American Behavioral Scientist

http://abs.sagepub.com

The Role of Positivity and Connectivity in the Performance of Business Teams: A Nonlinear Dynamics Model

Marcial Losada and Emily Heaphy

American Behavioral Scientist 2004; 47; 740

DOI: 10.1177/0002764203260208

The online version of this article can be found at:
http://abs.sagepub.com/cgi/content/abstract/47/6/740

Published by:

SAGE

http://www.sagepublications.com

The Role of Positivity and Connectivity in the Performance of Business Teams

A Nonlinear Dynamics Model

MARCIAL LOSADA
Meta Learning
EMILY HEAPHY
University of Michigan Business School

Connectivity, the control parameter in a nonlinear dynamics model of team performance is mathematically linked to the ratio of positivity to negativity (P/N) in team interaction. By knowing the P/N ratio it is possible to run the nonlinear dynamics model that will portray what types of dynamics are possible for a team. These dynamics are of three types: point attractor, limit cycle, and complexor (complex order, or "chaotic" in the mathematical sense). Low performance teams end up in point attractor dynamics, medium perfomance teams in limit cycle dynamics, and high performance teams in complexor dynamics.

Keywords: *positivity; connectivity; team performance; nonlinear dynamics*

Positive organizational scholars have made an explicit call for the use of nonlinear models stating that their field "is especially interested in the nonlinear positive dynamics . . . that are frequently associated with positive organizational phenomena" (Cameron, Dutton, & Quinn, 2003, pp. 4-5). This article answers this call by showing how a nonlinear dynamics model, the *meta learning* (ML) model, developed and validated against empirical time series data of business teams by Losada (1999), can be used to link the positivity/negativity ratio (P/N) of a team with its connectivity, the control parameter in the ML model. P/N was obtained by coding the verbal communication of the team in terms of approving versus disapproving statements. In the ML model, positivity and negativity operate as powerful feedback systems: negativity dampens deviations from some standard, while positivity acts as amplifying or reinforcing feedback that expands behavior. We will demonstrate how these P/N ratios determine the

Authors' Note: *We thank Kim Cameron, Arran Caza, Barbara Fredrickson, Giovanna Morchio, Ryan Quinn, and two anonymous reviewers for valuable comments on an earlier draft.*

AMERICAN BEHAVIORAL SCIENTIST, Vol. 47 No. 6, February 2004 740-765
DOI: 10.1177/0002764203260208

types of dynamics possible for a team. By running the ML model, one can observe that different levels of connectivity create different nonlinear dynamics that, in turn, are associated with different levels of performance in business teams. Hence, by making explicit the relationship between P/N and connectivity, we will show that P/N can also be associated with the performance of these teams. This finding has important implications for the emerging field of positive organizational scholarship. In addition, the advantage of using P/N as a proxy for connectivity is that measures of P/N are much easier to generate than the measures of connectivity used in the ML model. We will define these measures later in the article, after providing the necessary context.

What is it that nonlinear dynamics models can contribute to our understanding of teams in organizations? Furthermore, what do they contribute to our understanding of the impact of P/N in the performance of teams? Drawing on a substantial literature in organizational and management theory, Stacey (1996) established that teams in particular and organizations in general are nonlinear feedback networks that are continuously involved in ongoing processes of positive and negative feedback. These networks cannot be fully understood using linear models because linear models fail to capture the complex dynamics inherent in these strong interaction processes that prevail in teams and organizations. One of the basic assumptions of linearity is that there is proportionality between the input and output of a system. Mathematically, this is expressed by saying that the *superposition principle* applies, which means that the sum of the parts is equal to the whole. This is only possible if there is no interaction among the parts (i.e., the parts are independent).

Let us address this interaction issue by a means of a metaphor. Imagine that we are trying to understand the complex structure of a piece of music by Bach (see Figure 1) with the purpose of creating a variation. The "parts" in this music are the different notes that comprise the score. If we use a linear approach, assuming that the superposition principle applies and, consequently, the "parts" are independent, we can try to address the problem by figuring out what are the principal components of this piece. So we proceed to sum the different notes and group them by categories, as we actually did in Figure 2. Now, how did that contribute to our goal of creating a variation on this piece? We learned that the principal components are a lot of Ds, B-flats, and Gs, which is a characteristic of any composition in G minor. We know what the principal components are, but we do not know anything about the relations, the connectivity, among these components. We missed the most essential characteristic of this piece of music, or of any work of art, or any complex phenomenon in general: It is the interaction among the parts, their connectivity, that is essential to our understanding of any phenomenon whose complexity cannot be fully apprehended by a linear approximation. This is something that Lao Tzu knew more than 2,500 years ago when he said, "nonlinearity begets completeness; misjudgment creates linearity" (Lao Tzu, circa 600 BC, quoted in Tong, 1990, p. 1).

Figure 1

Does a nonlinear approach provide a better way to create a musical variation? The answer was provided by Dabby (1996), an engineer and musician from MIT, who was able to create variations on music by Bach (and other composers) by utilizing a set of nonlinear differential equations that generate a phase space trajectory known as the *Lorenz attractor.* She used this attractor to map the original score into it and then changed the initial conditions in order to have a different set of trajectories in phase space while still preserving the overall dynamic

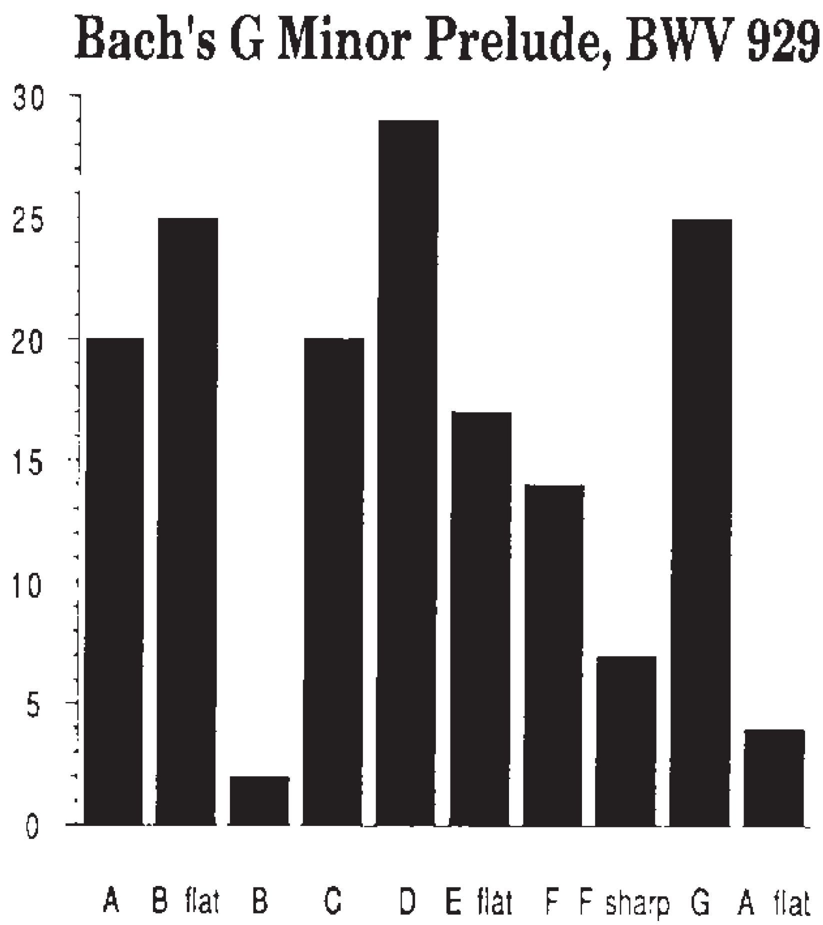

Figure 2

structure of the attractor (thus keeping the essence of Bach music). The result was a variation that professional musicians recognized as a variation of music by Bach. Interestingly, the nonlinear differential equations that underlie the ML model belong to the same set of equations that Dabby used. These equations are widely used across many scientific disciplines and are known as the *Lorenz system* (Thompson & Stewart, 1986) or *Lorenz equations* (Strogatz, 1994). Like Dabby's application of the Lorenz equations to music, we can map the complex interdependencies of team dynamics into the ML model.

In organizational studies, nonlinear dynamics is just beginning to enter the literature. To the extent that nonlinear dynamics has been used, it has been applied more as a metaphor than as a method (Daneke, 1999; Lumley 1997) and at the organizational level (Stacey, 1992, 1996; Thiétart & Forgues, 1995), not the individual or group level. Complexity theorists, however, have realized the appropriateness and potential of nonlinear dynamics to understanding organizational systems, including high-performing teams.

> Much of today's literature on high-performing teams seeks explanations . . . in terms of linear causal relationships. Such an approach is exposed to error. . . . New conceptual models are needed which can provide deeper insights. . . . Nonlinear models . . . appear to be prime candidates to open the door to more insightful ways of perceiving and managing organizations. (Lumley, 1997, pp. 14-15)

The second question (What do nonlinear models contribute to our understanding of the impact of P/N on the performance of teams?) is the guiding theme and main purpose of this article. To answer this question we will have to provide some context about the previous work of the first author (Losada, 1999) and then we will be able to systematically show the links that exist between connectivity and P/N.

METHODS AND DATA FROM CAPTURE LAB

We coded the verbal communication among team members along three bipolar dimensions, *positivity/negativity*, *inquiry/advocacy*, and *other/self*. By coding the verbal communication of teams along these dimensions, we captured how positivity and negativity interact as powerful feedback systems to generate different *emotional spaces*. Emotional spaces are created by the P/N ratios: high ratios create expansive emotional spaces and low ratios create restrictive emotional spaces (Losada, 1999). Although some previous research has demonstrated that affect is related to performance (Brief & Weiss, 2002), much of this research has looked at affect as a trait, and evaluated performance at the individual level (Staw & Barsade, 1993). We use the ML model to demonstrate how the emotional dynamics generated by P/N ratios differentiate teams into high, medium, and low performance levels.

The ML model was developed out of the time series generated by observing 60 strategic business unit (SBU) management teams from a large information processing corporation. These teams were observed in the Capture Lab (a computerized lab especially designed for team research) while developing their annual strategic plans. These SBU teams were selected on the basis of having complete performance records provided by their company. Each team consisted of eight people. The first step in the data collection was the coding and qualitative observations of team meetings. Then a time series analysis of the data was conducted. Coders were primarily University of Michigan students, trained by the first author, to code the speech acts of the group. A speech act is a verbal utterance that, if written, would be separated by a period; in other words, a typical speech act is a sentence or phrase. Each meeting was coded by three people. The interrater reliability coefficient was, on average, .97.

BIPOLAR DIMENSIONS

A speech act was coded as "positive" if the person speaking showed support, encouragement or appreciation (e.g., "that's a good idea"), and it was coded as "negative" if the person speaking showed disapproval (e.g., "that's about the dumbest thing I ever heard"), sarcasm, or cynicism. A speech act was coded as "inquiry" if it involved a question aimed at exploring and examining a position and as "advocacy" if it involved arguing in favor of the speaker's viewpoint. A speech act was coded as "self" if it referred to the person speaking or to the group present at the lab or to the company the person speaking belonged, and it was coded as "other" if the reference was to a person or group outside the company to which the person speaking belonged. The coders used a software system called GroupAnalyzer[1] (Losada & Markovitch, 1990), which labeled each code with a time stamp. Data generated by the coders were later aggregated in one-minute intervals. Time series analyses, including the auto-correlation and cross-correlation function, were performed on these aggregated data.

Positivity/negativity was used because of its high eliciting power as well as clarity for coding and feedback. It was an important dimension in Bales's early and later work on small group processes (Bales, 1950, Bales & Cohen, 1979). Echeverría (1994) argues that positivity generates expansive emotional spaces that open possibilities for action, whereas negativity creates restricted emotional spaces that close possibilities for action. He writes,

> Depending on the emotional space we are in, certain actions are possible and others are not—some possibilities open for us, others close. . . . In a state of enthusiasm, our horizon of possible actions is widened. . . . Fear narrows the space of what is possible. . . . Emotional spaces not only contain the actions that are possible, they also modulate the way in which we carry out those actions. (Echeverría, 1994, chap. 8)

This is similar to Fredrickson's (1998) argument that positive emotions broaden thought-action repertoires and build durable physical, intellectual, and social resources. Most psychological and organizational research examines the effects of either positive or negative emotions (Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Fredrickson, 1998; Staw, Sutton, & Pelled, 1994). We avoid these dichotomies (Rathunde, 2000) and look at the effects of different *ratios* of positivity to negativity on the performance of business teams. This parallels emotion researchers robust finding that valence (positive/negative dimension) is the best discriminator between emotional states (Larsen & Diener, 1992; Smith & Ellsworth, 1985). Gottman found that married couples who did not maintain a high ratio of positive to negative verbal and nonverbal behavior and expressions were unable to sustain their relationship (Gottman, 1994; Ryan, Gottman, Murray, Carrère, & Swanson, 2000). At the organizational level, the work of Stacey (1992, 1996) has shown that it is the nonlinear interplay between positive and negative feedback processes that characterizes an organization capacity to deal with increasingly complex environments.

Inquiry/advocacy was also chosen because of its eliciting power, and clarity for coding and feedback. It is prominent in the work of Argyris and Schön (1978), as well as in Senge (1990) and Senge, Roberts, Ross, Smith, & Kleiner, (1994). According to these authors, balancing inquiry and advocacy should lead to more effective action.

Other/self was also a highly eliciting variable that in addition was easy to code and provided clear and powerful feedback to participants. It has deep philosophical roots described in Buber's (1970) *I and Thou*, and has been developed extensively in social psychology by Aron and his associates (Aron & Fraley, 1999). Csikszentmihaly and Rathunde (1998) refer to the balance between other and self when they describe the "complex person" as "one who has the self-regulative capacity to move toward optimal experiences by negotiating a better fit or synchrony of self with environment" (p. 651). Organizational research tells us that this dimension plays a fundamental role in strategic planning, where "environmental scan" and "internal scrutiny" are key components. Environmental scan leads to the identification of opportunities and threats, whereas internal scrutiny leads to the recognition of basic strengths and weaknesses. One would expect high performance teams to be balanced in this dimension (Hax & Majluf, 1991). Previous research has shown that teams with the greatest orientation to their external environment had the highest performance ratings over time (Ancona, 1990).

The sample of 60 business teams was subdivided into three performance levels based on extensive business performance data. These data consisted of measures of profitability (SBU profit and loss statements), customer satisfaction (surveys and interviews) and 360-degree evaluations (assessments of the team members by superiors, peers, and subordinates). By using standardized data, teams were categorized into high, medium, and low performance depending on the levels achieved on these three criteria. A team was assigned to the high performance category if it achieved high ratings in all three measures. A team was assigned to the low performance category if it had low ratings in all three measures. Medium performance teams did not achieve ratings that were either consistently high or consistently low. The coders were blind to the performance level of the teams at the time of observation. Performance data were used to categorize the teams only after their meeting had been observed and coded. There were 15 high performance teams, 26 medium performance teams, and 19 low performance teams.

TABLE 1: Ratios for the Three Bipolar Dimensions

	Inquiry/Advocacy	*Positivity/Negativity*	*Other/Self*
High-performance teams	1.143	5.614	.935
Medium-performance teams	.667	1.855	.622
Low-performance teams	.052	.363	.034

FINDINGS FROM CAPTURE LAB

Analyses of the data showed that the teams varied systematically by performance level on each of the three bipolar dimensions (see Table 1). The P/N ratio showed strikingly different results for each performance category. For high performance teams, the ratio was 5.614, for medium performance teams was 1.855 and for low performance teams was .363. On the inquiry/advocacy and other/self dimensions, high performance teams achieved a balance between inquiry/advocacy and other/self speech acts throughout the meeting, with ratios of 1.143 and .935, respectively. Low performance teams were highly unbalanced toward advocacy and self from early in the meeting, with ratios of .052 and .034, respectively. Medium performance teams achieved a balance of inquiry/advocacy and other/self until the last fourth of the meeting, at which time they ended in disequilibrium toward advocacy and self, with ratios of .667 and .622, respectively.

The P/N ratio for high performance teams is very similar to the one that Gottman (1994) found for couples that were able to achieve a harmonious and sustainable relationship over time. Gottman also found that couples whose marriages ended in divorce had a preponderance of negativity over positivity in their overall interaction over time, just like the low performance team in our study: "Dissolution is related to positive-to-negative ratios of less than one (there is more negative than positive), whereas stability is associated with ratios that are around 5.0" (Gottman, 1994, p. 331).

CONNECTIVITY

In nonlinear dynamics models of networks, connectivity is a critical parameter driving the transition from rigidly ordered attractor structures to chaotic ones (Kaufman, 1993). In the ML model, connectivity is indicated by *nexi* (Latin plural of *nexus*), which are strong and sustained patterns of interlocked behaviors among team members that lasted during the entire meeting and are indicative of a process of mutual influence (Losada, 1999). Nexi were measured by means of the cross-correlation function (inverse Fourier transform of the cross-spectral density function) among all the time series data generated during a meeting. The cross-correlation function provides a measure of how strongly and at what lag a

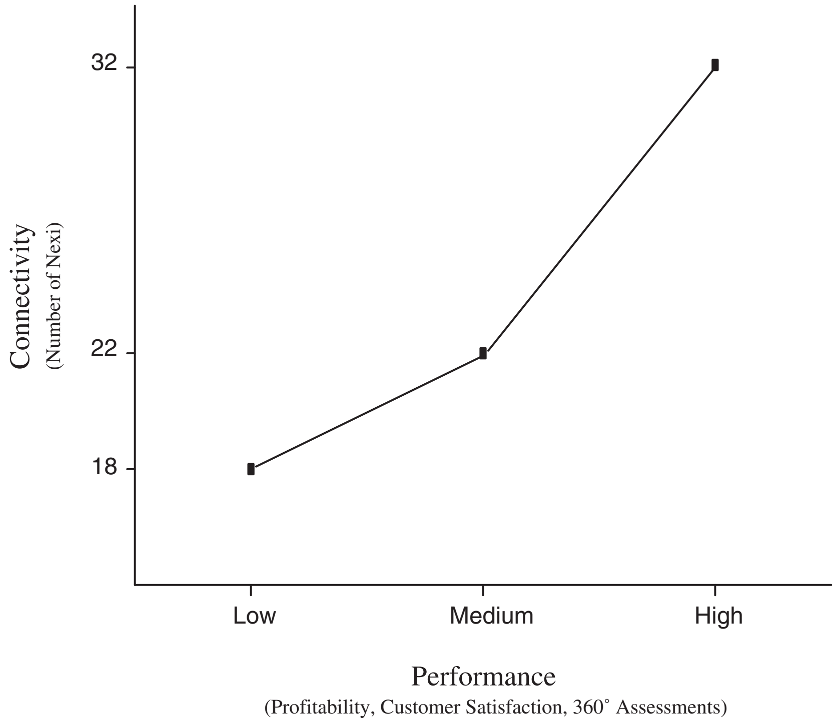

Figure 3: The Relationship Between Performance and Connectivity

particular behavior of one person over time is interlocked with the behavior of another person. Only cross-correlations significant at the $p \leq .001$ level were used. These strong cross-correlations are the nexi that a team is able to generate and represent the level of connectivity of the team.[2]

The rounded average nexi for high performance teams was 32, for medium performance teams was 22, and for low performance teams was 18. These rounded averages are equal to the modes of each category. All three categories had small coefficients of variation in their nexi number: 6.8% for high performance teams, 6.3% for medium performance teams, and 4.6% for low performance teams. These nexi are "significant" in the nonlinear dynamics sense because, as we will see, they produce different dynamics in phase space for each performance level. It would not make sense to talk about their significance in terms of traditional linear methodology because, in a nonlinear model, slight changes in the control parameter can produce dramatic changes in the behavior of a system as observed in phase space. Consequently, these nexi numbers are highly representative of each team performance category and suggest that the connectivity of the team is strongly linked to its performance (see Figure 3).

QUALITATIVE OBSERVATIONS

Qualitative observations of the teams showed that high performance teams were characterized by an atmosphere of buoyancy that lasted during the whole meeting. By showing appreciation and encouragement to other members of the team, they created emotional spaces that were expansive and opened possibilities for action and creativity as shown in their strategic mission statements. In stark contrast, low performance teams operated in very restrictive emotional spaces created by lack of mutual support and enthusiasm, often in an atmosphere charged with distrust and cynicism. The medium performance teams generated emotional spaces that were not as restrictive as the low performance teams, but definitively not as expansive as the high performance teams. They did not show the distrust and cynicism of low performance teams, but they also did not manifest the mutual support and enthusiasm characteristic of high performance teams.

NONLINEAR DYNAMICS MODELING

When time series data reveal strong interactions, as the existence of nexi between team members did, the best way to model such interactions appropriately is by means of a nonlinear dynamics model. The purpose of the nonlinear dynamics model is to enable us to understand what dynamics result from the different connectivity levels of the teams. As described earlier, Echeverría's (1994) concept of emotional space and Fredrickson's (1998) broaden-and-build theory would predict that greater positivity would broaden possible action, whereas more negativity would narrow it. A nonlinear model will enable us to look at the systematic effects of the P/N ratio on the system.

BACKGROUND ON NONLINEAR DYNAMICS MODELING

Phase space is a mathematical space spanned by the number of dimensions in the system. In this case, the three bipolar variables represent three dimensions in the system we are modeling. The *control parameter* is a critical component in the sense that by varying it, and keeping all other parameters constant, one can obtain different configurations in phase space that will portray the dynamics of the team. *State variables* are the variables entered into the model. The three bipolar dimensions are the state variables for this model.

To build a nonlinear dynamics model, one must select state variables that will have well-defined structures in phase space; if the variables entered into the model are not critical to the model's functioning (e.g., if any of the bipolar dimensions were not significant) or if the patterns themselves are random (e.g., there is no systematic differences in the speech acts of teams), no structure will be generated. Nowak and Vallacher (1998) describe this property of nonlinear dynamics models in the following passage:

> If the selected variables are irrelevant to the dynamics of the system, then no structure . . . appears, which is an indication that one should repeat this procedure with a different set of variables. The appearance of a well-defined pattern, on the other hand, is a clear indication that one's choice of variables is appropriate. The shape of this pattern, meanwhile, provides insight into the relationships among the chosen variables. (p. 69)

In nonlinear dynamics, there are four different types of structure (Barton, 1994; Ruelle, 1989). These structures are known as *attractors*. Mathematically, attractors represent the asymptotic tendency of the trajectories in phase space. In nonmathematical terms, attractors are like a gravitational field pulling behaviors toward it. The attractors vary in the degree to which they are rigid or flexible. The most rigid is the fixed-point attractor, followed by the limit cycle or periodic attractor, the torus or quasi-periodic attractor, and finally, the most flexible is the chaotic attractor. We have coined the term *complexor* to describe chaotic attractors. As we will see, chaotic attractors are important to our model, and we wanted a term that would accurately represent the nature of chaotic attractors. The common usage of the adjective chaotic implies disorder, which is the opposite of what a chaotic attractor represents. Disorder is produced by randomness. In contrast, all chaotic attractors are, by definition, deterministic. Mathematically, the complexity of a chaotic attractor is given, among other things, by its fractal nature, which is not observed in the other types of attractors. Thus, the word *complexor* is a contraction of two words: *COMPLEX ORder*. This more accurately portrays the structure and dynamics of what were originally named *chaotic attractors*.

A sense of the explanatory power of complexors is given by Goldberger's (Goldberger & Rigney, 1990) research at the Harvard Medical School. This research casts new light in our understanding of health and disease by showing that disease can be considered as *decomplexification* (i.e., the onsetting of rigid order such as limit cycles or fixed-point attractors), whereas health is associated with chaotic dynamics:

> Chaotic dynamics appear to underlie the variability and adaptability necessary for responding to a fluctuating environment . . . It is, to a large extent, the periodicities and patterns, the *loss* of chaos, in pathology that allow physicians to identify and classify many features of the abnormal appearance and behavior of their patients . . . Health with its broadband spectrum and strange attractor dynamics is, necessarily, much harder to classify. (Goldberger & Rigney, 1990, p. 30)

In organization studies, the work of Brown and Eisenhardt (1997, p. 29) reflects similar ideas about complexors when they argue that "systems, which stay constantly poised between order and disorder, exhibit the most prolific, complex and continuous change."

META LEARNING MODEL

The nonlinear differential equations on which the ML model was built can be found in Losada (1999). Here, we illustrate the ML model graphically and show how to interpret the connections among the control parameter and state variables of the model, as well as the resulting dynamics that are linked to each performance category.

Meta learning is defined as the "ability of a team to dissolve attractors that close possibilities for effective action and to evolve attractors that open possibilities for effective action" (Losada, 1999, p. 190). Dissolving attractors is a process that has similar implications to what Fredrickson and Levenson's (1998) call the "undoing hypothesis"—positive emotions undo the effect of negative emotions (see also Fredrickson, Mancuso, Branigan, & Tugade, 2000). Evolving attractors that open possibilities for effective action is a process similar to Fredrickson's "broaden-and-build" theory of positive emotions (Fredrickson, 1998, 2001). Fixed-point and limit cycle attractors are very rigid and stable dynamical structures that are hard to dissolve. By "meta learning," teams are able to transcend these limiting attractors and reach the dynamics of complexors. Complexors have a very different type of stability. The stability of complexors is dynamic, flexible, and innovating (trajectories in a complexor never repeat themselves). This important characteristic of complexors allows high performing teams to respond adaptively and innovatively to continuously changing and challenging environmental demands.

Figure 4 shows that the control parameter of the ML model is connectivity, which is characterized by the average number of nexi found at each performance level. The effects of connectivity on the equilibrium structure of the three state variables is described below.

When connectivity is high (nexi = 32), a dynamical balance is observed between inquiry/advocacy and other/self as well as a higher ratio of positivity to negativity. When connectivity is at a medium level (nexi = 22), the ratio of positivity to negativity is much lower than for high performance teams, and there is an unbalance toward advocacy and self. When connectivity is low (nexi = 18) there is a preponderance of negativity over positivity, and a very definitive unbalance toward advocacy and self.

These different equilibrium states lead to different dynamics in phase space (shown in Figure 5). The equilibrium states generated by high connectivity on each of the state variables leads to complexor dynamics, while medium connectivity and its associated equilibria in the state variables leads to limit cycle dynamics. Low connectivity and its corresponding equilibria leads to fixed-point dynamics. Each one of these dynamics, in turn, is associated with different performance levels: point attractor dynamics lead to low performance, limit cycle attractor dynamics lead to medium performance and complexors lead to high performance.

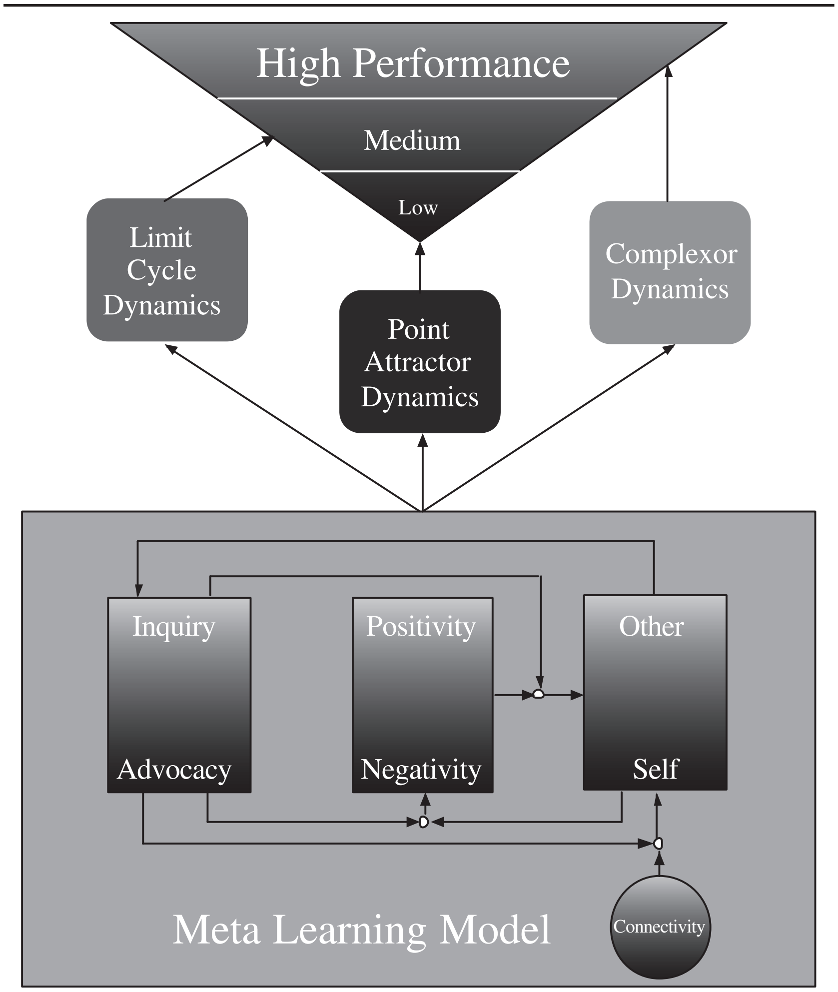

Figure 4: Meta Learning Model
SOURCE: ©2000 Meta Learning, 2280 Georgetown Blvd., Ann Arbor, MI 48105, 734-622-2340; mlosada@earthlink.net.

The relationship among the state variables is one of the most important features of the ML model. These relationships are mapped according to the nonlinear differential equations described in Losada (1999). The small circles in the model represent interactions (multiplication) between the variables. We can see that P/N has two inputs coming from other/self and inquiry/advocacy. These two inputs multiply, reflecting the nonlinearity produced by their interaction. It is this nonlinear interaction that affects the ratio of positivity to negativity. When

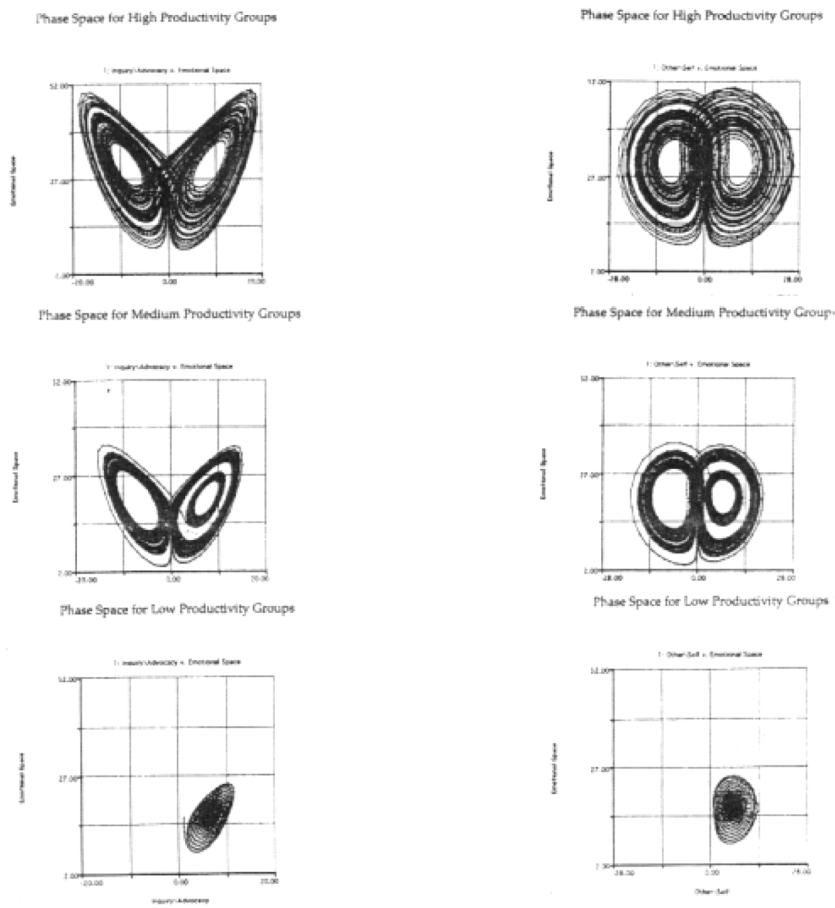

Figure 5: Attractor Dynamics for High-, Medium-, and Low-Performing Teams

P/N is high, it generates an expansive emotional space, and when it is low, it generates a restrictive emotional space.

Turning to the inputs and outputs of inquiry/advocacy, we can see that its input comes from other/self, meaning that the balance between inquiry/advocacy will depend upon the balance achieved between other/self. Thus, for example, to do powerful inquiry, we need to put ourselves sympathetically in the place of the person to whom we are asking the question. There has to be as much interest in the question we are asking as in the answer we are receiving. If not, inquiry can be motivated by a desire to show off or to embarrass the other person, in which case it will not create a nexus with that team member. The outputs of inquiry/advocacy go to the input and output of positivity/negativity via a nonlinear interaction, which will create complex and subtle effects both in the emotional space generated by P/N and in how that space will affect the balance between other/self.

The control parameter, connectivity, enters the ML model via other/self after interacting with the inquiry/advocacy's equilibria. Other/self also receives a nonlinear input from the interaction of inquiry/advocacy with positivity/negativity. That is, the balance between other/self will be affected by the emotional space generated as the pattern of inquiry/advocacy interacts with the balance achieved between positivity and negativity.

RUNNING THE META LEARNING MODEL: PHASE SPACE FINDINGS

A nonlinear dynamics model does not show cause and effect in a simple, linear way. The "result" of a nonlinear dynamics model is a path in phase space that reveals the dynamics of the system, not, as social scientists are accustomed to seeing, a regression coefficient revealing the slope of a line. When we run the ML model, we get the attractor dynamics in phase space, shown in Figure 5. The top graphs represent the dynamics of high performance teams; the middle graphs, the dynamics of medium performance teams; the bottom graphs correspond to low performance teams. The graphs on the left refer to inquiry/advocacy (x-axis) versus emotional space (y-axis). The graphs on the right correspond to other/self (x-axis) versus emotional space (y-axis). On the x-axis of the left-hand graphs, inquiry is to the left of the middle line and advocacy to the right side. On the x-axis of the right-side graphs, other is to the left side of the middle line and self to the right side.

We know that emotional space is generated by the P/N ratio. The scale of the y-axis does not represent directly the P/N ratio, but the outcome of the initial value (16) entered into the equation to eliminate the transient (this is a standard procedure in nonlinear dynamics and in modeling in general) and the multiplication by the constant 8/3 (a constant used in all Lorenz system models). By introducing the initial value and multiplying by a constant we are creating an initial emotional space that will stay there increased or decreased by the P/N ratio.

The top two graphs show that high performance teams are able to generate complexors in their dynamical interaction.[3] It is interesting to note that complexors can be generated only within a system where positive feedback is stronger than negative feedback. Both are needed because, without negative feedback, the trajectories in phase space would be out of bounds, meaning that there would be no structure, but just scattered trajectories. On the other hand, if negative feedback were prevalent, the system would rapidly converge to a point attractor or a limit cycle, depending on the strength of the negative feedback. High performance teams do not get trapped into limiting dynamics such as limit cycles and fixed-points because they are able to maintain a high ratio of positivity to negativity. They also maintain an equilibrium between inquiry and advocacy as well as between other and self. This dynamical equilibrium is validated by the empirical ratios reported in Table 1.

By contrast, the reader can observe that medium performance teams (middle graphs) eventually settle into limit cycle attractors because there is not enough positivity in their interaction. By focusing on the right-hand side of each middle graph, where the typical trajectory of a limit cycle is traced, one can readily see this. These unbalanced dynamics are validated by the empirical ratios reported in Table 1.

Because of the prevalence of negativity over positivity, low performance teams have much poorer dynamics than the other teams: they settle very rapidly into a fixed-point attractor that is located in the advocacy side (bottom left graph) and self side (bottom right graph). Again, the unbalances of these dynamics are validated by the empirical ratios reported in Table 1.

If we now look at all the phase space dynamics from bottom to top (i.e., from restrictive emotional spaces with low P/N ratios to expansive emotional spaces with high P/N ratios) we can readily see a broadening pattern that supports Fredrickson's theory that positive emotions broaden behavioral repertoires. That is, teams enact a broader range of behaviors at each successive level, from low to high performance teams (Fredrickson, 1998, 2001).

LINKING EMOTIONAL SPACE AND CONNECTIVITY

We now address the question of whether emotional space is linked to connectivity and how emotional space is specifically related to the positivity to negativity ratio. To examine these relationships we need to introduce the notion of attractor *focus*.[4] In Figure 3, the top four graphs, right and left, show a blank space approximately in the middle of the attractor in each of its wings. These blank spaces are like the eye of a hurricane. Their centroids are the *foci* of the attractor. They keep the trajectories within bounds. If there were no foci we would not have an attractor creating the dynamical structure we observe in these figures. In the bottom two graphs, for low performance teams, the foci are the point attractors toward which the trajectories very rapidly settle.

If we project all these foci over the y-axis (emotional space) we see that the numbers we obtain are indeed very meaningful and illustrate how emotional space is linked to connectivity. The number obtained on the y-axis for high performance teams (both for inquiry/advocacy and other/self) is 31, for medium performance teams is 21, and for low performance teams is 17. These numbers are exactly the number of nexi minus one. Thus, we can now introduce the equation

$$E = c - 1, \tag{1}$$

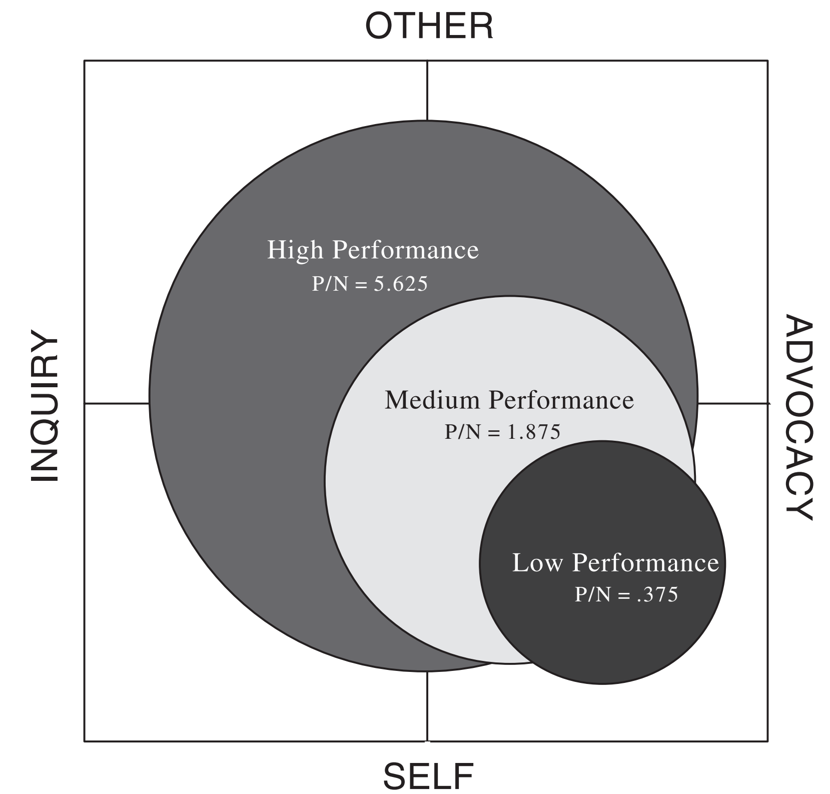

Figure 6: Emotional Space Projected Over Inquiry/Advocacy and Other/Self

where E is emotional space, and c is connectivity (represented by the number of nexi). Therefore, there is a direct and measurable relationship between emotional space and connectivity, as represented by the ML model. The consequences of this relationship are straightforward: Because connectivity is the control parameter in the ML model, we can equally say that emotional space plays a crucial and determinant role in differentiating high-performance teams from medium- and low-performance teams.

We can project emotional space by using the emotional space number ($E = c - 1$) as the radius of a circle over a plane with inquiry/advocacy and other/self as the coordinates (see Figure 6). This alternative representation to a phase space diagram allows us to visualize the emotional space areas for each performance level in relation to inquiry/advocacy and other-self in a single graph. The formula for calculating the area of a circle is πr^2; therefore we can represent emotional space as the area of a circle by πE^2. For high-performance teams, the area is 3,019.07; medium performance is 1,385.44, and low performance is 907.92. Looking at these values, we can see that high performance teams create emotional spaces with areas that are approximately three times larger than low performance teams, and approximately twice those of medium performance teams. Medium performance teams create areas that are about half as large as low performance teams. Notice also that high-performance teams are centered right at the intersection of inquiry/advocacy and other/self, medium teams are off-centered toward other and self, whereas low-performance teams are definitively centered in self and advocacy.

LINKING EMOTIONAL SPACE AND P/N RATIOS

Examining the relationship between emotional space and P/N ratios provides further validation of the ML model by showing the relationship between the original time series data and the nonlinear dynamics model. When running the ML model initial values as well as scaling constants must be assigned. The initial values eliminate transients, which represent features of the model that are neither essential nor lasting. The initial value for positivity/negativity is 16. The constants are used to scale the data, namely to be able to see the dynamics more clearly. The structure of this model resembles a Lorenz attractor, a widely used set of nonlinear differential equations, and scholars who use Lorenz attractors agree to use 8/3 as a constant, in order to be able to compare findings across models and dynamics in many disciplines by just varying the control parameter.

With this background information, we can now calculate the P/N ratio. To derive the P/N ratio from the attractor's foci, we subtract the initial value and multiply it by the inverse of the scaling constant (0.375). For example, for high performance teams, we start with 31, subtract 16, and multiply by 0.375. The result is 5.625, which is very close to 5.614, the result obtained by looking at the original time series data. We can now introduce the equation that allows us to calculate the positivity to negativity ratio (P/N) from emotional space (E):

$$\mathrm{P/N} = (E - i)\, b^{-1} \tag{2}$$

where E is emotional space, i is the initial value of the positivity/negativity state variable (equal to 16), and b^{-1} is the inverse scaling constant (equal to 0.375). If we apply this formula to the E numbers for medium (21) and low-performance teams (17), we obtain results that are equally close to the ones obtained by looking directly at the time series data, thus further validating the ML model (see Table 2).

TABLE 2: Positivity/Negativity Ratios From Time Series and Model

	Time Series Data	*Model Data*
High-performance teams	5.614	5.625
Medium-performance teams	1.855	1.875
Low-performance teams	0.363	0.375

LINKING CONNECTIVITY AND P/N RATIOS

The final link we will make is between connectivity and P/N ratios. To do this, we examine the effects of connectivity and P/N ratios separately on performance. First, we calculate the distances between the P/N ratios in the data generated by the model. The distance between high performance (5.625) and medium performance (1.875) is 3.75 (i.e., 10 units of 0.375—the inverse constant of the ML model). The distance between medium and low performance is 1.5 (i.e., 4 inverse constant units). These distances are equivalent to the distances found between the different performance levels in terms of nexi. So, we can conclude that positivity and connectivity have equivalent distances for each performance category.

This is illustrated by plotting the P/N ratios against performance (see Figure 7). If we compare Figure 7 with Figure 3 (connectivity vs. performance) the relationship between connectivity and positivity is obvious. We can formalize the relationship between positivity and connectivity by means of the equation

$$\text{P/N} = (c - i - 1)\, b^{-1} \tag{3}$$

where P/N is the ratio of positivity to negativity, c is connectivity defined by the number of nexi, i is the initial value of the positivity/negativity state variable and b^{-1} is the inverse scaling constant.

Because connectivity is the control parameter in the ML model, we can conclude that the ratio of positivity to negativity plays a determinant role as well in differentiating high- from medium- and low-performance teams. Investigating this relationship was our main objective, as stated in the introduction.

DISCUSSION

THE POWER OF A *RATIO* OF P/N IN HUMAN INTERACTION

These analyses demonstrate a rather remarkable finding. Mathematically, we have shown that the positivity/negativity state variable is as important as

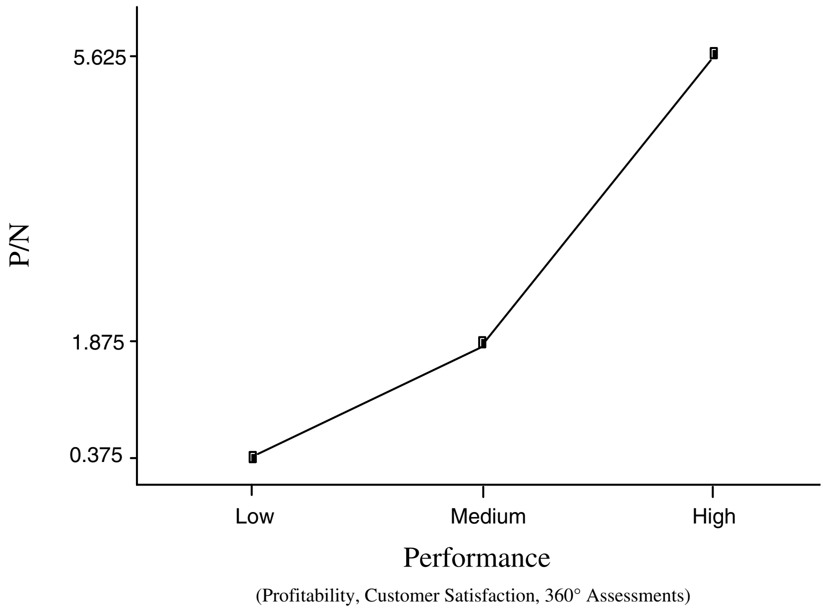

Figure 7: Positivity to Negativity Ratios Versus Performance

connectivity, the control parameter, in determining the attractors in the nonlinear dynamics model. This means that in order to predict team performance, one only has to know the ratio of positive to negative interactions to find the nexi value (connectivity), then run the ML model and find the type of attractor dynamics (fixed point, limit cycle, complexor) that, in turn, indicate the level of performance associated with each of those particular attractors.

Interestingly, this finding parallels research on positivity and negativity in human dyadic interaction and neuroanatomy. On the dyadic level, Gottman's research on married couples has shown that the best predictor of stable marriages is the *ratio* of positive to negative interactions: "In fact, the best discrimination was obtained by a ratio of positive to negative codes" (Gottman, 1994, p. 413). Where his "performance" variable was the sustainability and quality of a marital relationship, we found that this same ratio of positive to negative interactions is the critical differentiator between high-, medium-, and low-performing teams.

At the neurological level, recent research from the Laboratory of Affective Neuroscience proposes that there are two partially separable neural systems linking neuroanatomy to emotions and affective style (Davidson, 1999). Located in the left prefrontal cortex, the approach system generates positive affect and is associated with moving toward a desired goal, whereas the withdrawal system, located in the amygdala and the right prefrontal cortex, generates negative affect and is associated with aversive stimulation. An individual's typical mood range can be predicted with a high level of accuracy by looking at the *ratio* of activity in these two parts of the brain: "The more the ratio tilts to the right, the more unhappy or distressed a person tends to be, whereas the more activity tilts to the left, the more happy and enthusiastic" (Goleman, 2003. p. D5).

In our model, positivity and negativity operate as powerful feedback systems: negativity dampens deviations from some standard, whereas positivity acts as amplifying or reinforcing feedback that expands behavior. The ML model demonstrates how these P/N ratios then determine the types of dynamics possible for a team. When the P/N ratio is high, we get the dynamics of complexors, which leads to high performance. With an inverted ratio in which there is more negative to positive interaction, a point attractor develops.

What would happen if the P/N ratio was extremely high, say 100 to 1? Is there such a thing as excess positivity? We learn from running the ML model with a P/N = 100, that a limit cycle would develop and the complexor structure would be lost. The lesson here is that there can be excessive positivity, in which case a team can become unrealistically Pollyannaish. By getting themselves locked in a limit cycle of positivity they lose the generating and innovating power of a complexor. As we have seen, a complexor is generated and sustained by an adequate proportion of positivity/negativity where the tension of the polarity is maintained.

One might wonder why are ratios powerful, and what there is in a ratio that is not in a subtraction. The answer might be that ratios preserve the proportion of the elements in a compound. This is important for bipolar variables where one wants to have some measure of the "tension" inherent in the polarity. Subtraction reduces the compound to one element (if it is a binary compound) and, consequently, the tension is lost and, with it, a critical piece of information.

CONNECTIONS, POSITIVITY, AND DURABLE RESOURCES

Underlying the ML model there is a complex interplay among human connections, P/N, emotions, and actions. Teams, according to their performance level, generated vastly different areas of emotional space depending on their connectivity and P/N ratio. In agreement with the theories of both Echeverría and Fredrickson, expansive emotional spaces generated by high P/N ratios opened possibilities for effective action. This is the "broaden" part of the broaden-and-build theory. What is the "build" part? What are the durable resources of these teams? According to the ML model, the durable psychological and social resources are the strength and quantity of the connections (nexi) among team members. Low and medium performance teams do not have enough of these resources to reach and sustain the level of performance we

TABLE 3: Team Performance Matrix

	Dynamics	*Connectivity*	*Inquiry-Advocacy*	*Other-Self*	*Emotional Space*
High performance	Complexor	High	Balanced	Balanced	Expansive P >> N
Medium performance	Limit cycle	Medium	Unbalanced toward advocacy	Unbalanced toward self	Restrictive P > N
Low performance	Fixed point	Low	Entirely unbalanced toward self	Entirely unbalanced toward self	Highly restrictive N > P

observe in high performance teams. An important dynamical characteristic of these durable resources is that they enable or disable complexor dynamics. This finding points to new research questions regarding how relationships and the quality of connections (Dutton & Heaphy, 2003) affect organizational processes.

CONCLUSION

To have a comprehensive view of all the findings, we have summarized them in Table 3. In this table each of the team performance categories is characterized by five descriptors: the type of dynamics generated in phase space, the level of connectivity achieved, the balanced obtained in terms of inquiry/advocacy, the balance achieved in terms of other/self, and the emotional space generated by the P/N ratio.

This table shows that low performance teams have a low level of connectivity, which leads them to get stuck in negativity as well in advocacy and self-absorption. All of this generates the dynamics of a point attractor. Once a team or an organization settles into the dynamics of point attractors, it is extremely difficult to exit. Baumeister et al.'s (2001) article titled *Bad Is Stronger Than Good* is correct in the sense that a point attractor (where negativity is larger than positivity) is an extremely stable and powerful attractor. It is the stability achieved by the second law of thermodynamics, when eventually everything settles into total homogeneity, an everlasting constant where nothing new ever happens. A point attractor in the time domain is a constant whose archetypical image is that of the cardiac monitor in emergency rooms reaching the flat line accompanied by the monotone beep that signals death. Organizations and teams where point attractors predominate are doomed to die in a chaotically complex world that demands constant adaptation and innovation.

Medium-performance teams fare better in the sense that they show an initial capacity to balance inquiry/advocacy as well as other/self. They also have a P/N ratio in which positivity is slightly larger than negativity. Their connectivity is also slightly greater than that of low-performance teams. The problem is that they are not able to sustain the benefits of these patterns. This is because their connectivity and positivity are not high enough to escape the entropic gravitational pull of negativity. So they end up in the dynamics of limit cycles without ever reaching new places. In the end, medium-performance teams finished in the same place where low-performance teams ended earlier in their interaction: advocacy and self-absorption.

In the Capture Lab sample, 75% of the teams were stuck in either point attractors or limit cycles. Only 25% managed to escape these limiting attractors by creating and sustaining a completely different type of dynamic that reflects a different type of order, the "complex order" of a complexor. What is necessary to reach the liberating dynamics of a complexor? Whitehead, the eloquent philosopher of process, wrote

> Order is not sufficient. What is required, is something much more complex. It is order entering upon novelty; so that the massiveness of order does not degenerate into mere repetition. (Whitehead, 1978, p. 339)

This is the big challenge. Our call, to teams and organizations, as well as for positive organizational scholars, is to take on the challenge of identifying how to create a new, liberating and enriching order within organizations. This article contributes some of the answers that could lead to creating and implementing the new order that "enters upon novelty." We need to have teams within organizations that are able to tap into the liberating and creative power of positivity. Not the excess positivity of Pollyannaish optimism, but the grounded positivity where measured negative feedback has a necessary place in keeping things going within agreed objectives. We need to have organizations with teams that are highly connected with the kind of durable resources that strong and lasting nexi generate. We need to have organizations where the polarity of other and self, of you and I, is integrated into a sense of *we*; where the polarity of inquiry and advocacy, of questions and answers, can drive a productive and ongoing *dialogue*; where the abundance of positivity, grounded in constructive negative feedback, can generate the state of realistic *enthusiasm* that can propel organizations to reach and uphold the heights of excellence.

NOTES

1. The software used in this data collection is a more advanced version of the one described in Losada and Markovitch (1990); the version used to collect data in this study generated its own time series analyses. More important, in the new version, any three dimensions could be programmed into

the software. Inquiry/Advocacy (I/A), Other/Self (O/S), and Positivity/Negativity (P/N) were used in this study, but only P-N is mentioned in the 1990 text.

2. For a graphical representation of nexi (a *group interaction diagram*) using the cross-correlation function, see Losada, Sánchez, and Noble (1990). A good introduction for social scientists to the cross-correlation function can be found in Gottman (1981). Vittengl and Holt (1998) provide a clear application of it to a study of mood and social interaction.

3. We know these are complexors because they have a fractal dimension of 2.06.

4. The foci of the attractor are also the points at which a *Poincaré section* is done. The Poincaré section allows us to capture the dynamics of the system while reducing its dimensionality. See Guckenheimer and Holmes (1983, p. 95), for an illustration of a Poincaré section.

REFERENCES

Ancona, D. (1990). Outward bound: Strategies for team survival in an organization. *The Academy of Management Journal*, *33*(2), 334-365.

Argyris, C., & Schön, D. (1978). *Organizational learning: A theory of action perspective*. Reading, MA: Addison-Wesley.

Aron, A., & Fraley, B. (1999). Relationship closeness as including other in self: cognitive underpinnings and measures. *Social Cognition*, *17*(2), 140-160.

Bales, R. F. (1950). *Interaction process analysis: A method for the study of small groups*. Reading, MA: Addison-Wesley.

Bales, R. F., & Cohen, S. P. (1979). *SYMLOG: A system for the multilevel observation of groups*. New York: Free Press.

Barton, S. (1994). Chaos, self-organization, and psychology. *American Psychologist*, *49*(1), 5-14.

Baumeister, R. F., Bratslavsky, E., Finkenauer, C., & Vohs, K. D. (2001). Bad is stronger than good. *Review of General Psychology*, *5*(4), 323-370.

Brief, A. P., & Weiss, H. M. (2002). Organizational behavior: Affect in the workplace. *Annual Review of Psychology*, *53*, 279-307.

Brown, S. L., & Eisenhardt, K. M. (1997). The art of continuous change: Linking complexity theory and time-paced evolution in relentlessly shifting organizations. *Administrative Science Quarterly*, *42*(1), 1-34.

Buber, M. (1970). *I and Thou* (W. Kauffman, Trans.). New York: Touchstone.

Cameron, K. S., Dutton, J. E., & Quinn, R. E. (2003). Foundations of positive organizational scholarship. In K. Cameron, J. E. Dutton, & R. Quinn (Eds.), *Positive Organizational Scholarship* (pp. 3-13). Thousand Oaks, CA: Berrett-Kohler.

Csikszentmihaly, M., & Rathunde, K. (1998). The development of the person: An experiential perspective on the ontogenesis of psychological complexity. In W. Damon (Series Ed.) & R. M. Lerner (Vol. Ed.), *Theoretical models of human development: Vol. 1. Handbook of Child Psychology* (5th ed., pp. 635-684). New York: Wiley.

Dabby, D. S. (1996). Musical variations from a chaotic mapping. *Chaos*, *6*, 95-107.

Daneke, G. A. (1999). *Systemic choices: Nonlinear dynamics and practical management*. Ann Arbor: University of Michigan Press.

Davidson, R. (1999). The functional neuroanatomy of emotion and affective style. *Trends in Cognitive Science*, *3*(1), 11-21.

Dutton, J. E., & Heaphy, E. D. (2003). Coming to life: The power of high quality connections at work. In K. Cameron, J. E. Dutton, & R. Quinn. (Eds.), *Positive Organizational Scholarship* (pp. 263-278). Thousand Oaks, CA: Berrett-Kohler.

Echeverría, R. (1994). *Ontologa del Lenguaje* [Ontology of language]. Santiago de Chile: Dolmen Ediciones.

Fredrickson, B. L. (1998). What good are positive emotions? *Review of General Psychology*, *2*(3), 300-319.

Fredrickson, B. L. (2001). The role of positive emotions in positive psychology. *American Psychologist*, *56*(3), 218-226.

Fredrickson, B. L., & Levenson, R. W. (1998). Positive emotions speed recovery from the cardiovascular sequelae of negative emotions. *Cognition and Emotion*, *12*, 191-200.

Fredrickson, B. L., Mancuso, R. A., Branigan, C., & Tugade, M. M. (2000). The undoing effect of positive emotions. *Motivation and Emotion*, *24*(4), 237-259.

Goldberger, A. L., & Rigney, D. R. (1990). Sudden death is not chaos. In S. Krasner (Ed.), *The Ubiquity of Chaos* (pp. 23-34). Washington, DC: American Association for the Advancement of Science.

Goleman, D. (2003,February 4). Finding happiness: Cajole your brain to move to the left. *The New York Times*, p. D5.

Gottman, J. M. (1981). *Time-series analysis: A comprehensive introduction for social scientists*. New York: Cambridge University Press.

Gottman, J. M. (1994). *What predicts divorce: The relationship between marital processes & marital outcomes*. New York: Lawrence Earlbaum.

Guckenheimer, J., & Holmes, P. (1983). *Nonlinear oscillations, dynamical systems, and bifurcations of vector fields*. New York: Springer-Verlag.

Hax, A. C., & Majluf, N. S. (1991). *The strategy concept and process: A pragmatic approach*. Reading. MA: Addison-Wesley.

Isen, A. (2000). Positive affect and decision-making. In M. Lewis & J. M. Haviland-Jones (Eds.), *Handbook of emotions* (2nd ed., pp. 417-435). New York: Guilford Press.

Kaufman, S. A. (1993). *The origins of order.* Oxford, UK: Oxford University Press.

Larsen, R. J., & Diener, E. E. (1992). Promises and problems with the circumplex model of emotion. *Review of Personality and Social Psychology: Emotion and Social Behavior, 114*, 25-59.

Losada, M. (1999). The complex dynamics of high performance teams. *Mathematical and Computer Modelling*, *30*, 179-192.

Losada, M., & Markovitch, S. (1990). A system for dynamic analysis of group interaction. *Proceedings of the 23rd Hawaii International Conference on System Sciences* (vol. IV, pp. 101-110). Los Alamitos, CA: IEEE Computer Society Press.

Losada, M., Sánchez, P., & Noble, E. E. (1990, October 7-10). Collaborative technology and group process feedback: Their impact on interactive sequences in meetings. *Proceedings of the Conference on Computer-Supported Cooperative Work*, 53-64.

Lumley, T. (1997). Complexity and the learning organization: Addressing team performance in new science terms. *Complexity*, *2*(5), 14-22.

Nowak, A., & Vallacher, R. R. (1998). *Dynamical social psychology.* Cambridge, UK: Cambridge University Press.

Parkinson, B. (1996). Emotions are social. *British Journal of Psychology*, *87*, 663-683.

Rathunde, K. (2000). Broadening and narrowing in the creative process: A commentary on Fredrickson's "broaden-and-build" model. *Prevention and Treatment*, *3*(6), 1-6.

Ruelle, D. (1989). *Chaotic evolution and strange attractors*. Cambridge, UK: Cambridge University Press.

Ryan, K. D., Gottman, J. M., Murray, J. D., Carrre, S., & Swanson, C. (2000). Theoretical and mathematical modeling of marriage. In M. D. Lewis & I. Granic (Eds.), *Emotion, development, and self-organization: Dynamic systems approaches to emotional development* (pp. 349-372). Cambridge, UK: Cambridge University Press.

Senge, P. M. (1990). *The fifth discipline: The art and practice of the learning organization.* New York: Currency/Doubleday.

Senge, P. M., Roberts, C., Ross, R. B., Smith, B. J., & Kleiner, A. (1994). *The fifth discipline fieldbook: Strategies and tools for building a learning organization.* New York: Currency/Doubleday.

Smith, C. A., & Ellsworth, P. C. (1985). Patterns of cognitive appraisal in emotion. *Journal of Personality and Social Psychology*, *48*(4), 813-838.

Stacey, R. D. (1992). *Managing the unknowable: Strategic boundaries between order and chaos in organizations*. San Francisco: Jossey-Bass.

Stacey, R. D. (1996). *Strategic management and organisational dynamics* (2nd ed.). London: Pitman.

Staw, B. M., & Barsade, S. G. (1993). Affect and managerial performance: A test of the sadder-but-wiser vs. happier-and-smarter hypotheses. *Administrative Science Quarterly*, *28*, 304-331.

Staw, B. M., Sutton, R. I., & Pelled, L. H. (1994). Employee positive emotion and favorable outcomes at the workplace. *Organization Science*, *5*(1), 51-71.

Strogatz, S. H. (1994). *Nonlinear dynamics and chaos theory.* Reading, MA: Addison-Wesley.

Thiétart, R. A., & Forgues, B. (1995). Chaos theory and organization. *Organization Science*, *6*(1), 19-31.

Thompson, J. M. T., & Stewart, H. B. (1986). *Nonlinear dynamics and chaos*. New York: John Wiley.

Tong, H. (1990). *Non-linear time series: A dynamical system approach*. Oxford, UK: Clarendon Press.

Vittengl, J. R., & Holt, C. S. (1998). A time-series study of mood and social interaction. *Motivation and Emotion*, *22*(3), 255-275.

Whitehead, A. N. (1978). *Process and reality* (corrected ed.). New York: Free Press.

MARCIAL LOSADA *is cofounder and executive director of Meta Learning, a consulting organization that specializes in team productivity. He pioneered work on applications of nonlinear dynamics and complexity theory to detect patterns of interaction that undermine productivity in business organizations and conducted studies on the interaction dynamics and productivity of business teams that led to the implementation of a unique, scientifically based, approach to increase productivity in low-performance teams.*

EMILY HEAPHY*'s research focuses on how high-quality relationships and social identity affect organizational and interpersonal processes. She is a doctoral student of organizational behavior and human resource management at the University of Michigan.*