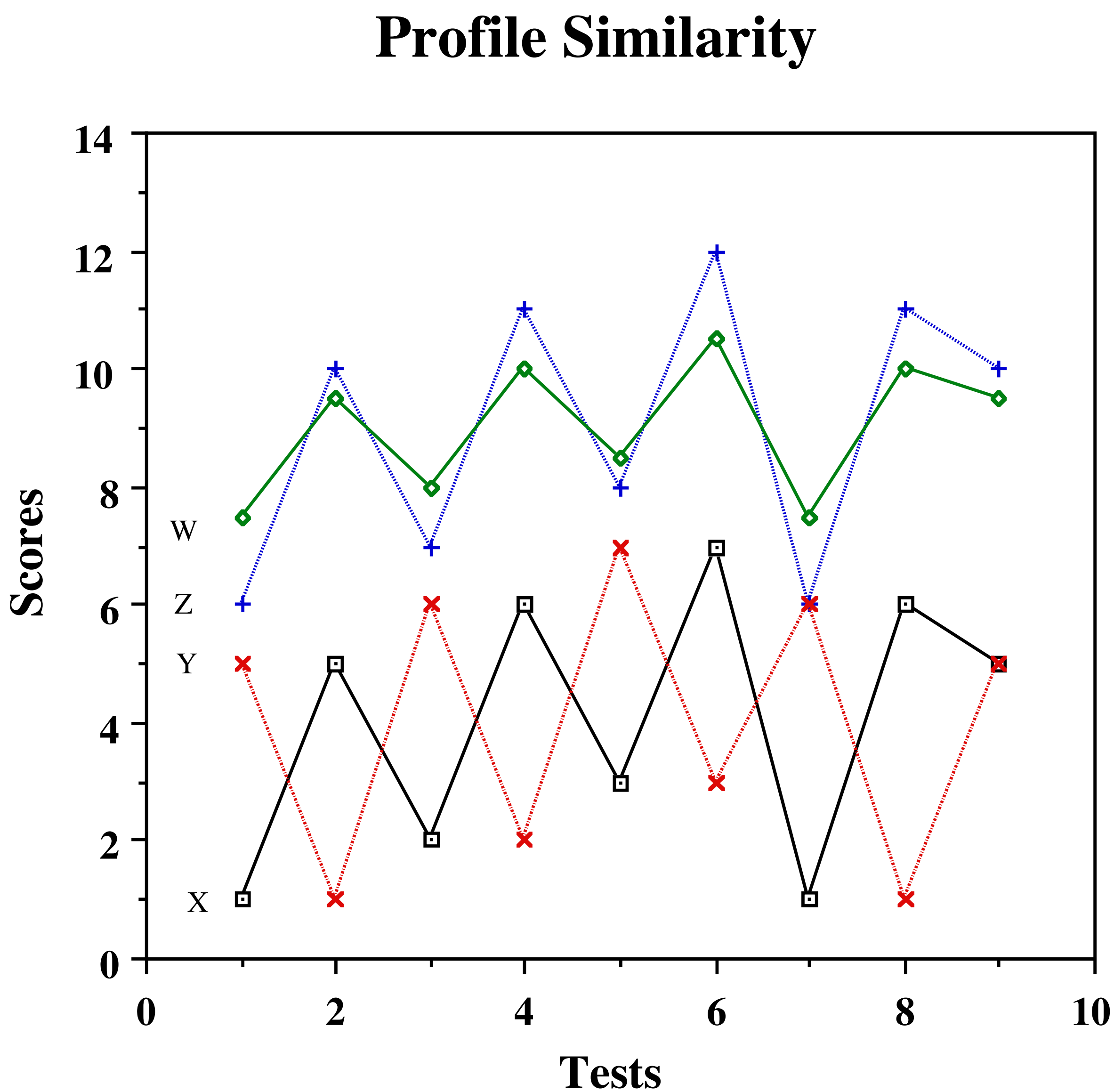
Given a set of scores on multiple tests (a subject profile), how should we measure the similarity between different profiles? What does it mean to have a similar profile?

What metric to use?

Minkowski Distances = $\sqrt[r]{\sum (X_i - Y_i)^r}$

r=1 city block metric ==> all distances equally important (no diagonals)
r=2 Euclidean metric ==> diagonals are shorter than sums
r>2 non-Euclidean ==> emphasizes biggest differences
r=∞ non-Euclidean ==> distance = biggest difference

Measuring similarity



Consider different metrics

A						B
	C					
				D		

	X	Y
A	1	7
B	7	7
C	2	4
D	5	1

Min

	A	B	C	D
A				
B	0			
C	1	3		
D	4	2	3	

Euclidean

	A	B	C	D
A				
B	6			
C	3.2	5.8		
D	7.2	6.3	4.2	

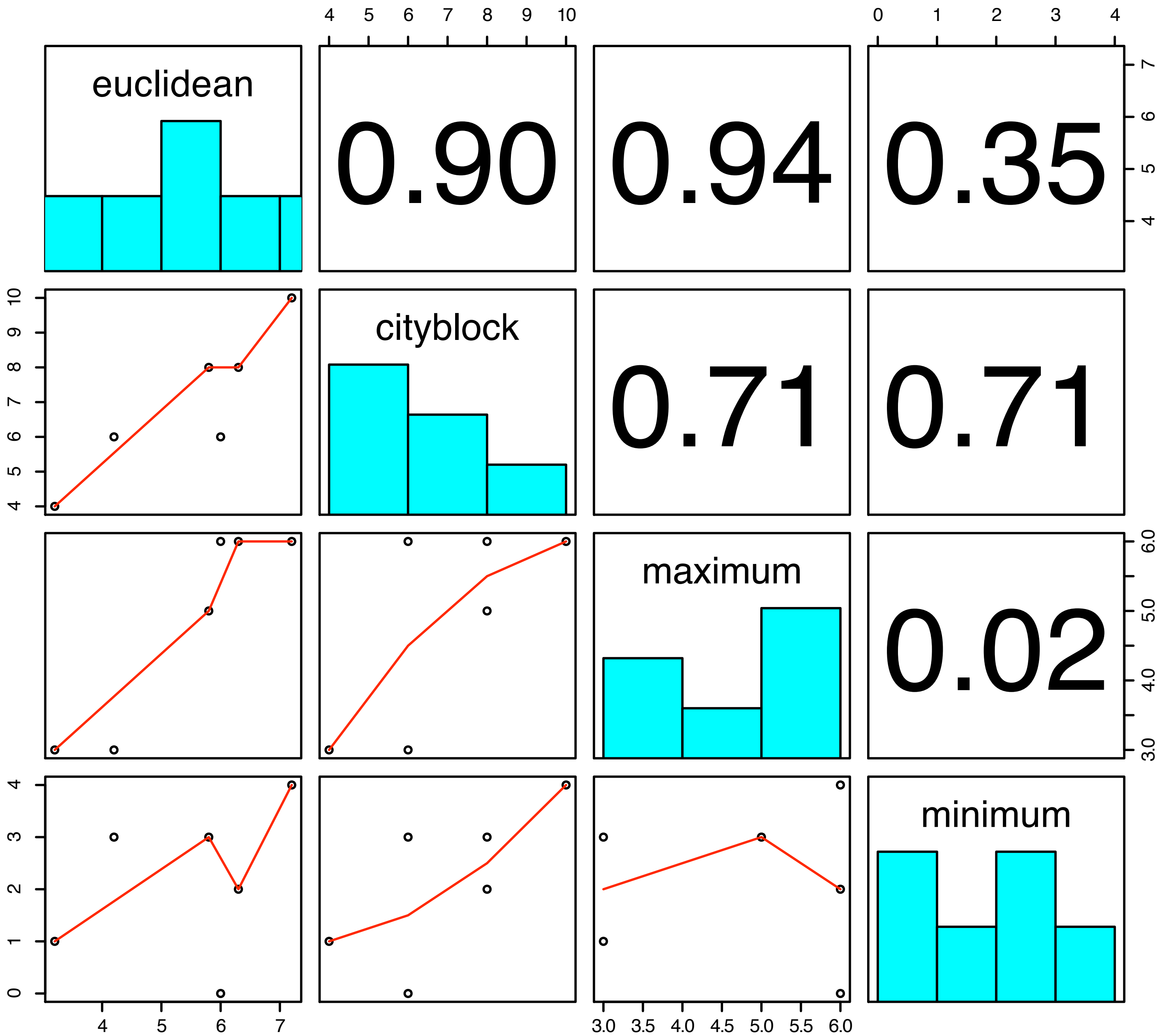
City block

	A	B	C	D
A				
B	6			
C	4	8		
D	10	8	6	

Max

	A	B	C	D
A				
B	6			
C	3	5		
D	6	6	3	

A comparison of metrics



Similarity and correlation

$$D = \sqrt{\sum (X_i - Y_i)^2}$$

let M_x= mean X M_y=mean Y $L=M_x-M_y$

$x=X-M_x$ $y=Y-M_y$

$$D = \sqrt{\sum (X_i - Y_i)^2} = \sqrt{\sum \{(X_i - M_x) - (Y_i - M_y) + L\}^2}$$

$$D = \sqrt{\sum (x-y+L)^2} \implies D = \sqrt{Var_x + Var_y - 2Cov_{xy} + L^2}$$

Distance is a function of differences of Level, Scatter, and Pattern

Level ==> differences of means $L^2 = (M_x - M_y)^2$

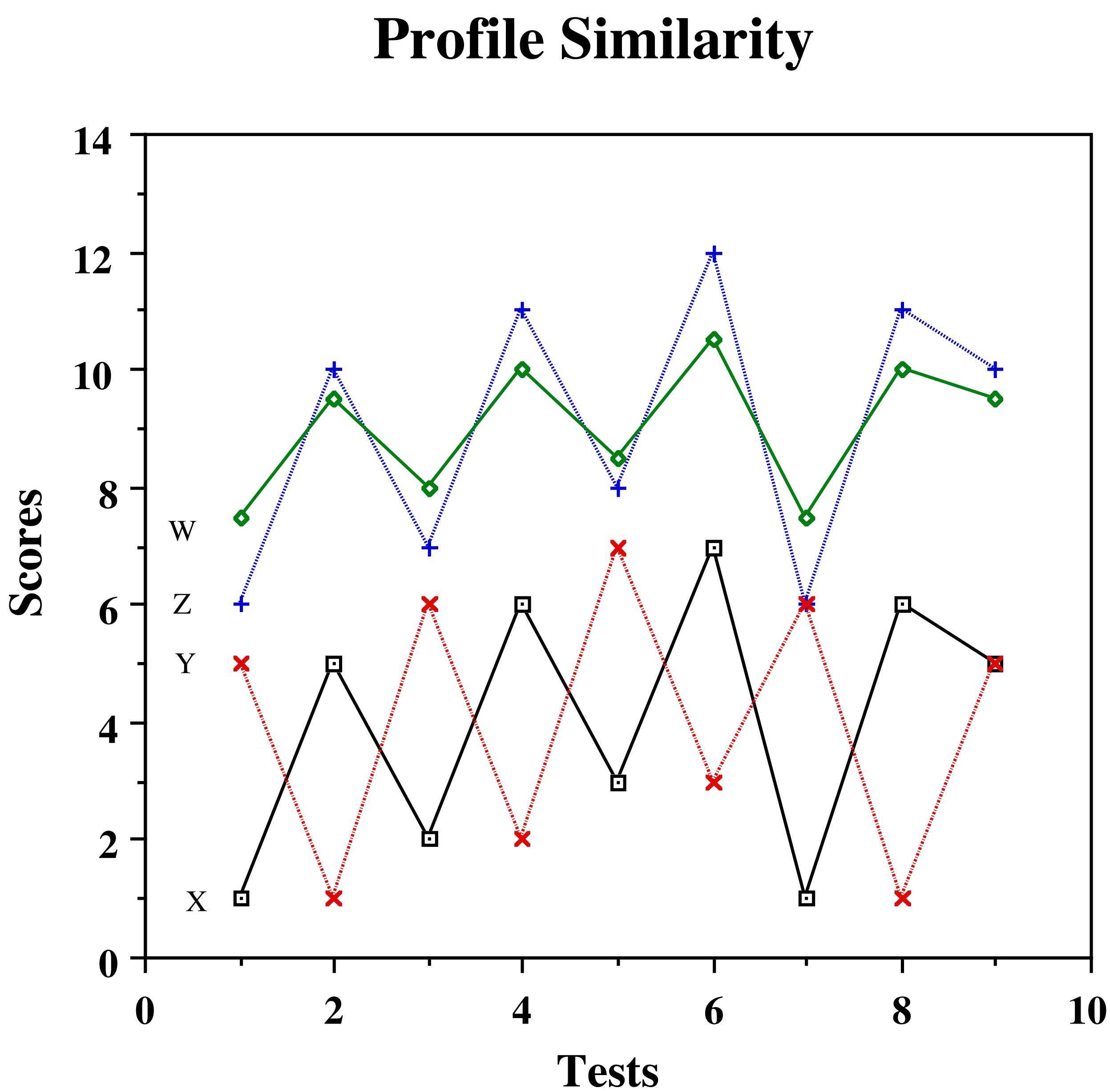
Scatter ==> Variances $Var_x + Var_y$

Pattern ==> Covariance $2Cov_{xy}$

If variables are standardized (means set to zero and variances to 1) then distance is a function of the correlation between the two profiles.

$$D^2 = 2\,(1 - r_{xy})$$

Similarity



Profile Similarity
Scores
Tests
W
Z
Y
X
0
2
4
6
8
10
12
14
0
2
4
6
8
10

City blocks vs. Euclid

MATRIX OF CITY BLOCK DISTANCES

	X	Y	Z	W
X	0.000			
Y	3.778	0.000		
Z	5.000	5.000	0.000	
W	5.000	5.000	1.000	0.000

(W and Z are most similar, followed by X and Y)

MATRIX OF NORMALIZED EUCLIDEAN DISTANCES

	X	Y	Z	W
X	0.000			
Y	4.028	0.000		
Z	5.000	6.420	0.000	
W	5.115	5.855	1.080	0.000

(W and Z are most similar, followed by X and Y)

Covariance and Correlation

COVARIANCE MATRIX

	X	Y	Z	W
X	5.250			
Y	-3.875	5.250		
Z	5.250	-3.875	5.250	
W	2.625	-1.938	2.625	1.313

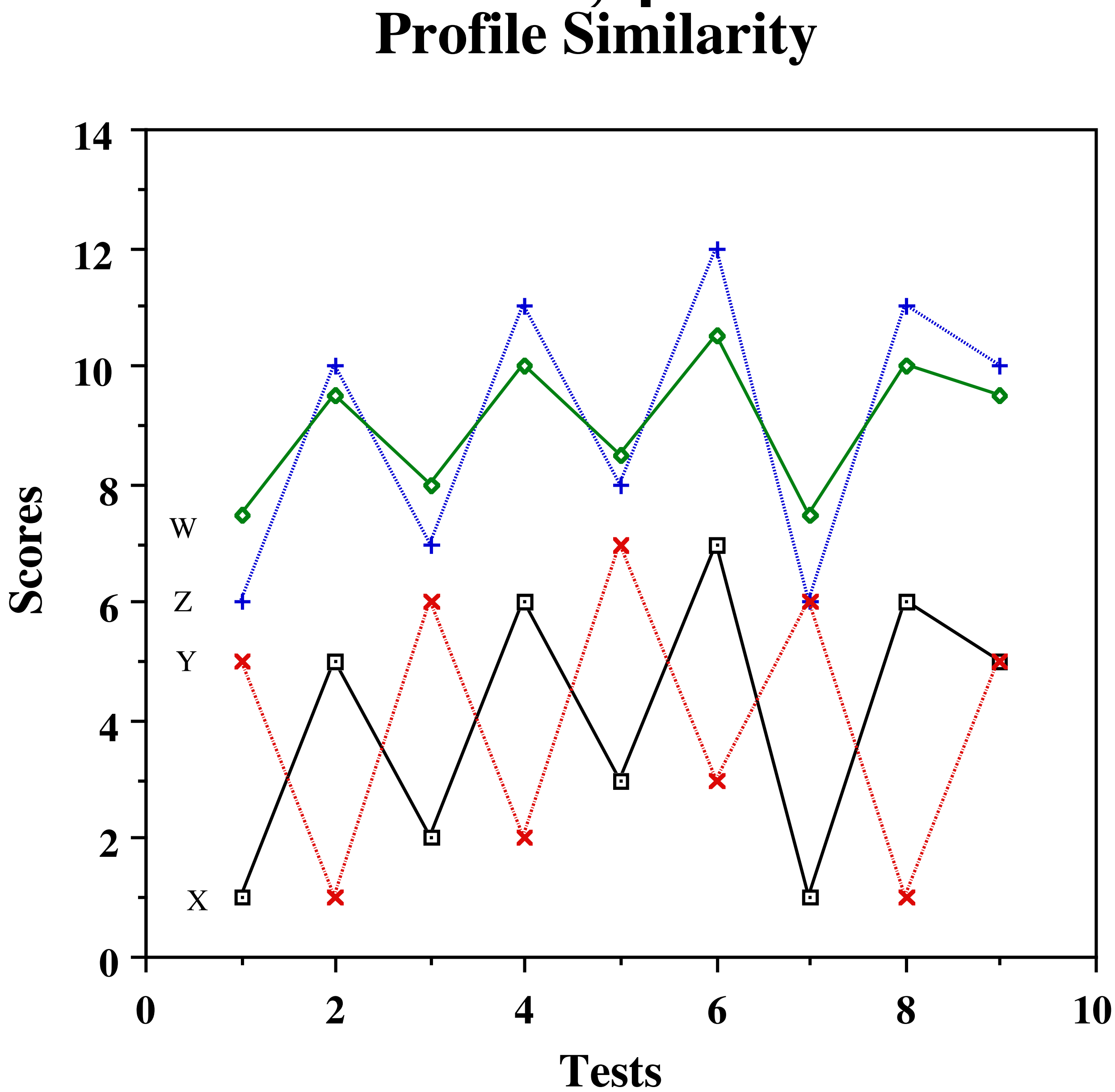
(X and W are most similar, X is negatively related to Y)

PEARSON CORRELATION MATRIX

	X	Y	Z	W
X	1.000			
Y	-0.738	1.000		
Z	1.000	-0.738	1.000	
W	1.000	-0.738	1.000	1.000

(X is identical to W and Z, negatively related to Y)

Similarity of Profiles: Level, scatter, pattern



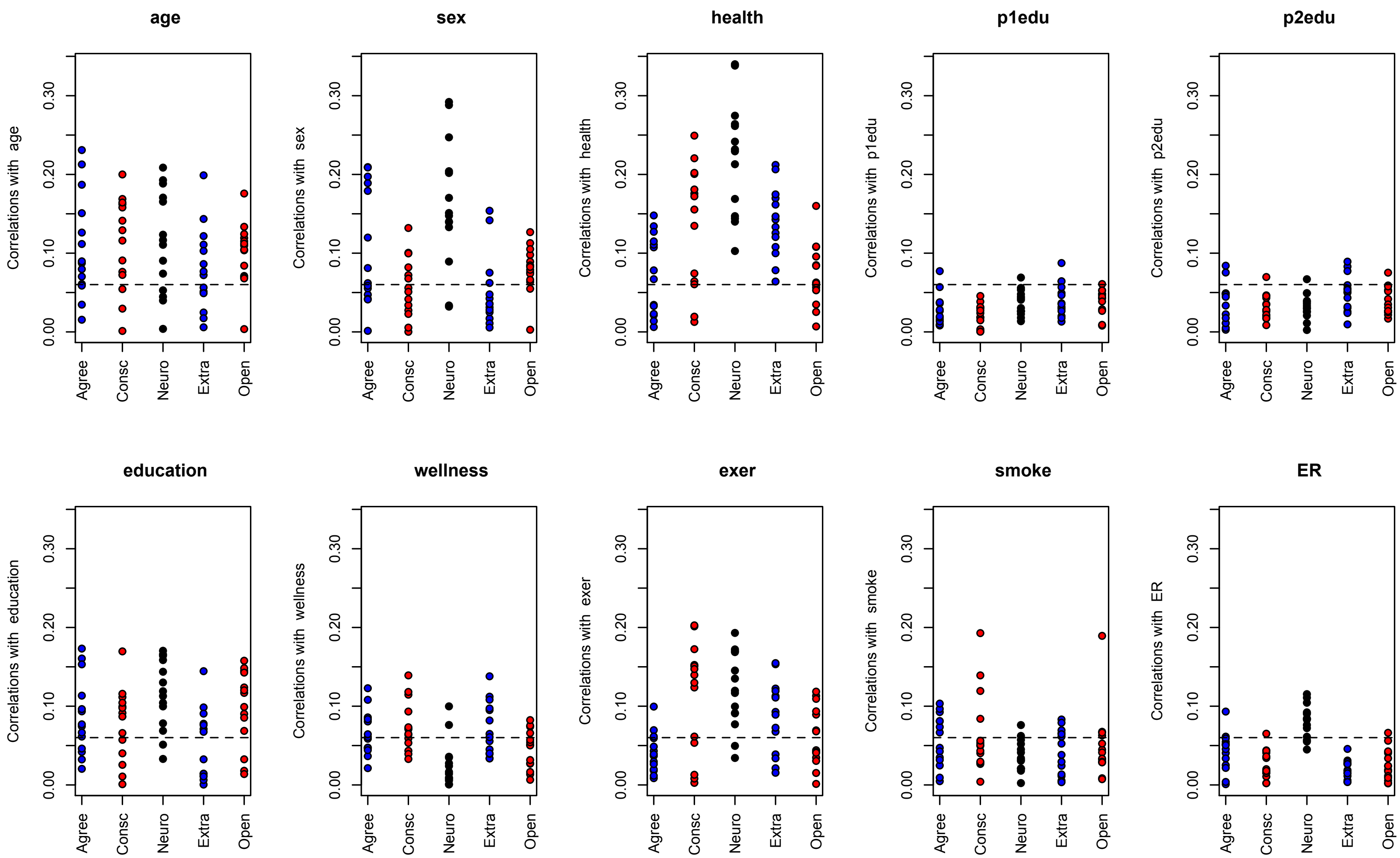
How useful are items?

1. Common observation is that items have low correlations with other items.
2. From a classical reliability perspective: Item variance = general + group + specific + error.
3. The “gospel” is that items are mainly error variance.
4. This is true from a latent variable perspective, but less true if we actually examine item variance.
5. Perhaps 20% of an item is general factor variance, another 10-20% group variance but about 40% is specific and reliable variance.
6. We can see this by doing a variance decomposition of items that are repeated across time.
7. So what?
8. Lets look at the correlates of items.

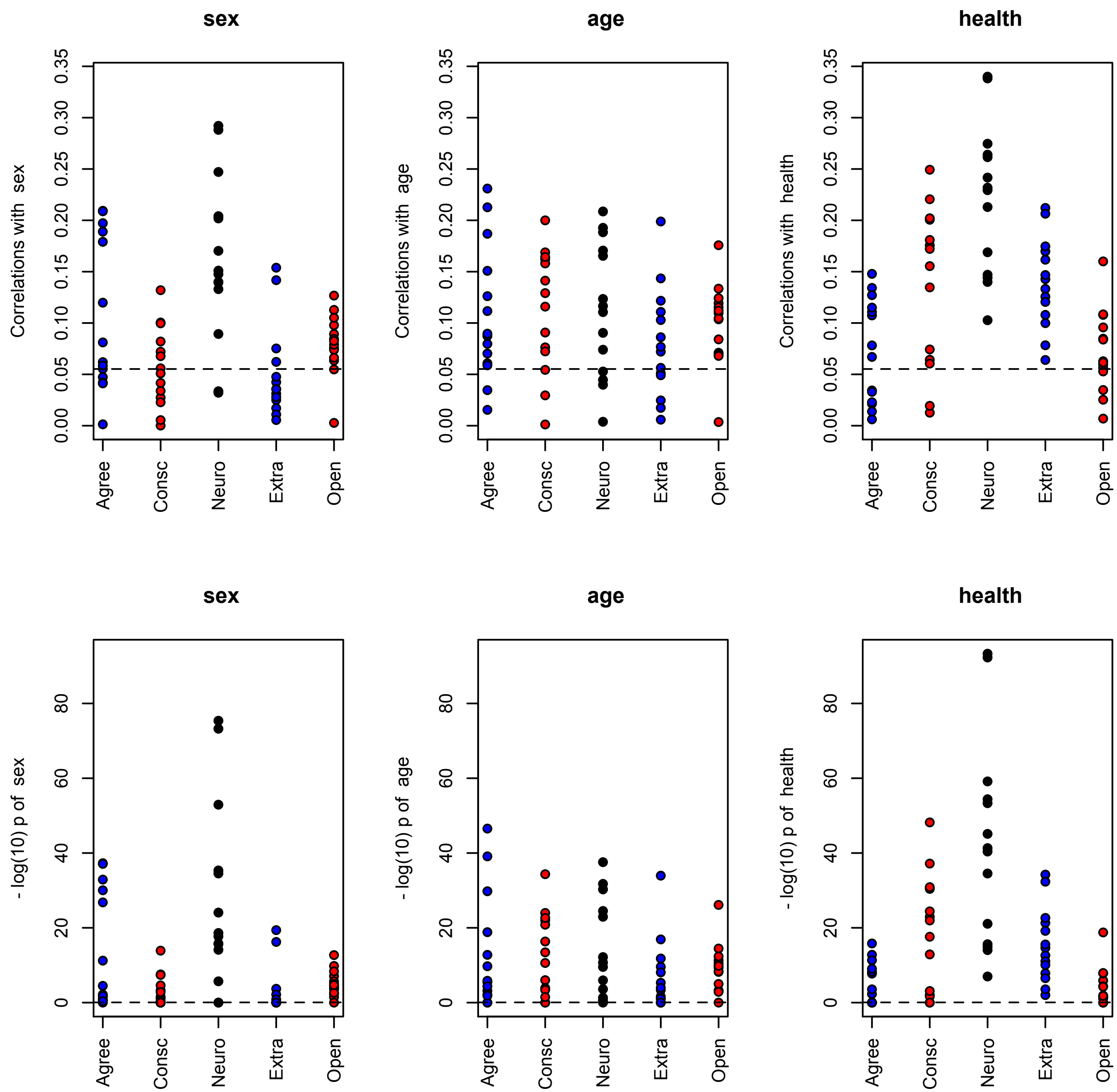
Items as analogous to SNPs in GWAS studies

1. In Genome Wide Association Studies one examines phenotypic variation as it correlates with differences in SNP frequencies across the genome.
2. Do the same by examining phenotypic variation and correlation across the persome (Möttus, Sinick, A.Terracciano, Hřebíckova, Kandler & Jang, 2018)
3. A typical approach is to show the correlations and their probability values (corrected for multiple tests)
   - Typically displayed in “Manhattan Plots” across the genome. We do this across the “Persome”.
4. First show plots for an open source data set (spi) available in the *psych* package.
   - This is a set of 135 temperament items with 10 criteria for 4,000 subjects.
5. Then do the same for items from the Big 5, then an extend set (the little 27), then for a bigger data set with even more items.

A “Manhattan plot” of the spi items on the big 5 for 10 criteria



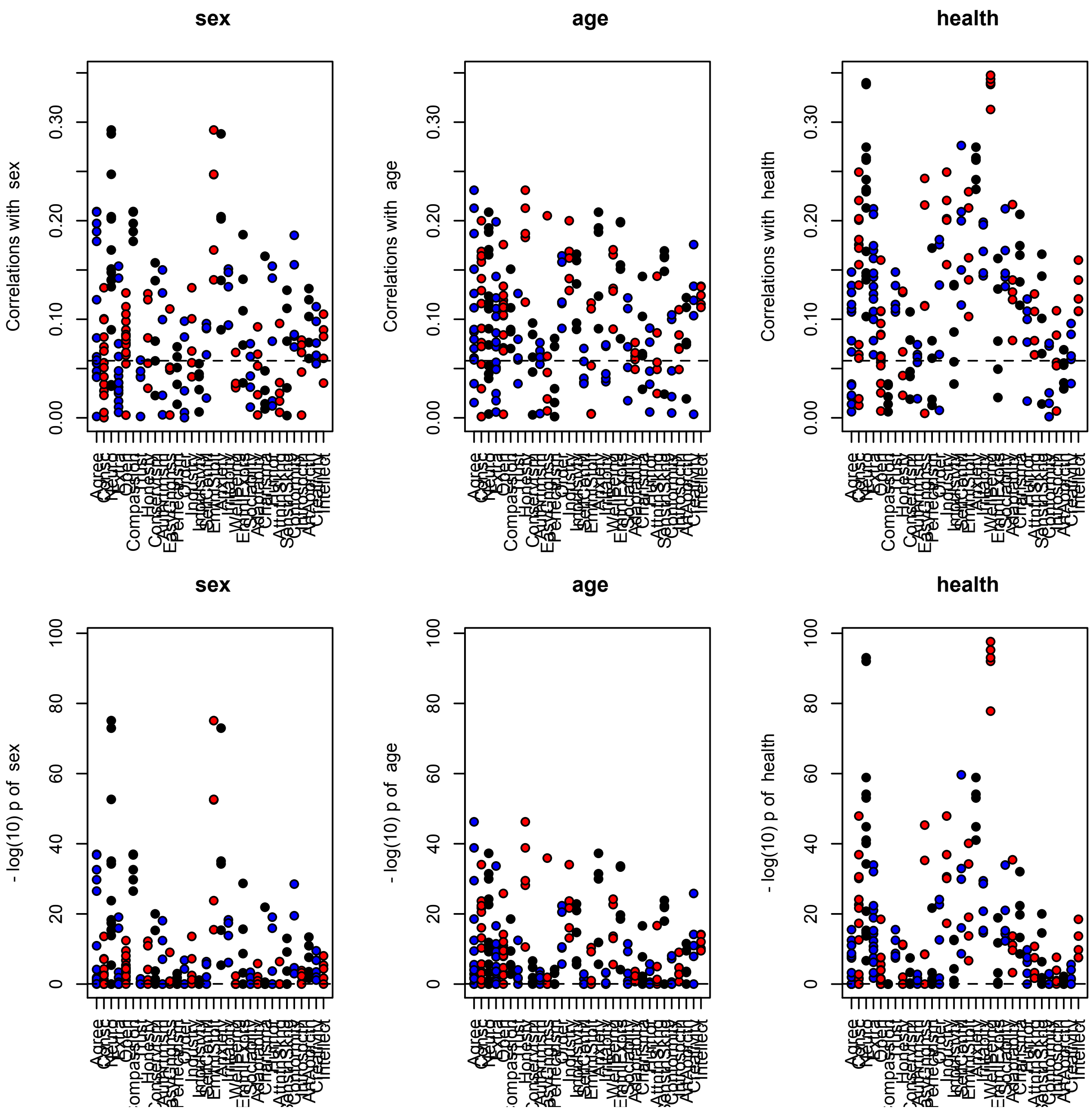
A "Manhattan plot" of the spi items for 3 criteria big 5



Correlations (absolute values)

Log p values (Holm corrected for multiple tests)

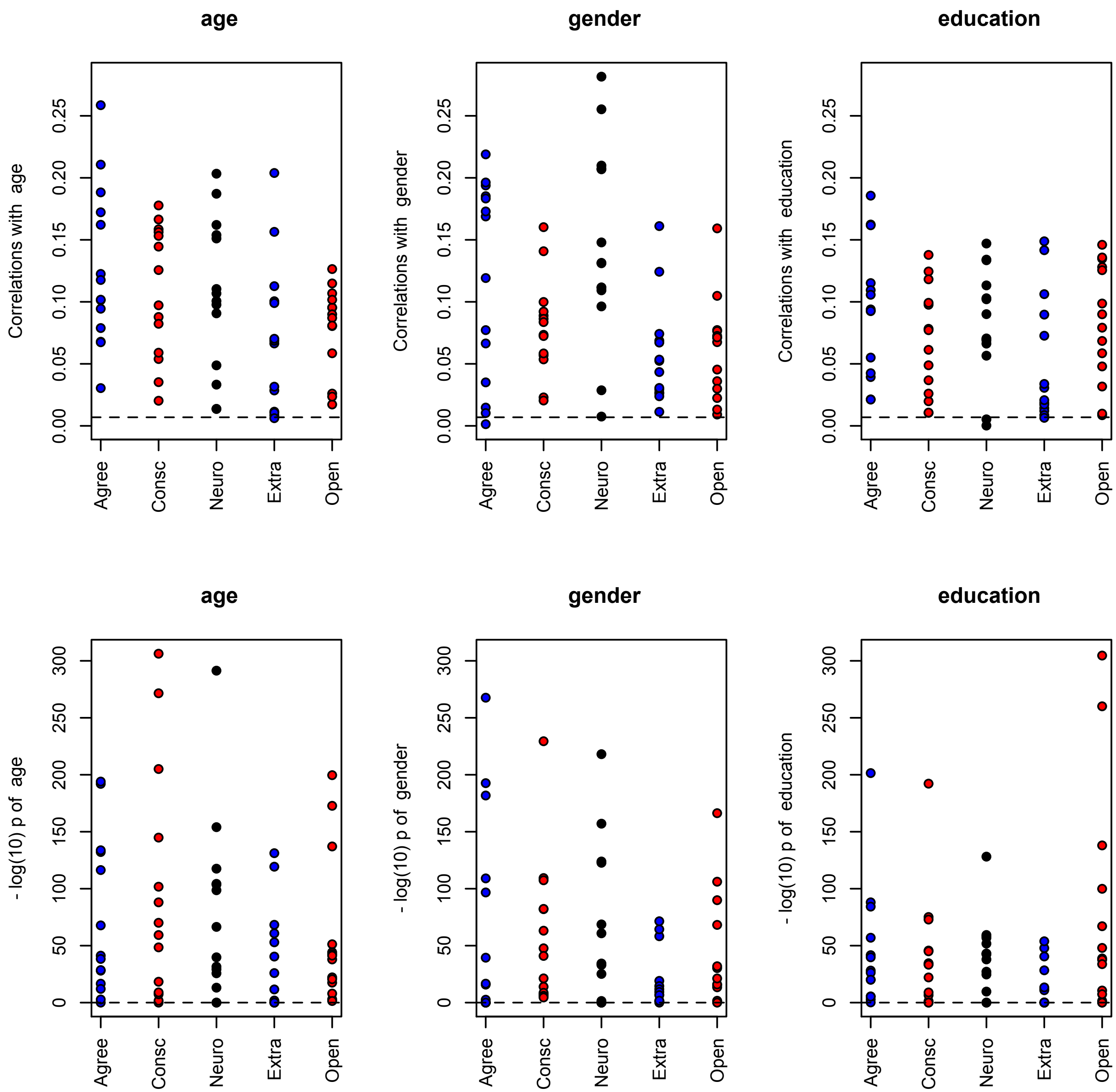
More predictors: 3 criteria big 5 + spi 27, N =4000



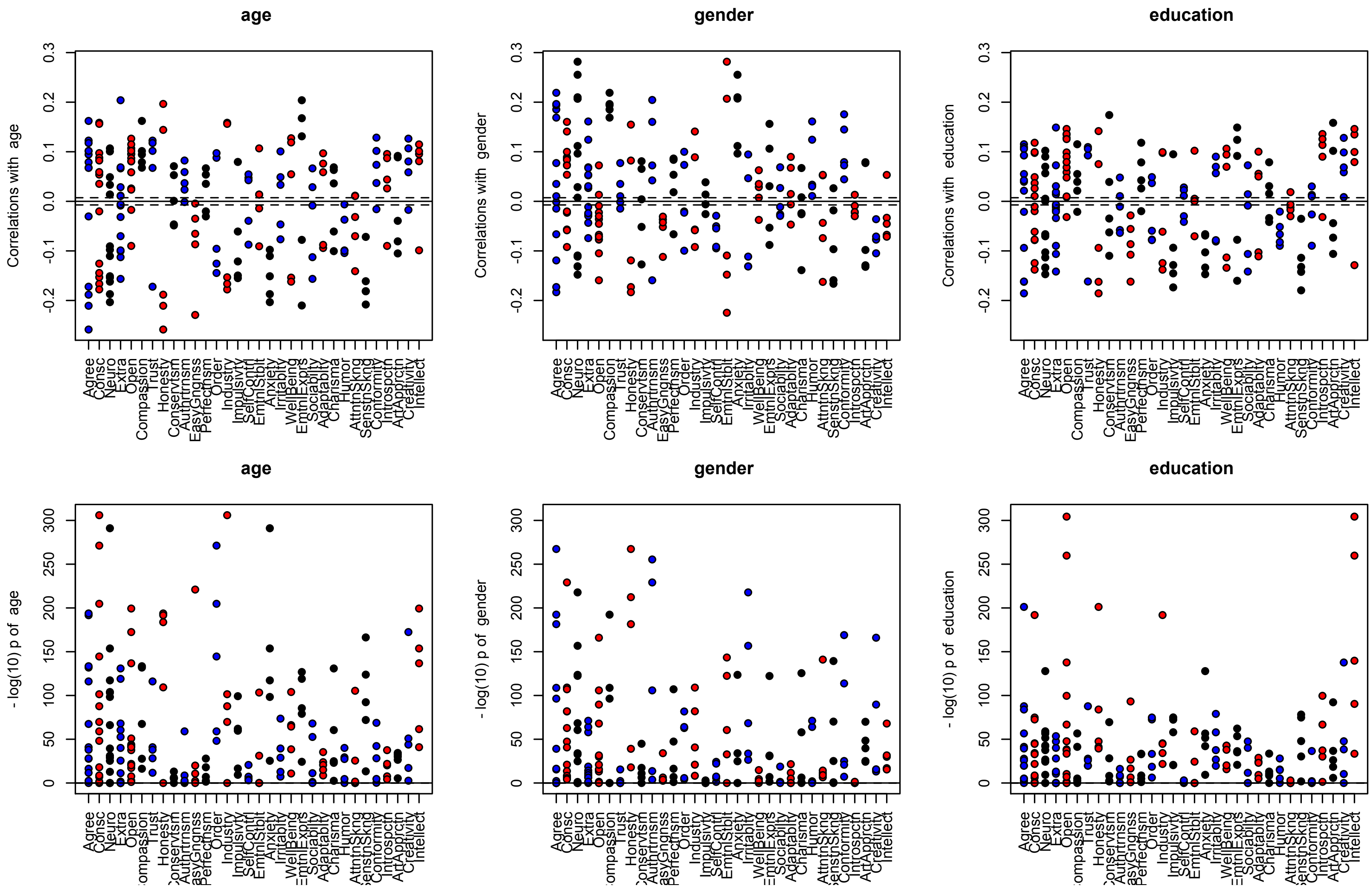
Correlations (absolute values)

Log p values (Holm corrected for multiple tests)

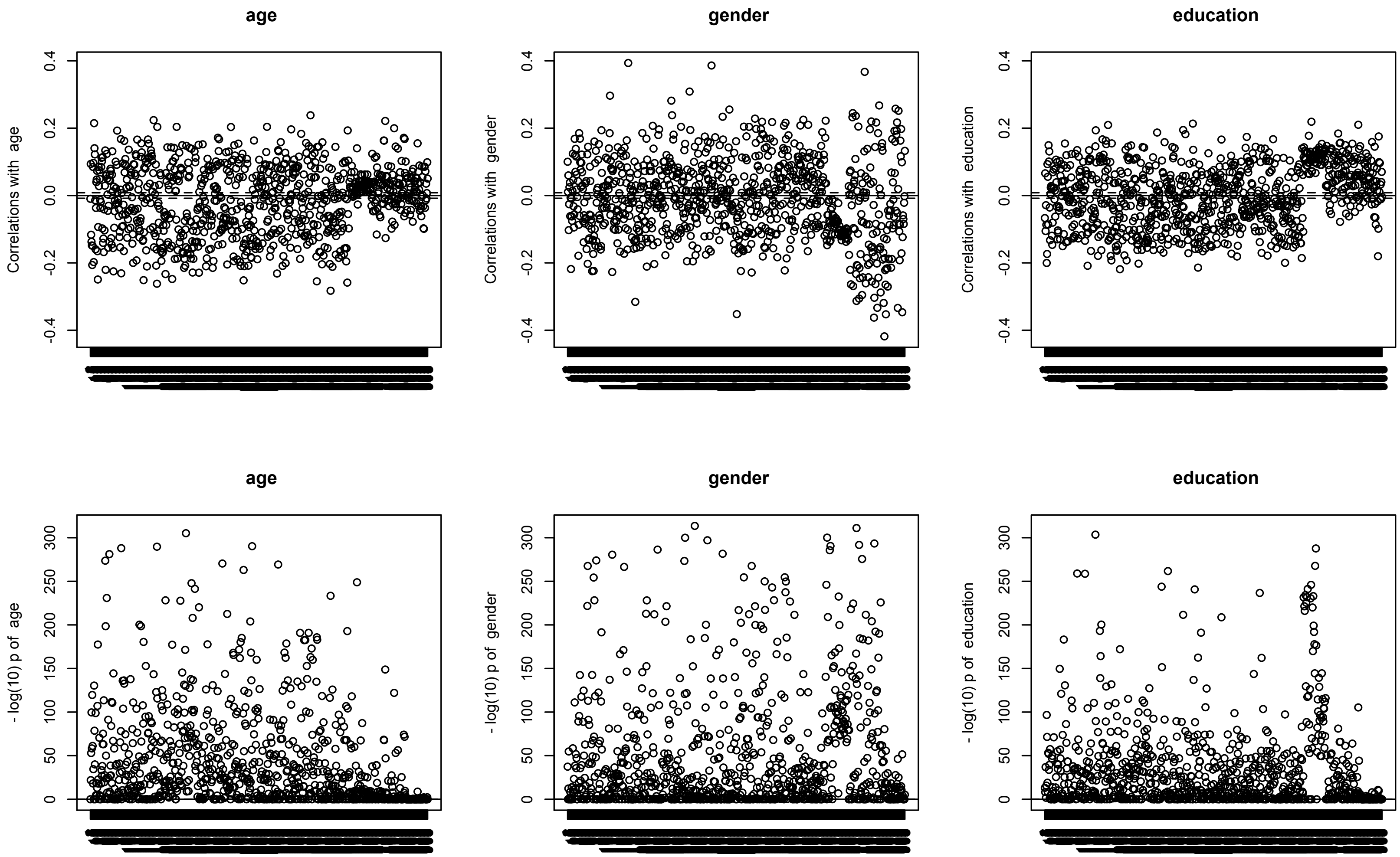
More subjects: 3 criteria big 5, N = 255,000



More subjects: 3 criteria - Big 5 + little 27 items, N = 255,000



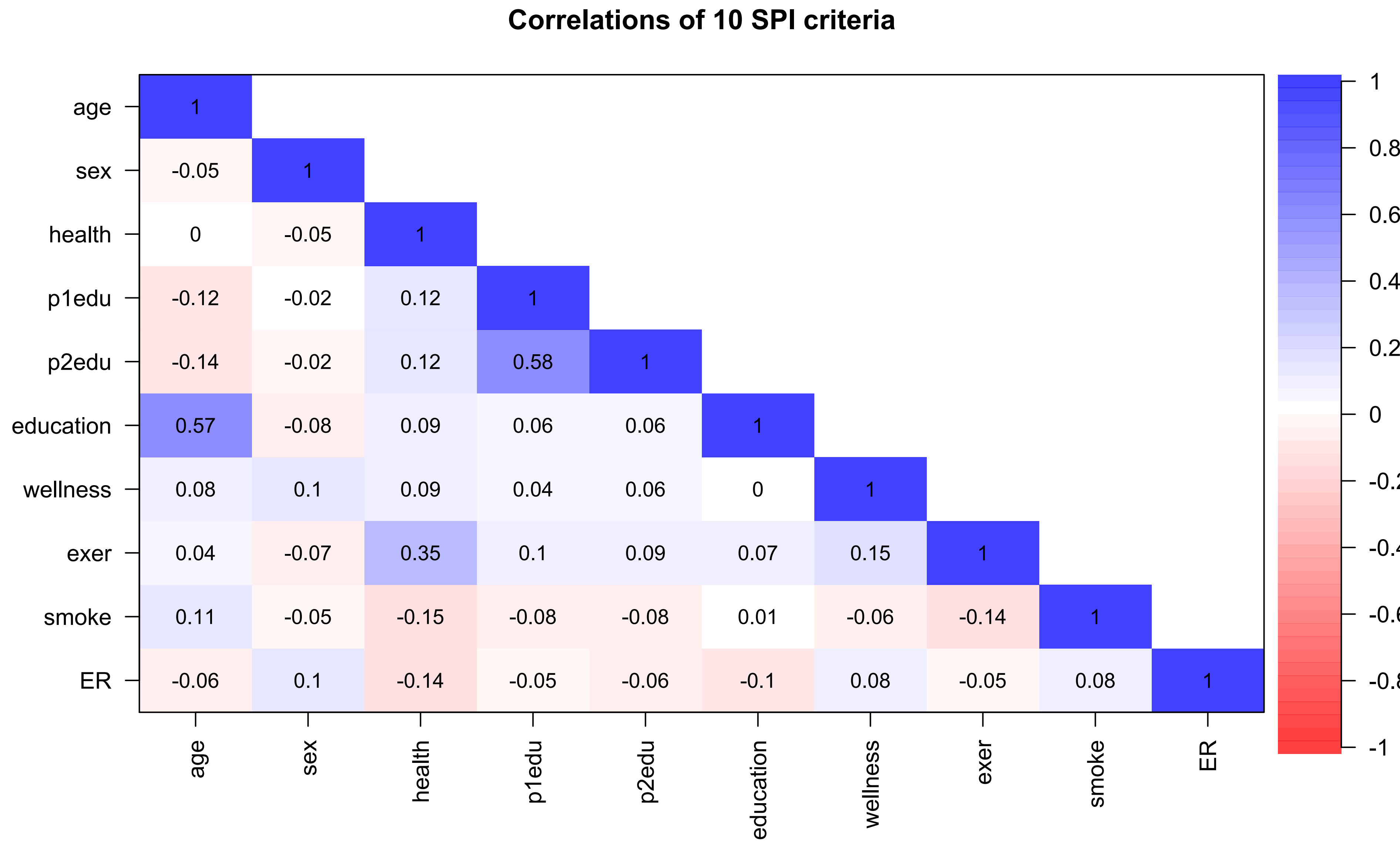
More subjects: 3 criteria - 904 items (temperament, abilities, interests)



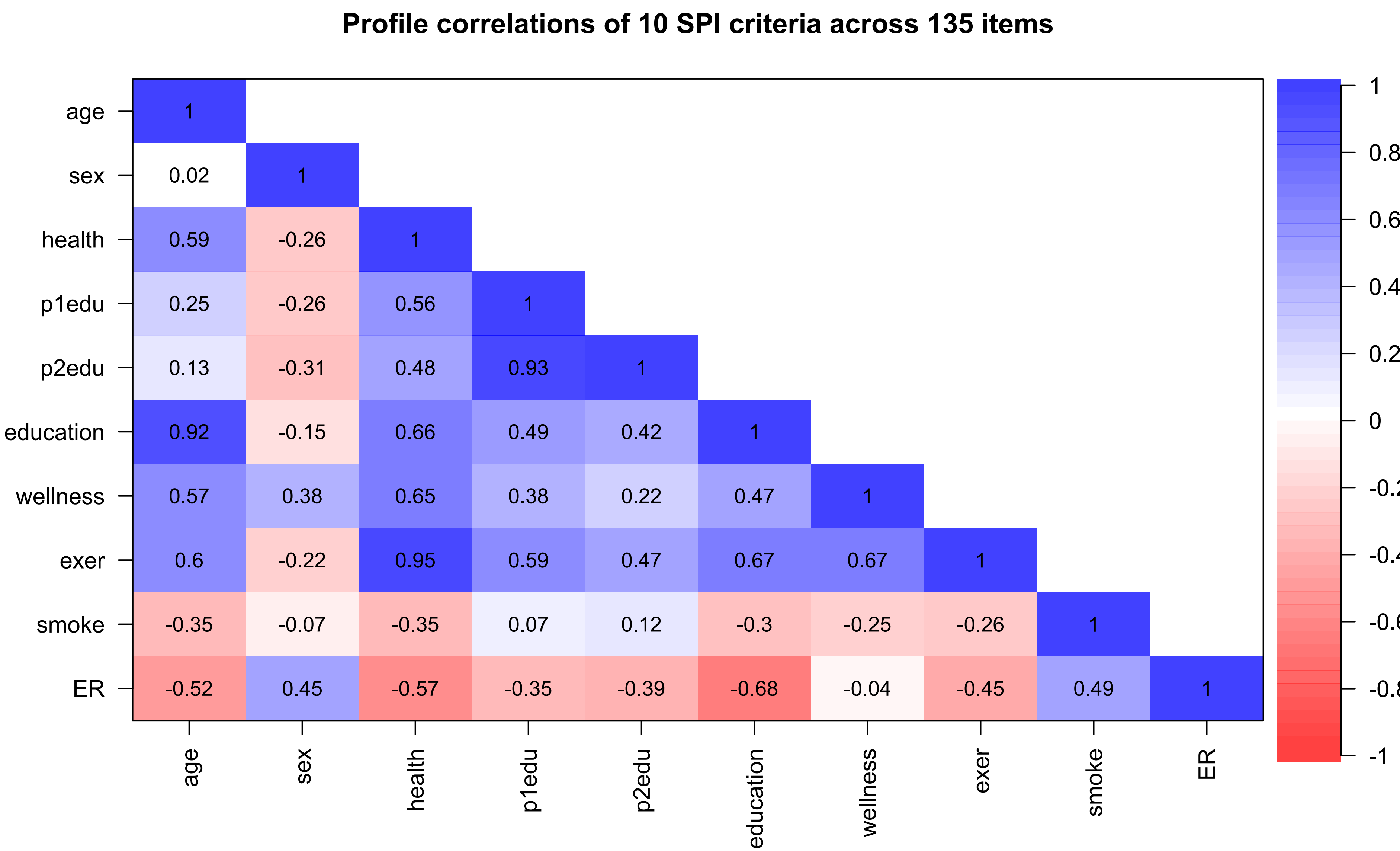
Profile correlations are analogous to the "genetic correlation"

1. For any set of criteria or grouping variables we can find a vector of validity correlations across our predictor set.
2. We can then correlate these vectors. This is analogous to the genetic correlation across SNPs.
3. Basically, we are correlating the profiles of the Manhattan plots
4. I show this using the 10 criteria in the `spi` data set
5. First the raw correlations, then the profile correlations

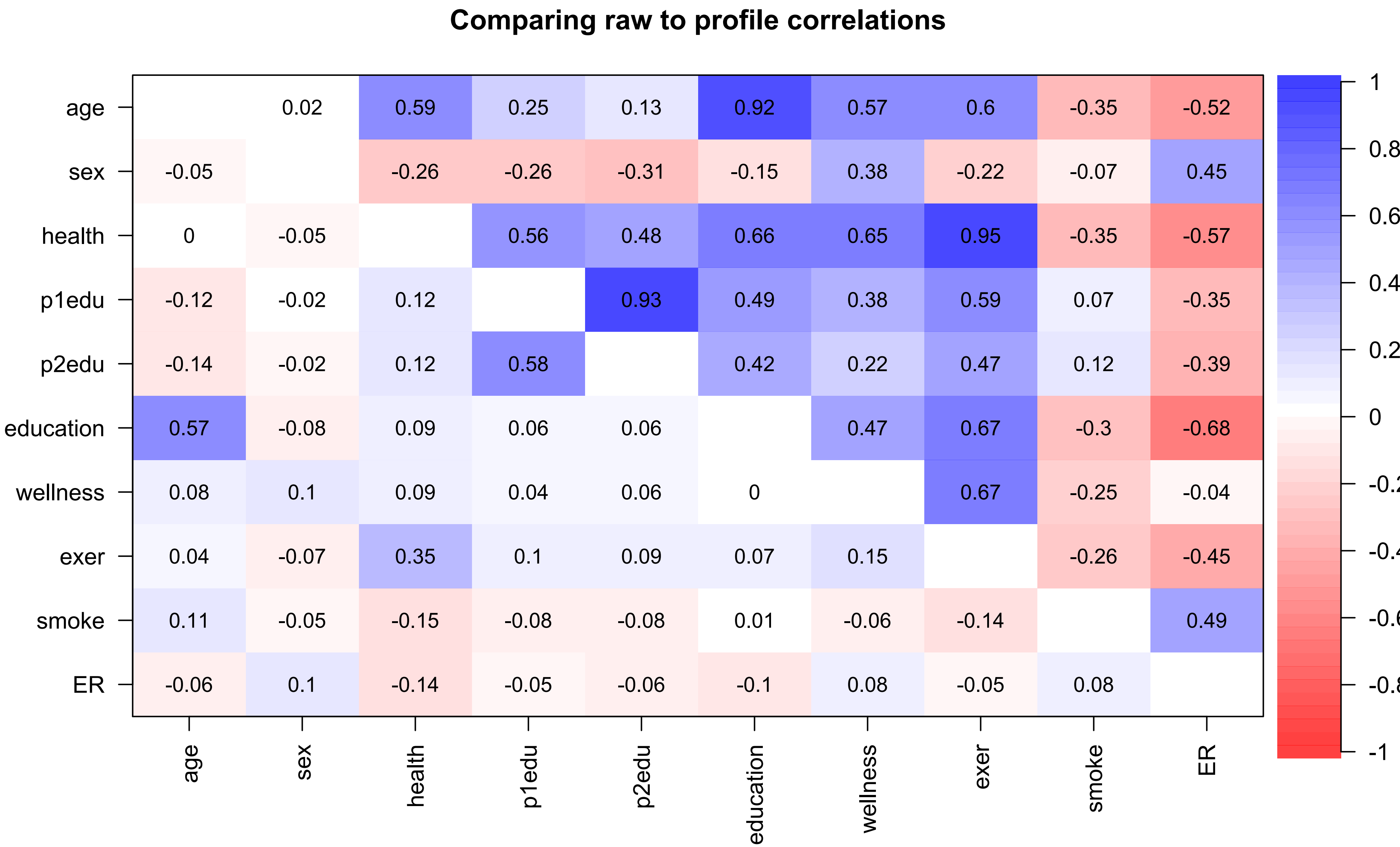
10 criteria from the SPI data set, raw correlations



10 criteria from the SPI data set, profile correlations



Comparing raw and profile correlations from the SPI dataset



Sources of Data

Self Report

- Direct subjective
  - empirical scales: MMPI/Strong-Campbell
  - factorial scales: EPI/16PF/NEOPI-R
  - rational scales: PRF
- Indirect/projective (access to subconscious?)
  - TAT
  - Rorschach
- Indirect/objective
  - Cattell objective test battery
  - Implicit Attitudes Test (RT measures)
  - Emotional “Stroop”
- Indirect/other
  - a) Kelly Construct Repetory Grid
  - a) Carroll INDSCAL

George Kelly and the theory of Personal Constructs

- Man as scientist:
  - "each man contemplates in his own personal way the stream of events upon which he finds himself so swiftly borne"
  - "Man looks at his world through transparent patterns or templates which he creates and then attempts to fit over the realities of which the world is composed. The fit is not always very good. Yet without such patterns the world appears to be such an undifferentiated homogeneity that man is unable to make any sense out of it. Even a poor fit is more helpful to him than nothing at all.

George Kelly and the theory of Personal Constructs

- Fundamental postulate:
  - "A person's processes are psychological channelized by the ways in which he anticipates events."
- Measurement:
  - The role construct repertory test (REP test).
- Analysis:
  - What are the fundamental constructs with which one views the world? This can be the entire set of constructs elicited by the REP test, or some clustering or grouping of these constructs.

Kelly Rep Test

self	O		O				
lover	O						
mother		O					
father				O			
sib	O						
teacher			O				
Best friend		O		O			
Boss			O				
coworker		O		O			
construct							

REP test: complications

- Completely idiosyncratic. There is no concern with any fundamental dimensions. However, it is possible to apply same group space and still detect individual construct dimensions
- But consider a similar model: individuals as having unique distortions of shared space. The INDSCAL and ALSCAL algorithms are available to solve for joint and individual spaces.

Multidimensional Scaling

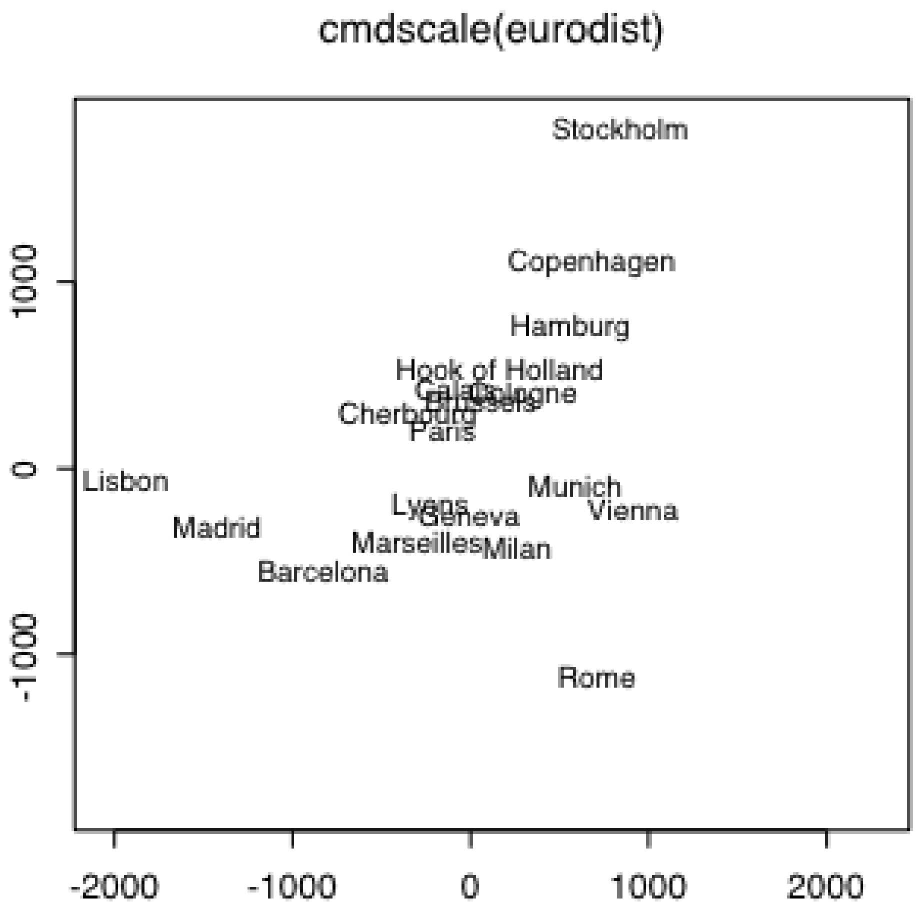
- Application of metric or non-metric scaling
- Metric scaling:
  - Find dimensional representation of observed distances (e.g., latitude and longitude)
  - Strong assumption of data and metric
- Non-metric scaling
  - Scaling to minimize a criterion insensitive to ordinal transformations

Distances between cities

	Athen	Barcelona	Brussels	Calais	Cherburg	Cologne	Copenhage	Geneva	Gilbralter	Hamburg
Barcelona	3313									
Brussels	2963	1318								
Calais	3175	1326	204							
Cherbourg	3339	1294	583	460						
Cologne	2762	1498	206	409	785					
Copenhagen	3276	2218	966	1136	1545	760				
Geneva	2610	803	677	747	853	1662	1418			
Gibralta	4485	1172	2256	2224	2047	2436	3196	1975		
Hamburg	2977	2018	597	714	1115	460	460	1118	2897	
Hook of Holkan	3030	1490	172	330	731	269	269	895	2428	550

What is the best representation of these distances in a two dimensional space?

Scaling of European Cities

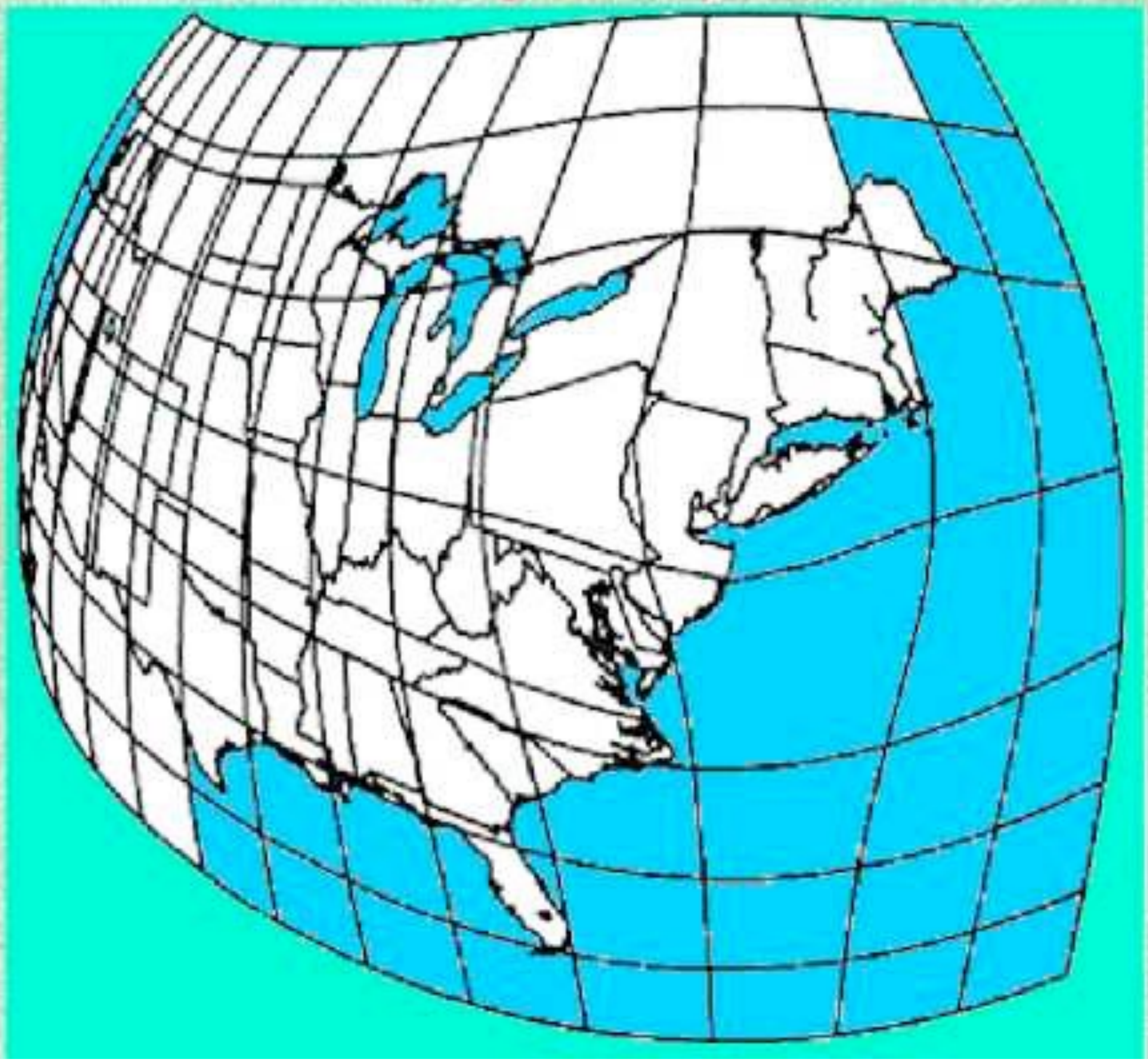


Individual Differences in MDS INDSCAL

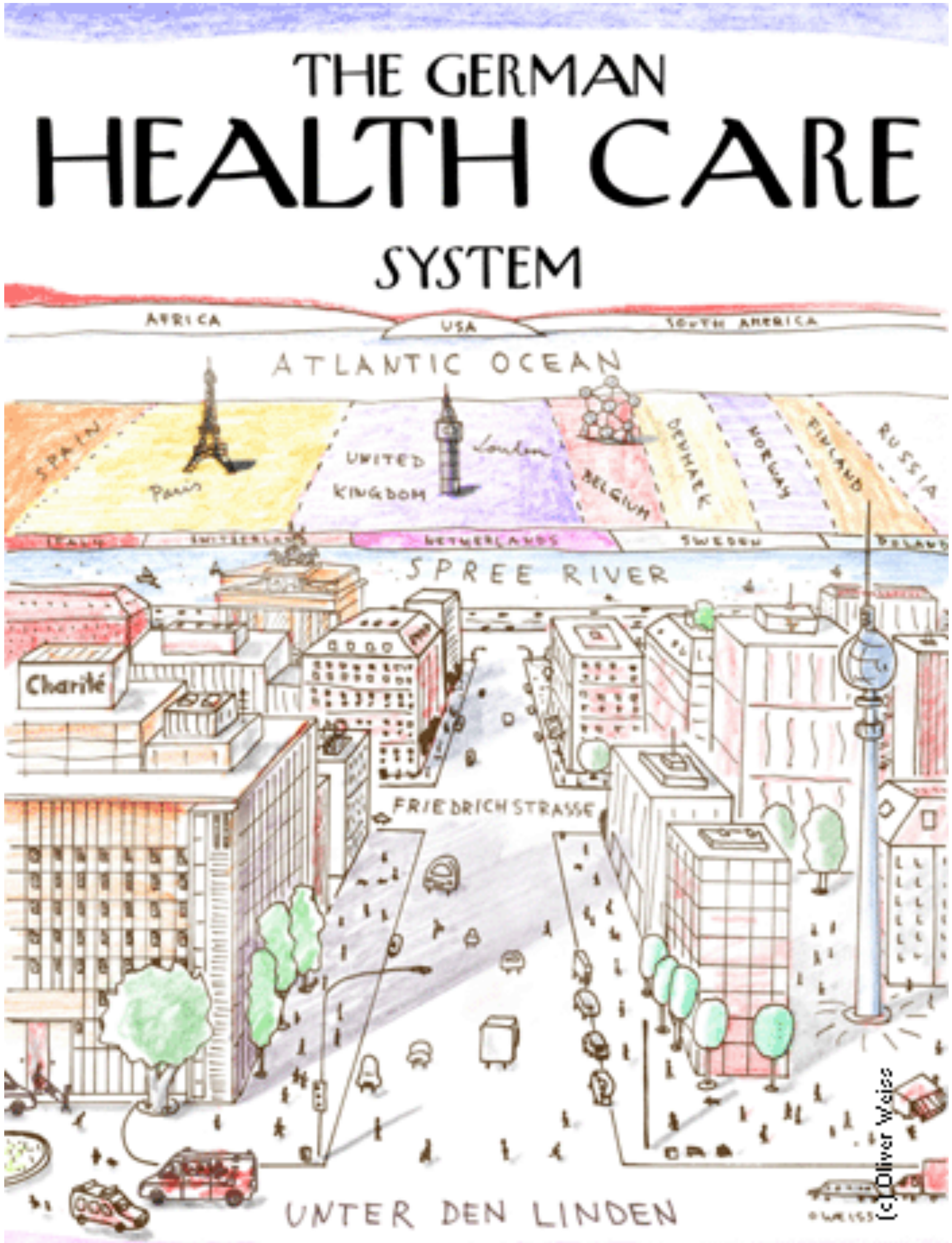
- Consider individual differences in MDS
  - Each individual applies a unique weighting to the MDS dimensions
- Solve for Group space as well as individual weights to be applied to the group space

A New Yorker's View

Square root azimuthal projection, with obvious distortion




THE NEW YORKER
HUDSON RIVER
10TH AVE
9TH AVE

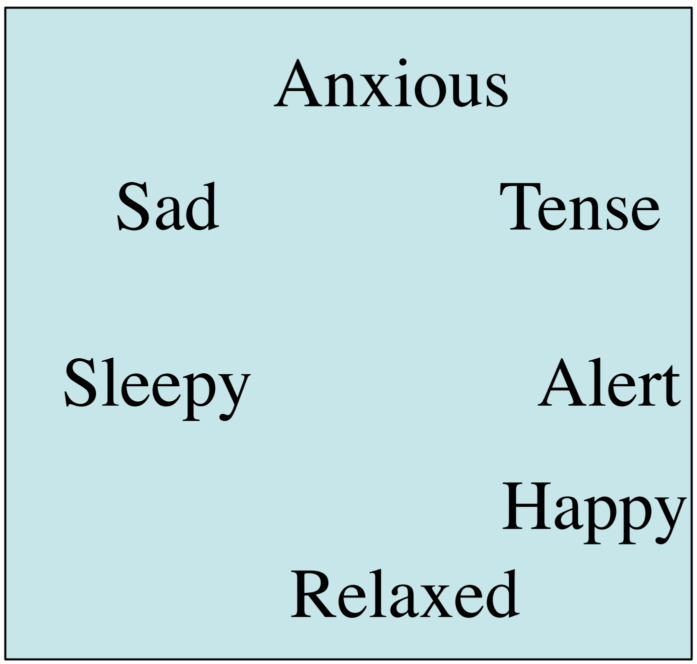

THE GERMAN
HEALTH CARE
SYSTEM
AFRICA
USA
SOUTH AMERICA
ATLANTIC OCEAN
SPAIN
Paris
UNITED KINGDOM
London
BELGIUM
DENMARK
NORWAY
FINLAND
RUSSIA
NETHERLANDS
SWEDEN
POLAND
SPREE RIVER
Charité
FRIEDRICHSTRASSE
UNTER DEN LINDEN
(c) Oliver Weiss

INDSCAL

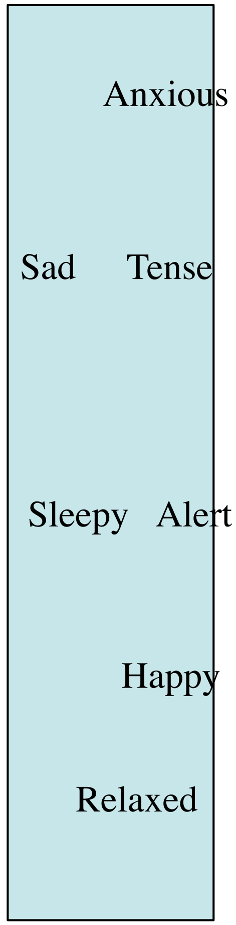
- Consider a set of points X_i with a corresponding set of distances in K dimensional space:
  - $D_{ij} = (\sum (x_{ik} - x_{jk})^2)^{.5}$ (k=1 .. K)
- Consider individuals 1 .. n who differ in the relative importance (weight) they place on the dimensions $w_{k.}$
- Then, the distances for individual_l are
  - $D_{ijl} = (\sum \{w_{lk} * (x_{ik} - x_{jk})\}^2)^{.5}$ (k=1 .. K)

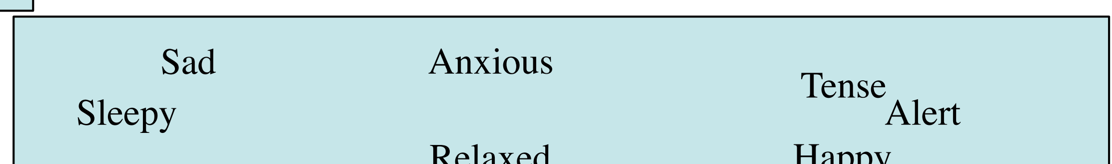
Carroll IndScal model
Individual Differences in MDS

Group Space

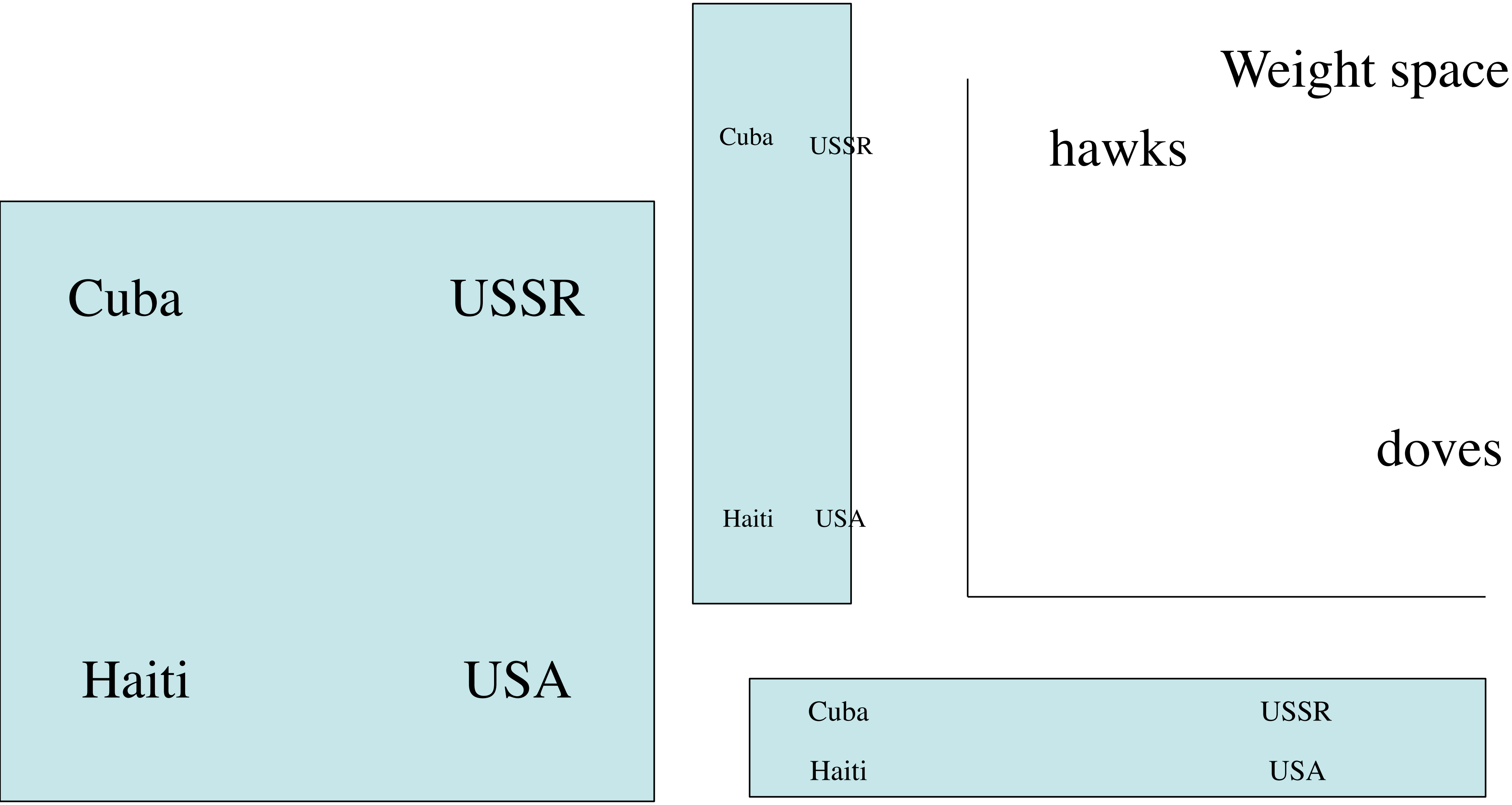


Individual Spaces as
Distortions of group space

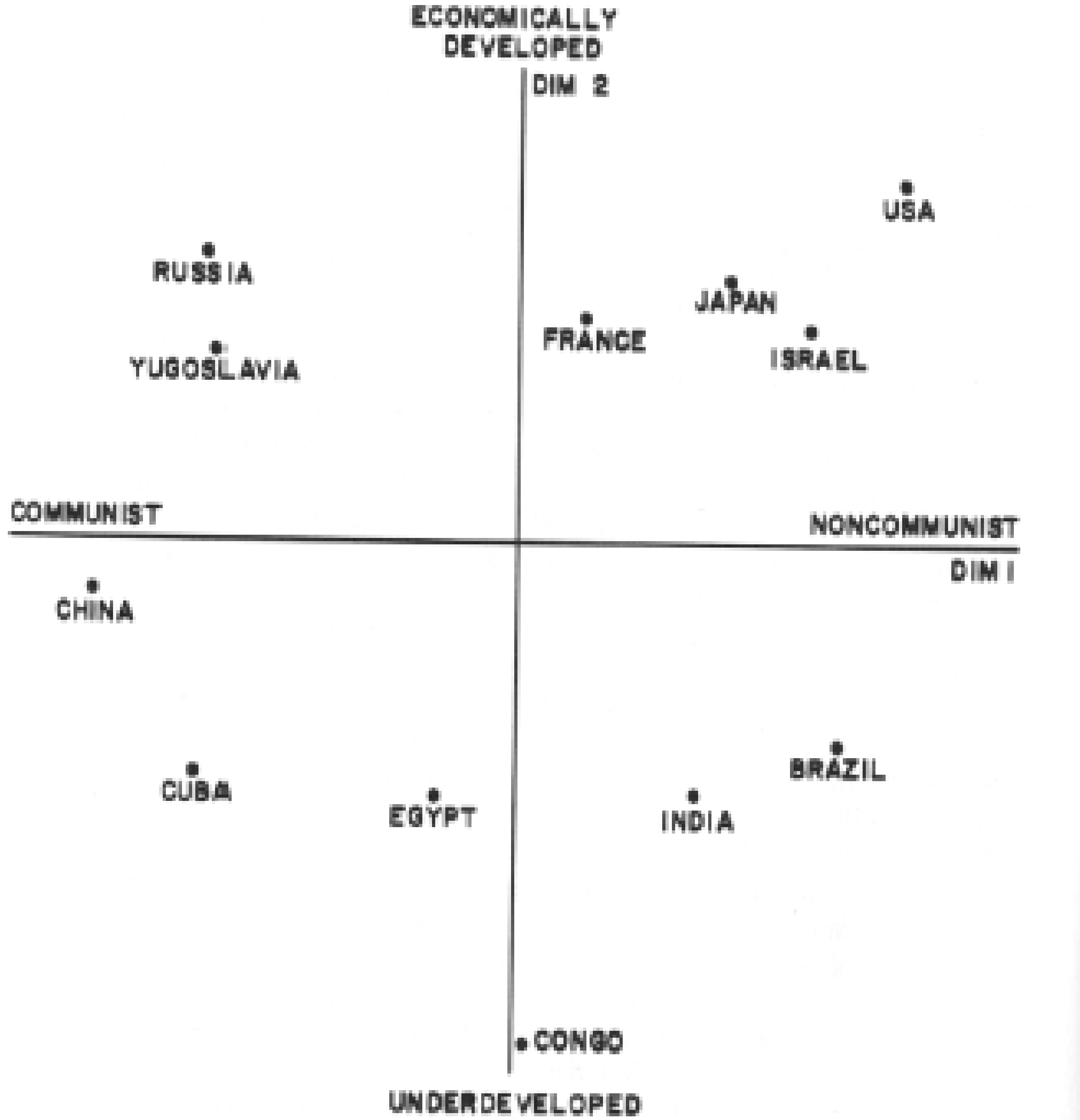




Representation of Countries and attitudes towards Vietnam



INDSCAL- Wish data of countries



from J.D. Carroll and M. Wish, 2002

Weight space - Wish data

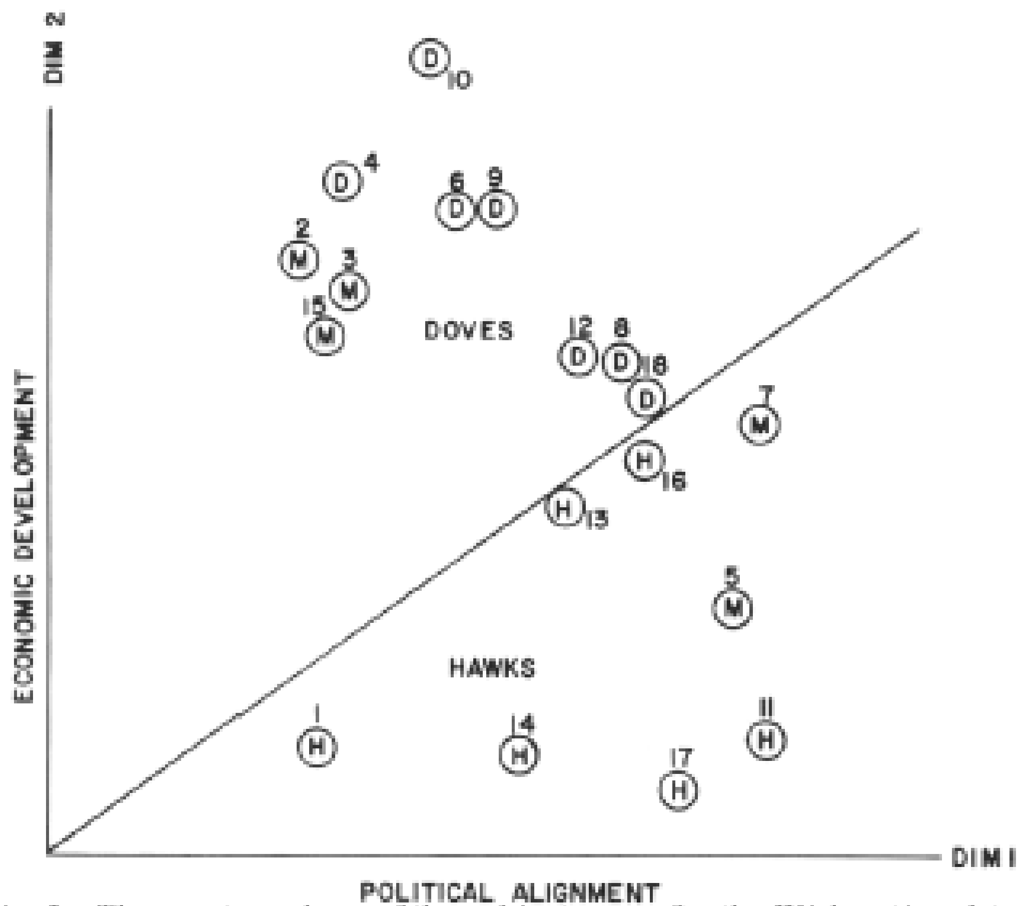


Fig. 3. The one-two plane of the subject space for the Wish nation data. *D*, *H* and M stand for "dove," "hawk," and "moderate" (as determined by subjects' self-report) vis-a-vis attitudes on Vietnam War. Forty-five-degree line divides "doves" from "hawks," with "moderates" on both sides.

Sources of Data

Structured interviews (e.g., SCID)

Other ratings

- Peer ratings
- supervisory ratings
- subordinate ratings

archival/unobtrusive measures

- unobtrusive measures
- historical record
  - GPA
  - Publications
  - Citations
  - Neuropsychological
    - a) neurometrics
    - b) "lie detection”

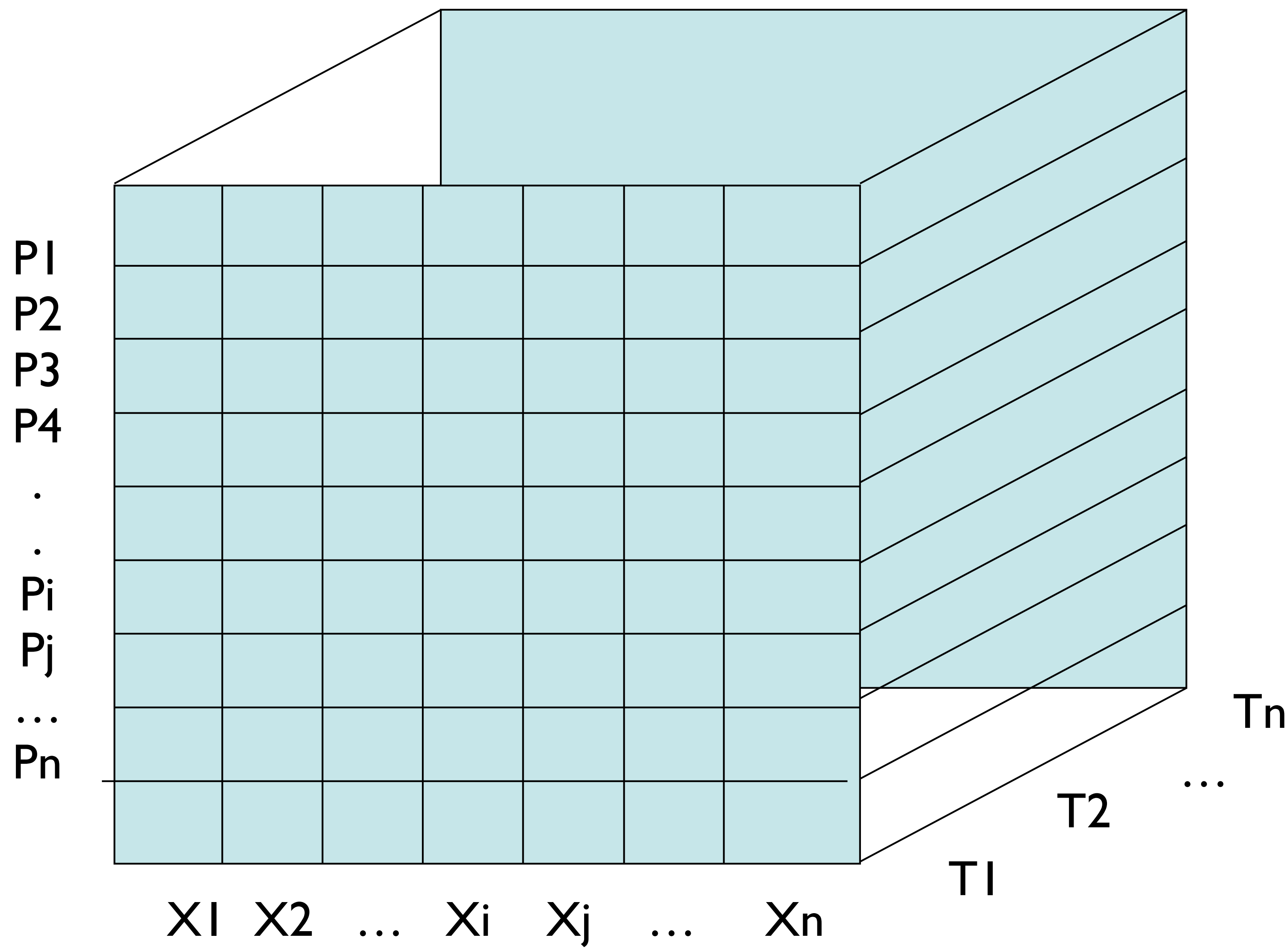
Sources of Data

- Performance tests
  - OSS stress tests
  - New faculty job talks
  - Clinical graduate applicant interviews
  - Internships
  - Probationary Periods
- Web based instrumentation
  - self report
  - indirect (IAT)

The data box

Multiple ways of assessment

The data box: measurement across time, situations, items, and people



Cattell's data box

Integrating People, Variables, and Occasions

- Person x Variables
  - Variables over People, fixed Occasion (R)
  - People over Variables, fixed Occasion (Q)
- Person x Occasions
  - Occasions over People, fixed Variable (S)
  - People over Occasions, fixed Variable (T)
- Variables x Occasions
  - Variables over Occasions, fixed People (O)
  - Occasions over Variables, fixed People (P)

Cattell, R.B (1978) The scientific use of factor analysis. p 323

Traditional measures

- Individuals across items
  - correlations of items taken over people to identify dimensions of items which are in turn used to describe dimensions of individual differences
    - Ability
    - Non-cognitive measures of individual differences
      - stable: trait
      - unstable: state
- INDSCAL type comparisons of differences in structure of items across people
- 3 Mode Factor Analysis

Other ways of measurement

- Example of measurement of the structure of mood
  – between subjects
  – within subjects

Introversion/Extraversion as one dimension of affect/behavior space

- Personality trait description
  - Introversion/Extraversion
  - Neuroticism Stability
- Affective Space
  - Positive Affect
  - Negative Affect
- Behavior
  - Activation and Approach
  - Inhibition and Avoidance

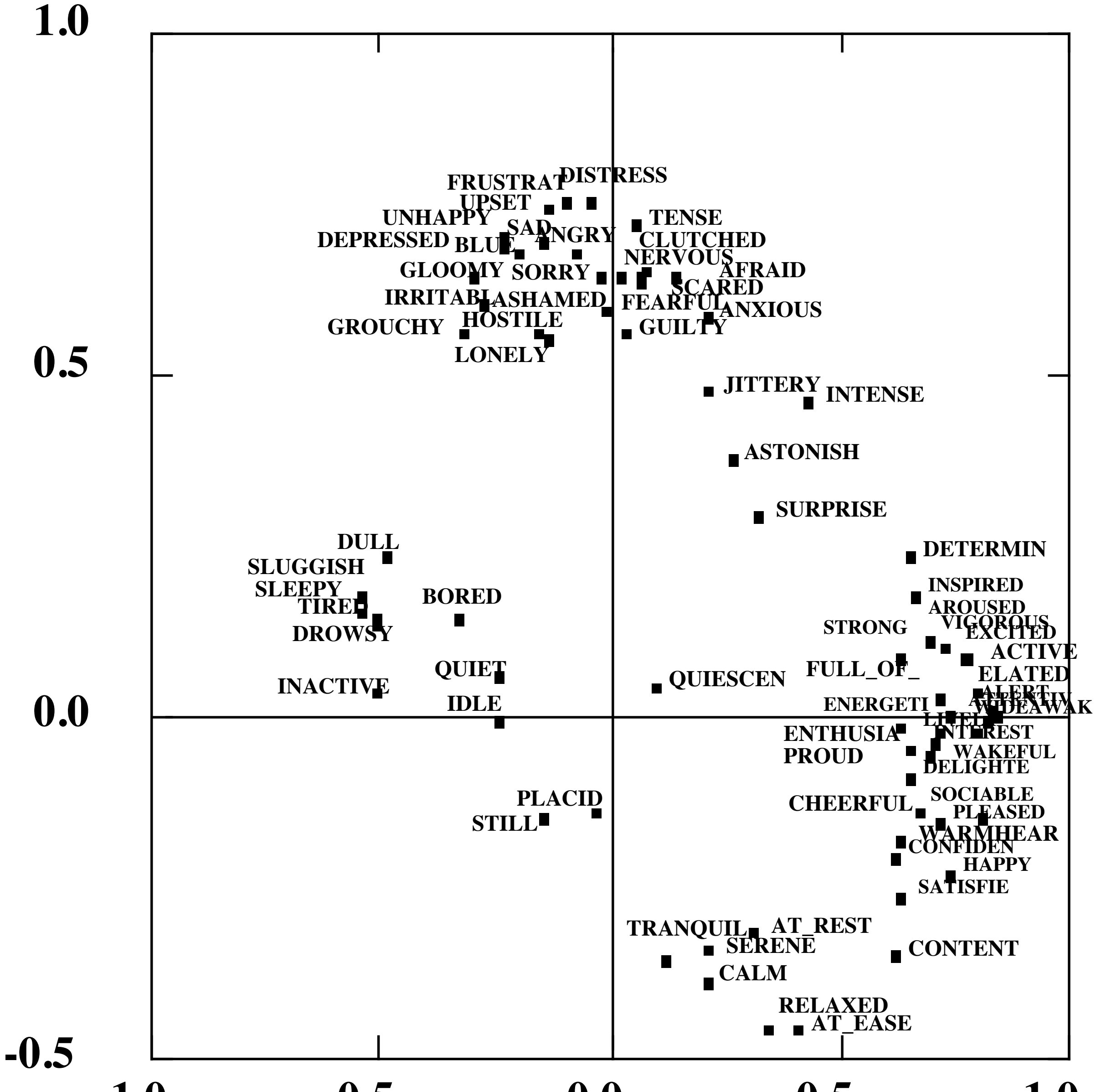
Personality and Emotions

- Standard model
  - Dimensional model of personality
    - Particularly Extraversion and Neuroticism
  - Dimensional model of emotions
    - Positive Affect and Negative Affect
  - Dimensional congruence
    - Extraversion and Positive Affectivity
    - Neuroticism and Negative Affectivity

Measuring the dimensions of affect

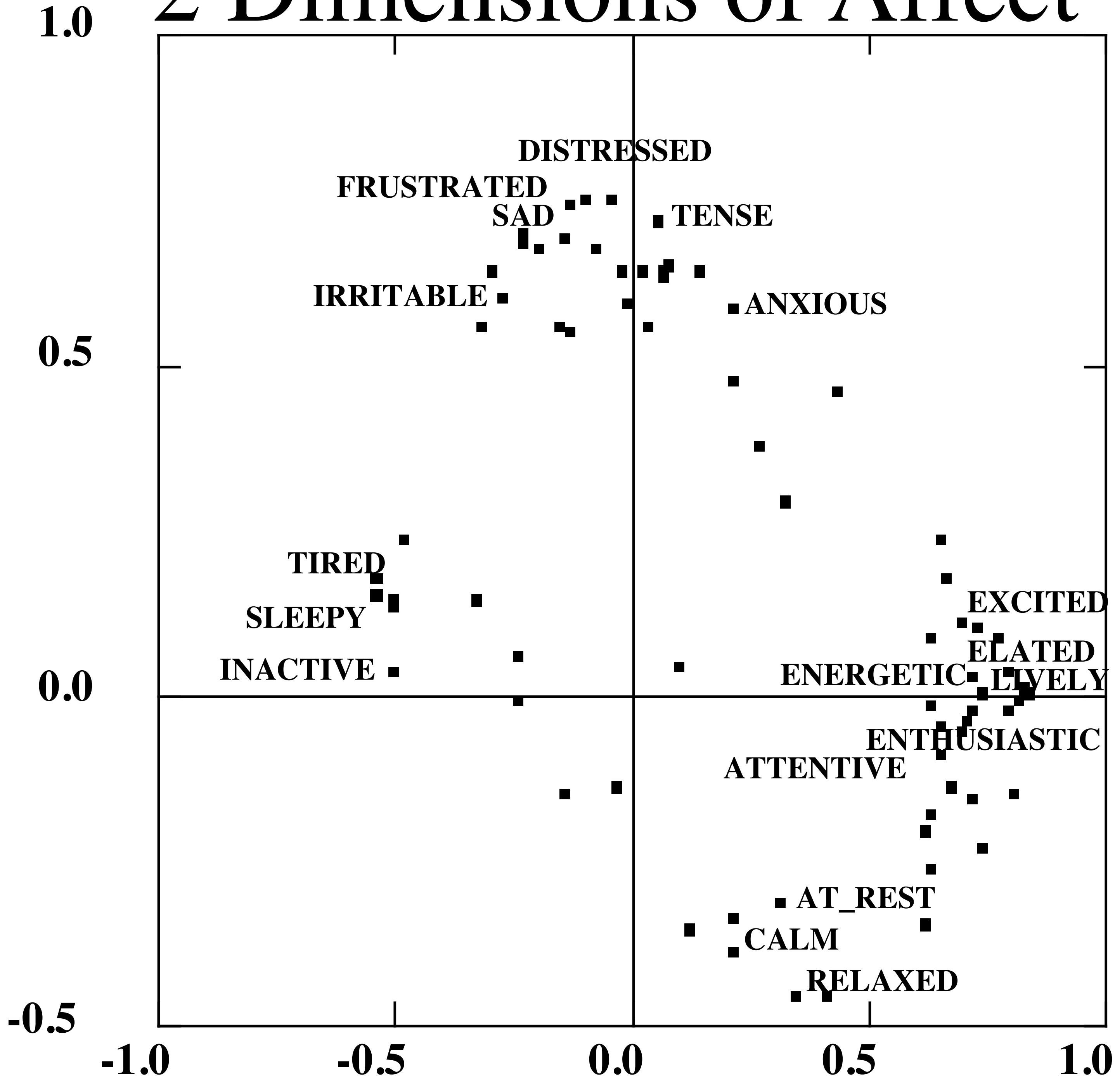
- Motivational state questionnaire (MSQ)
  - 70-72 items given as part of multiple studies on personality and cognitive performance
  - Items taken from
    - Thayer's Activation-Deactivation Adjective Checklist (ADACL)
    - Watson and Clark Positive Affect Negative Affect Scale (PANAS)
    - Larsen and Diener adjective circumplex
  - MSQ given before and after various mood manipulations
    - Structural data is from before
- Structural results based upon factor analyses of correlation matrix to best summarize data

2 Dimensions of Affect



Energetic Arousal/Positive Affect

2 Dimensions of Affect



Representative MSQ items (arranged by angular location)

Item	EA-PA	TA-NA	Angle
energetic	**0.8**	0.0	1
elated	**0.7**	0.0	2
excited	**0.8**	0.1	6
anxious	0.2	**0.6**	70
tense	0.1	**0.7**	85
distressed	0.0	**0.8**	93
frustrated	-0.1	**0.8**	98
sad	-0.1	**0.7**	101
irritable	-0.3	**0.6**	114
sleepy	**-0.5**	0.1	164
tired	**-0.5**	0.2	164
inactive	**-0.5**	0.0	177
calm	0.2	**-0.4**	298
relaxed	0.4	**-0.5**	307
at ease	0.4	**-0.5**	312
attentive	**0.7**	0.0	357
enthusiastic	**0.8**	0.0	358
lively	**0.9**	0.0	360

Personality and Emotions

- Standard model
  - Dimensional model of Personality
    - Behavioral Activation/Approach <-> Extraversion
    - Behavioral Inhibition <-> Neuroticism
  - Dimensional model of Emotions
    - Positive Affect
    - Negative Affect
    - Arousal?
  - Dimensional congruence
    - Extraversion, Approach, and Positive Affectivity
    - Neuroticism, Inhibition, and Negative Affectivity

Personality measurement: snapshot or movie?

- Cross sectional measurement of a person is similar to a photograph-- a snapshot of a person at an instant.
- Appropriate measurement requires the integration of affect, behavior, and cognition across time.

Personality and affect: within subject measurements

- High frequency sampling: the example of body temperature

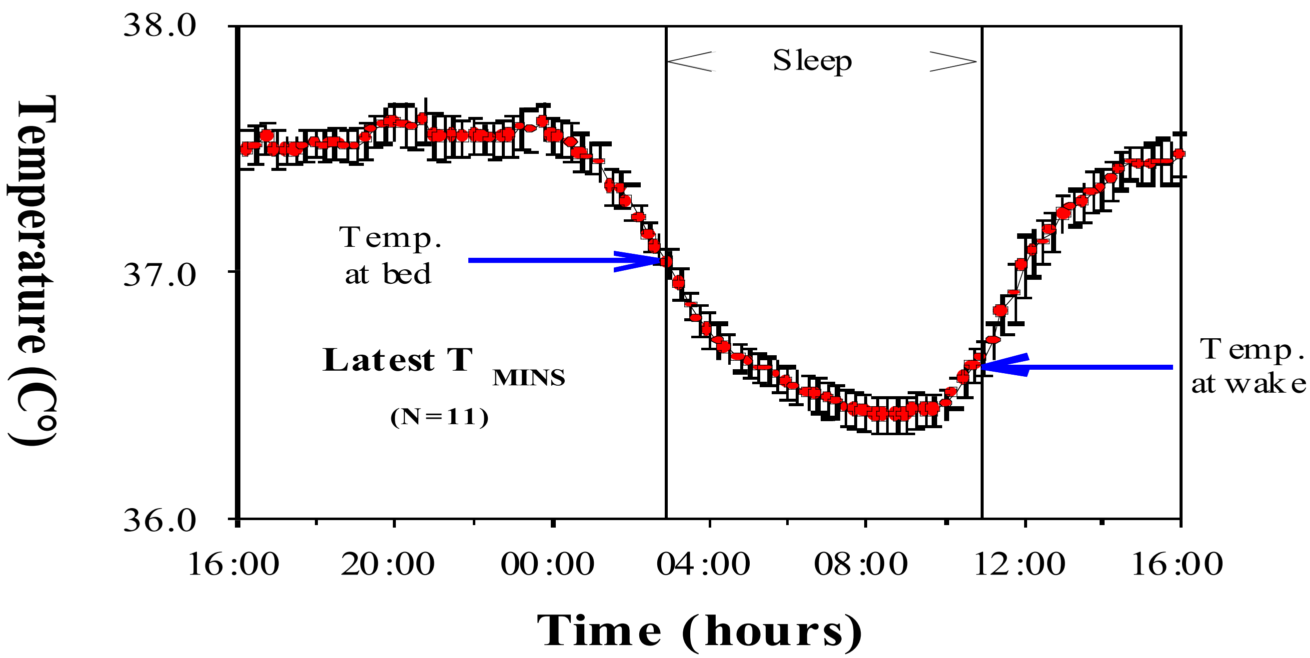
- Low frequency sampling: palm pilot sampling of affect

Within subject diary studies-1

- Very High Frequency (continuous) measurements
  - Physiological assays
    - Cortisol
    - Body temperature <--
      - Core body temperature collected for ≈ 2 weeks
      - Data taken by aggregating subjects from multiple studies conducted by Eastman and Baehr on phase shifting by light and exercise

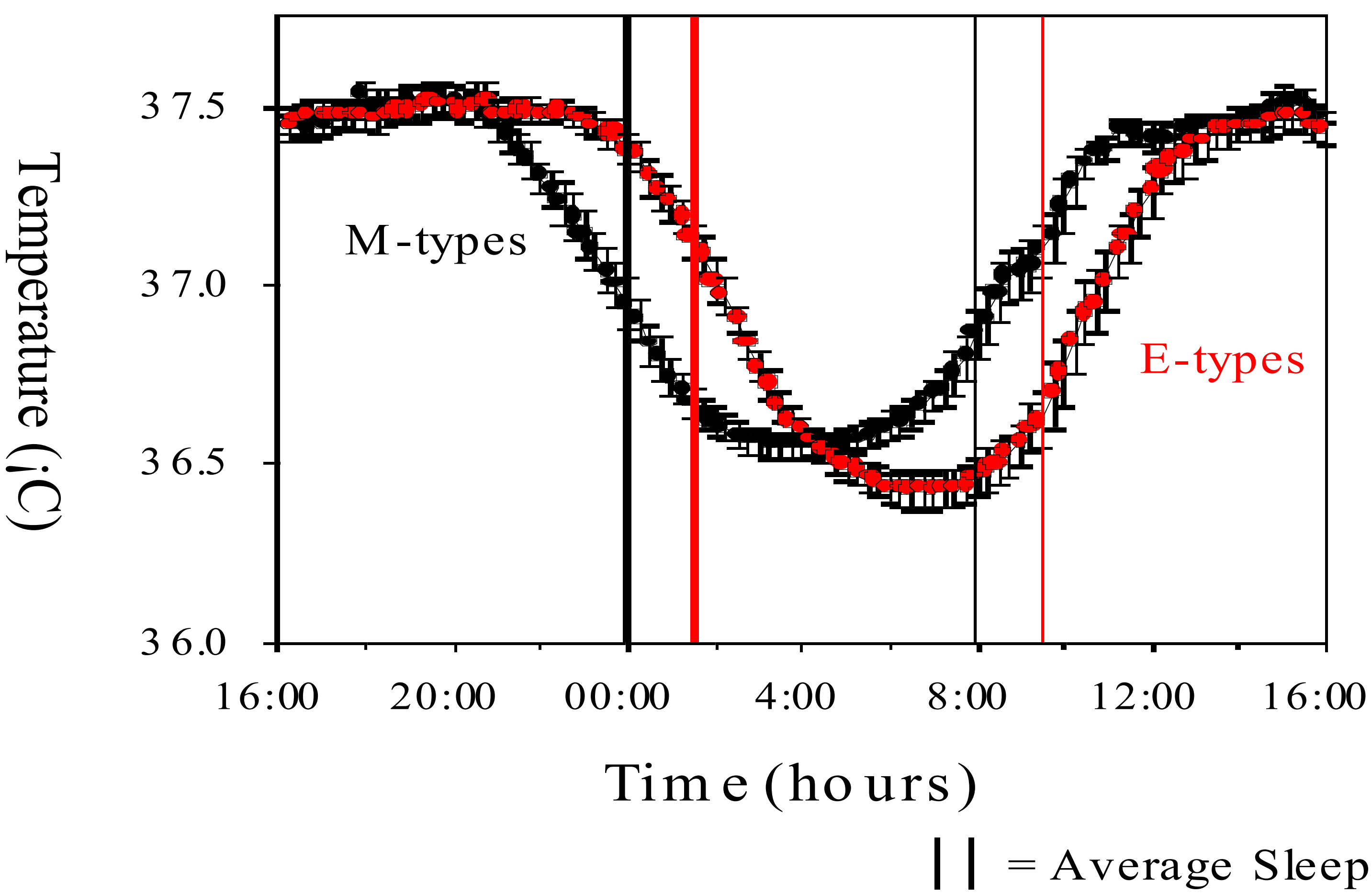
Body Temperature as f(time of day)

(Baehr, Revelle & Eastman, 2000)



Morningness/Eveningness and BT

(Baehr, Revelle and Eastman, 2000)



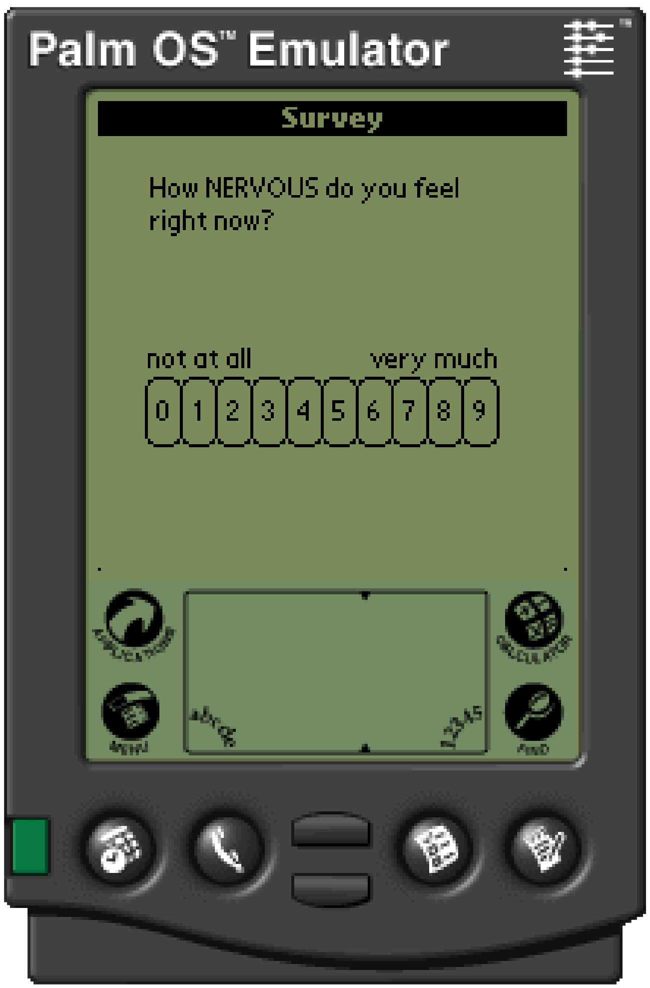
Within subject diary studies-2

- Measures
  - Check lists
  - Rating scales
- High frequency sampling <--
  - Multiple samples per day
- Low frequency sampling
  - Once a day
  - Sometimes at different times

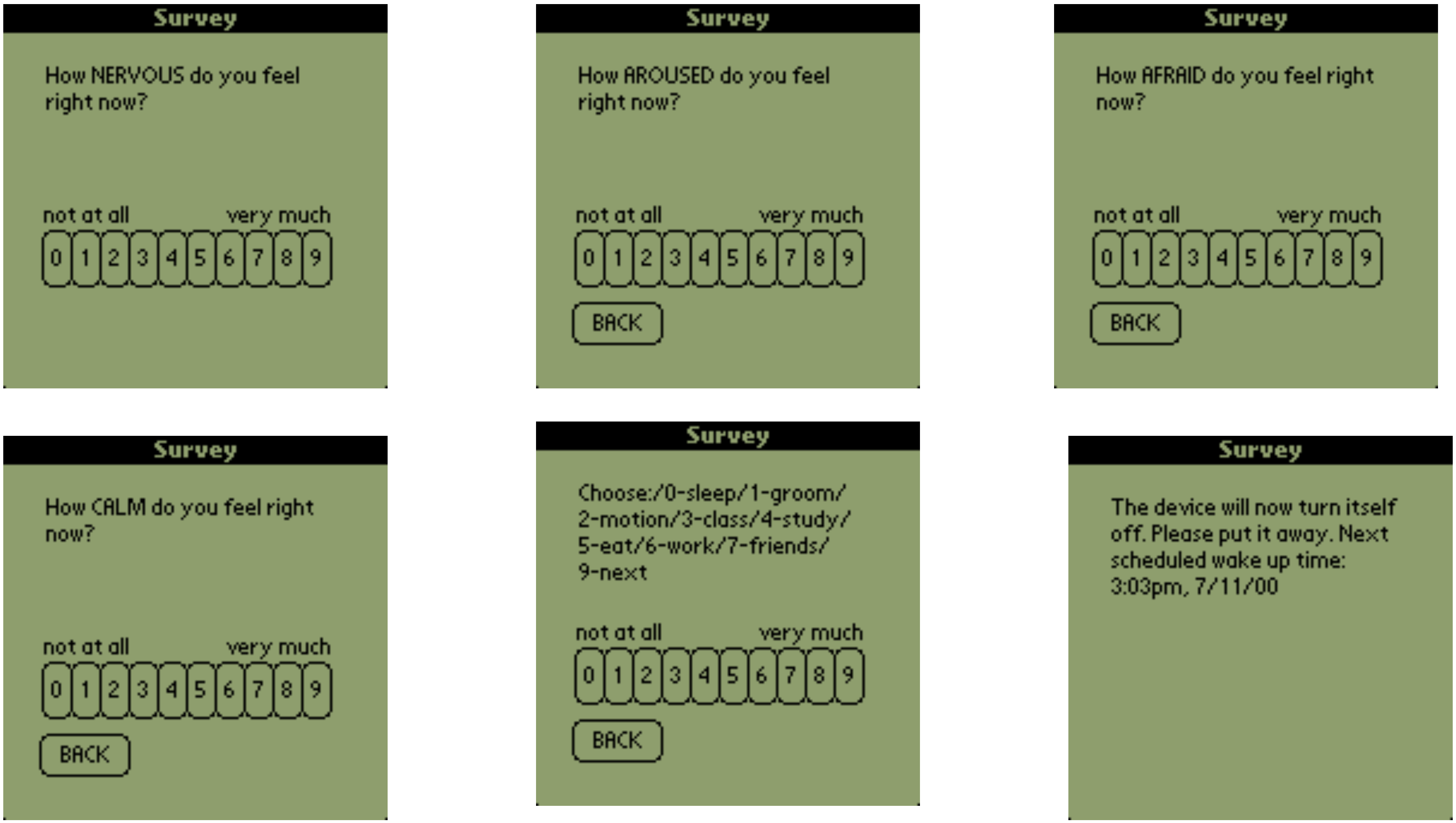
High frequency measures of affect

- Measures taken every 3 hours during waking day for 6-14 days
- Paper and pencil mood ratings
  - Short form of the MSQ -- Visual Analog Scale
  - Sampled every 3 hours
- Portable computer (Palm) mood ratings <--
  - Short form of the MSQ
  - Sampled every 3 hours

Palm Affect Survey



Palm affect and activity survey



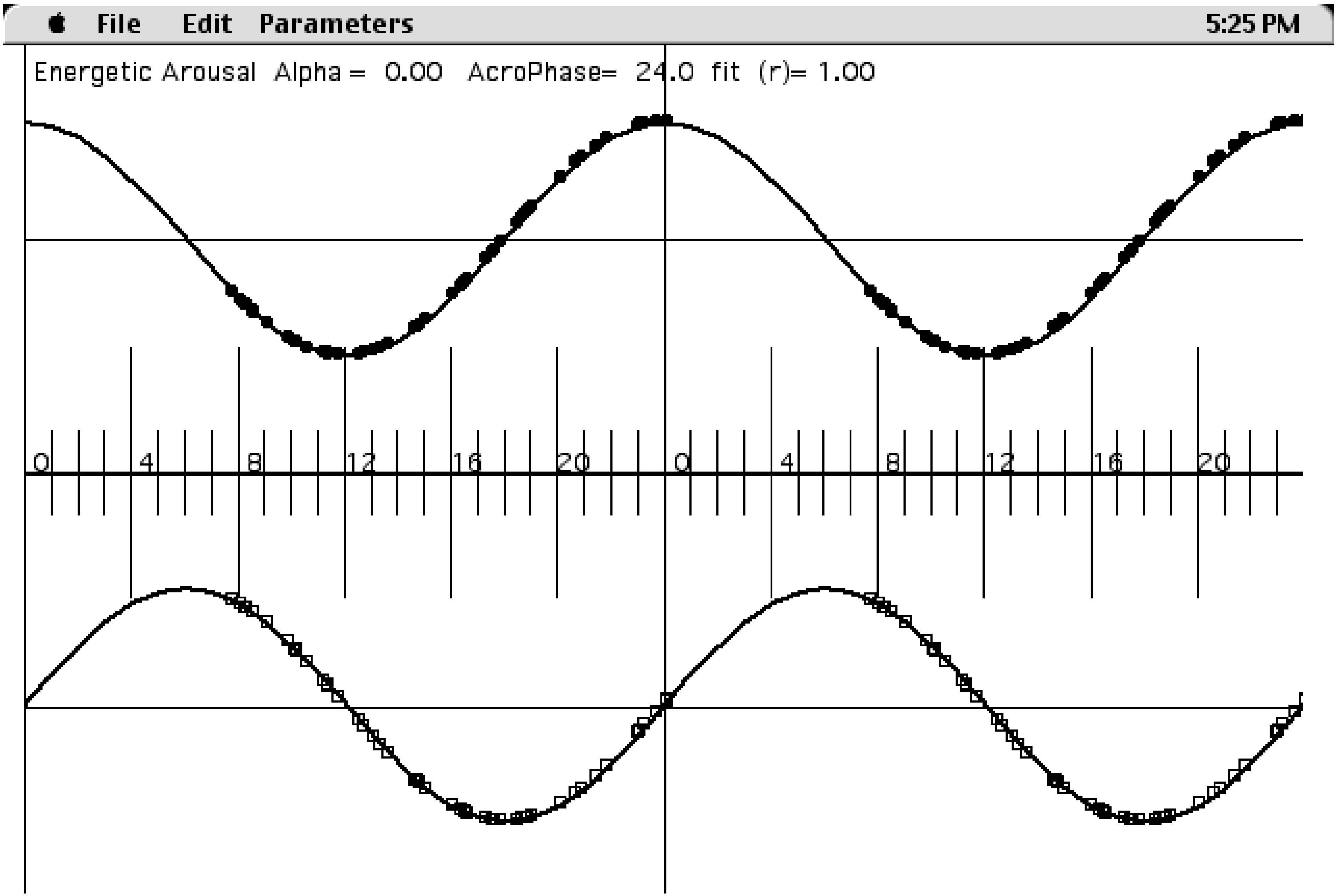
Traditional measures

- Mean level
  - Energetic arousal
  - Tense arousal
  - Positive affect
  - Negative affect
- Variability
- Correlation across measures (Synchrony)

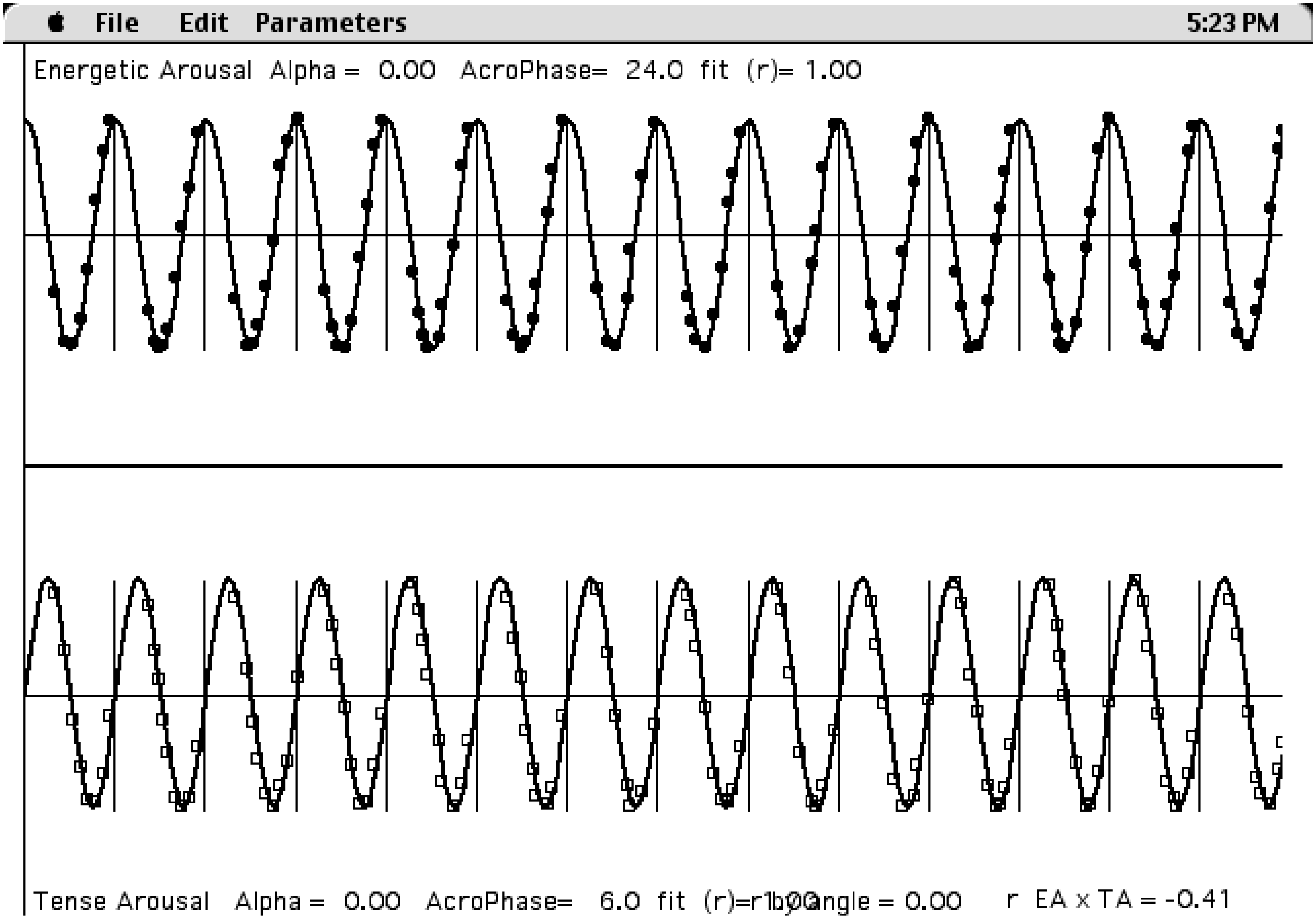
Phasic measures of affect

- Fit 24 hour cosine to data
  - Iterative fit for best fitting cosine
  - Permutation test of significance of fit
- Measure
  - Fit (coherence)
  - Amplitude
  - Phase

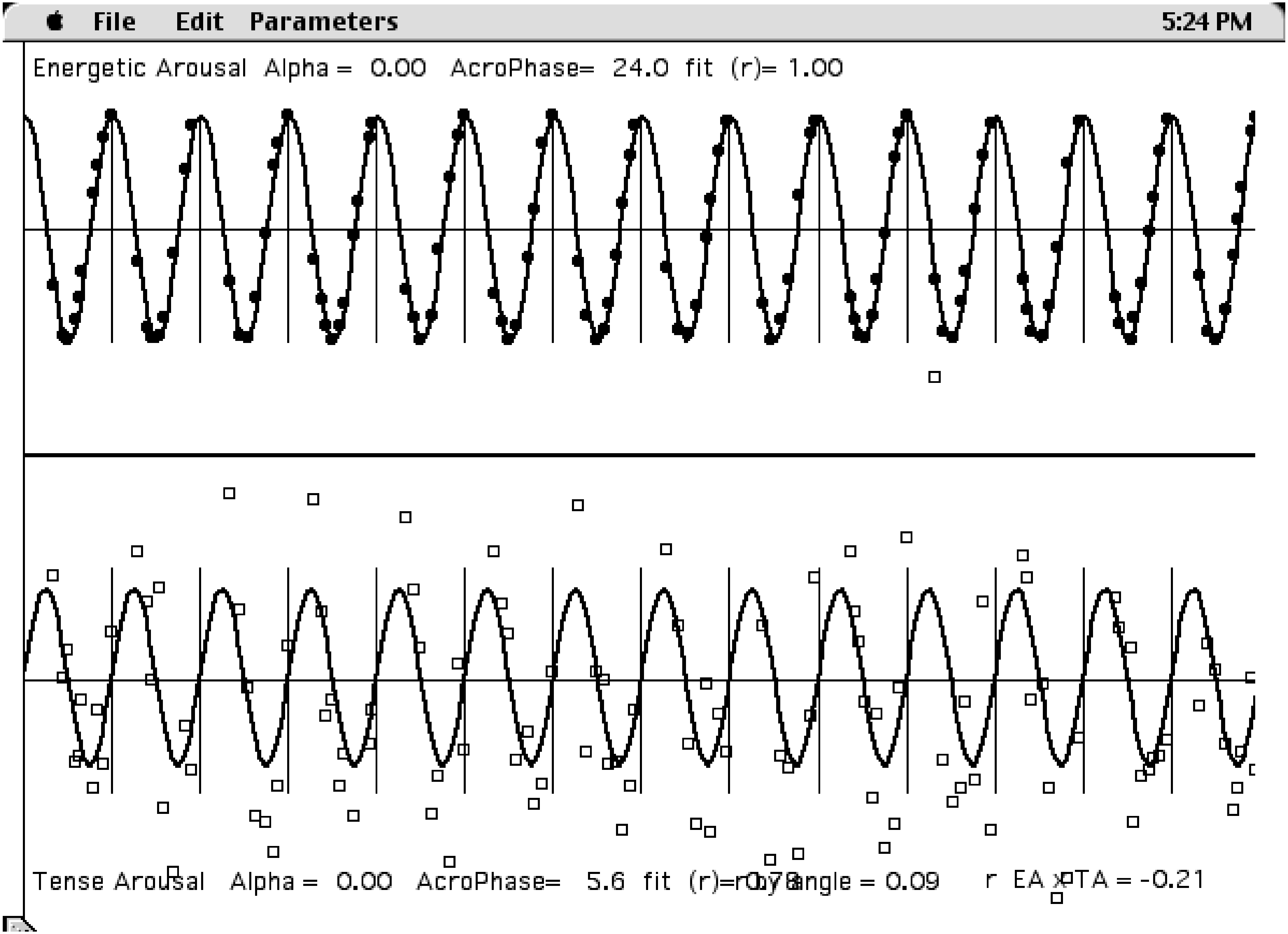
Affective rhythms can differ in phase
(simulation - double plotted to show rhythm)



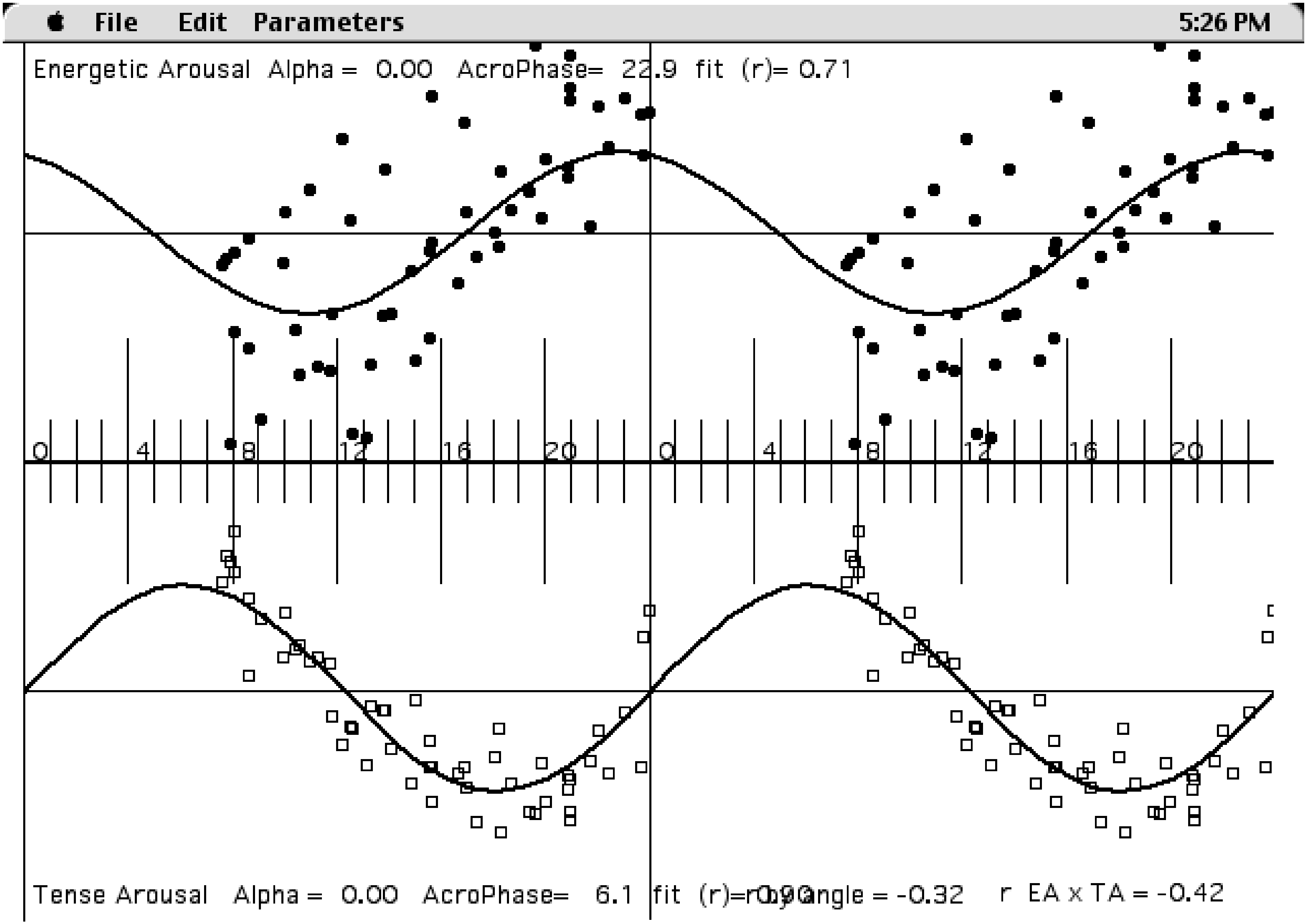
Phase differences of simulated daily data



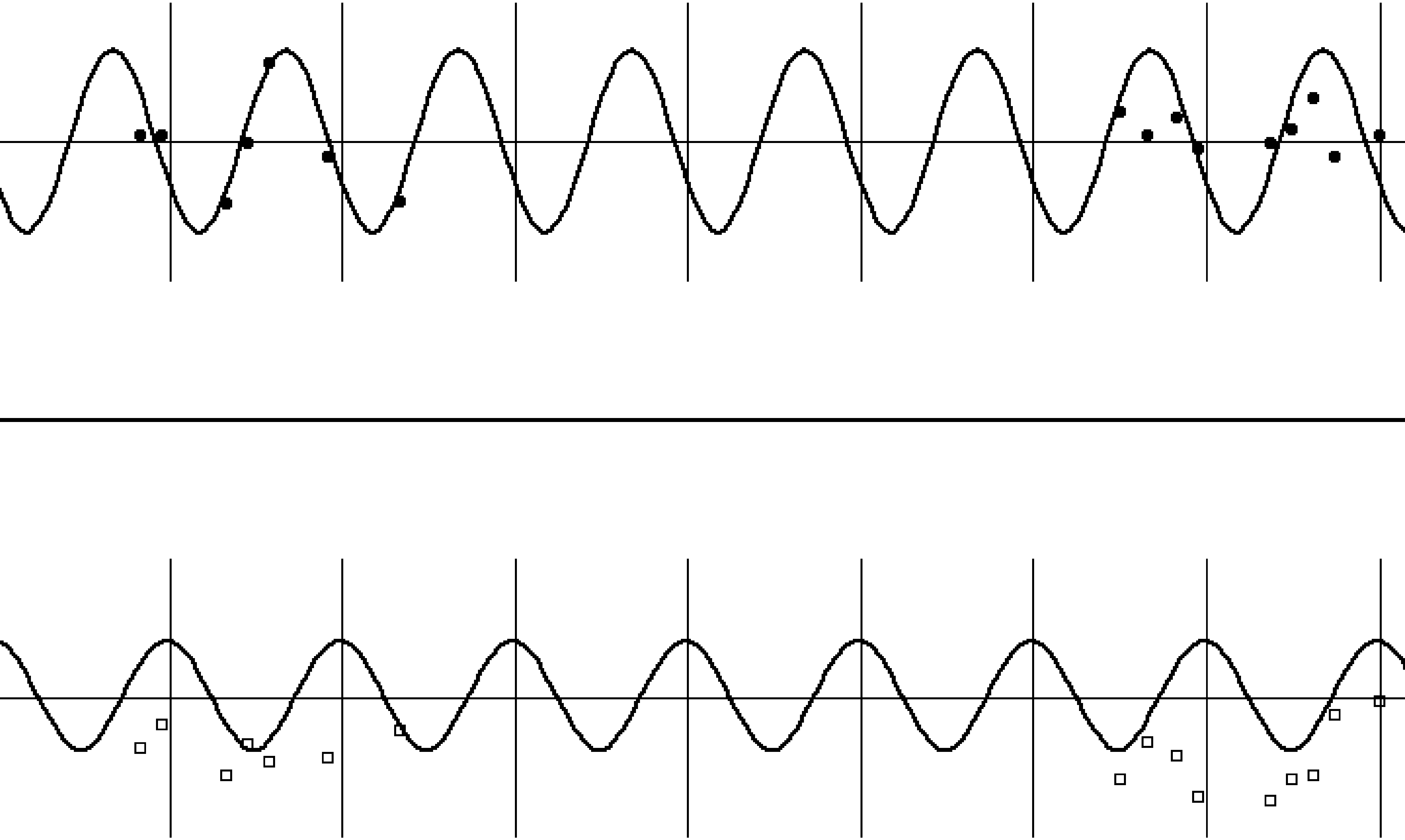
Differences in coherence (fit) simulated daily data



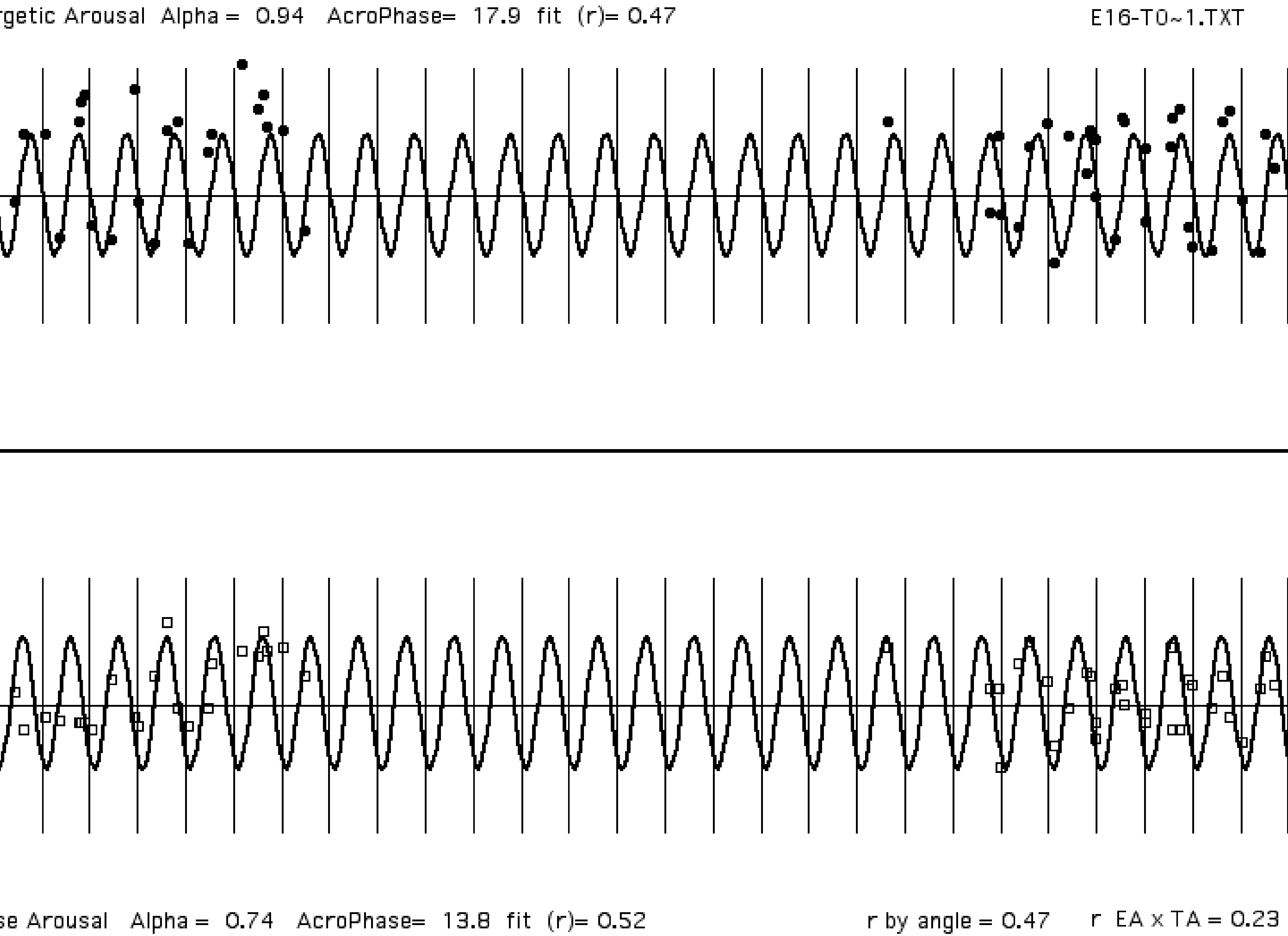
Phase and Coherence differences
(simulated data -- double plotted)

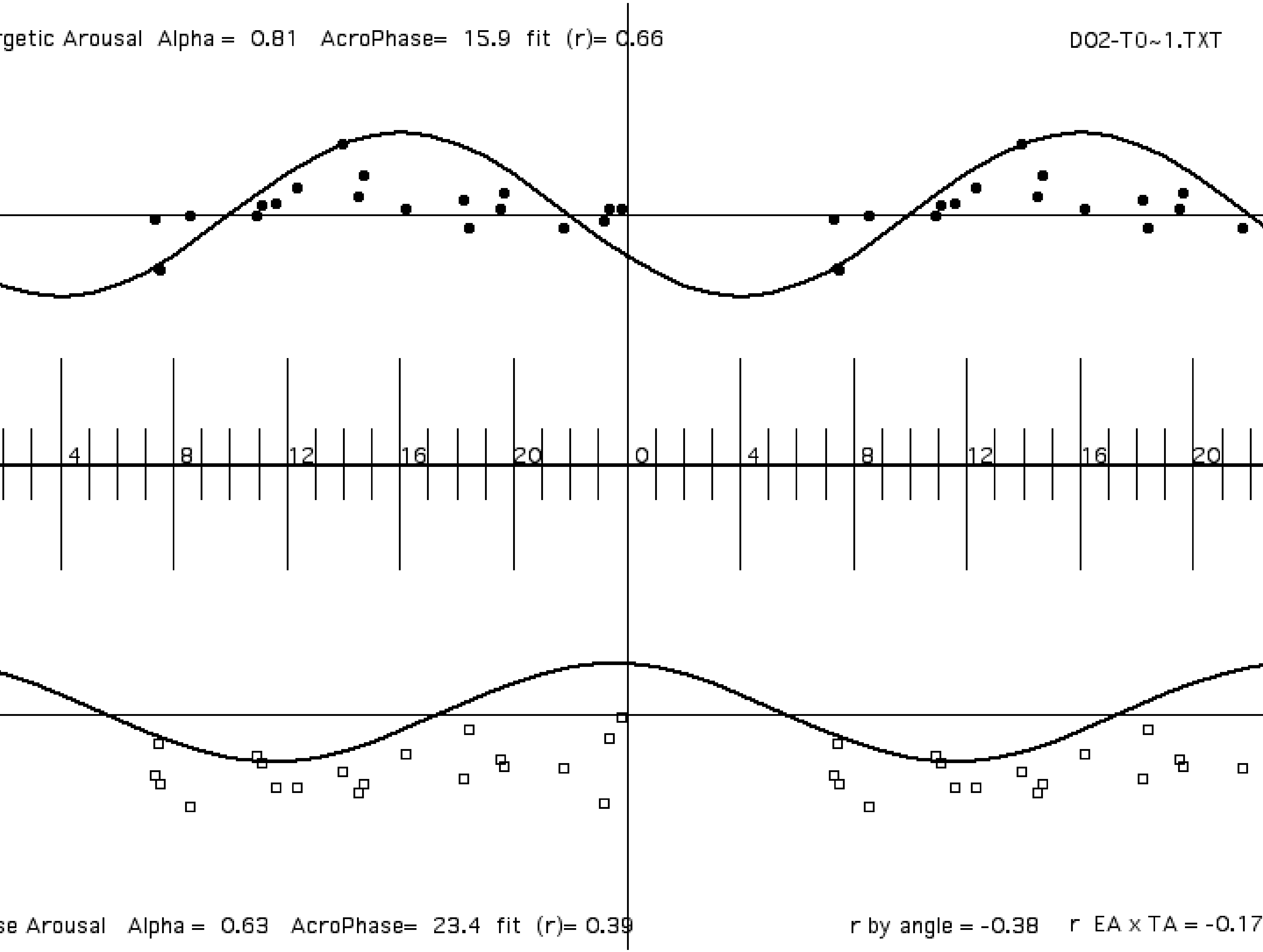


Energetic Arousal Alpha = 0.81 AcroPhase= 15.9 fit (r)= 0.66 DO2-TO~1.TX

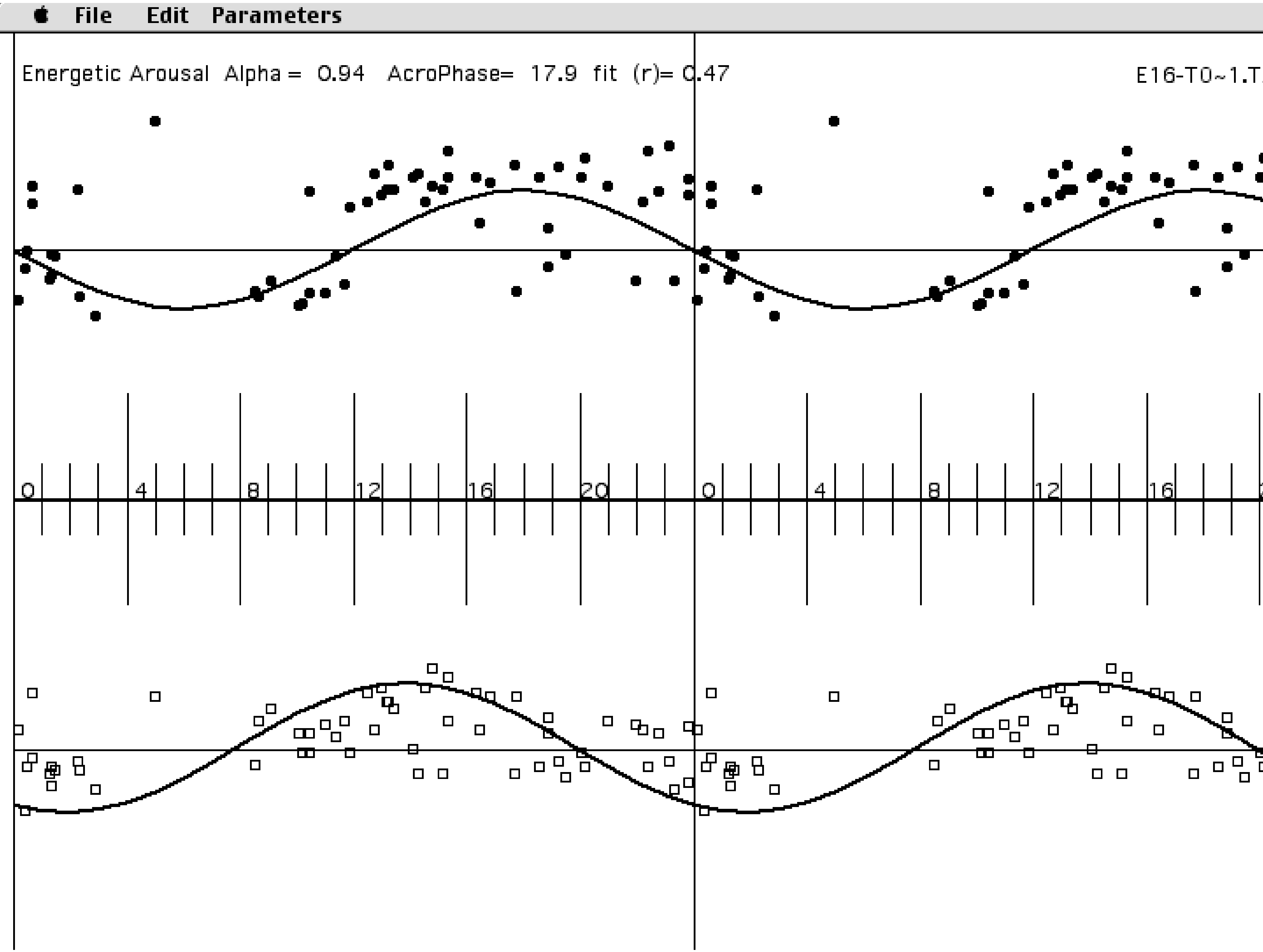


Tense Arousal Alpha = 0.63 AcroPhase= 23.4 fit (r)= 0.39 r by angle = -0.38 r EA x TA = -


rgetic Arousal Alpha = 0.94 AcroPhase= 17.9 fit (r)= 0.47
E16-T0~1.TXT
se Arousal Alpha = 0.74 AcroPhase= 13.8 fit (r)= 0.52
r by angle = 0.47
r EA x TA = 0.23



rgetic Arousal Alpha = 0.81 AcroPhase= 15.9 fit (r)= 0.66
DO2-T0~1.TXT
4 8 12 16 20 0 4 8 12 16 20
se Arousal Alpha = 0.63 AcroPhase= 23.4 fit (r)= 0.39
r by angle = -0.38 r EA x TA = -0.17


File Edit Parameters
Energetic Arousal Alpha = 0.94 AcroPhase= 17.9 fit (r)= 0.47
E16-T0~1.T
0 4 8 12 16 20 0 4 8 12 16

Multi-level analysis of patterns of affect across time-1: Method

- Within subject estimates of basic parameters
  - Level
  - Scatter (variability)
  - Phase
  - Coherence (fit)
- Between subject measures of reliability
  - Week 1/Gap/Week 2

Multi-level analyses of affect-2: 1-2 week Test-Retest Reliability

	VAS-1	VAS-2	Palm
Energetic Arousal	.67	.81	.82
Tense Arousal	.68	.57	.81
Fit EA	.55	.41	.07
Fit TA	.61	.25	.17
Phase EA	.69	.36	.58
Phase TA	.39	.25	.36
EA -TA Synchrony	.63	.48	.35

Affective rhythms and cognitive performance-1

- Design:High frequency diary study of affect combined with a low frequency study of reaction time
- Subjects: 28 NU undergraduate voluneteers
- Method:
  - 1 week diary study 5 times a day
  - Simple reaction time once a day at 5 different times using a Mac program at home

Affective rhythms and cognitive performance-2

- Low negative correlations of RT with concurrent measures of Energetic Arousal
- Stronger negative correlations of RT with Cosine fitted Energetic Arousal
- => Diurnal variation in RT may be fitted by immediate and patterns of arousal

Behavioral variation over time

- William Fleeson and studies of personality variability over time
- Personality traits and personality states
- Traits as aggregated states

Multilevel analysis can yield surprising results

Although it is well known that the structure within a level does not imply anything about the structure at a different level, this distinction is frequently forgotten.

1. Various names for the phenomena:
   - Yule-Simpson paradox (Simpson, 1951; Yule, 1903)
   - The fallacy of ecological correlations (Robinson, 1950)
   - The within group–between group problem (Pedhazur, 1997)
   - Ergodicity (Molenaar, 2004)
2. This distinction will be important as we consider models of coherency and differences within-individuals, between-individuals, and between groups of individuals.

Thinking by analogy

1. Anna Baumert and colleagues considered the many theoretical problems facing those of us who want to propose integrative theories (Baumert, Schmitt, Perugini, Johnson, Blum, Borkenau, Costantini, Denissen, Fleeson, Grafton, Jayawickreme, Kurzius, MacLeod, Miller, Read, Robinson, Roberts & Wood, 2017).
2. In a commentary on that article David Condon and I have suggested that it useful when searching for explanations at these multiple levels to consider the physical analogy of weather, climate, and climate change which are all driven by the same underlying cause (the balance of solar radiation and re-radiation) but have complex lower level drivers that have larger immediate effects (Revelle & Condon, 2017).
3. We argued that weather:climate:climate change :: emotion:personality:personality development
4. Thus we search for general models that can be applied at these multiple levels.
5. One such model is the Dynamics of Action (Atkinson & Birch, 1970)

Modeling individual dynamics

Personality is an abstraction used to describe and explain the coherent patterning over time and space of affect, cognition, and desire as they result in behavior for an individual.

1. That people change their behavior over situations is obvious.
2. That people also change their behavior in the same situation is less obvious, but equally important.
3. We need to model the processes that lead to change within and across situations.
4. One such model is the Dynamics of Action (Atkinson & Birch, 1970).
5. Such dynamic models, assessed at different lengths of time, are useful to understand within individual, between individual, and between group differences.

Dynamics of Action: A theory before its time

1. Atkinson & Birch (1970) proposed a motivational model that was both very simple and very complex.
   - A set of simple assumptions such as that motives have inertia and only change if acted upon.
   - Complex in that it required understanding differential equations.
   - Early evidence was supportive but limited to achievement motivation (Revelle & Michaels, 1976; Kuhl & Blankenship, 1979; Atkinson, 1981).
2. A reparameterization of the DoA is also very simple and is somewhat less complex.
   - The Cues-Tendencies-Actions (CTA) model (Revelle, 1986) has been discussed before (Revelle, 2012) and is implemented as part of the `psych` package (Revelle, 2018) in R (R Core Team, 2018).
   - Used in various computer simulations of affective and cognitive behavior (Fua, Horswill, Ortony & Revelle, 2009; Fua, Revelle & Ortony, 2010; Quek & Ortony, 2012).
   - Still requires some understanding of differential equations.

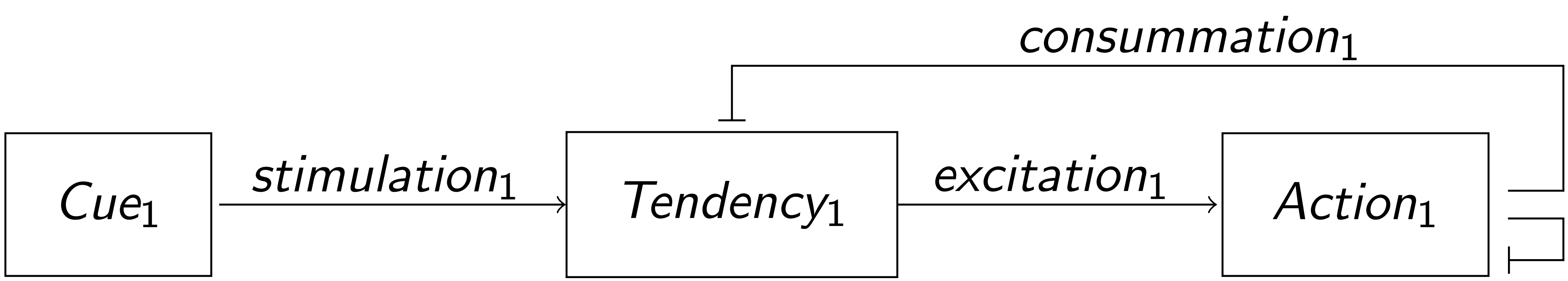
1. David Condon and I reported on the CTA model and showed how it could model personality at three levels of analysis (Revelle & Condon, 2015): within individual changes, between person behavior, and even the niche selection that differentiates groups of individuals as personality develops over time.
   - This paper was light on data and heavy on theory with examples that were said to fit the model but with little evidence.
2. Ashley Brown (Brown, 2017) has extended CTA to include Reinforcement Sensitivity Theory (Gray & McNaughton, 2000; Corr, 2008; Revelle, 2008; Corr, 2016) into the CTARST model.
   - She has implemented the CTARST model as an R package that is still under development and not yet released to CRAN.
   - The CTARST model was tested against several empirical studies we have conducted and shows a good fit to real behavior.
   - We will discuss this in some detail

The basic concepts: Cues, Tendencies, and Actions

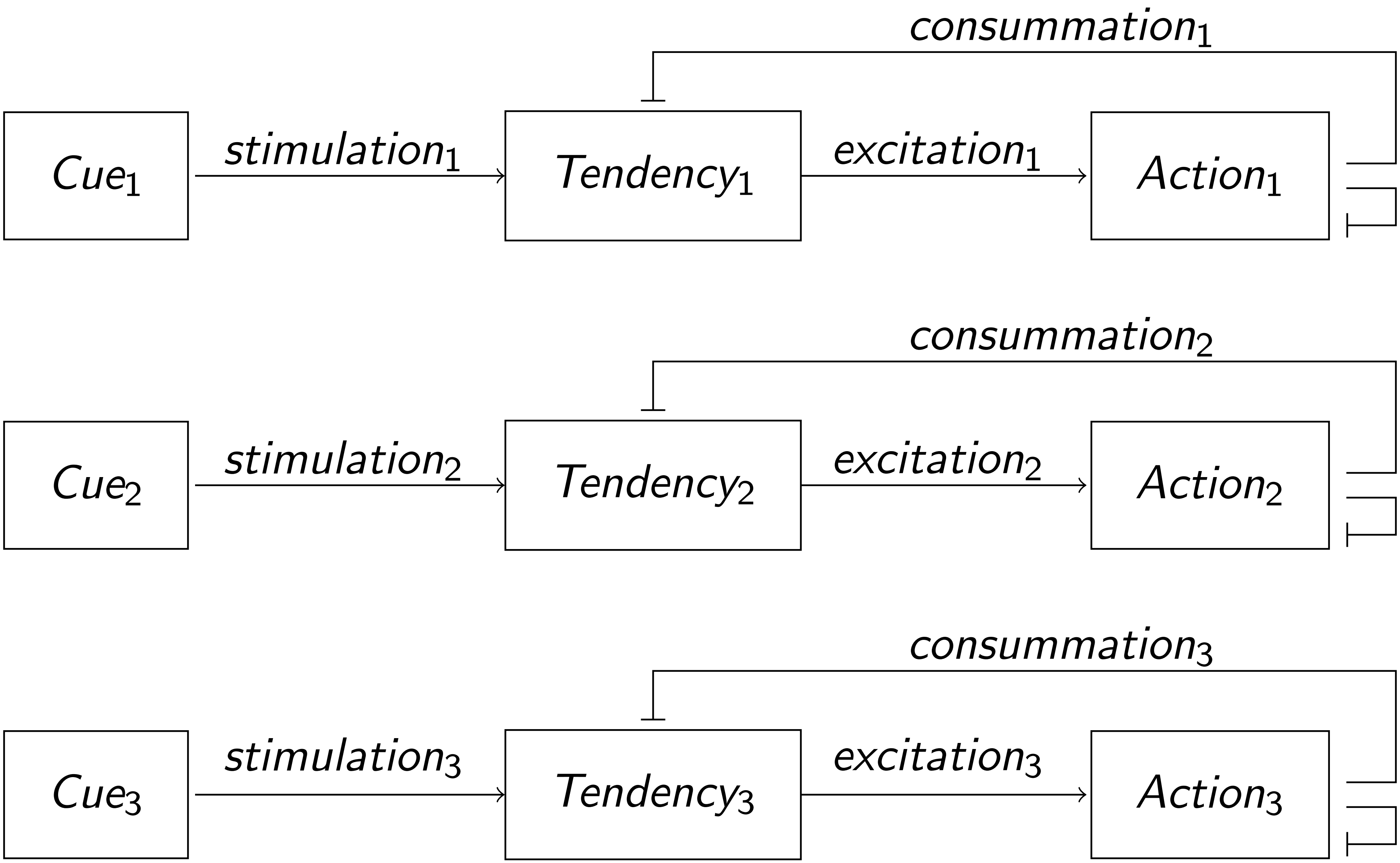
1. Environmental Cues evoke action Tendencies
2. Action Tendencies evoke Actions
3. Actions reduce Action Tendencies
4. Actions inhibit other Actions

This may be summarized in two differential equations

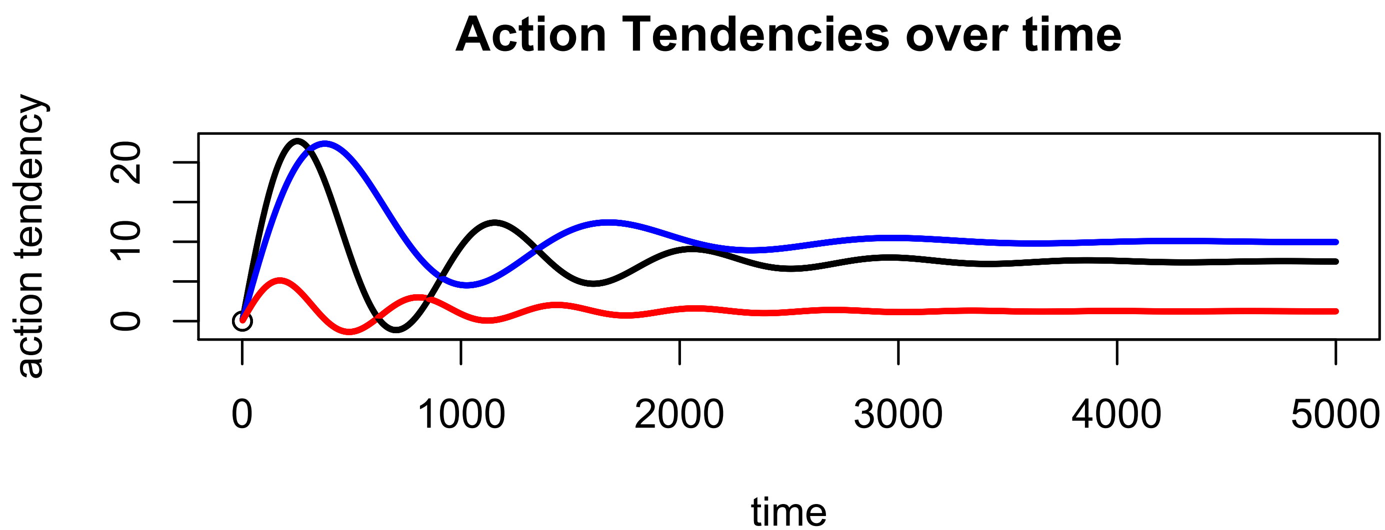
1. $d\text{T} = \text{sC - cA}$
2. $d\text{A} = \text{eT - iA}$
3. where
    - C, T, and A are vectors
    - s, e, c and i are matrices of association strength

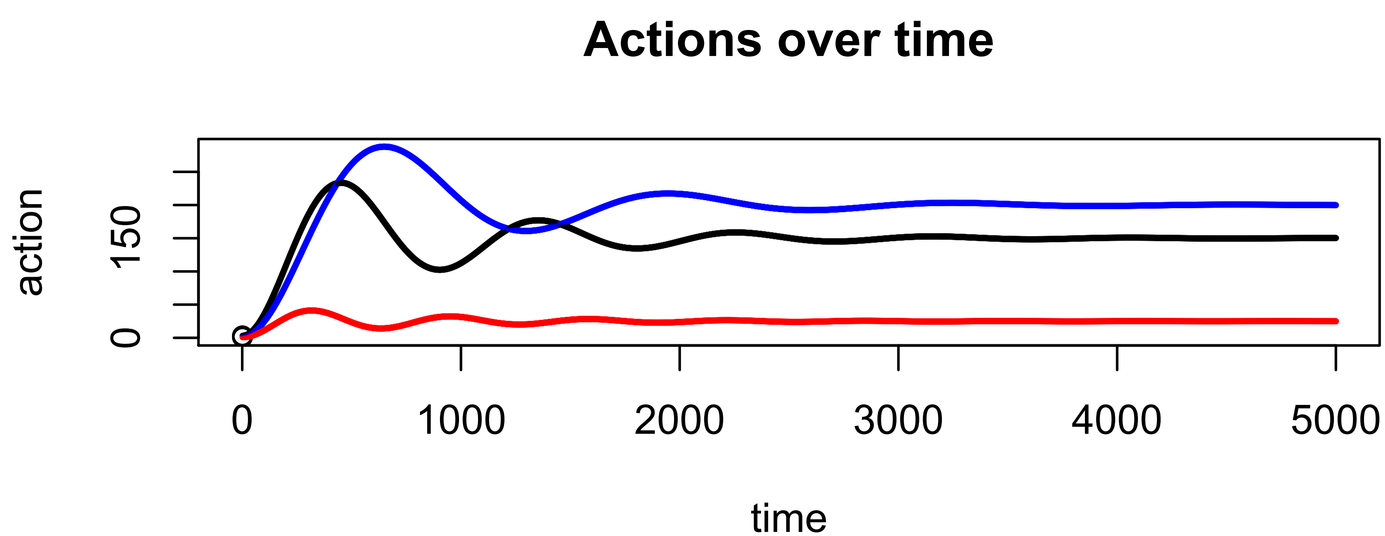


3 Cues, 3 Tendencies, 3 Mutually compatible Actions

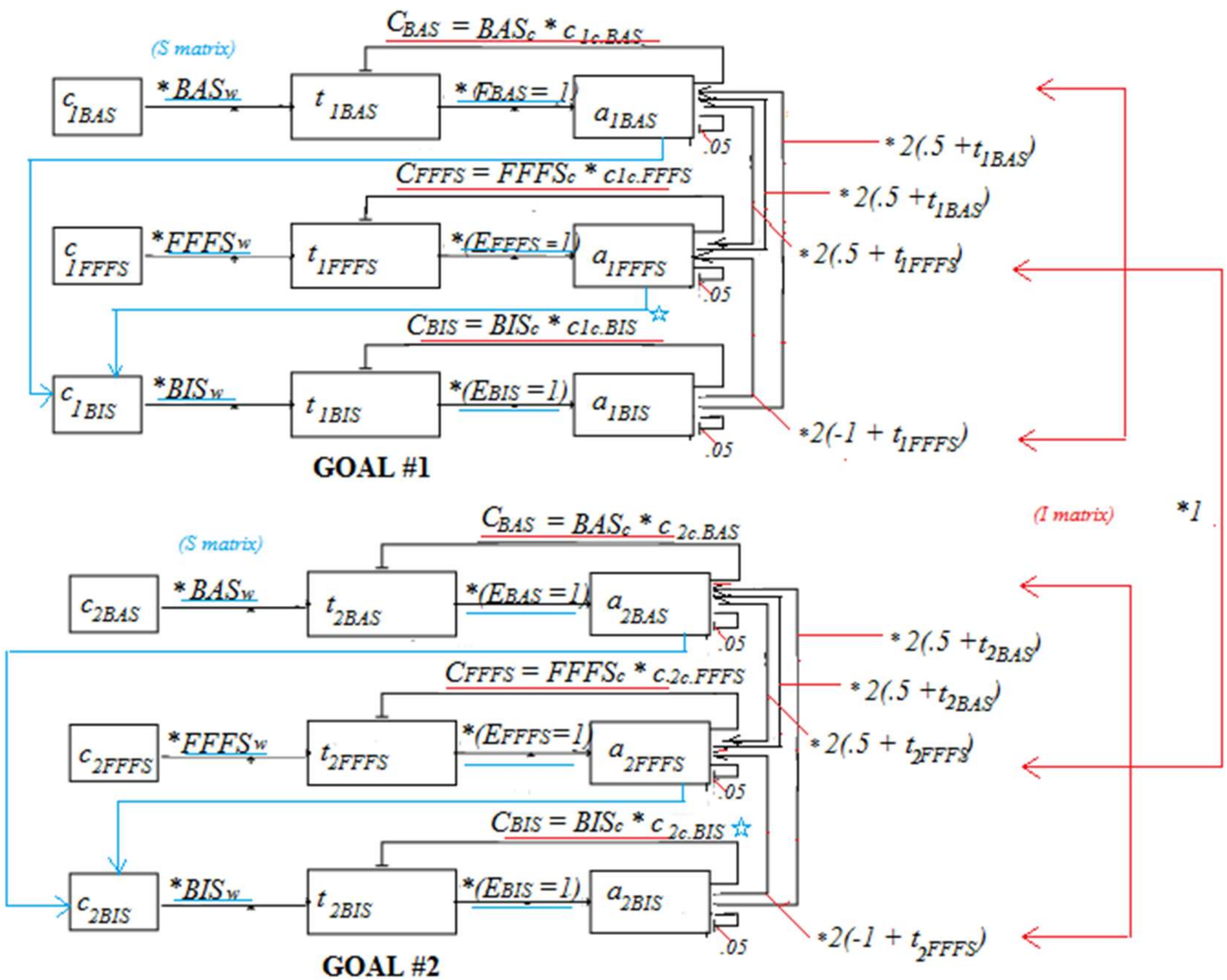


Three compatible behaviors in a constant environment

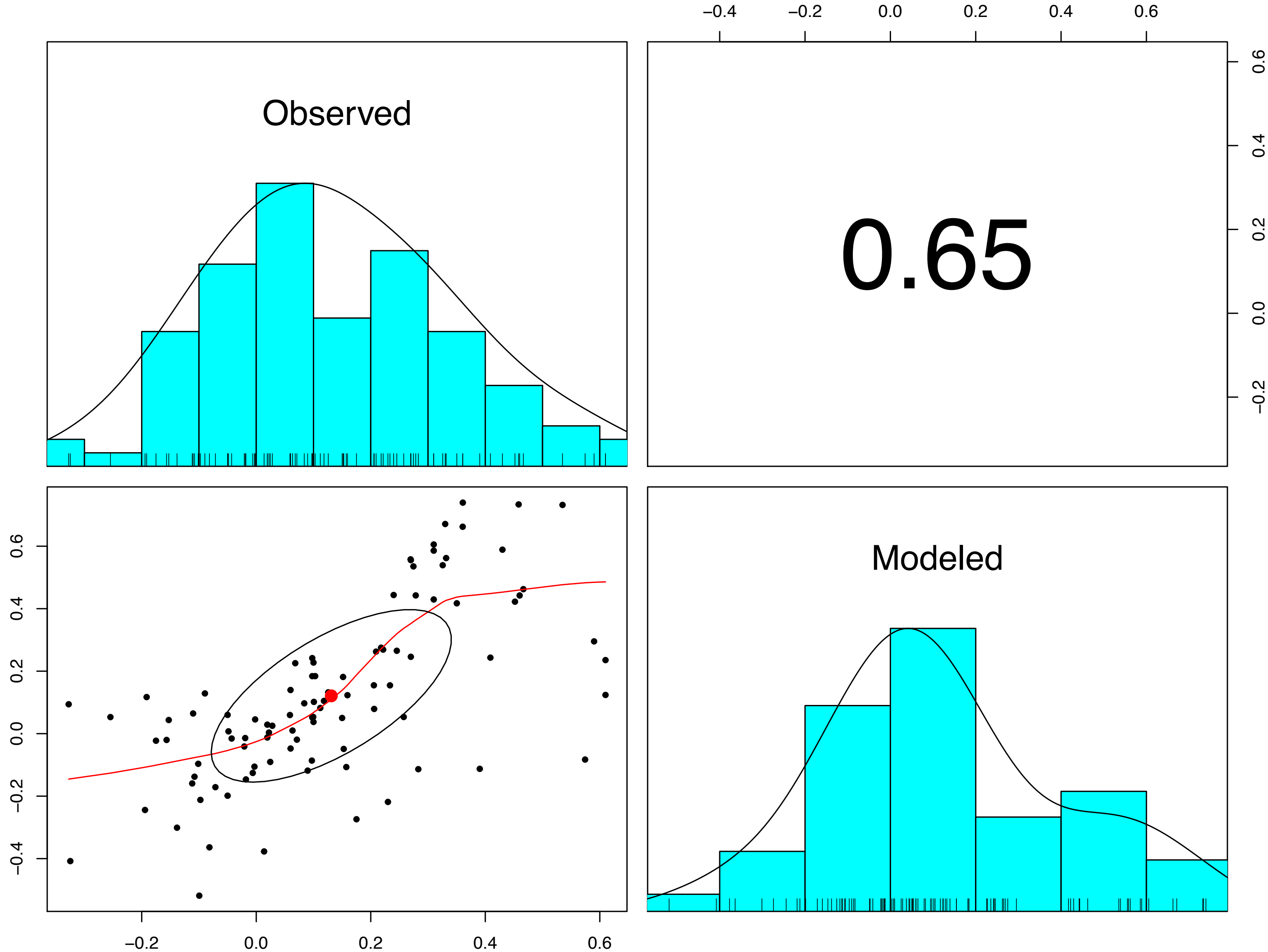




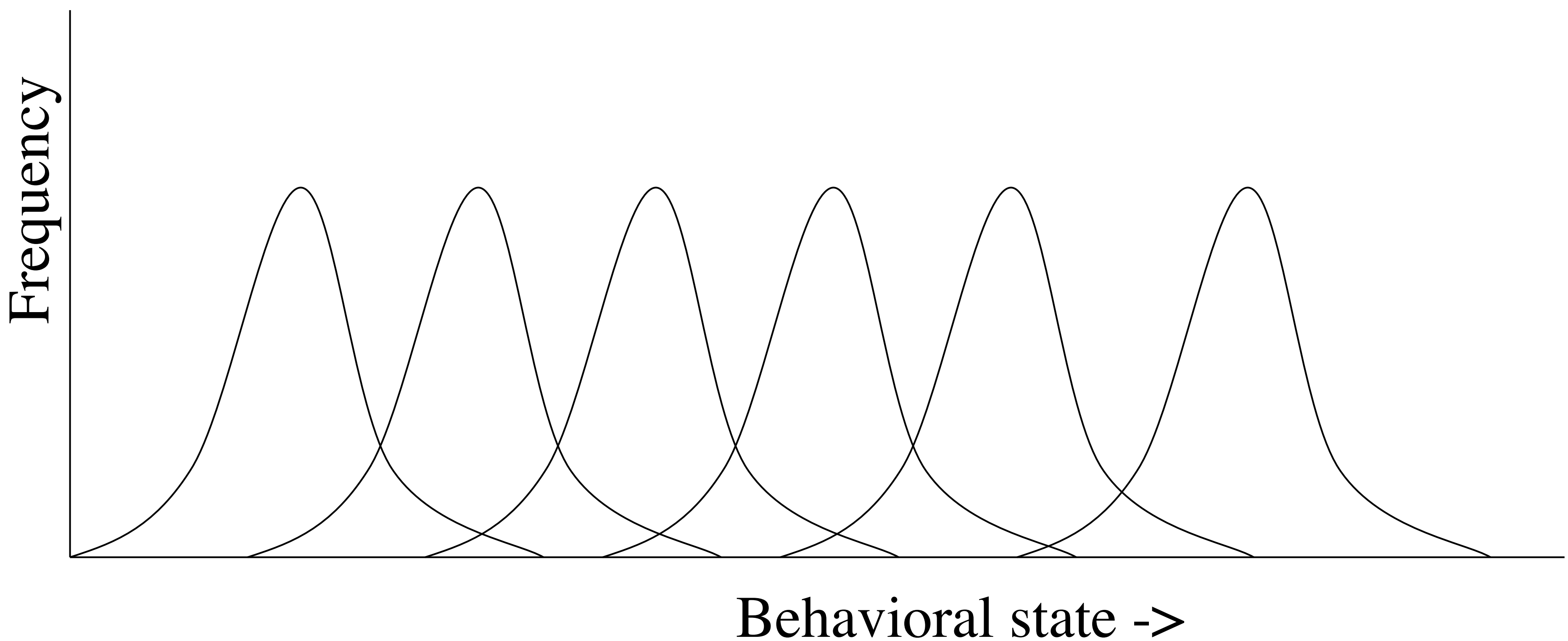
CTA + RST = CTARST



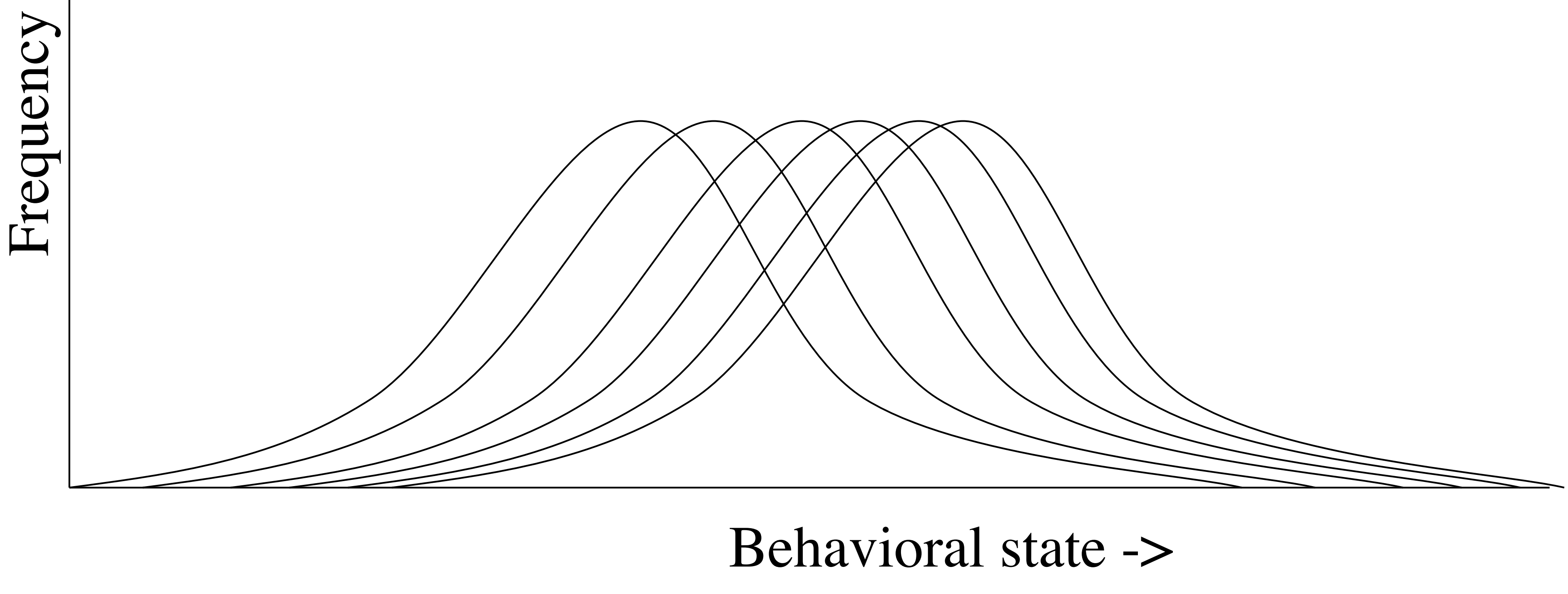
Model fit of effect sizes for these studies is not based upon tweaking parameters



Behavioral Variability:
Model 1:



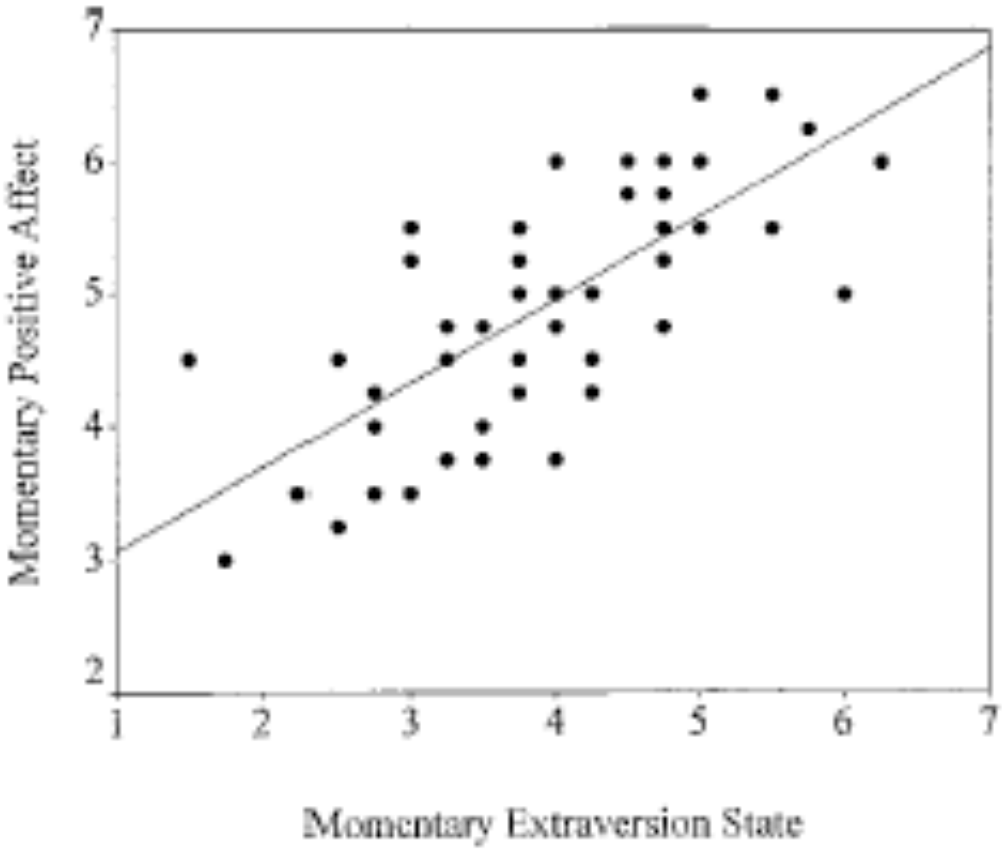
Behavioral Variability:



Stability of trait means and variances

- Fleeson examined within and between day levels of behaviors and affects
- Low correlations of single measurement with other single measurements
- High correlations of means over multiple days with similar means over different days
- High correlations of variability over multiple days with similar estimates over different days

Extraversion and Affect



Positive Affect and acting Extraverted