

Chapter 2

State Space Grids

Now that some of the dynamic systems (DS) terminology is familiar to you, we can see how the concepts of state space, attractors, repellers, and phase transitions can be applied with state space grids. In this chapter, I will describe how state space grids were derived from the abstraction of state space. Next, I will describe the essential features of state space grids. In the last section, I will review state space grid studies to date, so that you may get a sense of the versatility of the technique.

From Continuous to Categorical

State space is often depicted in its most simple form as a two-dimensional plane formed by the intersection of two perpendicular dimensions or axes. There is no theoretical limit to the number of orthogonal dimensions necessary to describe a system on a state space, but after the third dimension it becomes difficult to visualize. Since there is nothing ostensibly different about higher dimensional state spaces, the utilization of two dimensions is sufficient for illustrative and analytical purposes (see Chap. 7 for an expansion beyond two-dimensional state space).

Consider the state space landscape depicted in Fig. 2.1. Here, each position on the landscape is a possible state in which the system could *hypothetically* be at any one time. Furthermore, each location is a combination of one value along the x -dimension and another value along the y -dimension (let us leave the z -dimension out for the moment). Thus, it is possible to identify each point on the landscape in terms of an x and a y coordinate, similar to a map. At the risk of being overly simplistic, there are at least four important considerations of such an arrangement. First, the values on any one of those dimensions must be mutually exclusive. If, for example, the y -dimension ranged from 0 at the bottom-right corner to 100 at the top-right corner in Fig. 2.1, then at any given time point there could only be one value to represent the system on that dimension. That is, y could only be at value 15 or 34, not 15 *and* 34. The same is true for the other dimensions. This may seem obvious but, as you will see later, mutual exclusivity is a necessary condition for state space grids.

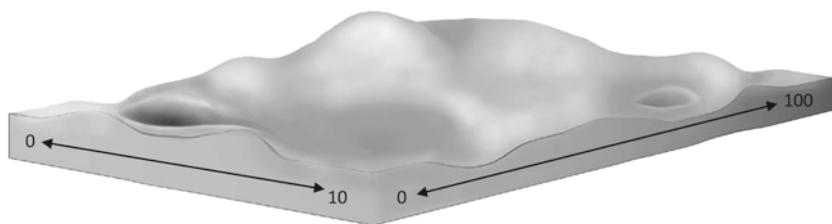


Fig. 2.1 Hypothetical state space with ordinal dimensions

Second, the range of values along each dimension must be exhaustive in which there are no other possible values that could ever occur. Using the previous 0–100 example, this could be exhaustive if the dimension represented a percentage wherein values below 0 or above 100 were simply not possible. If each dimension conforms to this requirement, then the state space will also by definition be exhaustive as well. Again, this may seem obvious or overly simplistic, but it will be important later.

Third, although most often the state space is depicted as square, the scale and/or range of each dimension does not have to be equivalent. The y -dimension could be 0–100 while the x -dimension could be a range of 0–10. Of course, with continuous scales (i.e., ratio scaling), the number of intervals between values is a function of the level of precision of the measure or index. If the level of precision is one unit for the y -dimension (0–100) and $1/10$ of a unit for the x -dimension (0–10), then both the dimensions would have 100 scale units between minimum and maximum values. Furthermore, the distance between those values depicted on the state space diagram can be arbitrarily determined—they may be constrained to equivalent lengths to make a square state space or allowed to maintain the same scale units to make a rectangular (10×100) state space. As we will see in Chap. 7, there are ways to relate continuous measures to categorical dimensions. For now, we will proceed by considering categorical dimensions.

The final consideration stems from the third: the state space can be derived from ordinal, categorical, or nominal dimensions, as long as each dimension is comprised of mutually exclusive and exhaustive values. For example, if the dimension of interest was an index of emotional valence—ranging from negative to positive—the degree of continuity of the values on that dimension would be a function of the measurement precision. Valence could be captured by a self-report joystick that recorded values ranging from 0 (negative) to 100 (positive), or a visual analogue scale ranging from 0 to 10, or from the real-time ratings of a trained observer in only three categories (negative, neutral, positive). All three measurement methods would be appropriate as a dimension of state space; the only difference would be in the number of scale intervals or categories (100, 10, or 3). Two points can be taken from this example. One is that beyond the limits of the precision of the measurement all dimensional variables become categorical—a measurement unit of miles seems continuous from space but is categorical when looking at a 4 square mile area (as-

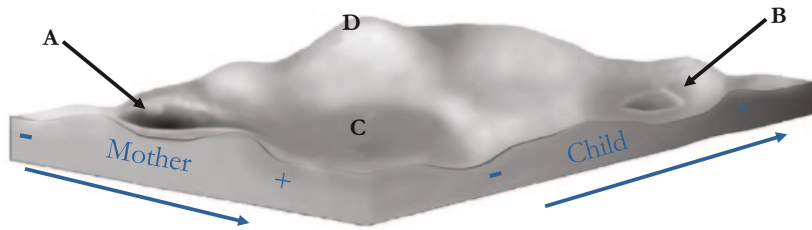
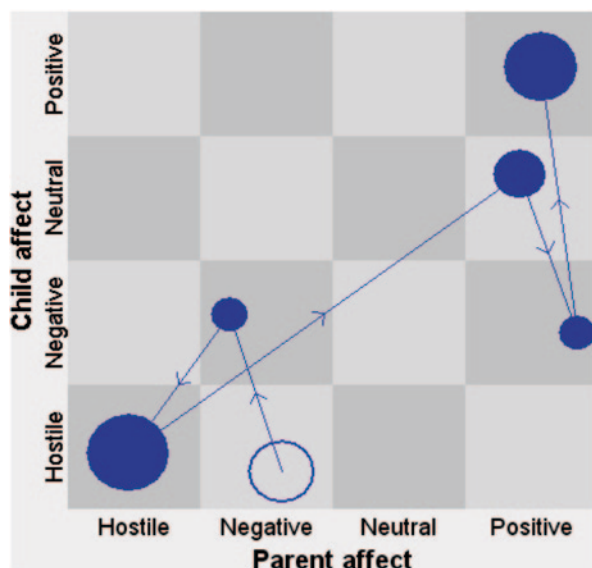


Fig. 2.2 Hypothetical state space of a parent–child system. *A* Deep (strong) attractor: Mother Negative with Child Negative (“Mutual Negative”); *B* Shallow (weak) attractor: Mother Positive with Child Positive (“Mutual Positive”); *C* Attractor basin: Mother Positive with Child Negative (“Permissive Parenting”); *D* Repellor: Mother Negative with Child Positive (“Harsh Parenting”)

suming no further break down in units). The other is that each dimension of the state space can be broken down into categories, similar to the A–Z and 1–10 format of road maps, to create a grid of intersecting categories. Now, with such a categorical approach to the dimensions of the state space, then, the range no longer needs to be an ordinal or quasiordinal sequence, but can also be in nominal categories with no numerical values or ranking to determine their order or adjacency. In other words, to analyze the state space of a system, we can overlay a grid of meaningful boundaries to discriminate distinct x/y states. This is the basis of state space grids.

Before describing state space grids, let us consider a real-world example of the state space depicted in Fig. 2.1. Often the system being analyzed by state space grids has been the parent–child system, with individual states for each dyad member ranging in valence from negative to positive. Superimposing that system on the hypothetical landscape, we can get something similar to the state space depicted in Fig. 2.2. Here, Mother behavior is depicted from negative to positive along the x -dimension and Child behavior is depicted from negative to positive on the y -dimension. Now, the configuration of valleys and peaks representing attractors and repellors, respectively, can correspond to the structure that underlies this particular dyadic system. The dyad in this example struggles with problematic behavior. The strongest attractors are in the mutual negative region indicating that when they get into that state it is difficult for them to get out of it. Fortunately, they are also “pulled” into a mutual positive state at times, though not as strongly as the mutual negative state. Although not a strong influence in the Child negative with Mother positive basin, the dyad covers a broad area that could be labeled permissive parenting. Finally, as seen from the repellors “hill,” this parent is never harsh or negative while the child is positive. In this way, the state space landscape can provide a static picture to depict the structure and the range of system behavior. The state space grid method goes a step further by taking this general idea and using it to analyze the temporal dynamics—the sequence of system states as they progress through time—in order to derive the structure and function of these systems.

Fig. 2.3 A hypothetical state space grid example of a mother–child interaction sequence



State Space Grids

State space grids are two-dimensional state spaces with at least two mutually exclusive and exhaustive categories on each dimension. The intersection of these categories forms a grid of cells representing each categorical combination. The number of categories on each dimension does not need to be the same, so the state space grid can be any size rectangle. The cells themselves do not need to be square either, though square cells are perhaps the clearest way to present a grid and this is the manner in which all state space grids have been presented to date. Remember that the state space is the space of all possible states so that what must be in that space are literally ALL the possibilities, theoretical and actual. See Chap. 4 for further discussion of this issue.

Most often, the blank state space is generic in that the combination of states could correspond to any number of systems of the same type. Some systems might spend most of their time in one region while other systems spend their time in other regions, with little or no overlap. For example, as we shall see later in this chapter, many of the published reports of state space grids focus on the parent–child system. In these studies, the state space grid remains constant (e.g., Parent negative, neutral, positive with Child negative, neutral, positive) but each parent–child dyad behaves differently. That is, their sequence of states is unique on a generic state space. Thus, it is the plotting of this sequence of states—the *trajectory*—on the state space that reveals the structure of any particular system (Fig. 2.3).

The trajectories are plotted on a state space grid as nodes or plot points connected by lines to indicate the transition from one state to the next. Thus, the sequence of

states is a series of *visits* to cells on the grid. When information about the duration of each state is available, the size of the node corresponds to the duration of that state. In Fig. 2.3, we see a short trajectory of behavior on a state space grid that is similar to an aerial view of the state space landscape in Fig. 2.2. With four categories of affective valence for both mother and child, the behavior depicted for this dyad begins in their mutually negative attractor (the open node depicts the starting point) but then they resolve into mutual positivity.

A wide range of measures can be derived from trajectories plotted on state space grids in this way. These measures can tap both the content (i.e., the frequency and duration of specific states) as well as the structure (i.e., the configuration of attractors and repellers) by quantifying the dynamics. All of these measures are described in great detail in subsequent chapters.

State space grids are a flexible analytical tool, which can be useful in a wide array of research circumstances. This book will highlight many of these possibilities but as many or more of these applications of the method are yet on the horizon. In general, though, for any user there are three potential uses of state space grids. First, state space grids may simply be useful as a tool for visual inspection of data. I happen to ascribe to John Tukey's notion of exploratory data analysis (Tukey 1977) as an essential, though often neglected, research function. Indeed, in any new domain of inquiry, the first order of business is description. If that is all state space grid analysis achieves, it would be a great contribution to science.

Second, by extension, the DS approach in general and the exploratory data analyses facilitated by state space grids in particular are a rich source of hypotheses about behavioral *processes*. As I presented in Chap. 1, DS approaches require a different way of thinking about intrapersonal and interpersonal behavior, time, and causality. Though there is growing theoretical interest in the processes and mechanisms underlying behavior, especially in the developmental sciences, there is a paucity of research tools with which to test these theoretical claims (Granic and Hollenstein 2006; Richters 1997). Thus, in the state space grid method lies the potential generation of testable hypotheses and the enactment of both inductive and deductive scientific means.

Finally, state space grids are a source of variables and analyses of both structure and content. These measures and analyses can then be combined with or compared to existing, more traditional methodologies to test various content-specific and structural hypotheses. As it is a metatheoretical framework (Witherington 2007), DS techniques such as state space grid analysis can be incorporated into existing theoretical or statistical models that are domain specific (e.g., Granic and Patterson 2006). Realistically, the scope and power of state space grids as a dynamic analysis tool has not yet been fully realized and it is up to the current and next generation of researchers to push and extend the technique into the greater prominence it deserves.

A Review of Studies Using State Space Grids

I will briefly review the state space grid studies that have been published as of 2011. This will be followed by a review of the work in progress or otherwise unpublished to give the reader a sense of a wider range of possibilities. Details presented here are necessarily brief, though we will return to some details of these studies in later chapters that focus on analysis. The reader is encouraged to read the original sources identified in Box 2.1.

Box 2.1 State Space Grid Studies to Date

Study	System	Age	Structure	Content	Grid size
Granic et al. (2012)	Mother–child	8–12 years	Variability/ flexibility	Specific affect	9×9
Granic et al. (2003)	Parent–boy	9–18 years	Variability; phase transition	Emotion valence	4×4
Granic and Lamey (2002)	Mother–child	8–12 years	Attractors	Emotion valence	4×4
Granic et al. (2007)	Mother–child	8–12 years	Variability/ flexibility; repair	Specific affect	9×9
Hollenstein and Lewis (2006)	Mother– daughter	11–12 years	Variability/ flexibility	Specific affect	10×10
Hollenstein (2007)	Mother– daughter	10–14 years	Variability; phase transition	Specific affect	10×10
Hollenstein et al. (2004)	Parent–child	4–6 years	Variability/ flexibility	Emotion valence	4×4
Lewis et al. (1999)	Infant	2–6 months	Attractors	Distress and attention	5×5
Lewis et al. (2004)	Toddler	14–24 months	Variability; phase transition	Engagement with mother and frustrating toy	5×5
Lunkenheimer et al. (2011)	Parent– toddler	3–4 years	Variability	Emotion valence	4×4
Martin et al. (2005)	Peer interac- tions	4–5 years	Attractors	Gender, social compe- tence, valence	2×3×5

The first study to use state space grids was the one for which they were developed (Lewis et al. 1999). Marc Lewis and Alex Lamey devised the method to be able

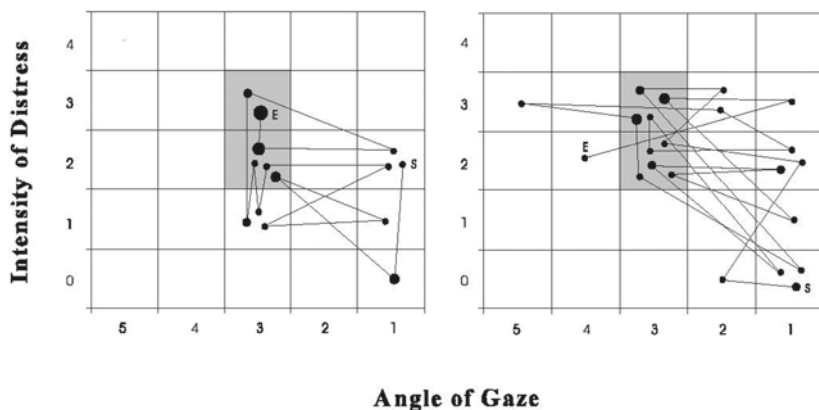


Fig. 2.4 State space grids from Lewis et al. (1999)

to depict and measure the sequence and recurrence of infant socioemotional states corresponding with their simultaneous levels of distress and attention to their own mother who was sitting close by. That is, the infant's emotional state and social behaviors to regulate that emotion could be analyzed as distinct but coordinated processes. Infants were given frustrating toys while playing on the floor next to their mothers. One minute of their level of distress (0–4) and angle of gaze toward mother (1 = gaze averted to 5 = direct attention to mom) were recorded and plotted on state space grids (see Fig. 2.4). The authors examined whether infants' socioemotional attractors at 2 months of age were stable through 6 months of age.

The Lewis et al. (1999) study introduced attractor analysis using state space grids through a two-step process. First attractors were identified through a winnowing process based on the proportional duration in each cell. For each infant, one or two cells were identified for which proportional durations exceeded chance. Second, they measured the strength of these attractors as *return time*, the duration of intervals between visits to the attractor cells. Shorter return times indicated a stronger attractor. As hypothesized, infants tended to have the same attractors at both 2 and 6 months of age and the correlations between the strength of those attractors over those 4 months range from 0.7 to 0.8. Thus, individual differences in emotional and regulatory habits of infants seem to be well established early in infancy and remain stable for the first half year.

Granic and Lamey (2002) extended the state space grid technique from the focus on an individual as the system to the parent–child dyad. In this study, the authors were interested in distinguishing subtypes of children with externalizing problems, specifically those who were comorbid with internalizing problems (MIXED) and those who were pure externalizers (EXT). These children and their mothers were observed during a 6-minute conflict discussion. As the best way to reveal the nature of system dynamics is through perturbation, a mild perturbation was included in this research design. With 2 minutes left to go, dyads were perturbed by the research assistant who knocked on the door, came into the room, and told the dyad to “wrap

up on a good note.” Before the perturbation, the MIXED and EXT dyads were indistinguishable. However, after the perturbation, the MIXED dyads shifted to a mutually hostile attractor (the state space grids were 4×4 as in Fig. 2.3) while the EXT dyads remained in the permissive region as these mothers pleaded with affection to get the child to focus on and resolve the conflict. Thus, this study revealed unique system dynamics associated with differential socioemotional experiences of MIXED and EXT children.

Following the ground-breaking Granic and Lamey (2002) study, the next group of studies focused on the parent–child dyad as the system and specifically examined the variability in these interactions. In one subset of these studies, the connection between the dyadic variability and the development of psychopathology was explored (Granic et al. 2012; Granic et al. 2007; Hollenstein et al. 2004; Lunkenheimer et al. 2011). The other set of variability studies tested the developmental phase transition hypothesis: transitions between stable developmental periods would be evidenced by the temporary increase in variability characteristic of a phase transition (Granic et al. 2003; Hollenstein 2007; Lewis et al. 2004). Before reviewing these two sets of studies, it is important to first consider the psychological meaning of real-time emotional or affective variability.

Variability and Flexibility

As mentioned in Chap. 1, variability is considered vital information about a system. Yet, variability is a broad term with many viable ways to define or operationalize it. It can be taxonomic, simply denoting that a range of elements exist in a particular domain (e.g., eye color). It can also be used statistically, in terms of deviations from a fixed value (e.g., standard deviations). Variability can refer to variations in temporally contiguous events (e.g., walking stride) or a range of consistency across sporadic events (e.g., hit-or-miss food quality at a restaurant). Of these different meanings of variability, some can be interpreted as flexibility, or the process by which a state transforms into a different state in an adaptive response. For developmental DS applications, most often we have been concerned with variability at two scales.

At the first scale, there are the moment-to-moment fluctuations of system behavior that vary because of the reciprocal influence of the elements of the system (micro scale in Fig. 1.1). For example, try standing on one leg for a few minutes. You will notice that in order to maintain the stance, you will engage in many small muscle contractions throughout your body, mostly in your feet. Let us call this kind of moment-to-moment change *dynamic variability*. At the second level or scale are the variations in system behavior that come from larger, typically exogenous, perturbations. Variability at this scale reflects the degree to which a system can adapt to the changes in the environment. To continue the example, notice what you do differently when someone pushes you while you stand on one leg—different muscle groups become involved. Perhaps you need to swing your arms or bend at the

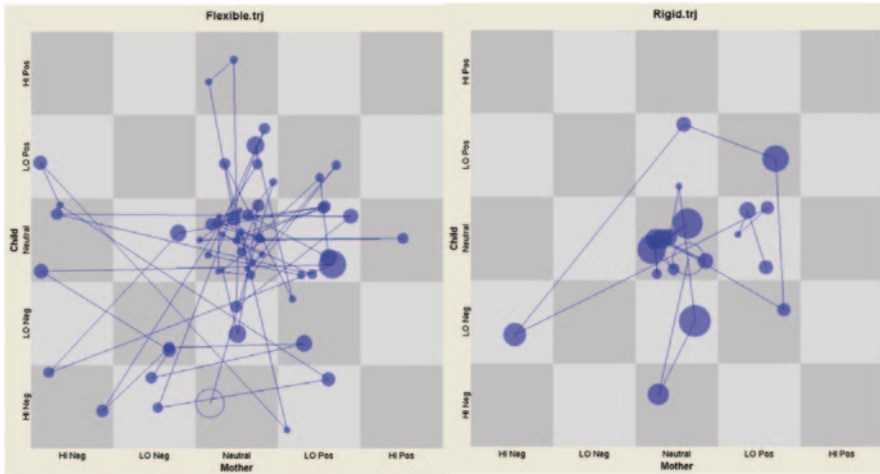


Fig. 2.5 Examples of flexible and rigid interactions on state space grids. The grid on the *left* depicts a more flexible interaction by dint of greater dispersion across the state space, more transitions, and lower mean durations (*smaller nodes*). In contrast, the grid on the *right* depicts a relatively less flexible interaction due to less dispersion, fewer transitions, and longer mean durations

waist. Let us call this adjustment to environmental demands *reactive variability*. In both cases, not dynamically adjusting or not reacting to contextual changes would characterize a rigid system (standing rigidly assures falling over). For dynamic systems in the natural world, the “hallmark of successful adaptation is flexibility in the face of changing physiological and environmental demands” (Thayer et al. 2012, p. 748). Thus, some aspects of variability can be interpreted as *dynamic flexibility* and others as *reactive flexibility* (Hollenstein et al. in press).

With state space grids, dynamic flexibility can be examined through within-grid analyses (Chap. 5) and reactive flexibility with between-grid analyses (Chap. 6). Consider the examples of dyadic emotional valence in Fig. 2.5. Immediate visual inspection of these two trajectories typically leads to the conclusion that the one on the left is more flexible than the one on the right. State space grid analysis offers the means to quantify those qualities with measures such as dispersion (range of cells occupied controlling for relative durations), transitions, and average mean duration across all of the cells. Thus, dynamic flexibility can be reliably measured. Taking this example a step further, instead of thinking of these two trajectories as representing two different dyads, consider them as the same dyad in two different contexts. The dyad could have started with the flexible behavior depicted on the left of Fig. 2.5, but following a perturbation shifted their behavior to that depicted on the right of Fig. 2.5. This would be an example of reactive flexibility indicating an adaptation to environmental demands.

With this in mind, we explored both dynamic and reactive flexibility with mother–daughter dyads (Hollenstein and Lewis 2006). For this study, we used state space grids to measure the real-time dynamic flexibility of mother–daughter affect in an

A–B–A design of three discussion contexts: positive, conflict, positive. As expected, there was more negative affect during conflict and dynamic flexibility changed with the context—the dyads became more rigid during the conflict but returned to higher levels of flexibility in the final positive discussion. Thus, consistent with the effect of emotions on cognitive flexibility (e.g., Isen 2000; Matthews and McLeod 1985), we showed that the presence of negative affect actually restricted the dynamic structure of how that affect was expressed.

Variability, Flexibility, and Developmental Psychopathology

Interpreting variability as flexibility is also consistent with clinical observations that many psychopathologies are characterized by overly rigid behavior. My colleagues and I have explored this in several ways at several ages. In a large kindergarten sample, Hollenstein et al. (2004) showed that dynamic rigidity of parent–child affect during 2 hours of interaction was associated with concurrent levels of child internalizing and externalizing problems as well as the growth in externalizing problems over the course of 2 years. Moreover, partial correlations demonstrated that these differences in structural dynamics (rigidity) were not related to differences in the affective content.

Granic et al. (2007) compared externalizing children who had improved with treatment (self-regulation training and parent management training) to those whose externalizing behavior did not drop below clinical levels by the end of treatment. While there were no differences between these groups pretreatment, the parent–child dyads with improvers became significantly more dynamically flexible by the end of the treatment period. This study also employed some innovations in region analyses based on four areas of the parent–child state space grid hypothesized to be the most important (see Fig. 2.6). These regions were mutual positivity, mutual hostility, permissive parenting, and mother attack—similar to the regions identified in the example for Fig. 2.2. There were no differences between improvers and nonimprovers in terms of duration in mutual hostile, permissive, or mother-attack regions, but improvers increased in mutual positivity from pretreatment to post-treatment. Moreover, using the same A–B–A discussion design as Hollenstein and Lewis (2006) described above, there was diminished reactive flexibility for the nonimprovers. These dyads could not repair from the conflict topic and shift to a positive topic without continuing to express negative affect (area *outside* of mutual positive region in Fig. 2.6). In the latest extension of this work, Granic et al. (2012) have shown strong correlations between *dyadic* flexibility and the amplitude of the child’s electroencephalography (EEG) event-related potential called the inhibitory N2, even after controlling for many factors. The N2 is thought to be an index of inhibitory control, a key component in emotion regulation. Thus, the ability to inhibit behavior and emotions may be a key mechanism of affective flexibility.

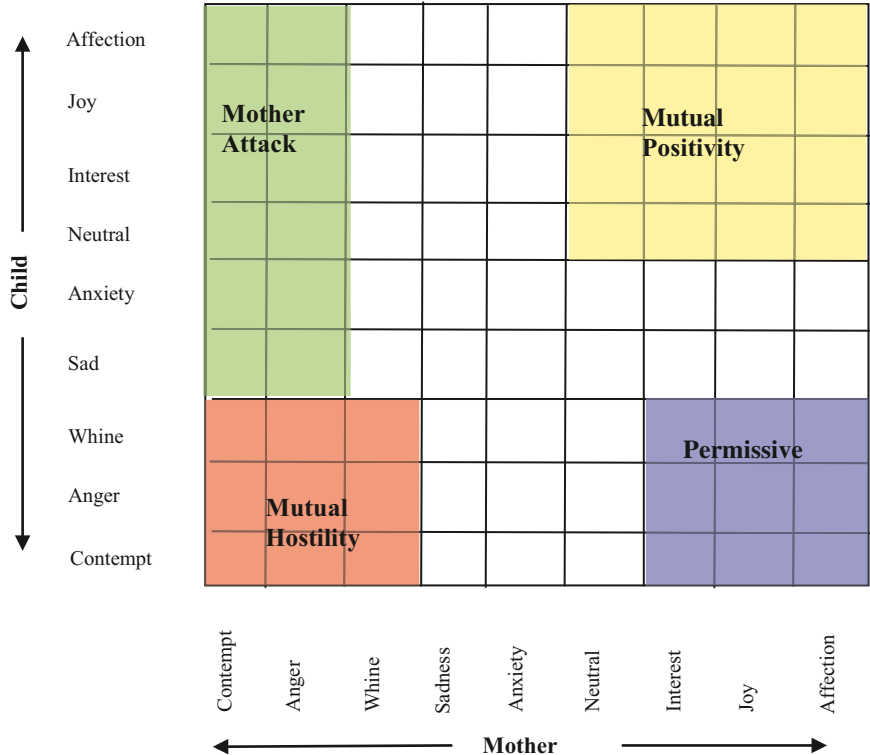
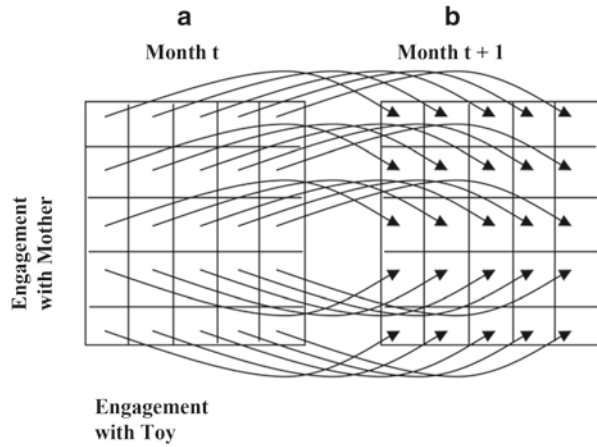


Fig. 2.6 Regions on a parent–child affect state space grid

Another study examining the link between flexibility and the development of psychopathology explored the interaction between positive affect and flexibility. Lunkenheimer et al. (2011) tested for the differences in positive versus negative flexibility in a sample of young children during interactions with mothers and fathers. During father–child interactions, flexibility and the flexibility by positive affect interaction predicted lower levels of externalizing behavior 2 years later when the children were 5 years old. Interactions with mothers revealed a different pattern. While the flexibility-positivity interaction predicted lower externalizing similar to the fathers’ results, the direct effect of mother–child flexibility predicted higher levels of externalizing behavior. It is not yet clear why these results were different than in other studies. This was the youngest sample that has been tested for the flexibility-psychopathology link and these data were coded in a different way than most of the other studies reported here. Still, it begs the possibility of an upside-down u-shaped function of flexibility—too much or too little may be detrimental. What is needed is an examination of flexibility across more diverse contexts and pathologies.

Fig. 2.7 Illustration of the calculation of the intergrid distance score (IDS). (Lewis et al. 2004)



Developmental Phase Transitions

Longitudinal studies testing the developmental phase transition hypothesis comprise the second set of studies on variability (Granic et al. 2003; Hollenstein 2007; Lewis et al. 2004). Here the general hypothesis is predicated on a stage approach to development that has long noted key transition periods. The first to be examined was the 18–20 month transition point, at which toddlers make a tremendous cognitive shift as they enter into the “terrible twos.” This period is replete with a demonstrative “no!” dominating toddler communication as well as disturbances to sleeping and eating habits among other things. Lewis et al. (2004) observed toddlers once a month from 14 to 24 months of age as they engaged in two frustrating toy tasks. State space grids were created from one dimension of child’s engagement with the toy (1–5) and engagement with his or her mother (1–5) who sat nearby reading magazines. Thus, each child had 11 trajectories, one for each month. The phase transition was hypothesized to result in greater month-to-month change during the 18–20 month window than either before or after. Monthly change was measured in two ways. First, we created an intergrid distance score (IDS) that was a calculation of the Euclidian differences between corresponding cells in adjacent monthly grids through the formula:

$$IDS = \sum_{i=1}^{\# \text{ of cells}} (A_i - B_i)^2$$

where A_i is a cell from the state space grid from month t and B_i is a cell from the state space grid from month $t+1$, as shown in Fig. 2.7.

The second method for detecting month-to-month change was through a longitudinal cluster analysis. The 25 duration values of every grid for every month for every child were put into a single k -means cluster analysis to obtain a cluster membership for each grid. Grids that had similar patterns were grouped into the same

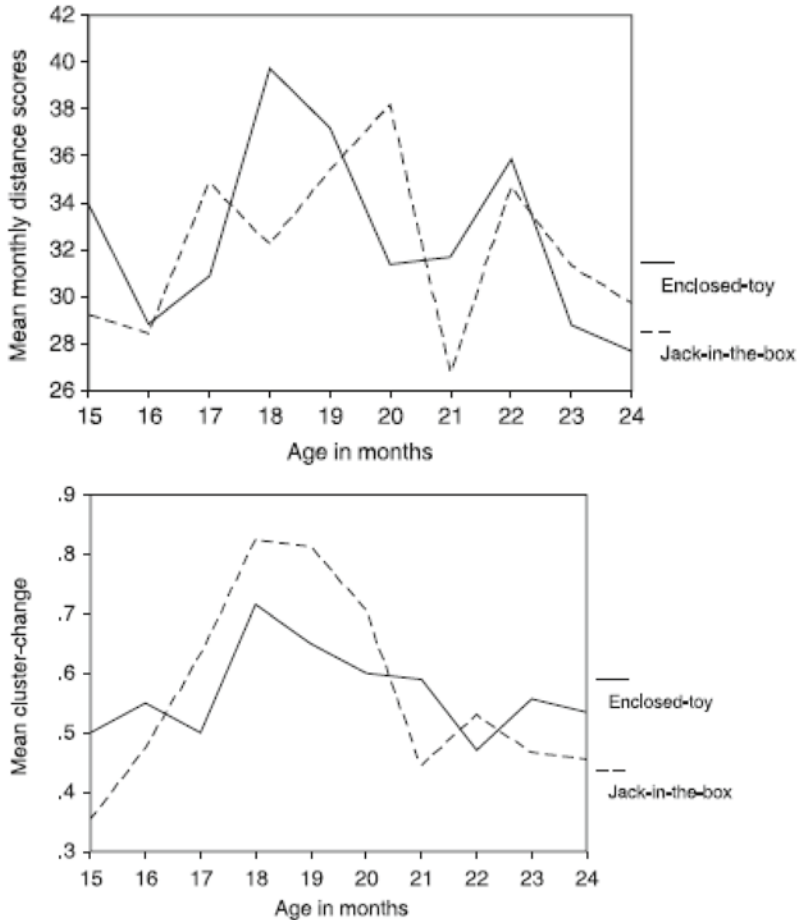


Fig. 2.8 IDS and cluster change scores from Lewis et al. (2004)

cluster. Then, for each child, a month-to-month cluster change score was created, giving a value of zero if the child stayed in the same cluster from time t to time $t + 1$ and 1 if the child switched clusters from the previous month.

Using profile analysis, both the IDS and cluster change scores showed a quadratic pattern across months with the peaks occurring in the 18–20 month period (Fig. 2.8). Moreover this occurred with both tasks and despite their repetition over 11 months. This was the first study to provide dramatic evidence of a developmental phase transition using state space grids and it inspired two subsequent studies to test the phase transition hypothesis in adolescence.

Adolescence is one of the most tumultuous transitions in the lifespan, perhaps only second to the 18–20 month transition. The range and depth of changes in the physical, cognitive, social, and emotional domains certainly make this age period a leading candidate for a developmental phase transition. With a five-wave longitu-

dinal sample of boys' interactions with their parents, starting at the age of 9–10 and continuing every 2 years, Granic et al. (2003) tested the adolescent phase transition hypothesis with state space grids. Two measures, the number of cells and the number of transitions, were derived from the 4×4 parent–boy grids. As expected, both measures peaked in the third wave when the adolescents were aged 13–14 years, the start of puberty and early adolescence for boys. Importantly this peak in variability was not just due to increases in conflict, as negativity peaked later, when the boys were 15–16 years old and variability had already dropped back down to pretransition levels.

To follow up this finding with boys, another study was conducted with girls to see if they went through the same phase transition 2 years earlier (Hollenstein 2007). Mother–daughter dyadic affect during conflict discussions were recorded over four longitudinal waves starting when the girls were in the spring of their grade-6 year (age 11.5 years) and every 6 months thereafter. All girls transitioned to a new school between the first and second waves. Possibly, because of the narrower time frame or the school transition, the results for the girls were not as straightforward as with the boys' study. Instead, only dyads with girls who did not experience stressful events concurrently with the school transition in wave 2 showed the hypothesized quadratic pattern. Interestingly, dyads with girls who experienced two or more stressful events concurrent with the school transition showed the opposite pattern. The quadratic was u-shaped because these dyads became more rigid over the transition period. It is possible that these girls (and their mothers) were resisting the change, clinging on to old habits in order to maintain emotional stability during a tumultuous period. Unfortunately, this study raised as many questions as it answered. Certainly more tests of developmental phase transitions are warranted.

Group Dynamics

Just as state space grid studies of individuals led to the examination of dyadic systems, there is an interest among many developmental scholars to tap the group dynamics of peer interactions. Martin et al. (2005) created some solutions to this problem in a study that recorded the gender and social competency category (competent, externalizing, and internalizing) of the target child's play partners, as well as the target child's emotional valence, on the playground across an entire preschool year. Of course, pragmatic issues led to the observations being random and distributed throughout the year. Hence, transitional measures were not realistic, but measures of states were. The main finding was in support of increasing homophily across the year: girls increased their play with girls and boys with boys across the year. There were also interesting distributions of play partners by competency. This study provides one approach to the analysis of *n*-dimensional systems. Another approach was taken for the analysis of coach–athlete interactions with a team of athletes (Erickson et al. 2011). In this study, the coach and each athlete was coded continuously during

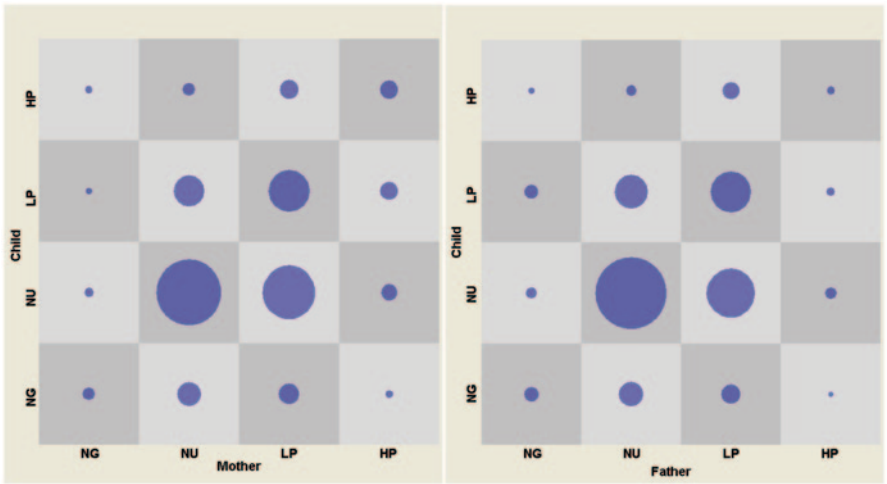


Fig. 2.9 Summary state space grids of proportional durations in each cell for mother–child (*left*) and father–child (*right*) interactions. (Lunkenheimer et al. 2011)

practice sessions, with a state space grid dimension corresponding to each. From this starting point, each coach–athlete combination could be analyzed and the athletes could be combined to go beyond two dimensions. Further discussion of ways to go beyond two dimensions is covered in Chap. 7.

Summary Grids

State space grids have also been used to depict static visualizations of summary information. Similar to a 2×2 matrix of values, these grids use a single node, centered in each cell, to depict the magnitude (e.g., mean duration or frequency) of the activity in that cell for subgroups or for an entire sample. In the Lunkenheimer et al. (2011) study, the proportional durations in each parent–child affective state were displayed for mother–child and father–child dyads (Fig. 2.9). Comparing these two grids, it is easy to quickly get a sense of how similar and how different these two groups were. Although it was not presented in the original Martin et al. (2005) study, Fig. 2.10 shows a summary of the play–partner combinations across the year (Hollenstein 2007). Here, the size of the plot point indicates the relative frequency of that particular target child with peer competency-type combination. With this display we can see that competent girls tended to play with each other and externalizing boys tended to play with everyone. The means to create these summary grids will be described in Chap. 5.

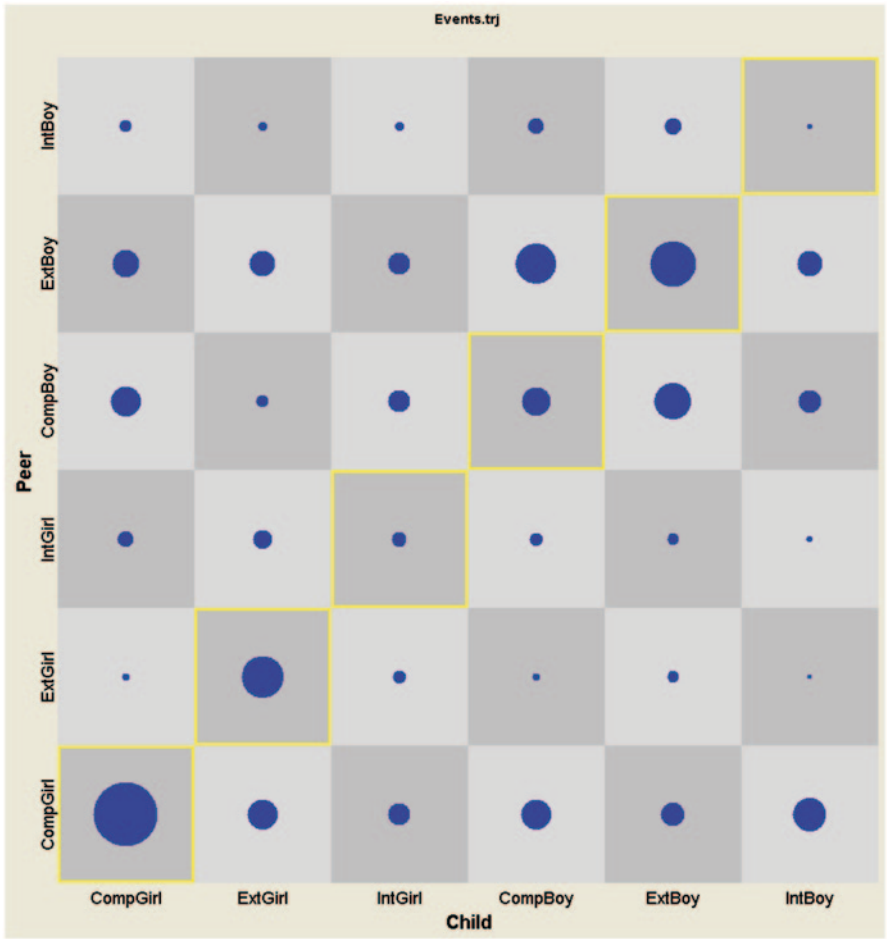
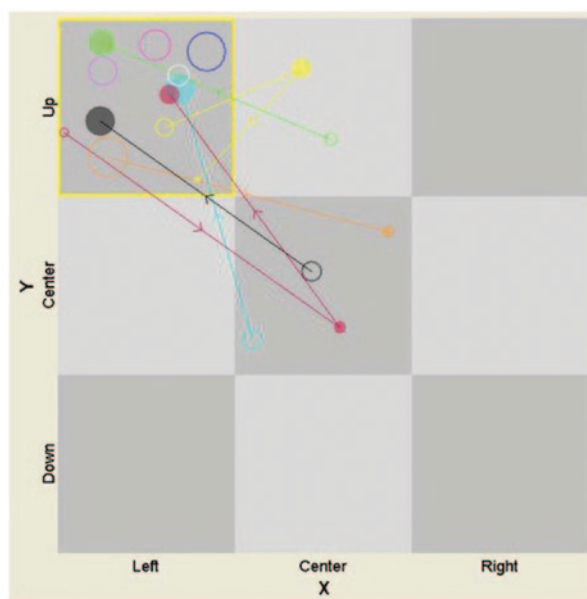


Fig. 2.10 Summary of preschool playground peer interactions from the Martin et al. (2005) study (from Hollenstein 2007). The target child’s identity (gender and competency category) is on the x-dimension and the identity of the peer play partner is on the y-dimension. The size of the plot point indicates the relative frequency of that play combination across the year. The *highlighted diagonal* indicates homophily

State Space Grid Studies: Unpublished or in Preparation

The studies published till date represent a fraction of the state space grid analyses that have been conducted till date. Some of these are in the process of reviewed or prepared for submission, some were just used for conference presentations, some are languishing in file drawers somewhere, and others were used in studies that ultimately did not report using grids for simplicity. Through consultations, workshops, and collaborations, I have worked on no less than 100 data sets to create state space

Fig. 2.11. Example of an individual eye gaze state space grid. Trajectories indicate the direction of gaze following each of the ten questions that required episodic recall for one subject

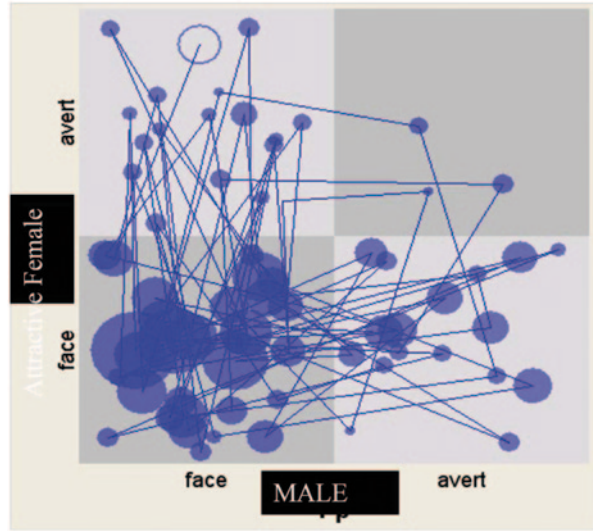


grids. Through these experiences, I have gathered a range of different grid types and techniques that depart from the dyadic emotion grids that have been my personal mainstay. Seeing the diversity of approaches is always one of the highlights of a workshop—I can see the light bulbs turning on. I hope these descriptions in the following sections will do the same here.

Eye Gaze The first variation to explore is using state space grids for tracking eye gaze trajectories. Individual eye gaze grids plot the direction of gaze using the x-dimension as left–center–right positions and the y-dimensions as down–center–up positions relative to a focal target. McCarthy et al. (2007) documented the direction of gaze at an experimenter who asked questions that required episodic recall (see Fig. 2.11). Most people in western cultures look up and to the left while accessing a memory prior to responding. This provides a social cue to others to not interrupt while thinking. McCarthy et al. showed that this eye gaze tendency does not reliably occur before the age of 7.

In a dyadic eye gaze study, van Straaten et al. (2009) examined the eye gaze patterns of males and females having a discussion with an opposite sex confederate who was independently rated as either attractive or average-looking. Although state space grids were used for analyses, these were not reported in the final journal article. This was a 2x2 grid of a binary categorization of gaze: looking directly at the other person’s face or away from their face (see Fig. 2.12). Compared with average discussion partners, males tended to have longer staring events at the face of attractive confederates. In contrast, females tended to have more frequent but extremely short mutual gaze durations with attractive partners compared with average

Fig. 2.12 Dyadic eye gaze state space grid of a male with an attractive female confederate



partners. While this study demonstrated clear gender differences in interaction with attractive strangers, it also demonstrates for our purposes here that the minimum-sized 2×2 state space grid can provide insightful information about behavioral dynamics.

Diaries and Experience Sampling Another increasingly common research method is the examination of emotions or behavior over the course of days, weeks, or months. These studies may use diaries or electronic devices through what has been called the experience sampling method (ESM; e.g., Larsen and Csikszentmihalyi 1983) or ecological momentary assessment (EMA; Silk et al. 2011). The big difference here is that, rather than time units of seconds or events that occur within a short window of time, the intervals between events could be 24 hours or more. Trajectories in these instances would reflect sequences of daily assessments and would be useful for tracking such things as mood or developmental progressions that occur over the course of weeks, months, or years.

In a creative study with a nested longitudinal design, Lichtwarck-Aschoff et al. (2007) obtained daily diary reports from mothers and adolescent daughters over the course of 2 weeks, repeated every 6 weeks for 18 months. Although the dyadic results are unpublished as yet, the grids used for exploratory analyses are worth considering. In Fig. 2.13 there are three different dyads who report how they felt during the discussion and then how they felt later before going to bed. Thus, each trajectory is a two-step sequence indicating the degree to which both the mother and the daughter repaired (moved from negative to positive emotional states) from conflict. Vertical trajectories indicate instances when the mother but not the daughter repaired, horizontal trajectories indicate instances when the daughter but not the mother repaired, and diagonal trajectories indicate instances when both the mother

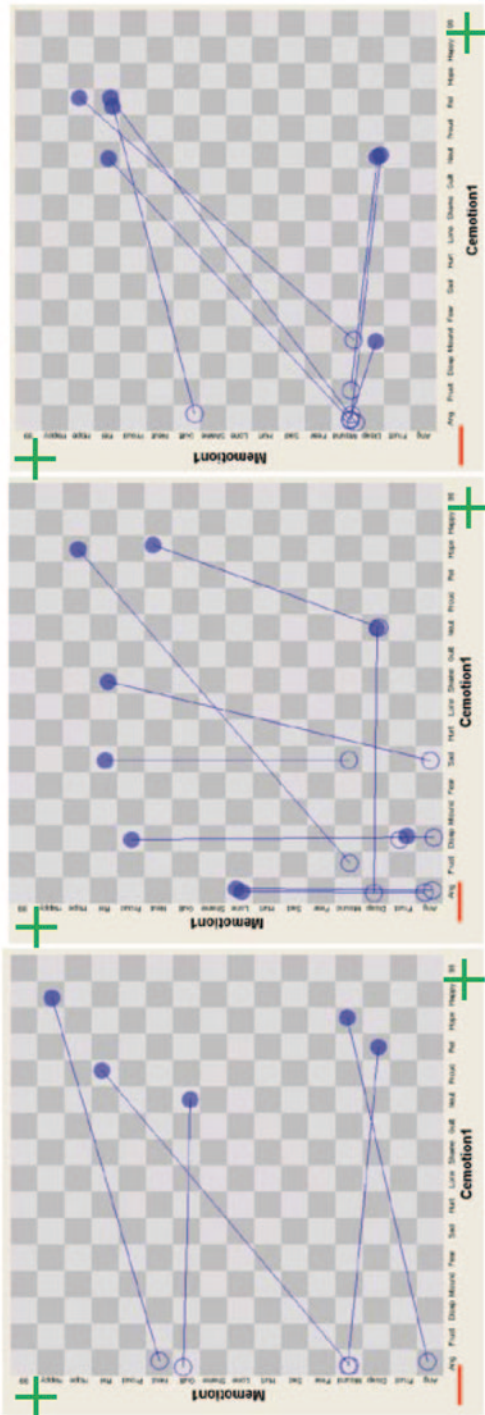


Fig. 2.13 Three example state space grids from a mother–daughter diary study. The x–dimension corresponds to the daughter’s report and the y–dimension corresponds to the mother’s report. Plot nodes indicate the most intense emotion during a conflict (*open nodes*) and then after the conflict before going to bed (*closed nodes*). Emotions are arranged on the dimensions in a quasiordinal fashion according to valence, with the most negative emotions to the *bottom* and *left* and the most positive to the *top* and *right*

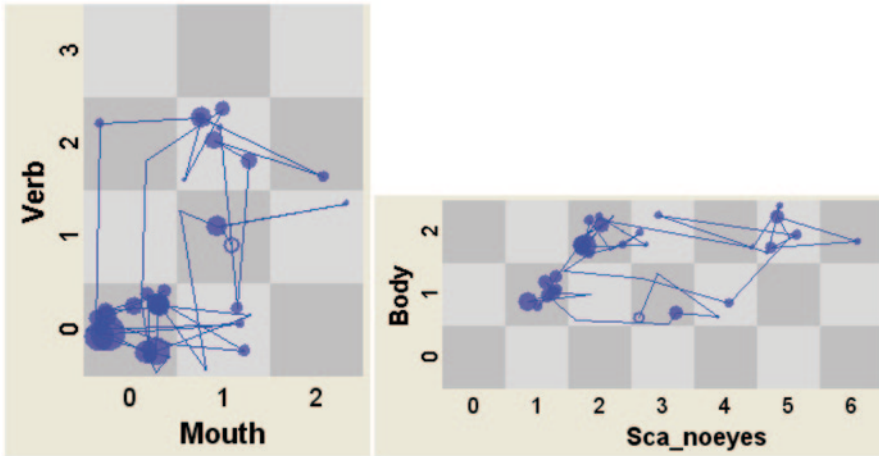


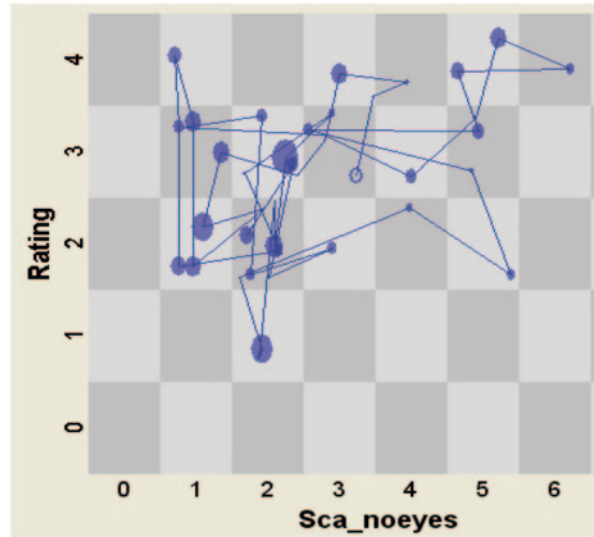
Fig. 2.14 Using state space grids to compare code categories. The state space grid on the *left* shows the relationship between the mouth tension and verbal tension codes for one participant, the one of the *right* shows the relation between the body tension code and the overall self-conscious affect score made from the combination of all the ordinal state variables (except for the Eye Gaze category)

and the daughter repaired. This example illustrates how even short trajectories can be used in state space grid analyses as well as how data at two time scales (within a day and across days) can be analyzed simultaneously with state space grids.

Measurement Analysis As many applications of state space grids involve coded observational data, it may be useful to examine the relations between code categories as part of the development of the measure. My students and I have developed a self-conscious affect coding system for participants giving a speech in the laboratory, for example, for which there are four primary categories, each of which vary in intensity (Lanteigne et al. 2011). That is, each code category is a state variable with ordinal levels of intensity as the states. Thus, we have a complete data stream for four domains of self-conscious behavior: Body Tension (none, medium, and high), Mouth Tension (none, medium, and high), Eye Gaze (direct and averted), and Verbal Tension (none, medium, silent, and high). The goal is to create an overall self-conscious affect score from the combination of these state variables and to compare these to self-reported self-conscious affect and psychophysiological measures. As part of this research, we examined the relations of the individual code variables to each other and in relation to other measures. Figure 2.14 shows a couple of state space grids derived for this purpose. Here, we can see how the dynamic states relate to one another in real time and how they contribute to the overall code score. From these explorations, we have since developed a revised version of the coding system.

We also were interested in the dynamic relations between self-conscious behavior and each person's appraisals of their own distress. Following the video-taped

Fig. 2.15 Using state space grids to compare code categories to dynamic self-report. The participant's real-time rating of their own distress is synchronized with their observed self-conscious affect



speech, participants watched their own speech on video and rated it along a single dimension of distress intensity. As shown in Fig. 2.15, we can then look at the psychological and behavioral dynamics simultaneously. The example shown here is of someone who was fairly distressed and moderately concordant across the psychological and behavioral domains.

Psychophysiology With the growing ease of measuring and analyzing psychophysiological processes in vivo, more and more researchers have detailed time series data that are ideal for state space analyses. The primary objective is to relate psychophysiological measures such as heart rate, galvanic skin response, and electrodermal activity, to behavior and psychological appraisals in real time. This is no simple task. State space grids can be adapted to perform some analyses that can be useful, though it requires turning continuous measurement into categorical values. As Chap. 7 covers this topic, I would not elaborate too much here. Instead, briefly, Fig. 2.16 shows an example of how the combination of self-report and physiological measures can be used for deeper understanding of coordinated behavioral processes for two participants who gave speeches as described in the previous section. In these examples, we see evidence of discordance between physiological and psychological measures. This discordance in emotional situations can reveal differences in emotional processing related to emotion regulation and the development of psychopathology (Lanteigne et al. 2012).

Triads Though state space grid analysis through GridWare (described in the subsequent chapters) is based on two-dimensional space, there is a need to go beyond two state variables for many research questions (e.g., Martin et al. 2005). The shift from two to three dimensions is tricky for many scientific endeavors (Diacu 1992), but

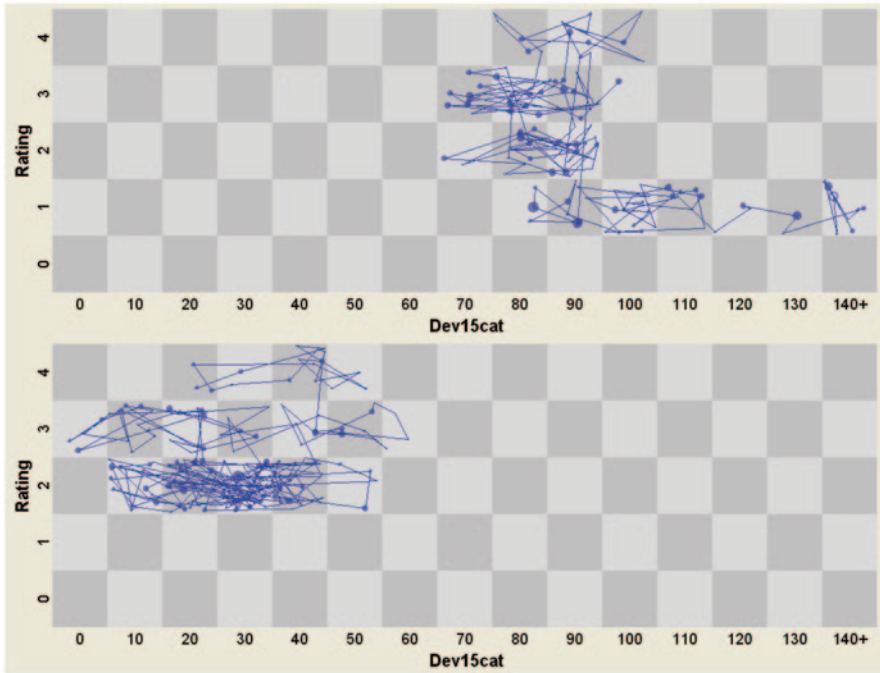


Fig. 2.16 State space grid of self-reported distress and percent change in heart rate. The state space grid on the *top* shows a high distress with low arousal participant and the one on the *bottom* shows a low distress with high arousal participant. Dev15Cat = 15 categories of percent deviations from baseline heart rate

with a few modifications state space grid analysis can accommodate other dimensions beyond two. From the interactions among three people (e.g., mother, father, child) to the coordinated dynamics of multiple measures (e.g., heart rate, self-report, and behavior), there are many instances for which a three-dimensional state space is desired. This is the focus of Chap. 7, so I will forego repeating the details here. It is sufficient at this point to note that state space grid analysis is flexible enough to accommodate many types of variations in state variables.

Lag Sequential Analysis Finally, although much of this book is dedicated to the analysis of simultaneous events, state space grids can also be used to analyze lagged events. In some cases, for example, researchers want to know the effect of one person's behavior on another (e.g., mother and child). Thus, it is important to quantify these lagged events. With state space grids, this can be done by plotting the trajectory with one dimension representing the original sequence and the other dimension representing the same sequence starting one event later. Lagged state space analysis is covered in more detail in Chaps. 5 and 7.

Conclusion

The contents of this chapter should give an indication of the depth and breadth of the state space grid technique. To date, we really have only scratched the surface. On one level, the technique is a deceptively simple variation of plotting data by embedding time within the two-dimensional space. However, just that small twist opens up worlds of possibilities. With the completion of these first two chapters, you now have all the background necessary to be able to start using state space grids yourself. In the next two chapters, I will describe the state space grid software, GridWare. First, I will walk through the software with a simple example and in the subsequent chapter I will describe how to set up your own projects.



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