

PERGAMON Mathematical and Computer Modelling 30 (1999) 179–192

MATHEMATICAL AND COMPUTER MODELLING

www.elsevier.nl/locate/mcm

The Complex Dynamics of High Performance Teams

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(Received and accepted November 1998)

Abstract—The connectivity of a team is highly correlated with its performance. Connectivity is measured by the strength and number of cross-correlations among time series of the coded speech acts of meeting participants. Connectivity is used as a control parameter in a nonlinear dynamical model derived from the observed time series. Different types of attractors occur in phase space depending on the team's connectivity and performance level: low performance teams show point attractors, medium performance teams show limit cycles, and high performance teams show low-dimensional chaotic attractors. © 1999 Elsevier Science Ltd. All rights reserved.

Keywords—Connectivity, Team performance, Nonlinear dynamics, Complexity, Team learning.

1. INTRODUCTION

For several years I had been the director of the Center for Advanced Research (CFAR), built by EDS in Ann Arbor and Cambridge, near the University of Michigan and MIT campuses. CFAR had a laboratory known as the Capture Lab. This lab had an observation room with a one-way mirror, computers, videotaping equipment, and other devices that allowed several observers to code speech acts of participants in a meeting using a specialized software [1,2]. As a speech act was coded, the computer put a time stamp indicating at what moment during the meeting the speech act occurred. By the end of the session, a protocol of the meeting was created from where time series were generated for each of the dimensions used in the coding of speech acts.

At the Capture Lab, I observed and analyzed the interaction patterns of many business teams from several corporations doing typical business tasks like strategic planning, brainstorming, and others. One of my principal findings was that the degree of connectivity of the team, measured by the number and strength of cross-correlations among time series of the participants, was an excellent predictor of team performance.

Kauffman, a biologist recipient of the MacArthur fellowship who has done extensive research on complex adaptive systems, has found that for highly interconnected Boolean networks the behavior in phase space—where the evolution of a system can be observed—shows chaotic dynamics, but as the average number of connections gets smaller, the behavior converges to limit cycles and point attractors. He asserts that the passage from chaotic to rigidly ordered regimes

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PII: S0895-7177(99)00189-2

and vice versa is a phase transition driven by critical control parameters: "one such parameter is the connectivity of the elements of the network" [3, p. 206].

What intrigued me about Kauffman's findings, was that highly interconnected teams might exhibit complex patterns of interaction leading to chaotic dynamics, while poorly interconnected teams might end up in much simpler dynamics such as limit cycles and point attractors. Knowing the correlation between degree of connectivity and performance, I wondered whether highly productive teams would have trajectories in phase space that could be classified as complex chaotic attractors. Chaos, in dynamical systems terms, not its common usage in English, exists in a region between rigid order and disorder. What I find fascinating about chaotic dynamics is that scientists at the Santa Fe Institute suggest that "for a given system the region which lies between order and disorder provides an optimal environment for learning and adaptation" [4, p. 713]. If this is the case, high performance teams will most likely show chaotic attractors, since they provide the type of nonlinear interactive dynamics leading to learning, adaptation, and innovation.

2. PERFORMANCE MEASURES AND CHARACTERIZATION OF TEAMS

Performance was evaluated using three indicators: profitability (measured by the P & Ls), customer satisfaction, and assessments of the team by their superiors, peers, and subordinates. Teams were classified according to their performance into high, medium, and low. 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 consistently high or consistently low.

A total of 60 teams were studied at the Capture Lab. According to the measures mentioned, 15 were classified as high performance teams, 26 as medium performance teams, and 19 as low performance teams.

In addition to performance measures, teams were characterized by their degree of connectivity. This was measured by the number of cross-correlations significant at the .001 level or better that were obtained through the time series analysis of the data generated by coding speech acts at the Capture Lab. I call these cross-correlations *nexi* (Latin plural of nexus). They represent sustained couplings or matching patterns of interlocked behaviors among participants throughout the whole meeting. 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 also correspond to the modes; i.e., the nexi number that occurs with the greatest frequency for 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. Consequently, these nexi numbers are highly representative of each team performance category.

From a qualitative perspective, my own assessments of these teams can be summarized as follows: high performance teams were characterized by an atmosphere of buoyancy that lasted during the whole meeting. By showing appreciation and encouragement to other members in the team, they created emotional spaces that were expansive and opened possibilities for action and creativity. They were also fun to watch and there was rarely a dull moment during their meetings. In addition, they accomplished their tasks with ease and grace. In stark contrast, low performance teams struggled with their tasks, 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 operated in emotional spaces that were not as restrictive as the low performance teams, but not nearly as expansive as the high performance

teams. They were able to finish their tasks as planned, but not with the novelty and creativity characteristic of high performance teams.

3. CODING DIMENSIONS AND EXPECTED RESULTS

Teams were coded at the Capture Lab facilities at the early stages of their strategic planning sessions while they were working on the mission of their business.

The three dimensions used in the coding of speech acts at the Capture Lab were: inquiry-advocacy, other-self, positivity-negativity. These dimensions were selected on the basis of previous research and practices. 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 lab and not part of the company to which the person speaking belonged. A speech act was coded as positive if the person speaking showed support, encouragement, or appreciation, and it was coded as negative if the person speaking showed disapproval, sarcasm, or cynicism.

Inquiry-advocacy is based on work done by Argyris and Schön [5] that Senge integrated with system dynamics in his book, *The Fifth Discipline* [6] and later Ross and Roberts expanded in the *Fifth Discipline Fieldbook* [7]. According to these authors, balancing inquiry and advocacy should lead to more effective action.

Other-self was derived from the fundamental role that "environmental scan" and "internal scrutiny" have in the strategic planning process; environmental scan leads to the identification of opportunities and threats, while internal scrutiny leads to the recognition of basic strengths and weaknesses [8]. One would expect high performance teams to be balanced in this dimension.

Positivity-negativity was extensively used by Bales at Harvard in several of his coding systems [9,10]. Gottman has done a remarkable study of couples using time series analysis of the positivity-negativity dimension to predict the sustainability of a couple's relationship. He found out that unless couples are able to maintain a high ratio of positivity to negativity, it is highly likely that the relationship will end [11–13]. Echeverría, through a process he calls "linguistic reconstruction of emotions", uses the concept of "emotional space" to refer to the effect of positivity in creating expansive emotional spaces that open possibilities for action, while negativity creates restrictive emotional spaces that close possibilities for action [14]. I will call "emotional space" the ratio of positivity to negativity; high ratios imply expansive emotional spaces and low ratios restrictive emotional spaces. High performance teams should be able to create expansive emotional spaces; consequently, the positivity-negativity ratio should be high and we would expect this dimension to be unbalanced towards positivity.

According to Kauffman's findings about connectivity, high performance teams should show a chaotic trajectory in phase space, while low performance teams should show trajectories converging to a point attractor, and medium performance teams should show a pattern somewhere in between the expectations for high and low performance teams. In addition, according to my observations at the Capture Lab, high performance teams should show expansive emotional spaces and balance between inquiry-advocacy and other-self, while low performance teams should have a low positivity to negativity ratio suggestive of a restrictive emotional space and be unbalanced towards advocacy and self orientation. Medium performance teams should have a more restrictive emotional space than high performance teams, but not as restrictive as low performance teams, while still showing some balance between inquiry-advocacy and other-self orientation.

4. THE MODEL

In order to build a suitable model that would match the time series observed at the Capture Lab, I found out first whether these time series had salient features that differentiated high,

medium, and low performance teams. This was indeed the case. High performance teams had time series that showed high amplitudes over the whole duration of the meeting in all three dimensions. Medium performance teams had time series that showed a smaller positivity to negativity ratio than high performance teams, and about the last fourth of the meeting, the time series in all dimensions tended to have patterns of decreasing amplitude. Low performance teams showed a dramatic decrease in amplitude for all three dimensions about the first fourth of the meeting and stayed locked in advocacy and self orientation for the rest of the meeting. For all teams, there was a consistent lead-lag relationship between other-self vs. inquiry-advocacy, with self orientation preceding advocacy and other orientation preceding inquiry.

Thinking about the model that would generate time series that would match the general characteristics of the actual time series observed at the Capture Lab, it was clear that it had to include nonlinear terms representing the dynamical interaction among the observed behaviors. One such interaction is that between inquiry-advocacy and other-self. If I call the first X and the second Y, their interaction should be represented by the product XY, which is a nonlinear term. I also knew from my observations at the lab, that this interaction should be a factor in the rate of change driving emotional space (which I will call Z). In addition, I would need a scaling parameter for Z. Consequently, the rate of change of Z should be written as

$$\frac{dZ}{dt} = XY - aZ,$$

where a is a scaling parameter that would be held constant.

From my observations at the lab, I also knew that connectivity had a critical incidence on the level of inquiry-advocacy and, consequently, it should interact with X and the product of this interaction should be part of the rate of change of Y, according to the characteristics of the time series observed, where there was a lead-lag relationship between Y and X. I also needed to discount the interaction between X and Z (which would be represented by the nonlinear term XZ) and Y with itself, so that the rate of change of Y should be written as

$$\frac{dY}{dt} = cX - XZ - Y,$$

where c is the control parameter representing connectivity, as measured by the nexi index, and should be varied according to the nexi number for each team performance category.

Finally, and in accordance with the characteristics of the time series generated at the lab, the rate of change of X should be a function of Y, discounting the level of X; so that with the inclusion of a scaling parameter, the rate of change of X should be written as

$$\frac{dX}{dt} = b(Y - X),$$

where is b is a scaling parameter to be held constant.

I realized that, except for some differences in the arrangement of the terms and the letters chosen to designate the parameters, these were the same set of coupled nonlinear differential equations that Lorenz had chosen for his model and published in one of the most often cited papers in science [15]. Lorenz obtained his equations from an idealized mathematical model of thermally driven fluid convection. The conduction of heat through a fluid can be described by partial differential equations, which Lorenz used as a starting point for deriving a simpler model using Fourier series.

This was the third time in my research career that I ended up using a model originally applied in the area of thermally driven fluid convection. The two previous ones were when I first used Fourier series to decompose the pattern of employee turnover in manufacturing industries [16] and, secondly, when I used inverse Fourier transformation to study the lead-lag relationship between

consumer attitudes and motor vehicle expenditures [17]. It is well known that Fourier discovered the coefficients that bear his name while working in problems of heat conduction. Models in fluid dynamics seem to offer a befitting template for the complexity of human interaction. They certainly appear to be more generative than those based on the physics of solids, which have prevailed in the social sciences for so long.

An interesting observation that highlights the usefulness of fluid dynamics concepts to describe human interaction arises from the fact that Lorenz chose the Rayleigh number as a critical control parameter in his model. This number represents the ratio of buoyancy to viscosity in fluids. A salient characteristic of my observations of teams at the Capture Lab was that high performance teams operated in a buoyant atmosphere created by the expansive emotional space in which they interacted and that allowed them to easily connect with one another. Low performance teams could be characterized as being stuck in a viscous atmosphere highly resistant to flow, created by the restrictive emotional space in which they operated and which made very difficult for them to connect with one another; hence, their nexi were much lower than the nexi for high performance teams.

I was intrigued by the power of models in fluid dynamics to generalize to other fields of research where one deals with highly complex dynamical systems. I found out that Lorenz equations have been used in a variety of disciplines and that a whole book was written on them by Sparrow, a mathematician at Cambridge University [18]. Several other researchers have analyzed the Lorenz model in depth [19, 20, 21]. Thompson and Stewart [22] classify Lorenz equations as "archetypal equations". A film has been made of a computer simulation of the equations [23] and Lorenz himself has written a book where he refers to the generality of his findings, 30 years after he wrote his original article [24].

5. RUNNING THE MODEL AND RESULTS

I ran the model using a fourth-order Runge-Kutta algorithm as the method for numerical integration with a $\triangle T$ of .02, which is small enough to avoid integration errors due to a large $\triangle T$. I varied the control parameter c according to the nexi index for each performance level, and following Lorenz, I set a to 10 and b to 8/3, leaving them constant for all runs. The time series generated by this model matched all the general characteristics of the time series observed at the lab for each team performance level.

Satisfied with the match between model and data, I was ready to observe the trajectories in phase space projected onto the three planes XZ, YZ, and XY. I started by setting the control parameter, c, at 32 (the value for high performance teams). I wanted to observe the trajectory in phase space for XZ, that is, inquiry-advocacy vs. emotional space. The trajectory traced the famous Lorenz butterfly with the two wings showing a high degree of symmetry representing the expected balance between advocacy and inquiry for high performance teams (see Figure 1). Next I ran the projection over the YZ plane (other-self vs. emotional space) and I found the expected balance between other and self orientation (see Figure 2). Finally, I ran the projection over the XY plane (inquiry-advocacy vs. other-self). As expected, other and inquiry were linked in one quadrant of phase space while self and advocacy were linked in the diagonally opposite quadrant (see Figure 3).

Overall and in agreement with expectations, high performance teams had expansive emotional spaces, and, most importantly, all the trajectories in phase space showed chaotic dynamics, like Kauffman had observed in his networks. These chaotic dynamics indicate that the type of balance reached by high performance teams, in terms of inquiry-advocacy and other-self orientation, is the product of a sophisticated pattern of interaction, typical of nonlinear systems, where the unpredictability of the trajectories creates the topology necessary for the creativity and novelty observed in highly productive teams.

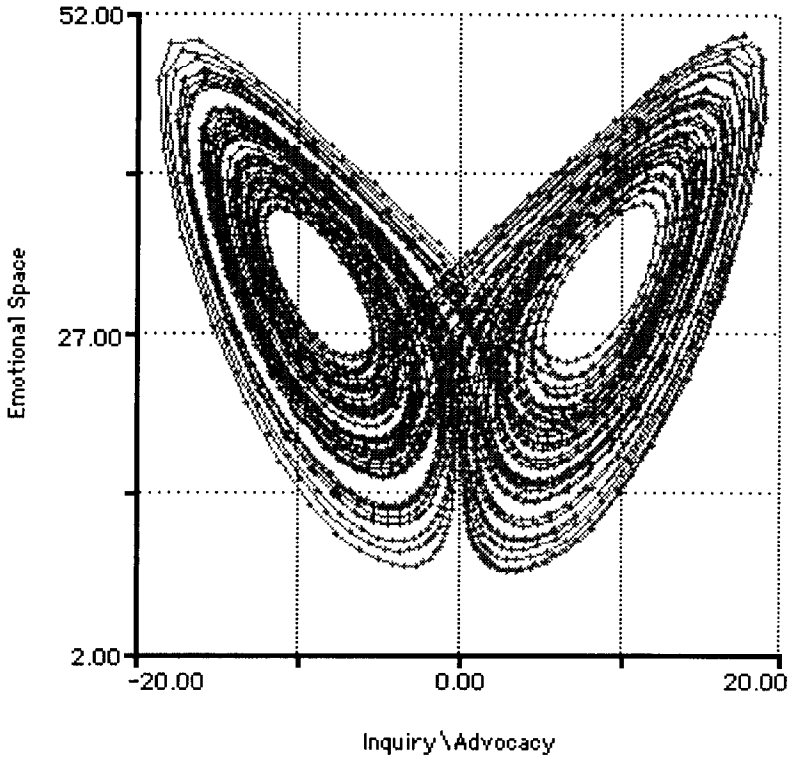


Figure 1. Phase space for high performance teams: inquire-advocacy vs. emotional space.

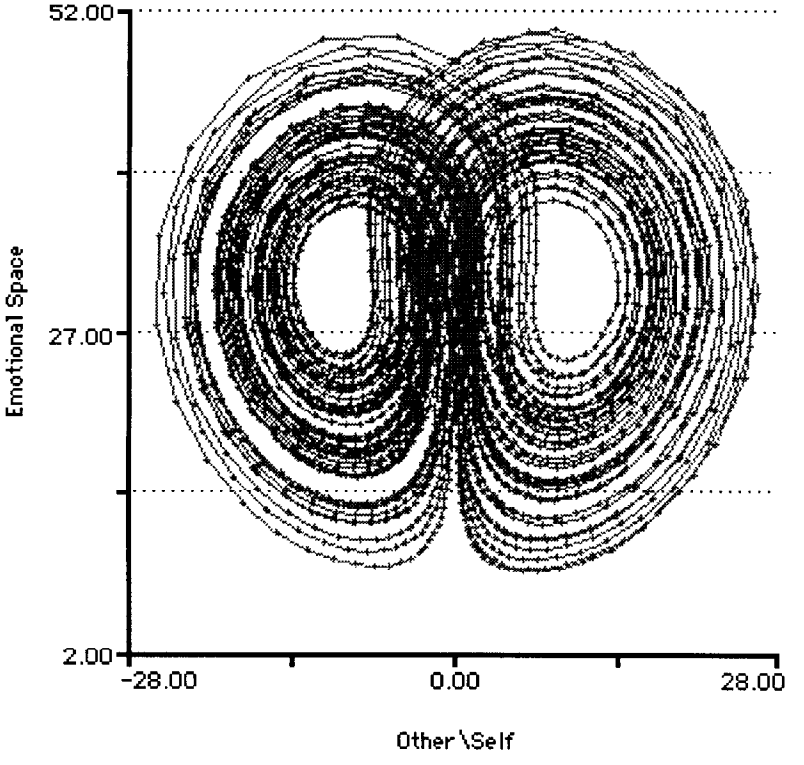


Figure 2. Phase space for high performance teams: other-self vs. emotional space.

Then I ran the low performance teams changing c to 18, the nexi index for these teams. All three projections started as a decreasing limit cycle that converged at the end into a point attractor,

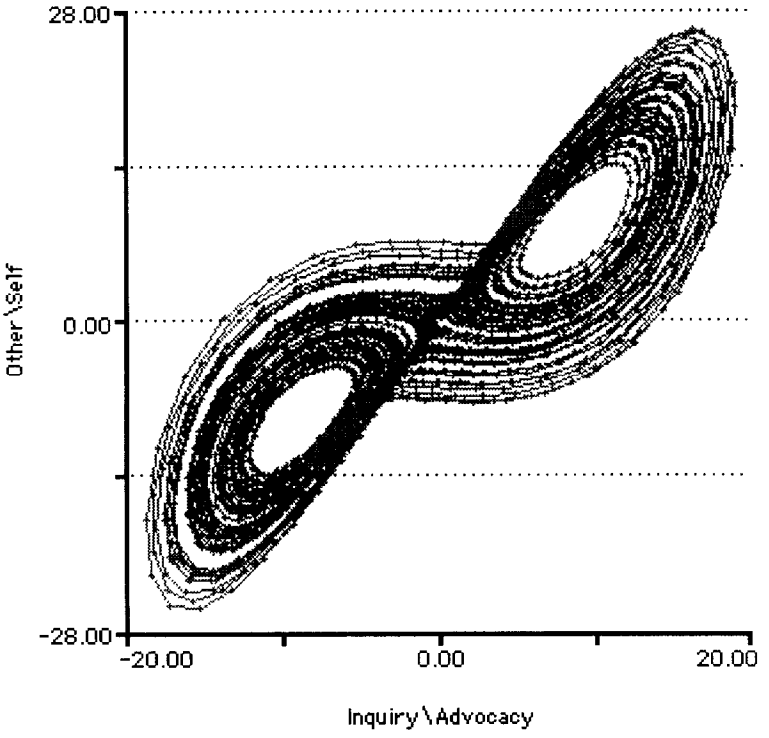


Figure 3. Phase space for high performance teams: inquire-advocacy vs. other-self.

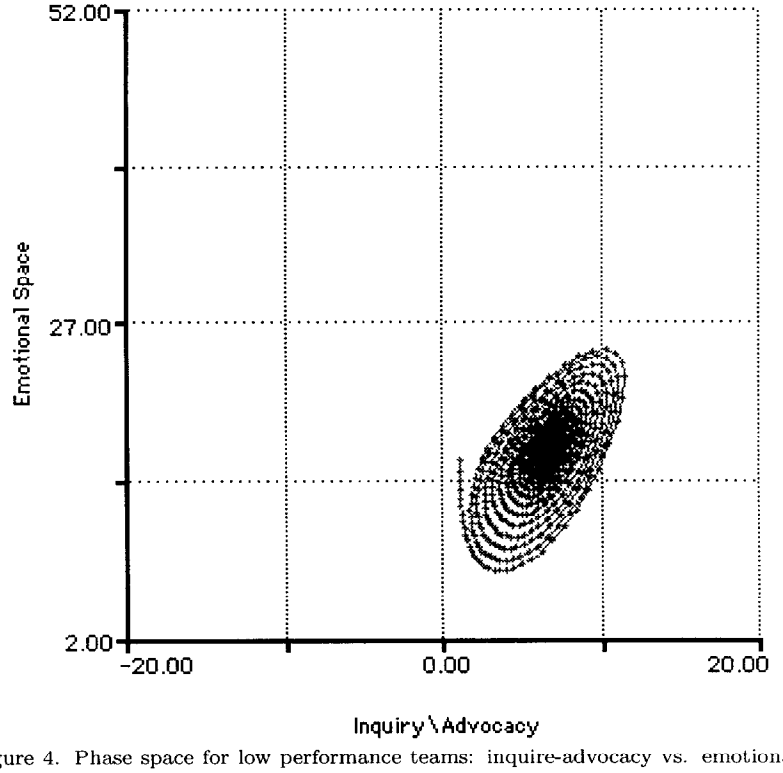


Figure 4. Phase space for low performance teams: inquire-advocacy vs. emotional space.

matching what Kauffman found in his networks. In addition, and as expected, low performance teams ended up locked in advocacy and self orientation, and had extremely restrictive emotional spaces (see Figures 4–6).

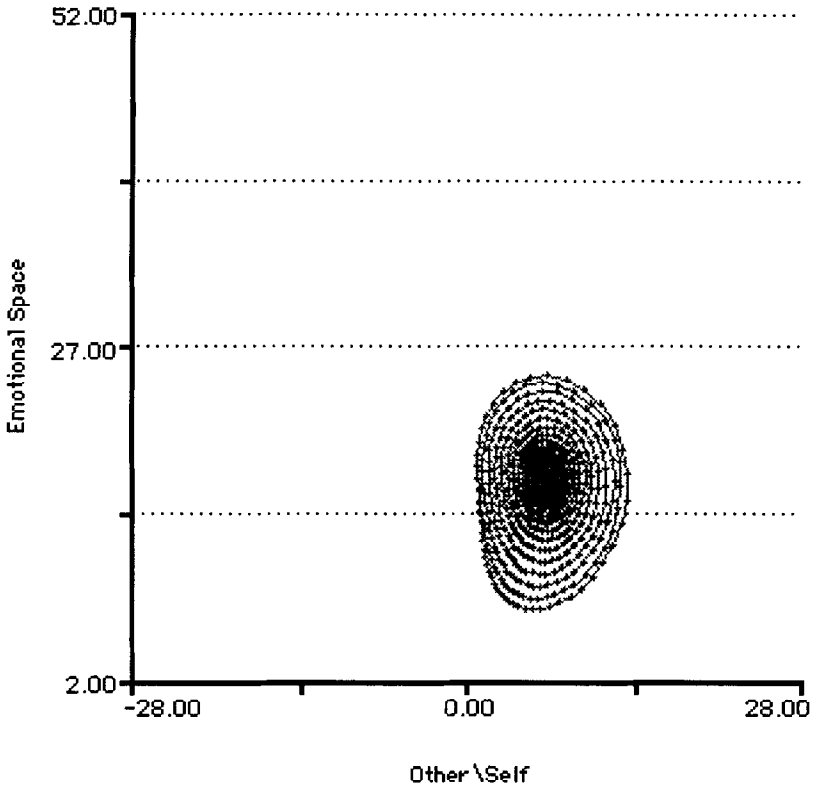


Figure 5. Phase space for low performance teams: other-self vs. emotional space.

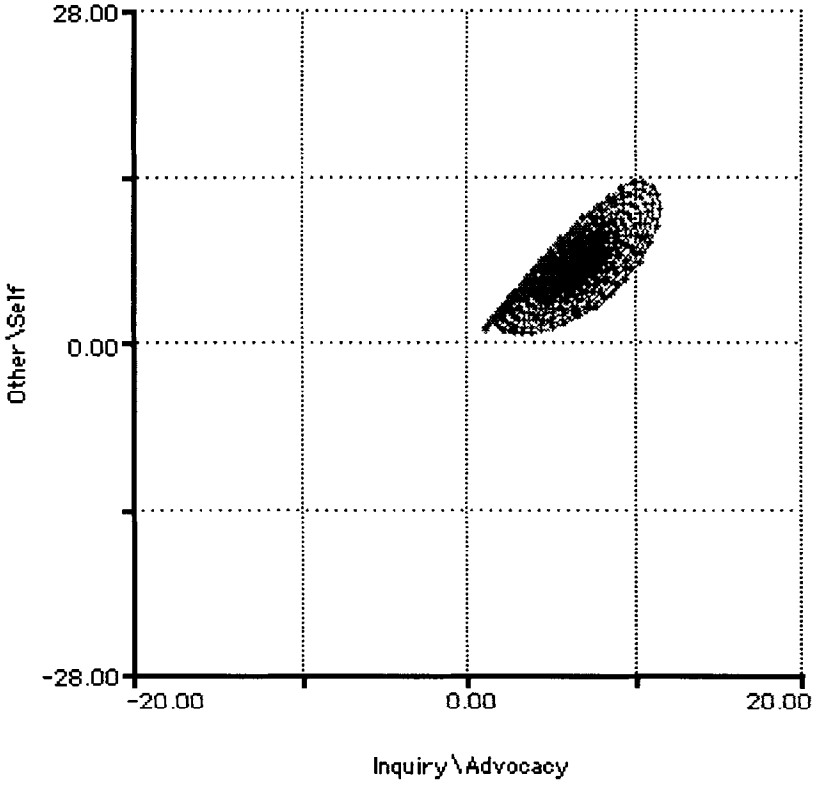


Figure 6. Phase space for low performance teams: inquiry-advocacy vs. other-self.

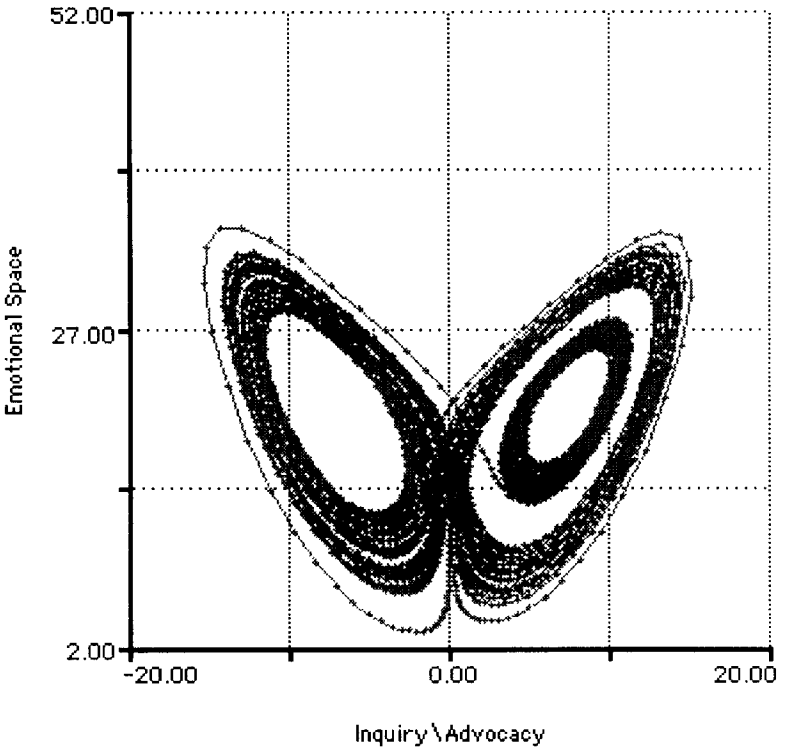


Figure 7. Phase space for medium performance teams: inquiry-advocacy vs. emotional space.

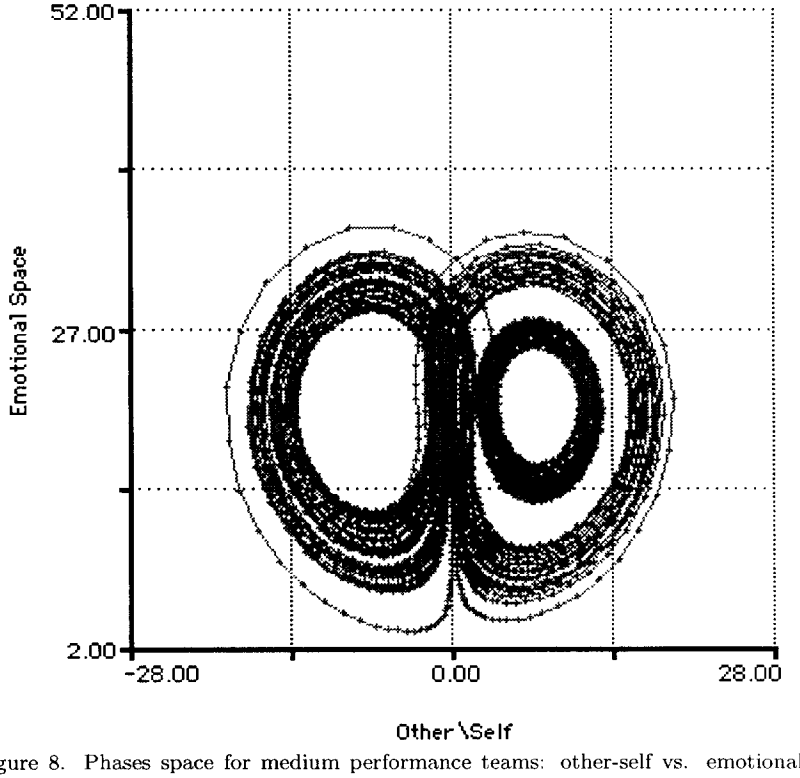


Figure 8. Phases space for medium performance teams: other-self vs. emotional space.

Finally, I set c to 22, the value for medium performance teams. All three projections started on a chaotic trajectory but in a more restrictive emotional space than high performance teams.

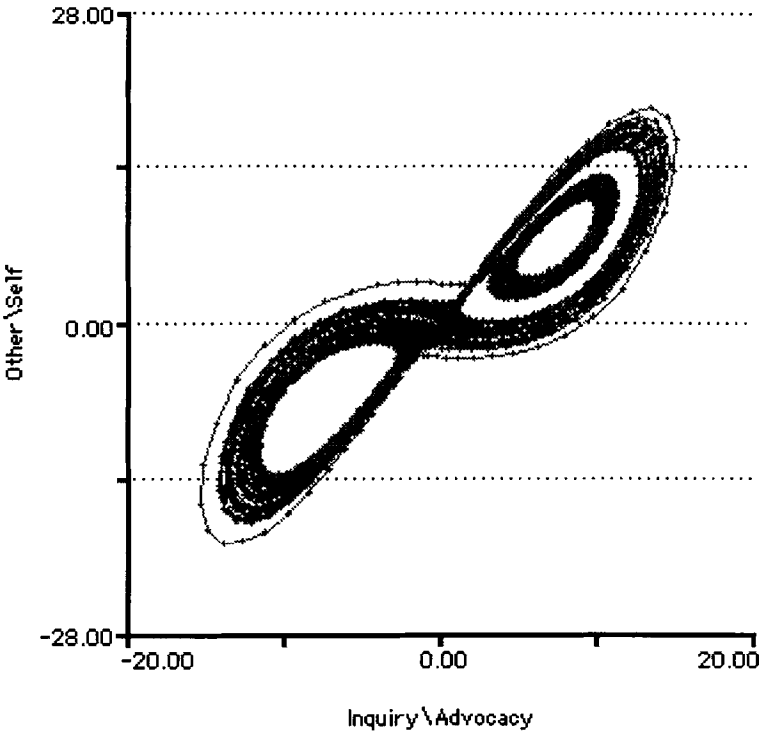


Figure 9. Phase space for medium performance teams: inquiry-advocacy vs. other-self.

At about three-fourths of the meeting, they ended up in a decreasing limit cycle situated in the advocacy and self regions of phase space, much like the low performance teams, but not converging to a point attractor. As expected, the medium performance teams ended right in between the high and low teams in terms of their dynamical trajectories in phase space (see Figures 7–9).

There was something else that intrigued me about Kauffman's findings. In his research, he finds that chaotic dynamics occurs when K (the number of links per element) is equal to or greater than four. When K drops to around two, however, the properties of Boolean networks have the dynamics of limit cycles and point attractors [3,25,26]. I wondered whether these findings would also apply to my work with business teams. In my research, the number of links per element (K) is equivalent to the number of nexi per participant in the team. Due to constraints in the capacity of the lab and the coding system, the teams coded at the Capture Lab were of size eight, so the K number for high performance teams is $32/8 = 4$, for medium performance teams is $22/8 = 2.75$, and for low performance teams is $18/8 = 2.25$. Consequently, according to Kauffman, one should expect chaotic dynamics for high performance teams, point attractors for low performance teams, and intermediate dynamic trajectories (transient chaotic dynamics ending in a limit cycle) for medium performance teams. This is precisely what I found in my research with business teams.

6. CONCLUSIONS

Why is chaotic dynamics associated with high performance? One answer to this question comes from the research cited earlier at the Santa Fe Institute linking chaotic dynamics to learning and adaptation which, in turn, would favor high performance. Neuroscientists at the University of California at Berkeley, have reached the conclusion that "chaos constitutes the basic form of collective neural activity for all perceptual processes and functions ... as a means to ensure continual access to previously learned sensory patterns, and as the means for learning new sensory patterns" [27, p. 161]. A few years later, Freeman concluded that "chaos underlies the ability to respond flexibly to the outside world and to generate novel activity patterns" [28, p. 78].

Chirikov, a physicist at the Institute of Nuclear Physics in Novosibirsk, refers to chaos and creativity in these terms:

> "The main idea I would like to convey is the inexhaustible diversity and richness of dynamical chaos ... it presents ... the surprising complexity of the structures and evolution characteristic of a broad range of processes in nature, including the highest levels of its organization. Moreover, dynamical chaos is ... a necessary part of creative activity" [29, p. 109].

Another piece to the puzzle is provided by the connection between emotion and learning. As we have seen, a distinctive characteristic of high performance teams is their capacity to generate expansive emotional spaces. In recent years, there has been an increasing interest in modeling emotions as explicit dynamical systems that lead to action and learning. In this research, emotions are conceptualized as driving cognition and action towards nonlinear dynamic attractors that configure the topology of the learning landscape [30].

There is an intriguing parallel between research in the area of health and my own findings which sheds light on the adaptive flexibility and innovative power of chaotic dynamics. In an article published in *Science*, Pool summarizes a series of research results by stating that "chaos may provide a healthy flexibility to the heart, brain, and other parts of the body. Conversely, many ailments may be associated with a loss of chaotic flexibility" [31, p. 604].

Goldberger has done a series of studies at the Harvard Medical School that cast new light in our understanding of health and disease [32]. This research shows that disease can be considered as "decomplexification", i.e., the onsetting of rigid order such as limit cycles or fixed-point attractors; while 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" [33, p. 30].

Goldberger refers to what he calls the "clinical paradox" in these terms:

> "Individuals with a wide range of different illnesses are often characterized by strikingly periodic and predictable (ordered) dynamics, even though the disease processes themselves are referred to as dis-orders ... Autistic children show highly repetitive behaviors; obsessive-compulsive individuals persevere monotously; Parkinsonian patients exhibit virtually indistinguishable tremors" [34, p. 543].

The analysis of electroencephalograms (EEGs) using the techniques of nonlinear dynamics, such as state space reconstruction by delay coordinates [35], reveals the presence of chaotic dynamics in normal brain activity, while in pathological states such as epilepsy the dynamics tends to a limit cycle. Nicolis, reflecting upon these EEG results, offers the following explanation:

> "This suggests the rather unexpected idea that a healthy physiological system needs a certain amount of internal variability whose loss, witnessed by the transition to a more 'ordered' state, signals the appearance of pathological behavior. It is important to realize that this healthy variability is not the result of random noise. Deterministic chaos combines here, in a subtle manner, order and reliability on the one side, and disorder and unpredictability on the other... chaos provides a system with the readiness needed to recognize a variety of external inputs and respond flexibly to a changing environment" [36, pp. 22-23].

Goldberger has shown that a healthy heart rate over time has a variability indicative of a chaotic pattern, while the heart rate variability a few days before cardiac arrest has a periodic structure,

and the heart rate variability a few hours before cardiac arrest has a phase space trajectory suggestive of a point attractor [37]. In a metaphorical sense, one can draw the conclusion that the limit cycle and point attractor dynamics characteristic of low performance business teams, with their concomitant low connectivity, self orientation, and unbalanced advocacy, are bad for an organization's "heart", and teams within organizations should do everything in their power to quickly move out of point attractors and limit cycles that stifle their performance before it is too late.

Gell-Mann, in a talk given at the Founding Workshops of the Santa Fe Institute stated: "Attractors might be connected with our human habit of getting stuck in a certain way of thinking and finding it extremely difficult to jump out of the rut into another way of thinking" [38, p. 4]. These attractors can trap individuals and organizations into rigid patterns of thinking that inevitably lead to limiting behaviors.

From a dynamical systems perspective, I will define "meta learning" 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. This view is supported by some of the current literature on learning where learning is conceptualized as "a process by which the system moves to another attractor by experiencing a... state that resembles a chaotic attractor" [39, p. 29].

The findings of this paper have had practical implications for my consulting work, where I have developed a strategy for organizational interventions that is coherent with a view of team learning as dissolving limiting attractors and evolving attractors that lead to effective action. I start by identifying which are the specific attractors that trap teams into low performance patterns and impede their learning, and then I design interventions aimed at dissolving these attractors, while at the same time evolving new ones that open possibilities for increased performance.

How can one help teams within organizations find the way out of limit cycles and point attractors? The complex dynamics of high performance teams indicate that the way out of these limiting attractors consists in developing teams that:

(a) are able to engage in patterns of interaction that reach a high degree of connectivity;
(b) are capable of striking a dynamic balance between inquiry and advocacy without getting stuck in either of them;
(c) can maintain a dynamic balance between other and self orientation, and consequently, be capable of honestly acknowledging their internal strengths and weaknesses, so that they can match opportunities in the external business environment;
(d) are capable of creating emotional spaces that are expansive and open possibilities for effective action, while avoiding getting stuck in restrictive emotional spaces that close possibilities for effective action.

It is important to realize where teams get stuck. Is it in endless advocacy? Is it in self absorption? Is it in an excess of negativity and destructive criticism that imprisons them in restrictive emotional spaces that close possibilities for effective action? Is it in their inability to create highly interconnected patterns of interaction? The more affirmative answers to these questions, the more difficult it is to find the way out of limit cycles and point attractors. In a thought provoking article, Peat has this to say about the incapacitating effect of limit cycles:

> "No matter where you enter the limit cycle you end up being locked into the same repetitive cycle. Hence, the more you are trapped in a repetitive response the more your personal story becomes impoverished and meaningless. Indeed, to an individual within such a state of mind, there may well appear to be no way of escaping from this predicament" [40, p. 369].

There is an urgent need for teams imprisoned in these confining attractors to find their way out, not only because they are internally dysfunctional for organizations, but also because the limited dynamics in which these teams are trapped offer too narrow a space of possibilities to deal with an increasingly demanding and chaotically complex world.

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