

A simple method for distinguishing within- versus between-subject effects using mixed models

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Here we describe a statistical procedure called within-subject centering (not to be confused with grand-mean centering; e.g. Kreft et al. 1995). This simple technique can be used in mixed models to separate within-subject effects (i.e. phenotypically plastic or facultative behavioural responses) from between-subject effects (i.e. evolutionarily fixed behavioural responses based on the individual or its class). Such a separation is important as it allows us to distinguish between alternative biological hypotheses and prevents us from erroneously generalizing within-subject relationships to between-subject relationships, or vice versa. We claim no originality for this statistical technique, which is commonly used in the social sciences (e.g. Davis et al. 1961; Raudenbush 1989; Kreft et al. 1995; Snijders & Bosker 1999; see also van de Pol & Verhulst 2006). However, we offer it as a piece of overlooked statistical methodology that we think is crucial to many researchers in animal behaviour, and in various other areas of biology as well. We illustrate our explanation of the technique with several biological examples and simulated data, but this method is widely applicable

and most readers will probably be able to identify appropriate examples from their own research.

LEVELS OF AGGREGATION AND MIXED MODELS

In biology in general and in the study of animal behaviour in particular we usually collect data that have different levels of aggregation. For example, one might collect multiple measurements of the same individual (i.e. subject), measure multiple members (e.g. offspring, helpers) of the same collective (e.g. nest, social group), or measure multiple individuals from the same area or time period. An important feature of such multilevel data is that measurements within a level of aggregation are often not independent. For example, some individuals might consistently behave differently from other individuals, and therefore the values of measurements of the same individuals are intercorrelated. This issue becomes particularly important when testing adaptive evolutionary hypotheses, because typically the individual subject represents the unit of analyses. We therefore have to be careful to avoid the problem of pseudoreplication (artificially inflating one's degrees of freedom) in any statistical analysis involving repeated observations of the same subjects (e.g. Snijders & Bosker 1999; Goldstein 2003).

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The simplest solution to overcome this problem is to aggregate all measurements of the same subject into an average value and make these the unit of analysis. However, this approach is usually undesirable, first because it omits potentially useful information on variation within subjects, and second because it rules out any investigation of hypotheses that specifically address questions concerning within-subject variation. Luckily two types of statistical models are available to account for interdependency and structuring of data: repeated measures models and mixed models. Of these two types of models, mixed models are by far the most generally applicable, because they can (1) easily account for complex data structures with various levels of aggregation (i.e. hierarchical linear mixed models) and (2) effectively deal with unbalanced data sets (i.e. situations with varying numbers of measurements per subject; Snijders & Bosker 1999; Goldstein 2003; Gelman & Hill 2006).

The basic idea of mixed models is that when data have different levels of aggregation (e.g. multiple measurements of the same individual), the identifier of the level of aggregation (e.g. individual identity) is included as a random intercept (and sometimes also as a random slope; see later). This random intercept allows us to separate the total variance in the dependent variable into a within- and between-subject (e.g. individual) variance component. If we then add a fixed predictor variable to this model we can investigate how much of the total variation in the dependent variable is explained by the fixed predictor variable, while accounting for the fact that measurements of the same subject are intercorrelated (Gelman & Hill 2006).

THE PROBLEM

Mixed models are now becoming widely used in biology, as they are ideally suited for analysing behavioural, ecological and evolutionary data (because such data sets typically have one or more levels of aggregation). Evolutionary and ecological hypotheses often specifically address either within- or between-subject differences, and thus it is important to be able to construct statistical models that produce unambiguous and unbiased estimates of such within- and between-subject effects. However, when talking to biologists that use mixed models we have noticed that there is some confusion concerning the extent to which fixed predictor variables quantify within- or between-subject effects on response variables. In fact, there seems to be a common misconception that because random effects account for consistent differences between subjects in the value of the dependent variable (y), this automatically means that any effect of a predictor variable (x) must reflect a within-subject effect. However, as we show below this is not necessarily the case, and it can lead to what sociologists and economists call an ‘ecological fallacy’, in which a relationship described at one level of aggregation is erroneously generalized to another level (Robinson 1950).

The problem lies in the fact that fixed predictor variables (x), as well as dependent variables (y), can vary at multiple levels of aggregation. This is because in nonexperimental studies we typically cannot choose the value of the predictor variable to be the same for all subjects, and we have to rely on natural variation in the predictor variable. For example, it is very possible that we will only be able to measure y for some subjects at low values of x , while for other subjects we will only be able to measure y at high values of x . Although random effects (intercepts) in mixed models can account for between-subject variation in y , they do not automatically account for possible between-subject variation in x . Thus, in cases where there is between-subject variation in x , an association between a predictor and response variable could be caused by a within-subject effect of x on y , but also by a between-subject effect of x on y (subjects with a high \bar{x} also have a high \bar{y}). As long as the within- and between-subject effects of x on y are similar, estimates

from standard mixed models will indeed reflect the within-subject effect in the presence of between-subject variation in x (Fig. 1a). However, in cases where we have between-subject variation in x , and the within- and between-subject effects of x on y are different (Fig. 1b–d), predictor variables in standard mixed models do not simply reflect within-subject effects (as commonly thought), but reflect a combination of within- and between-subject effects.

The biological relevance of this problem is illustrated by the following example from the classic question in cooperative breeding of whether genetic relatedness affects helping behaviour (see Brown 1987; Cockburn 1998; Koenig & Dickinson 2004). Typically, such studies have measured relatedness to the brood (x) and provisioning effort (y) of the same helpers (subjects) over several breeding attempts (i.e. unbalanced repeated measures data). Usually, some helpers will have a consistently higher provisioning effort than others and helper identity is included as a random intercept in the model to account for the fact that there is between-helper variation in provisioning effort (i.e. measurements of the same helper at different nests are interdependent). Moreover, usually some helpers will have a higher overall genetic relatedness (x) to the broods at which they help than others, for example, because some helpers are local offspring while others are immigrants. Consequently, if a positive relationship between relatedness and helping effort is found, this could be caused by: (1) a between-subject effect in which some more-related helpers always help at high levels, while other less-related helpers always help at low levels (as in Fig. 1b); or (2) a within-subject effect in which each helper provisions at higher levels at nests where it is more related and at lower levels at other nests where it is less related (as in Fig. 1c); or (3) a combination of both these within- and between-subject effects (as in Fig. 1a). From a biological perspective these patterns represent two different but not mutually exclusive biological mechanisms and hypotheses: (1) that helpers that are more related (e.g. those in their natal group) always help at higher levels irrespective of what nest they attend in that group; and (2) that helpers use specific cues concerning variation in kinship at different nests within the same group and facultatively adjust their helping effort accordingly. Importantly, neither of these hypotheses is actually explicitly tested in itself when using relatedness as a predictor variable in standard mixed models, because the result is potentially a mix of the two. In Table 1, we give some additional biological examples in which distinguishing between within- and between-subject hypotheses has been shown to be important (for a very illustrative example see Salomons et al. 2006). These examples aim to illustrate how general this problem is in ecological, evolutionary and behavioural studies and to help readers to identify similar examples from their own research.

Whether the effect of a predictor variable in standard mixed models is dominated by a within- or a between-subject effect depends on the structure of the unbalanced data set, and in particular how many different observations we have for how many different subjects, and over what range of circumstances per subject relative to the full range of values for the predictor variable. It is also important to note that there is no guarantee that the within- and between-subject effects contained within a single predictor variable go in the same direction. This raises the interesting possibility that a nonsignificant fixed effect may actually contain two significant effects (see Fig. 1d): a within-subject effect in one direction, and a between-subject effect in the opposite direction, with the two effectively cancelling each other out in the main association reported by the standard mixed model (see Table 2, Fig. 2d). Opposing within- and between-subject effects may in fact not be uncommon. For example (life history) trade-offs result in negative within-individual association between two variables, but between-individual quality/acquisition differences often cause some individuals to score high on both variables and

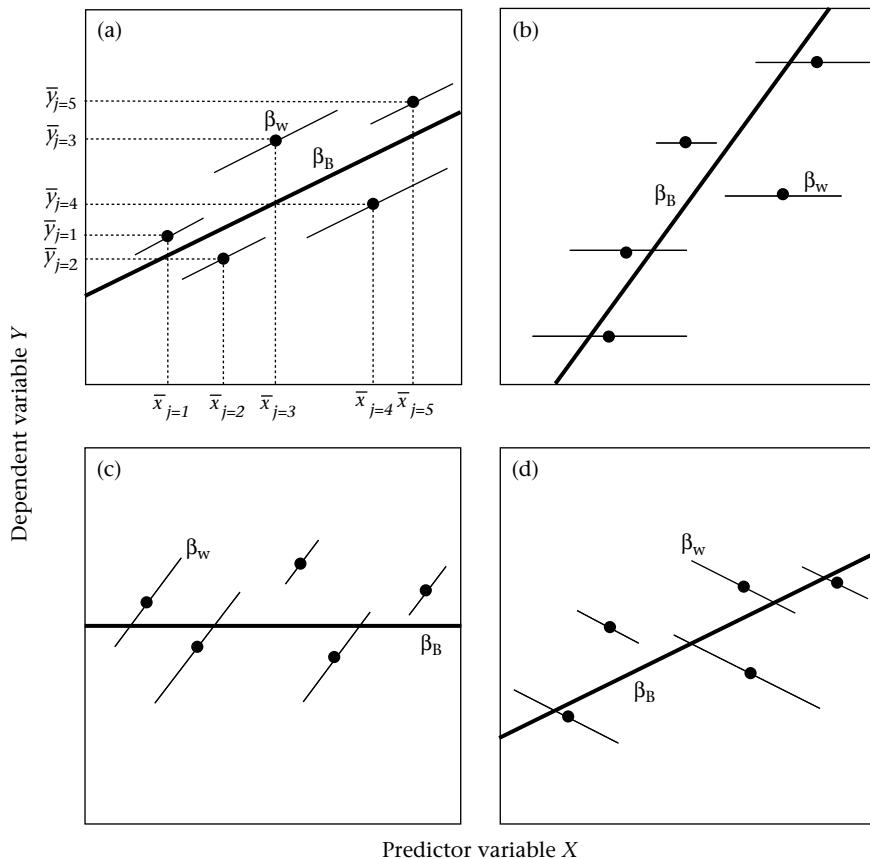


Figure 1. Four different scenarios for how within- and between-subject effects can differ within a data set. We schematically depict the within-subject slopes (thin solid lines; β_w) of five subjects ($j = 1$ to $j = 5$) with the corresponding between-subject slope (thick solid lines; β_B) resulting from the association between \bar{x}_j and \bar{y}_j (●).

others low on both variables (van Noordwijk & de Jong 1986; Reznick et al. 2000). Clearly, it is advisable always to tease apart the within- from between-subject effects in almost any behavioural study, not only because they represent alternative adaptive outcomes of selection favouring more or less behavioural flexibility, but also because it helps to determine in more detail the nature of any fixed effect.

WITHIN-SUBJECT CENTERING

The procedure for distinguishing within- versus between-subject effects is technically simple and has been around for some time (Davis et al. 1961; see also Raudenbush 1989; Kreft et al. 1995; Snijders & Bosker 1999). The technique is usually called ‘within-group centering’, but here we refer to it as ‘within-subject centering’ for the purposes of clarity when discussing analyses of behavioural data. The standard random effects model can be described by the following regression equation:

$$y_{ij} = \beta_0 + \beta_1 x_{ij} + u_{0j} + e_{0ij} \quad (1)$$

where subscripts i and j refer to the structuring of the data, where x_{ij} is the x value of measurement i from subject j . Furthermore, the intercept (constant) of the regression equation is given by β_0 and the slope of the dependency of y_{ij} on x_{ij} by β_1 . The random intercept u_{0j} and the residual error term e_{0ij} are assumed to be drawn from, for example, a normal distribution with zero mean and between-subject variance $\sigma_{u_{0j}}^2$ and within-subject variance $\sigma_{e_{0ij}}^2$, respectively.

Within-subject centering merely involves subtracting the subject’s mean value from each observation value ($x_{ij} - \bar{x}_j$). Thus, in the example of helping behaviour above, we would subtract the mean relatedness for each helper across all nests at which it was observed helping from its level of relatedness at each of these specific nests. Centering around subjects’ means effectively eliminates any between-subject variation, and we have derived a new predictor variable ($x_{ij} - \bar{x}_j$) to use as a fixed effect that expresses only the

Table 1

Some additional biological examples (with different types of data structure) where within- and between-subject hypotheses can differ

Topic	Structure of data	Within-subject hypothesis	Between-subject hypothesis
Timing of reproduction (e.g. Price et al. 1988)	Multiple breeding attempts measured per subject	Does earlier egg laying cause high reproductive success (the date hypothesis)?	Do the types of females that lay early also have higher reproductive success (the individual quality hypothesis)?
Sex allocation (e.g. Salomons et al. 2006)	Multiple offspring measured per nest	Do male offspring in a brood have shorter embryonic periods than female offspring?	Do nests with more male offspring also have a shorter embryonic period?
Cost of reproduction (e.g. Reznick et al. 2000)	Multiple breeding attempts per year	Does high reproductive output come at the cost of reduced survival (life history trade-off)?	Do environmental conditions result in years with both high reproduction and low survival (environmental covariance)?
Alternative breeding strategies (e.g. Gross 1985; Arak 1988)	Multiple subjects per social class	Do males become sneakers when there are too many other large dominant males around?	Do inherited differences in body size determine whether males become sneakers or dominants?
Antipredator behaviour (e.g. Abramsky et al. 1996)	Multiple subjects per population	Do foragers increase antipredator behaviour when they perceive more predation threat?	Do all foragers living in populations suffering high predation spend more time on antipredator behaviour?

Table 2

Parameter estimates of the standard mixed models (equation (1); see text) and mixed models that use within-subject centering (equations (2–3); see text) on the data sets displayed in Fig. 2 ($N = 250$)

Model parameter	Fig. 2a $\beta_W=1, \beta_B=1^*$ estimate \pm SE	Fig. 2b $\beta_W=0, \beta_B=2^*$ estimate \pm SE	Fig. 2c $\beta_W=2, \beta_B=0^*$ estimate \pm SE	Fig. 2d $\beta_W=-1, \beta_B=1^*$ estimate \pm SE
(1) $y_{ij} = \beta_0 + \beta_1 x_{ij} + u_{0j} + e_{0ij}$				
β_0 (intercept)	-0.07 ± 0.39	0.21 ± 0.50	-0.22 ± 0.50	0.26 ± 0.52
β_1 (combined within- & between-subject effect)	$1.04 \pm 0.12^\dagger$	$1.07 \pm 0.15^\dagger$	$1.01 \pm 0.14^\dagger$	-0.21 ± 0.16
$\sigma_{u_{0j}}^2$	6.44 ± 1.53	10.37 ± 2.38	10.75 ± 2.43	11.69 ± 2.66
$\sigma_{e_{0ij}}^2$	5.97 ± 0.60	7.76 ± 0.78	7.38 ± 0.74	8.05 ± 0.81
Deviance (-2log likelihood)	1246.8	1323.7	1313.0	1334.3
(2) $y_{ij} = \beta_0 + \beta_W(x_{ij} - \bar{x}_j) + \beta_B\bar{x}_j + u_{0j} + e_{0ij}$				
β_0 (intercept)	-0.09 ± 0.39	0.88 ± 0.39	-0.40 ± 0.34	0.06 ± 0.38
β_W (within-subject effect)	$1.11 \pm 0.18^\dagger$	0.25 ± 0.19	$1.83 \pm 0.17^\dagger$	$-1.12 \pm 0.20^\dagger$
β_B (between-subject effect)	$0.99 \pm 0.16^\dagger$	$2.09 \pm 0.17^\dagger$	-0.05 ± 0.14	$0.93 \pm 0.17^\dagger$
$\sigma_{u_{0j}}^2$	6.49 ± 1.54	5.62 ± 1.42	4.55 ± 1.18	5.54 ± 1.41
$\sigma_{e_{0ij}}^2$	5.98 ± 0.60	7.13 ± 0.71	6.65 ± 0.67	7.30 ± 0.73
Deviance (-2log likelihood)	1246.6	1277.3	1254.4	1281.7
(3) $y_{ij} = \beta_0 + \beta_W x_{ij} + (\beta_B - \beta_W)\bar{x}_j + u_{0j} + e_{0ij}$				
β_0 (intercept)	-0.09 ± 0.39	0.88 ± 0.39	-0.40 ± 0.34	0.06 ± 0.38
β_W (within-subject effect)	$1.11 \pm 0.18^\dagger$	0.25 ± 0.19	$1.83 \pm 0.17^\dagger$	$-1.12 \pm 0.20^\dagger$
$\beta_B - \beta_W$ (within- versus between-subject difference)	-0.12 ± 0.24	$1.84 \pm 0.25^\dagger$	$-1.88 \pm 0.23^\dagger$	$2.05 \pm 0.26^\dagger$
$\sigma_{u_{0j}}^2$	6.49 ± 1.54	5.62 ± 1.42	4.55 ± 1.18	5.54 ± 1.41
$\sigma_{e_{0ij}}^2$	5.98 ± 0.60	7.13 ± 0.71	6.65 ± 0.67	7.30 ± 0.73
Deviance (-2log likelihood)	1246.6	1277.3	1254.4	1281.7

Statistical significance is given for x covariates only and these are based on Wald test statistics ($df = 1$), with the important significant effects highlighted in bold and the nonsignificant effects underlined. Results were obtained using the RIGLS algorithm in MLwiN 2.0, which is equivalent to residual maximum likelihood (REML) under normality of random variables.

* Values used to generate the data (i.e. expected values).

† $P < 0.001$.

within-subject variation component. We then need to derive a second new fixed predictor variable to express only the between-subject variation component, and this is simply the subjects' means (\bar{x}_j , i.e. different observations for the same subject are all given the same \bar{x}_j value). The new model with these two new fixed effects is thus only slightly different from the standard mixed model in equation (1):

$$y_{ij} = \beta_0 + \beta_W(x_{ij} - \bar{x}_j) + \beta_B\bar{x}_j + u_{0j} + e_{0ij} \quad (2)$$

and it allows us to test whether either the within-subject effect (β_W) or the between-subject effect (β_B) is itself significant. Whenever the parameter estimates of these two effects seem to differ (Fig. 1b–d), we would then want to compare their estimated effects (slopes), to see whether they are statistically different from each other. To do this, we can rewrite equation (2) in an equivalent, but practically more convenient, way (e.g. Snijders & Bosker 1999, page 52):

$$y_{ij} = \beta_0 + \beta_W x_{ij} + (\beta_B - \beta_W)\bar{x}_j + u_{0j} + e_{0ij} \quad (3)$$

Here we are effectively including the original fixed predictor effect x_{ij} that combines both within- and between-subject effects alongside our new fixed predictor effect \bar{x}_j that expresses only between-individual variation. Since all these statistical models test for each effect while controlling for all other effects in the model, when this third model is assessing x_{ij} it is simply testing again for any within-subject effect, because it is already controlling for any between-subject effect caused by \bar{x}_j . The within-subject effects (β_W) in the second and third models will therefore be identical. More importantly, the between-subject effect in this third model (\bar{x}_j) now actually represents the difference between the between- and within-subject effects ($\beta_B - \beta_W$) in the second model. Thus the estimate of $\beta_B - \beta_W$ is expected to be close to zero and nonsignificant when the within- and between-subject effects are effectively the same (as in Fig. 1a).

For simplicity, in Fig. 1 and all the explanations given above, the fixed predictor variables (and their within- and between-subject

components) have been assumed to be continuous and linear (i.e. covariates). However, the logic here applies similarly to nonlinear effects and categorical variables with two groups (e.g. age or dominance). This method is also independent of the error distribution that is assumed, and so works just as well for logistic or Poisson regression, etc. Moreover, within-subject centering can easily be extended to situations with multiple levels of aggregation. Therefore, this easy-to-use addition to mixed-model analyses should provide behavioural studies with important biological detail concerning their results.

SOME SIMULATED DATA EXAMPLES

To illustrate further that within-subject centering does allow one to distinguish correctly and estimate accurately within- and between-subject effects, we simulated four data sets representing the four situations described in Fig. 1a–d. The data were generated using $\beta_W = 1$ and $\beta_B = 1$ in Fig. 2a, $\beta_W = 0$ and $\beta_B = 2$ in Fig. 2b, $\beta_W = 2$ and $\beta_B = 0$ in Fig. 2c, and $\beta_W = -1$ and $\beta_B = 1$ in Fig. 2d (see the Supplementary Material for the data set and details of the simulation procedure). We fitted the standard mixed model (equation (1)) and the two mixed models using within-subject centering (equations (2) and (3)) to these data sets using program MLwiN 2.0 (Rasbash et al. 2004) and compared their output (Table 2). We obtained similar results using SPSS (SPSS Inc., Chicago, IL, U.S.A.) and R (R Foundation for Statistical Computing, Vienna, Austria).

Our results in Table 2 confirm that mixed models that use within-subject centering produce estimates of the within- and between-subject effects that are very close to the effects that were used to generate the data (some minor deviations were to be expected given the sample size of $N = 250$ and sampling variance). In sharp contrast, the standard mixed models produced virtually the same result for the effect of x on y for the first three data sets in Fig. 2a–c, even though these represent three completely different scenarios. In addition, the estimated effect of x on y (β_1) in the standard mixed model described neither the within- (β_W) nor the between-subject (β_B) effect well. In a worst-case scenario,

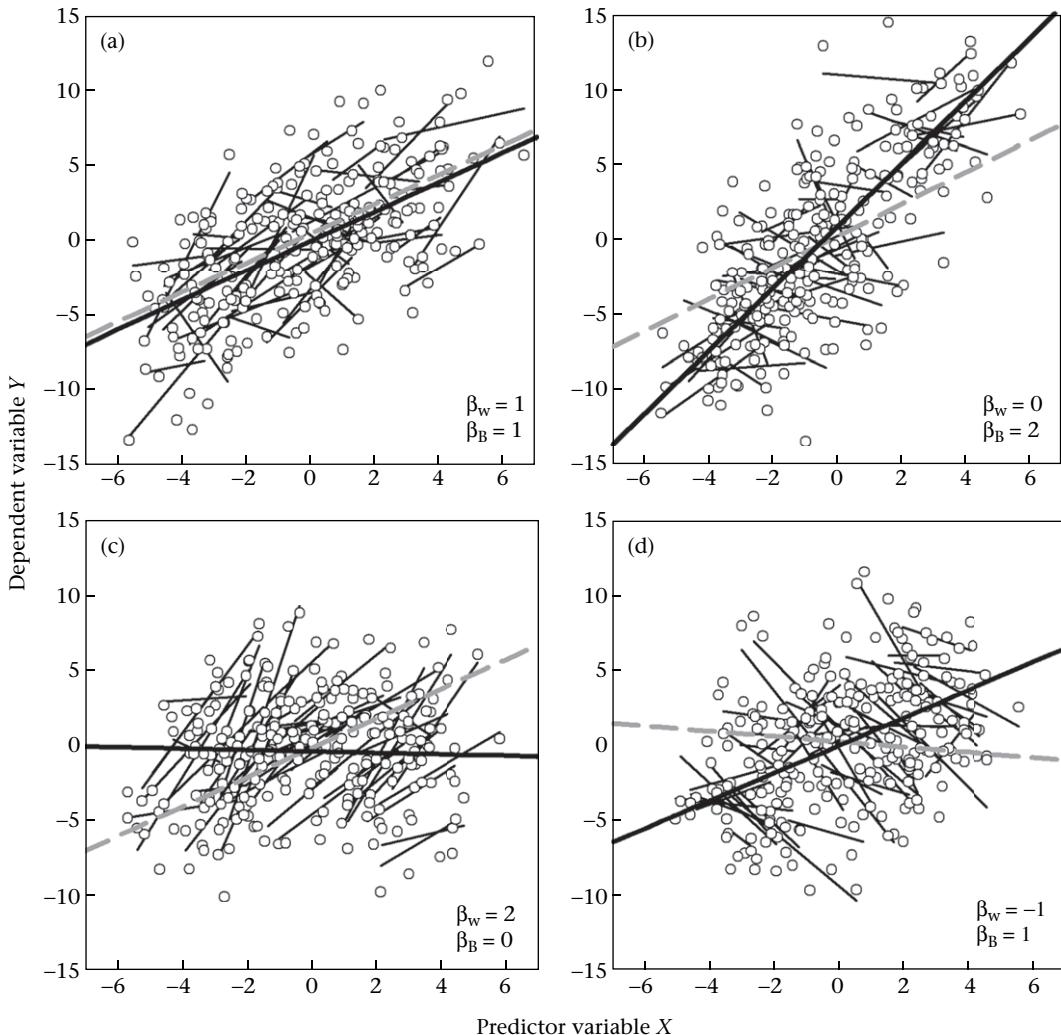


Figure 2. Simulated data sets with within-subject slopes and between-subject slopes that reflect the four different scenarios described in Fig. 1. The within- (β_W) and between- subject slopes (β_B) that were used to generate the data are given in the lower-right corner of each graph (i.e. expected values). Each dot (\circ ; $N = 250$) is one observation per subject and the thin solid lines depict individual within-subject slopes, while the thick solid lines describe the between-subject effect. The dashed grey line depicts the estimate from a standard mixed model of the effect of predictor variable x on the dependent variable y (β_1 ; equation (1)). See Table 2 for statistical output; data sets are provided in the Supplementary Material.

the standard mixed model even suggested there was no statistically detectable association between x and y , whereas there were actually two underlying associations cancelling each other out (Table 2, Fig. 2d). It is important to note that estimates of β_1 in the standard mixed model do not necessarily always lie roughly halfway between the within- and between-subject estimates of β_W and β_B . In fact, by manipulating the number of samples per subject and/or the relative amount of within- and between- subject variation in x or y , it is possible to generate data sets similar to Fig. 2a-d where β_1 is either closer to β_W or closer to β_B . Therefore, the advantage of using within-group centering is that it always produces unbiased estimates of β_W and β_B irrespective of how the data are structured.

A LOGICAL NEXT STEP: RANDOM SLOPES

When we find a within-subject effect, the logical next step would be to investigate whether there is substantial between- subject variation in the slopes of the within-subject effect. If subjects differ in how strong their y depends on x this could suggest that they, for example, have different phenotypic plasticity (e.g.

Nussey et al. 2005) or behavioural syndromes (e.g. Dingemanse et al. 2007). Quantifying the amount of between-subject variation in within-subject slopes around β_W is possible by adding a random slope (u_{Wj}) to the random intercept model of equation (2):

$$y_{ij} = (\beta_0 + u_{0j}) + (\beta_W + u_{Wj})(x_{ij} - \bar{x}_j) + \beta_B \bar{x}_j + e_{0ij} \quad (4)$$

where u_{Wj} is assumed to be drawn from, for example, a normal distribution with zero mean and between-subject variance $\sigma_{u_{Wj}}^2$. Applying equation (4) to the data sets of Fig. 2 results in estimates of the between-subject variation in within-subject slopes that are close to zero (see Supplementary Material), and thus provides no evidence for the existence of variation in phenotypic plasticity or behavioural syndromes. At first sight this result may appear in conflict with the fact that we do see some between-subject variation in within-subject slopes in Fig. 2 (the slopes of the thin lines in Fig. 2 do vary between individuals). However, the between- subject variation in slopes apparent in Fig. 2 is actually not more than expected from sampling variance (and thus $\sigma_{u_{Wj}}^2 \approx 0$). In the Supplementary Material we present an example of a data set where we do have substantial between-subject variation in within-subject slopes.

CONCLUSIONS

As behavioural ecologists, many of us are specifically interested in the evolution of within-individual variation and the nature of phenotypic plasticity/flexibility, learning and conditional or facultative responses. We also often want to distinguish such effects from evolutionarily fixed patterns of behaviour, and innate or individually consistent behavioural responses reflecting individual state, genetic quality or social class. However, in trying to do so using the latest sophisticated statistical techniques we are not always able to keep the individual as the central unit of our analyses. We therefore run the risk of pseudoreplication or misinterpreting the biological basis for some of the results we publish by erroneously extrapolating from between-subject effects to within-subject effects or vice versa (i.e. the ecological fallacy; Robinson 1950).

Unfortunately, the exact workings of mixed models can be relatively opaque to the average animal behaviour researcher. One reason for this could well be the bewildering variety of statistical programs on offer, each with its own terminology and notation. Reassuringly, for relatively simple mixed models as described in this paper the different statistical packages (we tried MLwiN, SPSS, R) are doing more or less the same thing, with only minor differences caused by the different algorithms used (see also <http://www.cmm.bristol.ac.uk/learning-training/multilevel-m-software/index.shtml>). Nevertheless, the diversity in terminology and software product approaches to mixed models may have hampered students of animal behaviour when attempting fully to understand and exploit their full potential. This seems to have been especially the case with regard to distinguishing between within- versus between-subject effects, which is a shame because the methods involved should be relatively straightforward, as we have shown here. We therefore hope that this paper provides a small step towards the more informed use of mixed-model statistical analyses in the behavioural sciences.

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Supplementary Material

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.anbehav.2008.11.006.

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Supplementary Material

Simulation Procedure of Data Sets Displayed in Fig. 2 and Table 2

Let x_{ij} be the x -value of observation i of subject j . We allowed x_{ij} to vary between subjects and within subjects, such that $x_{ij} = f_j + g_{ij}$ where f_j and g_{ij} are random variables with $f_j \sim Uniform(f_{j_{\min}}, f_{j_{\max}})$ and $g_{ij} \sim Normal(0, \sigma_{g_{ij}}^2)$. Subsequently, we assumed variation in y_{ij} was the result of (i) a within-subject effect of x_{ij} on y_{ij} ($\beta_W(x_{ij} - \bar{x}_j)$), (ii) a between-subject effect of \bar{x}_j on y_{ij} ($\beta_B \bar{x}_j$), (iii) a between-subject residual variation in y_{ij} (u_{0j}), and (iv) a within-subject residual variation in y_{ij} (e_{0ij}). More formally,

$$y_{ij} = \beta_0 + \beta_W(x_{ij} - \bar{x}_j) + \beta_B \bar{x}_j + u_{0j} + e_{0ij} \quad (\text{equation 2 in the main text}),$$

where u_{0j} and e_{0ij} are random variables with $u_{0j} \sim Normal(0, \sigma_{u_{0j}}^2)$ and $e_{0ij} \sim Normal(0, \sigma_{e_{0ij}}^2)$. From this model we drew 250 samples (i observations \times j subjects) using the following parameters: $i = 5$, $j = 50$, $\beta_0 = 0$, $f_{j_{\max}} = -f_{j_{\min}} = 3.9$, $\sigma_{g_{ij}}^2 = 1$, $\sigma_{u_{0j}}^2 = 5$, $\sigma_{e_{0ij}}^2 = 6.25$. In addition for Fig. 2a we set $\beta_W = 1$, $\beta_B = 1$, for Fig. 2b we set $\beta_W = 0$, $\beta_B = 2$, for Fig. 2c we set $\beta_W = 2$, $\beta_B = 0$ and for Fig. 2d we set $\beta_W = -1$, $\beta_B = 1$. The simulated data is given in Table S2. Note that for reasons of simplicity we have generated a balanced dataset with always 5 observations per individual, but the mixed models presented in this paper will work equally well for unbalanced data.

Simulation Procedure of Data with Between-subject Variation in Within-subject Slopes and Application of Random Slopes Model to this Data Set and the Data Sets of Fig. 2

The simulation procedure to generate a dataset with between-subject variation in within-subject slopes was similar as described above with identical parameter values used as in the dataset of Fig. 2d. The only difference is that we now also included between-subject variation in the within-subject slopes (u_{Wj}). More specifically, we used $y_{ij} = (\beta_0 + u_{0j}) + (\beta_W + u_{Wj})(x_{ij} - \bar{x}_j) + \beta_B \bar{x}_j + e_{0ij}$ (equation 4 in the main text) and modelled u_{Wj} as a random variable with $u_{Wj} \sim Normal(0, \sigma_{uWj}^2)$ and $\sigma_{uWj}^2 = 1.5$. The simulated dataset is given in Table S2 and is depicted in Fig. S1. The statistical output of applying the random slopes model described in equation 4 to the dataset of Figure 2 and Figure S1 is given Table S1.

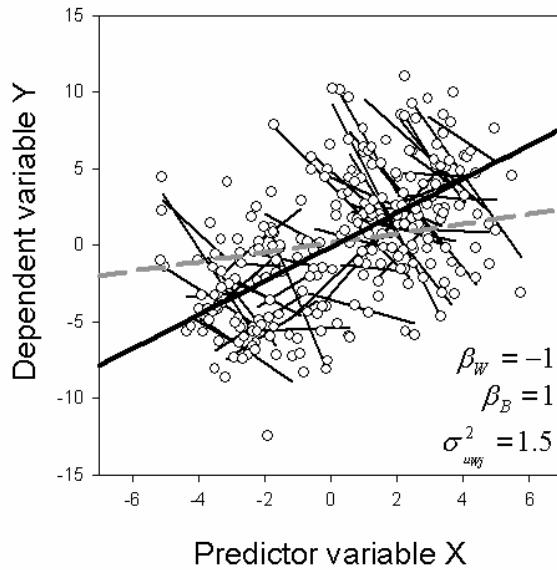


Figure S1: Simulated dataset with within-subject slopes and between-subjects slopes similar to the dataset described in Fig. 2d and additional between-subject variation in within-subject slopes ($\sigma_{uWj}^2 = 1.5$). The within (β_W) and between-subjects slopes (β_B) that were used to generate the data are given in the lower-right corner of the panel (i.e. expected values). Each dot (\circ ; $n=250$) is one observation per subject and the thin solid

lines depict individual within-subject slopes, while the thick solid lines describe the between-subjects effect. The dashed grey line depicts the estimate from a standard mixed model of the effect of predictor variable x on the dependent variable y (β_I ; equation 1). See Table S1 for statistical output; the dataset is provided in Table S2.

Table S1: Statistical output from Table 2 in the main text extended with results from a random slopes model (equation 4 in the main text). Parameter estimates of the standard mixed models (equation 1; see main text), mixed models that use within-subject centering (equations 2-3), and a random slopes model (equation 4) on the datasets displayed in Figure 2 and Figure S1 ($n=250$). Statistical significance is given for x -covariates based on Wald-test statistics ($df=1$) and the between-subject variation in within-subject slopes ($\sigma_{u_{wj}}^2$) based on a likelihood-ratio test ($df=1$), with the important significant effects highlighted in bold and the non-significant effects underlined. Results were obtained using the RIGLS algorithm in MLwiN 2.0, which is equivalent to residual maximum likelihood (REML) under normality of random variables. In the model that included both a random intercept and random slope (equation 4), for reasons of simplicity we did not estimate the covariance between the intercept and slope ($\sigma_{u_{0j},u_{wj}}$ was constrained to zero).

Model parameter	Figure 2a $\beta_w = 1, \beta_B = 1^\dagger$ estimate \pm s.e.	Figure 2b $\beta_w = 0, \beta_B = 2^\dagger$ estimate \pm s.e.	Figure 2c $\beta_w = 2, \beta_B = 0^\dagger$ estimate \pm s.e.	Figure 2d $\beta_w = -1, \beta_B = 1^\dagger$ estimate \pm s.e.	Figure S1 $\beta_w = -1, \beta_B = 1, \sigma_{u_{0j}}^2 = 1.5^\dagger$ estimate \pm s.e.
(1) $y_{ij} = \beta_0 + \beta_1 x_{ij} + u_{0j} + e_{0ij}$					
β_0 (intercept)	-0.07 \pm 0.39	0.21 \pm 0.50	-0.22 \pm 0.50	0.26 \pm 0.52	0.17 \pm 0.415
β_1 (combined within- & between-subjects effect)	1.04 \pm 0.12***	1.07 \pm 0.15***	1.01 \pm 0.14***	<u>-0.21 \pm 0.16^{N.S.}</u>	0.31 \pm 0.14*
$\sigma_{u_{0j}}^2$	6.44 \pm 1.53	10.37 \pm 2.38	10.75 \pm 2.43	11.69 \pm 2.66	8.01 \pm 1.98
$\sigma_{e_{0ij}}^2$	5.97 \pm 0.60	7.76 \pm 0.78	7.38 \pm 0.74	8.05 \pm 0.81	9.51 \pm 0.95
Deviance (-2LogLikelihood)	1246.8	1323.7	1313.0	1334.3	1353.0
(2) $y_{ij} = \beta_0 + \beta_w(x_{ij} - \bar{x}_j) + \beta_B\bar{x}_j + u_{0j} + e_{0ij}$					
β_0 (intercept)	-0.09 \pm 0.39	0.88 \pm 0.39	-0.40 \pm 0.34	0.06 \pm 0.38	-0.10 \pm 0.36
β_w (within-subjects effect)	1.11 \pm 0.18***	<u>0.25 \pm 0.19^{N.S.}</u>	1.83 \pm 0.17***	-1.12 \pm 0.20***	-0.87 \pm 0.21***
β_B (between-subjects effect)	0.99 \pm 0.16***	2.09 \pm 0.17***	<u>-0.05 \pm 0.14^{N.S.}</u>	0.93 \pm 0.17***	1.11 \pm 0.15***
$\sigma_{u_{0j}}^2$	6.49 \pm 1.54	5.62 \pm 1.42	4.55 \pm 1.18	5.54 \pm 1.41	4.55 \pm 1.25
$\sigma_{e_{0ij}}^2$	5.98 \pm 0.60	7.13 \pm 0.71	6.65 \pm 0.67	7.30 \pm 0.73	8.24 \pm 0.82
Deviance (-2LogLikelihood)	1246.6	1277.3	1254.4	1281.7	1299.9
(3) $y_{ij} = \beta_0 + \beta_w x_{ij} + (\beta_B - \beta_w)\bar{x}_j + u_{0j} + e_{0ij}$					
β_0 (intercept)	-0.09 \pm 0.39	0.88 \pm 0.39	-0.40 \pm 0.34	0.06 \pm 0.38	-0.10 \pm 0.36

β_w (within-subjects effect)	1.11 ± 0.18 ***	<u>0.25 ± 0.19 N.S.</u>	1.83 ± 0.17 ***	-1.12 ± 0.20 ***	-0.87 ± 0.21 ***
$\beta_B - \beta_w$ (within- vs between-subjects difference)	<u>-0.12 ± 0.24 N.S.</u>	1.84 ± 0.25 ***	-1.88 ± 0.23 ***	2.05 ± 0.26 ***	1.98 ± 0.26 ***
$\sigma_{u_{0j}}^2$	6.49 ± 1.54	5.62 ± 1.42	4.55 ± 1.18	5.54 ± 1.41	4.55 ± 1.25
$\sigma_{e_{0ij}}^2$	5.98 ± 0.60	7.13 ± 0.71	6.65 ± 0.67	7.30 ± 0.73	8.24 ± 0.82
Deviance (-2LogLikelihood)	1246.6	1277.3	1254.4	1281.7	1299.9
(4) $y_{ij} = (\beta_0 + u_{0j}) + (\beta_w + u_{wj})(x_{ij} - \bar{x}_j) + \beta_B \bar{x}_j + e_{0ij}$					
β_0 (intercept)	-0.09 ± 0.39	0.88 ± 0.39	-0.40 ± 0.34	0.06 ± 0.38	-0.10 ± 0.36
β_w (within-subjects effect)	1.11 ± 0.18 ***	<u>0.25 ± 0.19 N.S.</u>	1.85 ± 0.19 ***	-1.12 ± 0.20 ***	-0.93 ± 0.27 ***
β_B (between-subjects effect)	0.99 ± 0.16 ***	2.09 ± 0.17 ***	<u>-0.05 ± 0.14 N.S.</u>	0.93 ± 0.17 ***	1.11 ± 0.15 ***
$\sigma_{u_{0j}}^2$	6.51 ± 1.54	5.62 ± 1.42	4.60 ± 1.18	5.54 ± 1.41	4.83 ± 1.25
$\sigma_{u_{wj}}^2$	<u>0.12 ± 0.31 N.S.</u>	<u>0.00 ± 0.00 N.S.</u>	<u>0.23 ± 0.35 N.S.</u>	<u>0.004 ± 0.372 N.S.</u>	1.43 ± 0.69 ***
$\sigma_{e_{0ij}}^2$	5.86 ± 0.65	7.13 ± 0.71	6.41 ± 0.72	7.29 ± 0.80	6.80 ± 0.77
Deviance (-2LogLikelihood)	1246.5	1277.3	1254.1	1281.7	1288.9

Note: †Values used to generate the data (i.e. expected values); * $=P<0.05$; ** $=P<0.001$; N.S. $=P>0.05$

Table S2: The simulated datasets

Obs	Subject	Figure 2A				Figure 2B				Figure 2C				Figure 2D				Figure E1			
		i	j	y_{ij}	x_{ij}	\bar{x}_j	$x_{ij} - \bar{x}_j$		y_{ij}	x_{ij}	\bar{x}_j	$x_{ij} - \bar{x}_j$		y_{ij}	x_{ij}	\bar{x}_j	$x_{ij} - \bar{x}_j$	y_{ij}	x_{ij}	\bar{x}_j	$x_{ij} - \bar{x}_j$
1	1	3.6565	-0.6132	-0.8728	0.2596	-6.0191	1.3583	-0.0086	1.3669	-1.3960	0.4781	0.2887	0.1893	5.7795	3.1926	2.0162	1.1765	-8.6676	-3.1781	-1.9837	-1.1944
2	1	-4.6453	-2.1265	-0.8728	-1.2536	-6.1362	0.9262	-0.0086	0.9348	2.1287	-1.0423	0.2887	-1.3310	2.9782	1.5520	2.0162	-0.4642	-6.3445	-2.2668	-1.9837	-0.2832
3	1	7.0127	0.0712	-0.8728	0.9440	-1.9927	-1.6188	-0.0086	-1.6102	3.1358	0.6639	0.2887	0.3752	5.5259	2.5482	2.0162	0.5320	-4.7623	-1.8806	-1.9837	0.1031
4	1	1.2158	-1.1975	-0.8728	-0.3247	-0.0352	0.7848	-0.0086	0.7935	3.1244	1.3273	0.2887	1.0385	7.2101	0.1699	2.0162	-1.8463	-4.8748	-2.1882	-1.9837	-0.2045
5	1	-0.7660	-0.4982	-0.8728	0.3746	-3.1992	-1.4937	-0.0086	-1.4851	0.6327	0.0167	0.2887	-0.2720	3.0303	2.6182	2.0162	0.6020	-4.4678	-0.4046	-1.9837	1.5790
6	2	-1.4027	-2.3980	-3.3229	0.9249	-6.9818	-2.2878	-3.4545	1.1667	-1.0947	-2.5402	-2.9774	0.4372	3.3205	2.5597	3.6104	-1.0507	1.3774	2.6399	3.2370	-0.5971
7	2	0.6944	-1.8347	-3.3229	1.4881	-9.9171	-5.3450	-3.4545	-1.8905	-5.7201	-3.8365	-2.9774	-0.8592	-0.7063	4.5633	3.6104	0.9529	1.3451	2.0282	3.2370	-1.2087
8	2	-4.0973	-4.6178	-3.3229	-1.2950	-8.3347	-3.6534	-3.4545	-0.1989	-6.6763	-3.3190	-2.9774	-0.3416	4.2287	3.4239	3.6104	-0.1865	0.9298	4.9950	3.2370	1.7580
9	2	-5.9885	-4.3179	-3.3229	-0.9951	-7.1389	-3.1756	-3.4545	0.2789	-1.3994	-1.4691	-2.9774	1.5083	6.6303	4.0967	3.6104	0.4863	6.1390	2.4797	3.2370	-0.7573
10	2	-6.2792	-3.4458	-3.3229	-0.1230	-4.6711	-2.8106	-3.4545	0.6439	-8.2590	-3.7221	-2.9774	-0.7447	-0.3719	3.4084	3.6104	-0.2020	5.8695	4.0420	3.2370	0.8051
11	3	-0.3084	1.0142	1.7473	-0.7331	-7.2328	-2.7158	-1.9181	-0.7977	0.6404	-3.7112	-3.5807	-0.1305	-2.1571	1.0946	0.4334	0.6612	-1.2587	3.0141	2.3005	0.7135
12	3	2.2780	2.1086	1.7473	0.3613	-0.8974	-1.1184	-1.9181	0.7998	2.2887	-3.7814	-3.5807	-0.2007	-4.7547	1.2683	0.4334	0.8349	4.4844	2.4292	2.3005	0.1287
13	3	1.0832	1.7818	1.7473	0.0345	-4.2333	-1.6863	-1.9181	0.2318	-5.9435	-5.1072	-3.5807	-1.5264	-2.5056	0.2628	0.4334	-0.1706	4.4884	2.0276	2.3005	-0.2729
14	3	-0.4528	1.9944	1.7473	0.2470	0.8696	-0.4830	-1.9181	1.4351	0.9444	-3.4600	-3.5807	0.1207	0.3777	0.1191	0.4334	-0.3143	-2.4680	3.4484	2.3005	1.1479
15	3	2.0145	1.8376	1.7473	0.0903	1.8675	-3.5871	-1.9181	-1.6690	2.2740	-1.8439	-3.5807	1.7369	-2.6944	-0.5777	0.4334	-1.0111	0.1474	0.5834	2.3005	-1.7172
16	4	2.3819	1.3273	2.1473	-0.8200	-0.8278	0.9246	1.0373	-0.1127	-6.8837	1.1616	2.5153	-1.3537	0.2956	1.7133	0.2440	1.4693	5.0961	3.4652	0.9306	2.5346
17	4	-0.4516	1.1885	2.1473	-0.9588	4.3305	1.0129	1.0373	-0.0244	-2.1790	1.3012	2.5153	-1.2141	1.4150	0.1401	0.2440	-0.1039	-1.6049	0.0555	0.9306	-0.8752
18	4	-2.6207	1.3349	2.1473	-0.8125	-2.5499	1.5530	1.0373	0.5157	-1.2748	3.2598	2.5153	0.7446	0.0672	-0.4012	0.2440	-0.6451	0.6724	0.2975	0.9306	-0.6331
19	4	0.2765	3.0785	2.1473	0.9312	-3.3734	0.9570	1.0373	-0.0802	7.7013	4.3847	2.5153	1.8695	0.1726	-0.7652	0.2440	-1.0092	-0.8708	0.9425	0.9306	0.0119
20	4	0.9317	3.8075	2.1473	1.6601	0.0111	0.7389	1.0373	-0.2984	0.7149	2.4690	2.5153	-0.0463	3.2104	0.5328	0.2440	0.2888	-7.5329	-0.1075	0.9306	-1.0382
21	5	0.4509	2.0494	2.8559	-0.8065	3.7952	2.3131	1.5038	0.8093	-3.3036	1.8704	1.4624	0.4081	-6.4109	1.9256	1.0548	0.8708	4.7231	4.3885	3.9588	0.4297
22	5	-0.6459	4.0465	2.8559	1.1906	4.2183	1.8766	1.5038	0.3728	-6.5829	-0.9605	1.4624	-2.4229	0.4913	1.5217	1.0548	0.4670	8.0397	3.6263	3.9588	-0.3325
23	5	-0.6071	2.4714	2.8559	-0.3845	5.1244	0.5077	1.5038	-0.9960	-1.5058	2.7092	1.4624	1.2468	-5.1556	0.0083	1.0548	-1.0465	7.6058	4.9398	3.9588	0.9810
24	5	2.0689	3.3651	2.8559	0.5092	4.5852	0.5578	1.5038	-0.9460	0.7589	1.9232	1.4624	0.4608	0.4559	-0.3003	1.0548	-1.3551	4.8513	3.9102	3.9588	-0.0486
25	5	-1.1864	2.3471	2.8559	-0.5088	1.3219	2.2637	1.5038	0.7599	-1.0317	1.7695	1.4624	0.3071	-2.3987	2.1186	1.0548	1.0638	9.5722	2.9292	3.9588	-1.0296
26	6	-3.1027	-2.0280	-1.6248	-0.4032	-1.9789	-2.3660	-1.6155	-0.7505	2.8805	-0.2663	0.1276	-0.3939	1.4008	-1.6792	0.1162	-1.7954	4.9137	0.6330	1.3749	-0.7418
27	6	0.7524	-0.2472	-1.6248	1.3776	3.5179	-2.2728	-1.6155	-0.6573	1.0473	-1.0416	0.1276	-1.1692	-2.3794	1.4743	0.1162	1.3581	-3.8937	0.7099	1.3749	-0.6650
28	6	-4.1781	-2.0390	-1.6248	-0.4142	1.6116	-1.5096	-1.6155	0.1059	3.7676	0.4109	0.1276	0.2833	3.2324	0.4228	0.1162	0.3066	6.0724	0.9770	1.3749	-0.3979
29	6	-3.3089	-2.1020	-1.6248	-0.4772	0.2705	-1.3745	-1.6155	0.2410	-2.0235	0.3381	0.1276	0.2104	2.8463	-0.0698	0.1162	-0.1860	1.4322	2.3139	1.3749	0.9390
30	6	-5.3806	-1.7079	-1.6248	-0.0831	2.5843	-0.5546	-1.6155	1.0609	2.2808	1.1970	0.1276	1.0694	1.1763	0.4328	0.1162	0.3167	1.3694	2.2406	1.3749	0.8657
31	7	-6.6813	-3.6995	-3.5958	-0.1038	-9.0333	-1.6743	-2.5596	0.8853	-1.0190	3.4401	3.1105	0.3297	2.5653	-2.4253	-3.0414	0.6162	-3.3352	1.4313	2.1726	-0.7413
32	7	-4.2879	-4.5114	-3.5958	-0.9156	-4.8941	-2.6873	-2.5596	-0.1278	1.1000	4.0572	3.1105	0.9467	-4.6174	-4.6280	-3.0414	-1.5865	1.7657	2.4546	2.1726	0.2820
33	7	-2.4149	-3.9420	-3.5958	-0.3463	-6.3212	-1.6537	-2.5596	0.9059	2.2055	3.7263	3.1105	0.6159	-1.1765	-3.9832	-3.0414	-0.9417	0.7604	1.8239	2.1726	-0.3487
34	7	-7.8901	-2.6033	-3.5958	0.9925	-6.0654	-3.7689	-2.5596	-1.2094	-1.3099	3.1472	3.1105	0.0368	-3.8782	-1.9571	-3.0414	1.0843	0.6411	2.9135	2.1726	0.7409
35	7	-11.0027	-3.2226	-3.5958	0.3732	-5.0481	-3.0136	-2.5596	-0.4540	-3.6011	1.1814	3.1105	-1.9290	-2.8676	-2.2136	-3.0414	0.8278	-1.5752	2.2398	2.1726	0.0672
36	8	6.1658	4.0967	3.5410	0.5557	10.1293	3.8487	2.4290	1.4197	3.6505	1.3362	-0.2608	1.5969	1.1691	-3.4764	-2.5195	-0.9569	1.1583	-1.8080	-1.0819	-0.7262
37	8	6.0115	4.0531	3.5410	0.5120	2.5325	0.7982	2.4290	-1.6308	-2.5597	0.0364	-0.2608	0.2972	-3.2724	-2.7684	-2.5195	-0.2489	-6.1434	-1.0083	-1.0819	0.0736
38	8	6.2330	3.9942	3.5410	0.4531	7.0605	2.2322	2.4290	-0.1968	-2.9695	-0.7480	-0.2608	-0.4872	2.0854	-2.6986	-2.5195	-0.1790	-1.7037	-1.4522	-1.0819	-0.3704
39	8	5.1922	3.1077	3.5410	-0.4333	4.1339	1.8532	2.4290	-0.5758	1.2834	0.0517	-0.2608	0.3125	-1.8611	-1.7437	-2.5195	0.7758	-8.1056	-0.1267	-1.0819	0.9551
40	8	3.7176	2.4534	3.5410	-1.0876	4.9506	3.4128	2.4290	0.9838	-0.7381	-1.9802	-0.2608	-1.7194	-1.3082	-1.9106	-2.5195	0.6089	-0.7829	-1.0141	-1.0819	0.0678
41	9	-2.3721	-0.7810	-1.7448	0.9638	-9.9659	-2.2330	-3.0200	0.7871	-4.6279	3.0624	2.6978	0.3646	-8.2666	-3.3875	-3.1898	-0.1977	8.2532	2.5784	2.7852	-0.2068
42	9	-1.6397	-1.1263	-1.7448	0.6185	-6.2914	-3.7725	-3.0200	-0.7525	-6.6030	1.9643	2.6978	-0.7336	-7.1900	-2.9461	-3.1898	0.2437	-1.2048	4.8016	2.7852	2.0164
43	9	3.4251	-1.0597	-1.7448	0.6851	-9.8685	-3.1070	-3													

233	47	1.0942	2.6387	3.5326	-0.8939	-7.9664	-4.2113	-3.9100	-0.3012	-3.4794	-2.0266	-1.6654	-0.3612	-0.9635	2.1040	2.6474	-0.5434	1.7231	0.8038	0.6718	0.1320
234	47	-2.9800	3.6135	3.5326	0.0809	-6.0569	-3.4769	-3.9100	0.4332	8.8079	-0.3145	-1.6654	1.3508	7.1975	1.0761	2.6474	-1.5713	0.6930	1.5526	0.6718	0.8809
235	47	-1.1794	3.4527	3.5326	-0.0799	-6.3680	-5.4510	-3.9100	-1.5410	-0.0261	-2.2343	-1.6654	-0.5690	-0.9613	4.5610	2.6474	1.9136	1.4190	0.8162	0.6718	0.1444
236	48	-4.3116	-3.1791	-1.5978	-1.5813	1.2630	-0.0982	-0.2410	0.1428	-2.8167	-2.3242	-0.8254	-1.4988	2.9922	2.3131	1.9253	0.3878	-2.2933	-2.2303	-2.3955	0.1651
237	48	3.0496	-2.1511	-1.5978	-0.5533	2.9515	-0.5332	-0.2410	-0.2922	3.1491	0.2129	-0.8254	1.0383	5.9820	2.2039	1.9253	0.2787	-2.7652	-3.3055	-2.3955	-0.9100
238	48	-0.8433	-0.8518	-1.5978	0.7459	4.8168	-0.9817	-0.2410	-0.7407	0.6723	-1.1987	-0.8254	-0.3732	7.5378	1.7584	1.9253	-0.1668	1.8568	-2.4092	-2.3955	-0.0137
239	48	1.3952	-1.6736	-1.5978	-0.0759	3.0087	-0.1173	-0.2410	0.1238	-0.4281	-1.2482	-0.8254	-0.4227	3.6899	0.9574	1.9253	-0.9678	-0.0562	-1.7709	-2.3955	0.6246
240	48	2.9352	-0.1332	-1.5978	1.4646	-2.0230	0.5252	-0.2410	0.7663	2.0052	0.4310	-0.8254	1.2565	-1.9290	2.3934	1.9253	0.4681	2.5246	-2.2614	-2.3955	0.1341
241	49	-8.6221	-2.6166	-2.0100	-0.6066	-3.5288	-3.0343	-2.3140	-0.7203	0.4133	-0.9966	-0.9302	-0.0664	-1.1554	2.1379	2.3614	-0.2235	-2.0126	-0.4136	-1.3514	0.9378
242	49	-3.6287	-1.8773	-2.0100	0.1327	-4.2525	-1.2859	-2.3140	1.0281	1.2226	-1.6131	-0.9302	-0.6829	0.8615	3.1250	2.3614	0.7636	-2.0644	-0.6365	-1.3514	0.7149
243	49	-7.6126	-0.6835	-2.0100	1.3265	-5.2029	-2.5088	-2.3140	-0.1948	2.1613	-1.3907	-0.9302	-0.4605	1.2793	2.2019	2.3614	-0.1595	-5.6528	-2.2327	-1.3514	-0.8813
244	49	-4.1388	-2.3802	-2.0100	-0.3702	-4.0488	-2.2306	-2.3140	0.0834	4.2721	0.8450	-0.9302	1.7752	3.6645	2.3239	2.3614	-0.0375	-5.3393	-1.7326	-1.3514	-0.3813
245	49	-4.0723	-2.4924	-2.0100	-0.4824	0.7848	-2.5105	-2.3140	-0.1965	1.0489	-1.4955	-0.9302	-0.5653	1.9446	2.0184	2.3614	-0.3430	0.8443	-1.7415	-1.3514	-0.3901
246	50	0.1890	0.8114	0.9258	-0.1144	7.9287	3.9539	3.5045	0.4494	-2.4669	3.4570	2.9768	0.4801	-8.2940	-0.2795	-0.0917	-0.1878	-7.1176	-0.9220	-2.0195	1.0976
247	50	1.7472	1.4672	0.9258	0.5415	4.3359	2.6272	3.5045	-0.8773	3.9406	2.3890	2.9768	-0.5878	-3.8318	-1.6228	-0.0917	-1.5312	-2.1429	-1.9511	-2.0195	0.0685
248	50	0.3988	0.7788	0.9258	-0.1470	3.2249	2.5711	3.5045	-0.9334	0.2912	3.4234	2.9768	0.4466	-5.4489	0.4036	-0.0917	0.4952	-5.0643	-2.8963	-2.0195	-0.8768
249	50	0.0310	1.3274	0.9258	0.4016	6.4338	2.9618	3.5045	-0.5428	-1.5640	1.3518	2.9768	-1.6251	-7.3161	0.3399	-0.0917	0.4316	-1.1953	-2.6893	-2.0195	-0.6697
250	50	-4.2625	0.2441	0.9258	-0.6817	11.7252	5.4087	3.5045	1.9041	4.3458	4.2630	2.9768	1.2862	-4.6244	0.7006	-0.0917	0.7922	-1.0164	-1.6390	-2.0195	0.3805