Appendix

Quantum Relations Theory: A Brief Overview

By Hardy F. Schloer and Philip Gagner

How will we analyze data two hundred years from now? This question is not idle—it is of vital interest to those of us who are currently using computers to represent, manipulate, or acquire information as effectively as possible. To the extent that we can envision future technology, we can recognize our present technological limitations and take the right steps to overcome them.

Clearly, present computational methods of modeling reality are very limited. Much social science research, for example, relies on primitive, correlational, statistical methods. Merely calculating the Pearson correlation between two variables might test an important hypothesis, but does not say a whole lot about the reality that underlies it. A more complex study might examine a network of linear associations via a linear structural relations (LISREL) model, but even this model relies on simplistic assumptions: there is no reason to expect linear relationships between variables in the real world. A variable X does not necessarily have the same effect on variable Y at all levels of X. Nor is it reasonable to believe that X has the same effect on Y at all levels of a third variable Z. Such statistical methods are used not so much because of their intrinsic plausibility as because of paucity of alternatives. The rudimentary nature of the available analytic models in general considerably impairs the quality of social science that one can generate with their aid.

Although we cannot say for certain what the computing methods of the future will look like, we can at least make some educated guesses, as follows:

1. Computers will be much faster.
2. Computers will have vastly greater memories and stores of data.
3. Computer architectures will be different.
4. The current methodological sectarianism that compartmentalizes data analysis and data analysts into separate fields and approaches, such as "statistical," "artificial intelligence," or "neural network" ones, will

Notes for this section begin on page 195.

be replaced by modeling methods that will integrate many different approaches.

5. Data analysis models will be "hierarchical," that is, they will be able to consider a problem at multiple levels simultaneously. It is reasonable to expect this type of development, because the world itself appears to have a "hierarchical" or multilevel structure, and, therefore, an adequate modeling of the world must correspond to such a structure.

It is not too early to begin thinking about how to move in these directions. Indeed, we are motivated to do so both because of the limitations of existing methods and because to do otherwise would be self-defeating. At a very practical level, the only way to know what is technically feasible with current technology is to aim high and "push the envelope."

This appendix presents a broad and radically innovative approach to data analysis and modeling, particularly in the areas of social research and human psychology. We propose a general theory that can adequately describe and reasonably predict relationships and interactions among people, countries, and economic, social and cultural variables, as well as the basic emotional and intellectual dynamics of an individual mind. By its very nature, this theory is crossdisciplinary. We borrow ideas from many fields, including statistics, bioinformatics, the social sciences, psychology, neuroscience, artificial intelligence, physics, mathematics, and philosophy. However, we do not do so haphazardly. We aim for a unified theory of data modeling. While this enterprise is admittedly ambitious, we believe that it is appropriate and timely, for the reasons we have already stated. We do request a degree of patience from the reader—some ideas may seem complex at first. Some specific details might not "fall into place" until the entire appendix is read.

We have, for example, adapted some of our concepts from the New Physics, especially from the fields of relativity and quantum theory. These physical concepts apply to our theoretical model partly in a literal and partly in a metaphorical sense. No particular formulation of this model is indispensable for its further development and can easily be modified or readjusted. What we are proposing is a methodological vision, rather than a finalized method. Practical applications based on our model are currently in various stages of implementation. We will describe them in forthcoming papers, providing further details about the practical ramifications of our methodological vision.

We call our general theory *Quantum Relations* (QR). QR was first conceived by Hardy F. Schloer and later collaborated by Philip Gagner.[1] In this appendix we shall present the basic assumptions and features of this theory. We first introduce specific components of the model, such as frames of reference, QR objects, QR structure, and so on. We then discuss how the QR approach can be used as a tool for data analysis and knowledge representation/

acquisition in real-world applications. We also provide examples of the QR approach to real-world problems. Next we briefly consider the computational requirements for applying the method. Finally, we speculate on potential practical applications of QR theory in various domains of human activity.

1. QR Frames of Reference (FORs)

QR borrows the concept of *frames of reference* from the New Physics. In Newtonian physics, all movement occurs in absolute space. Once an origin is chosen (e.g., in Cartesian two-space, the point [0,0]), all distances can be measured from that point, and all motion occurs against the fixed background of that immutable space. Descartes, following Newton, believed that there was only one true, absolute, and fixed viewpoint ("the viewpoint of God"), and it is against this background that everything else moves, and all measurement occurs.

> *But, even in Newtonian physics this is not absolutely true. If I am driving my car next to the railroad tracks while a train is moving in the same direction at the same speed, then the train appears to me to be motionless. That is, in my frame of reference the train is not moving at all. However, most philosophers and scientists of the earlier paradigm were convinced that there was one metaphysical reality, an ultimate stillness, against which both my car and the train would be seen to be truly moving.*

A consequence of the Newtonian model is that objects have, for example, one "true" velocity. They also have a "true" weight, a "true" size, a "true" color, and so forth. Newton himself was aware that there was no physical evidence that this idea was correct. He adopted it by a method of reasoning which he called the "first rule of reasoning," or the principle of parsimony, and which we now call Ockham's razor. That rule states that given a number of possible explanations, one should select, in the absence of any other evidence, the simplest among them. To Newton, the simplest explanation of motion was that there was an absolute space in which things moved.

Modern science now believes Newton was wrong. The Newtonian model is not simple, because it cannot account for a significant number of behaviors of matter and energy that were, of course, unknown to science in Newton's time. A genuinely simpler explanation of the universe, one adopted by Einstein, is that there is no absolute space. Every movement occurs only with respect to some other objects, and the objects themselves generate the space in which they move. Einstein simplified Newton's equations of motion by eliminating any references to absolute position, absolute velocities, and indeed absolute space itself. To achieve this, Einstein discovered that he had to make another simplification—to eliminate absolute time as well. The only way to remove all references to a background space, and still to permit motion, is to make time, as well as space, relative to some observer. This breakthrough in physics is called the Special Theory of Relativity.

Einstein completely reinvented and made mathematically precise the concept of frame of reference with regard to motion of objects. He used the concept of transformations of a frame of reference. No longer were reference frames some fixed sets of axis coordinates (Cartesian axes). Rather, they became something flexible, something that changed over time. The frame of reference became a set of rules by which the objects within it interacted, and the rules themselves could change. They changed, however, in very precise and well-defined ways. In the Special Theory of Relativity, the rules change depending on the relative velocities of the objects within the frame of reference.

Indeed, for Einstein, every object and every observer has its, his, or her own frame of reference. Time proceeds at different rates for different observers. So, two observers who measure the same objects and then compare their measurements might find out that they have measured different lengths. It is not the case that one observer or the other is right or wrong. Rather, both will have measured the lengths in different frames of reference (moving with respect to each other, for example), and each is perfectly correct within his frame. Einstein's great achievement in the Special Theory of Relativity was to present a method that would predict precisely when this would happen and precisely by how much the measurements would differ.

> *The two observers will measure different lengths if they move relative to each other. The difference will be roughly proportional to* $1/\sqrt{1-v^2/c^2}$*, where v is their relative velocity and c is the speed of light. For everyday velocities, such as the 3,000 mph speed of the space shuttles, the difference in the length of the shuttle to its passengers and to a NASA observer on earth, for example, is less than a thousandth of an inch.*

In QR, however, the important concept is not the mathematics of relativity. Rather, it is that objects carry their own frame of reference with them, and that their interactions (making a measurement, for example) are determined by the rules that govern their frames of reference (FORs).

The concept of frame of reference was quickly adopted in science, mathematics, and philosophy, and with it the notion that an important characteristic of interactions is the way in which their reference frames relate to each other. Indeed, in the 1950s mathematicians developed a set of tools that deals with objects on very abstract levels, portraying their interactions as a set of relationships. This set of tools has been adopted by modern physics and termed *category theory*. A major branch of modern physics involves the attempt to apply category theory to physical frames of reference.

In turn, QR theory is an application and extension of the principles of frames of reference or FORs to objects. QR provides a description of the elements, structures, and interactions between objects. Most importantly, however, in QR objects need not be physical. They can also be concepts, relationships, or sets of objects, concepts, or relationships. QR attempts to derive, for each such set, the rules that govern the interactions of the objects in the set, as well as the interactions of different sets.

2. QR and Observation

In relativity theory, the observer's role is, in a certain sense, unimportant. For an observer, objects and their motions are described in relation to the observer's frame of reference, but they could just as easily be described with respect to any other observer's reference frame. By contrast, in QR theory, the individual observer plays a more important role. This philosophical idea is again borrowed from modern physics. To explain it, we need to dip briefly into the world of quantum mechanics.

In the early twentieth century, Heisenberg (among others) observed that there is a fundamental problem with measurement. Every measurement requires an instrument to make it with, and using this instrument changes whatever is being observed. That is, a measurement always requires that the observer interact with the object measured, and the interaction changes both the observer and the object.

Many attempts were made to overcome this difficulty, including calculating the exact effect that an observation would have on the object and the observer (and then calculating the effect of calculating the effect, and so on). The idea was to quantify and subtract, or calculate exactly, the amount of disturbance and thus to recover the exact state of the object before it was measured. This approach failed, however, to produce "corrected" observations that could be explained by physical theories. Paul Dirac eventually resolved the difficulty by declaring that the observer is part of the system being measured, and that there are concrete, physical limits to the degree to which one can treat an observer (including oneself) as an object separate from what is being observed. Both are simply part of one system, so the best one can do is to describe the behavior of the entire system, including the observer. Whenever one tries to extract information exclusively about the object, one introduces uncertainties that render the measurement imprecise. This phenomenon has come to be known as the Heisenberg uncertainty principle.

The uncertainty principle is not a failure of measurement, or of the measuring instruments. It is a fundamental principle of the universe, or at least of modern quantum mechanical theories about the universe. The principle states that one simply cannot separate the observer from a system and still obtain precise measurements about the objects being observed. The act of separating the observer's frame of reference from the object's frame of reference introduces these uncertainties.

If we apply the uncertainty principle at all levels of reality, it should be obvious that with regard to any single object (or set of objects), there are as many "realities" as there are observers.[2] Because each observer carries his or her own frame of reference, the results of observations between observers may differ. In addition, each observer, when making observations, cannot be too sure of what he or she has observed.

These physical concepts are most fully developed in the specialized cases of particle physics (the interaction of subatomic particles) and of objects moving in relativistic frames of reference. However, it is widely assumed that they apply more broadly in science. It is our belief that there is demonstrable utility in applying them, for example, in the area of social sciences.

Therefore, QR goes beyond the field of physics. The theory asserts that physical concepts such as frames of reference and processes of measurement can be used in much wider fashion to gain insights into complex processes in general. The assumption that the universe, at a fundamental level, does not behave like Newtonian, mechanical clockwork can bring forth new insights into human cognitive processes, behavior, and personality.

QR theory also involves a system of computation. That is, the QR model can be used in designing computing processes that model complex systems. Again, the model is derived from modern physics, but this time it employs other, more sophisticated tools. In later sections of this paper, we shall describe the methods of computation and the specific computational tools derived from QR theory.

In QR models of human behavior, one fundamental action is that of observation. An observation can be a measurement of a physical quantity (such as temperature). It can also be the result of different kinds of experiments, such as object recognition, or even the formulation of a hypothesis. The process of object *recognition* is perhaps the simplest example. Assume that we have a machine, called X, which uses a camera to "recognize" a certain face in a crowd. X starts by returning a value of 0, and it continues to do so until it detects a face that matches its template. From that point on, X returns a value of 1. If no face has been recognized, then X continues to return a value of 0. But assume that X is not a perfect machine—sometimes X gives false-positives (returning a 1 when the face is not in the crowd), and sometimes X gives false-negatives (returning a 0 when the face is actually in the crowd). In a certain sense, one can say that X "observes" the crowd and returns a value with a degree of uncertainty.

Moreover, we are in turn observing the machine X. We are hoping, perhaps, that a certain person will appear at the airport, and we've placed X at the gate, checking faces. We check the output of X from time to time. Obviously we may be mistaken about our observation of the value returned by X, perhaps because we are too hopeful. Our observations are subjective. Our conclusions are the result of our subjective interpretations of our observations.

The model of which the above is an instance is quite general. It involves a measurement instrument that potentially measures with less than perfect accuracy and an observer of the measurement who (a) perceives the output of the measuring device with less than perfect accuracy and (b) is subject to misinterpretation (cognitive distortion) of the results, once perceived.

QR provides conceptual and computational models for such situations. In fact, QR predicts that because X may return an erroneous value and because we may misinterpret the output of X, we may head to the airport to pick up our passenger at the wrong time. It also makes the stronger claim that it can predict with reasonable accuracy how often we will make this kind of incorrect decision. Of course, other statistical models can do the same thing. What is unique about the QR framework, however, is its ability to take into account the observer's cognitive distortions, subjective prejudices, intentions, and desires. It does this by making a model of human motivation and decision making, and then using that model to interact with the known or predicted behavior of X, the sensory device. Our QR model uses some of the tools of physics to compute these interactions. Moreover, it uses some of these same tools to predict the processes going on within the brain of the observer. It thus provides a rough model that approximates the computing operations of the human brain.[3]

3. Interactors, Observers, and QR Objects

We shall call *interactors* objects that interact with each other. Observers are a special case of interactors. Objects can interact with other objects in many ways. On a physical level, two marbles can, for example, interact through gravitational attraction, or through an exchange of particles, or through electromagnetic and other physical forces.[4] These interactions are modeled through sets of physical laws, such as the laws of gravitation or of electrodynamics.

Large collections of physical objects can be modeled with the laws of thermodynamics that describe the behavior of hundreds, thousands, or billions of individual interactions through statistical methods. In thermodynamics, or in statistical quantum mechanics, one disregards individual interactors and takes into account only the gross properties of their interactions. One trusts that any uncertainty about individual interactions will be negligible in comparison to the prediction derived from the knowledge of the physical laws that govern their collective behavior.

When it comes to human behavior, including the behavior of entire societies, we may no longer deal with physical objects and physical laws, but we are still dealing with interactors at multiple levels. One level of interactors may include social entities (people, organizations, countries, and so on). Another level (such as the psychology of an individual person or organization) may include concepts, emotions, memories, habits, preferences, and other mental objects. When dealing with human behavior, QR is concerned with understanding the dynamics that govern the interaction of these social or psychological entities or objects. It employs a set of tools for studying and predicting the complex relations of such conceptual, behavioral, and personality entities or objects.

Most importantly, we should recall that QR objects could indifferently be physical, natural, artificial, mental, ideal, and so on. A memory or a recording of past events by the brain is an example of a QR object. However, a memory is not a static object.[5] Memory changes over time. It may fade, becoming less accessible to the conscious mind, or it may intensify, becoming more vivid. It may be modified by later experience or change into another memory altogether. Memories interact with other memories, emotions, habits, beliefs, and observations. QR postulates that these changes can be modeled in a well-defined way, using the tools of QR.

Furthermore, the observation of memory is different from a memory itself. The observation of a memory is the recalling of the memory to the conscious mind. More precisely, it is the way that memory fits into the scheme of interactors associated with conscious self-awareness and behavior. The observation of memory may also change over time, even if the memory itself does not change, because of other factors in the scheme. We call this phenomenon the interpretation of memory objects. The interpretation of memory objects constitutes a significant part of one's individual reality. Therefore, interpretation represents objects of individual reality.

4. QR Superstructures and Data Fusion Objects (DFOs)

QR as applied to human behavior posits the existence of certain structures. It does not assert that these structures necessarily have physical existence—merely that they are constructs that permit predictions of behavior.

A basic QR concept is that of "superstructure." This simply means that zero, one, or more QR objects can be embedded into a higher-level QR object. In turn, the behavior of the higher-level QR object is determined by its own relational rules, plus the behaviors of the QR objects embedded within it.

A QR superstructure can be viewed as a "space" in which the lower-level objects are embedded. The space has rules that govern the interactions of the objects within it. In turn, the objects have properties that determine how they interact with other objects within the space and with the space itself. We call such objects *Data Fusion Objects*, or DFOs. We have chosen this name because the objects "fuse" two different characteristics: properties and methods.

> *This QR concept recalls object-oriented programming languages in design theory, where objects contain their own properties and methods. A property is some value*

that gets returned to the caller of the object, or is stored internally for later use. In turn, a method is some way of accessing or modifying the information within the object.

A simple example of a DFO with properties and methods is a house. A house has various properties, such as its paint color, the number of windows or floors, location, street address, inhabited or uninhabited, and so forth. A house may have methods as well, such as how to lock or unlock its doors, how to heat or cool it, or generally how to use it as a dwelling.

In QR, DFOs are generally interpreted through a frame of reference (FOR). The way this is done is to embed the DFO into a particular FOR, together with the model of the observer. In this case, the frame of reference is also the observer. In most realistic cases, the FOR "model" itself will be trivial (and it will usually be built into the FOR relational rules). Nevertheless, the fact that the DFO interacts with the observer cannot be disregarded.

More than one DFO may be inserted into a frame of reference. In fact, there may be millions of DFOs embedded within a particular FOR. In turn, the frame of reference itself has both properties and methods, and therefore can equally be regarded as a higher-level DFO. Furthermore, a DFO may be composed of lower-level DFOs (or may be decomposed into them when the need arises), or it may in turn be embedded within higher-level DFOs. In this way, one can build a modeling hierarchy of DFO structures to model any type of problems.

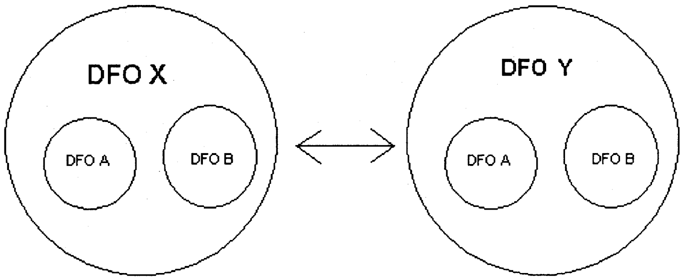
The concept of DFO is overarching, applying to objects, sets of objects, and frames of reference, as well as to various levels of aggregation among them. This flexible hierarchical structure is a fundamental strength of the QR approach. Applying a common concept across all levels and types of "entities" has two important advantages:

(1) It allows a common set of analytic and computational tools to be applied universally throughout the model. At a simple technical level, this means that, in the computer software used to apply the QR model to a particular problem, there are functions and subroutines that can be applied consistently across objects and frames of reference at various levels.

(2) It facilitates the development of analytic models that operate on several levels of aggregation (and logical category) simultaneously.

A ditty by Jonathan Swift:
Big fleas have little fleas upon their backs to bite them,
And littler fleas have littler still,
And so on ad infinitum.

A DFO may be an element in more than one FOR. Each frame of reference can be thought of as a "view" of that DFO. As noted above, each frame of reference is itself a DFO, so that one can have the following situation:



In this example, the DFO-A on the right and the DFO-A on the left are identical objects, embedded within two different reference-frame DFOs, labeled X and Y. However, X and Y interact with each other, presumably in some higher-level reference frame. X and Y can be thought of as two different "views" of A and B. Their type of interaction may represent, for example, the state of mind of a man who has two different views of the same car—one positive and one less so—and is, therefore, conflicted about buying it or not.

A particular set of "views," each of them being DFOs, may in turn be part of one or more higher-level DFOs. This hierarchical model, with the addition of some more detail, including the nature and restrictions of rules that may be applied between DFOs, is the fundamental concept of QR. One of the basic rules is that a DFO may communicate only through its higher-level DFO, which imposes an important formal constraint on DFO systems and prevents the DFO model from becoming impossibly complex.

5. What Makes Quantum Relations Quantum?

The term "quantum" as used in physics is derived from the Latin word *quantus*, meaning "how many?" It was first used to describe the behavior of systems in which only certain levels were permitted. In classical physics, a particle of light can have any amount of energy, but in quantum physics, only certain levels are permitted. In turn, these levels are highly constrained by the laws governing the atom that emitted the photon. The basic unit of which all other values must be a multiple is called a "quantum."

The term "quantized" means that a system can take on only certain values, and those are chosen according to particular rules. As an example, U.S. currency is quantized, and the quantum is the penny. In everyday life, nothing costs a fraction of a penny.

In QR, a DFO viewed through a frame of reference (and it can be viewed in no other way) can return only particular values according to particular rules. The rules that govern DFO interactions are highly constrained and obey definite patterns. In this sense, QR is a "quantized" version of everyday human reality. The fact that it is quantized means that one can model it on a computer and that one can also perform calculations with it.

In modern physics, a major concern is to create from a physical theory what is called an "algebra" over that theory. An algebra is a set of rules that govern the interaction of elements. For example, ordinary arithmetic has an algebra. The algebra of arithmetic is a set consisting of all the numbers[6] plus two operations, addition and multiplication, plus a few rules of interaction that explain how addition and multiplication work. Thus, the algebra of arithmetic is:

$$\{¥ , = , *\} \text{ with } ¥ = \{0, 1, 2, 3 \ldots\} \text{ onto } \mathfrak{R}$$

The symbol is simply all rational numbers, i.e., all the numbers one can get with arithmetic, like ½, or ¼, or 105, etc.; or all the numbers one can get by applying the stipulated arithmetic rules to the set of integers. Using the rules of multiplication, one can derive division, and using the rules of addition, one can derive subtraction.

Just as there is an algebra of arithmetic, there is an algebra of DFOs. One starts with defined objects and with operators one wishes to apply to the DFOs. One can then obtain an algebra over the DFOs. Whereas the algebra of arithmetic produces the "field" of rational numbers, the algebra of DFOs produces a different kind of field. We sometimes refer to that field as "RavenSpace." It obeys certain rules that are reminiscent of the fields of quantum physics.[7]

QR is therefore "quantum" because it attempts to quantize all types of objects, including concepts, perceptions, memories, behaviors, and so forth. Its objects are not numbers but processes, or functions, or "quantitative relations."

QR often places objects in a theoretical structure called a "space." If certain conditions are met, this space is a "metric space." A metric space is a space in which objects obey certain rules (for example, the concept of "distance" between objects is one such well-defined rule). One of the goals of QR is to represent many different kinds of objects—including ideas, emotions, behaviors, and the like—in metric spaces. In some cases, QR uses terms like "mass" or "energy" or "gravity" to model these systems. This does not mean, of course, that a system of, say, psychological or personality concepts has actual mass, energy, or gravitational fields. It means only that QR assumes that concepts within this kind of system behave and interact according to rules similar to the dynamics of physical objects. Because the rules of DFO interactions are part of the frame of reference of the DFO, such rules can be easily written, combined, and tested.

One simple operation is to compute the "center of gravity" of various DFO objects. For instance, consider the dynamics involving four hypothetical stock traders. We know, or at least speculate, that stock traders are largely motivated by "fear" and "greed," and that these factors influence their preference for a given stock. We also know that the relative influence of each factor and the degree to which a trader is either attracted or repelled by a given stock change over time. In the picture below, various DFO objects are modeled as a function of the "greed" and "fear" of four hypothetical stock traders at specific times when they committed to a buy or a sell trade, each being modeled by one DFO. Thus, let there be:

x = the degree to which a trader prefers the specific stock in the example on the basis of Fear

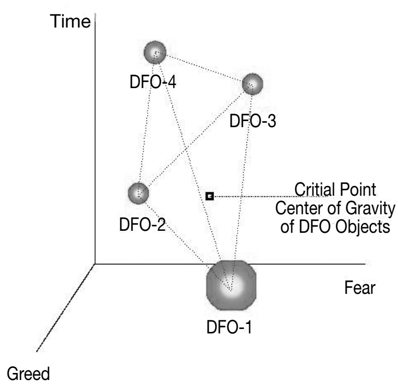
y = the degree to which a trader prefers the specific stock on the basis of Greed.

QR posits that for any stock, trader, and time, the trader evaluates his options based on a joint function of a greed motive and a fear motive. Generally, this means that:

$$P_i\,(t) = f_{i,t}[x(i,t),\, y(i,\, t)]$$

where:

Pi (t)	=	the preference for or against the stock for Trader i at time t
x(i,t)	=	the degree to which fear motivates Trader i to buy/sell the stock at time t
y(i,t)	=	the degree to which greed motivates Trader i to buy/sell the stock at time t
fi,t[ ]	=	a function that maps the combination of x(i,t) and y(i,t) into a total preference of Trader i to buy/sell the stock at Time t. For example, a simple form of the function might be a weighted composite, fi,t[x(i,t), y(i, t)] = wi,xx(i,t)+wi,yy(i,t), where wx and wy are the relative weights of fear and greed in determining Trader i's preferences.



DFO Model of Stock Trader Drives over Time

Our time axis in this example represents the trading day and is repetitive over time. That is, the time axis begins (t=0) at the opening and ends (t=4 p.m.) at the closing of the market every day, while the behavior is averaged over many days. In addition, the size of the DFO indicates its "mass," which might be the total trading dollars available to that trader on average. The position on the time axis indicates the time at which the particular trader is likely to buy or sell a particular stock. The trading behavior of one trader greatly influences the behaviors of the others, so that the actual model is dynamic, not static as shown here.

In this graph, there is a "critical point," which is the computed center of gravity of this particular situation. At this point we can expect certain behaviors in the market to start changing.

Another element is worth mentioning. The value of a trader along the axis "Fear" is actually shorthand for the trader's observed behavior over many days. For example, our trader may pass up opportunities that involve "objectively" perceived risk, even as other traders take advantage of them. Here the model postulates that the trader's behavior is driven by fear, but if one introduces any other factor, such as laziness or inability to marshal resources, the model will still work. If necessary, the property "fear" can be decomposed further, in order to create a more complex model. But that does not substantially affect the model's viewpoint, except that the paths of the DFOs will change over time.[8] The decomposition of "fear" that is applied to the stock trader scenario might be applied to other scenarios as well, and may give better results in those systems, or vice versa. Finally, the entire DFO model may be viewed through one or more frames of reference, and these may be combined to build a model of the market as a whole.

6. Time and QR Systems

QR systems evolve over time. That means that the functions governing the interaction of subobjects (i.e., some FOR rule) depend upon a parameter "t." For example, one can imagine a frame of reference or FOR containing two DFOs, called CLOCK1 and CLOCK2. These two DFOs and, indeed, the FOR itself have a method, called "tell-time." When the FOR invokes the tell-time method for itself, it gets answer 23. When it invokes it for CLOCK1, it still gets answer 23. But, when it invokes it for CLOCK2, it may get answer 27. In this example, CLOCK1 and CLOCK2 are experiencing time at a different rate.

QR has developed some basic (i.e., default) principles of time in QR systems, as stated below:

- Time is unique to systems and observers (i.e., the rate at which things happen is dependent on the frame of reference).
- Time is measured through increments of change within systems. That is, time is discreet, not continuous, although in some cases it can be modeled through differential equations, which assume continuity.
- Time advance can decline to *zero* in a system without ending the system's existence.
- A DFO concerned with time can always be asked what its (local) time is, but the answer may be different for different FORs.

Because all DFO time is local, two DFOs that interact through an FOR will never need to worry that their times do not match. They will perceive the passage of intervals according to their interaction with their FOR, and for each of the DFOs the time will always be "the present."

7. DFOs and Self-Organizing Structures

A self-organizing structure is a structure in which (a) the elements obey certain rules and (b) the rules modify the structure over time in such a way that certain features are emphasized. A simple example of a self-organizing structure is a two-dimensional array of numbers, with the organizing rule for each element being: "If I am equal to zero, and not already on the left margin, then switch me with the element on my immediate left."

1	0	1
1	9	0
0	1	0

t = 0

⇒

0	1	1
1	0	9
0	0	1

t = 1

0	1	1
0	1	9
0	0	1

t = 2

Zero values migrate to the left as t (time) increases

This rule moves all the zero values of the array to the left. This may be a useful rule if, for example, the array is very large and one wants to know how many zeroes there are in it. Many more useful examples can be found in the literature on self-organizing maps. (Kohonen 1997)

It is often useful in QR systems to make the FOR rules self-organizing with respect to their DFO elements. In this case, the passage of time will itself drive the DFO into organized behavior, and this can be used, in some cases, to find patterns within the DFO structure that were previously not recognized. In such cases, the FOR must have appropriate pattern recognition algorithms built into it, exactly as with any other self-organizing, map-based system. One difference is that in QR the pattern-recognition systems themselves can be DFO- based. This gives rise to a natural parallelism, because the sub-DFO objects can be shared by multiple FORs that can run on parallel computing hardware.

8. Adaptive Processing in the DFO Model

As described earlier, the manner in which DFOs communicate with each other within an FOR is determined by the rules built into the FOR. These rules need not be static. Indeed, a DFO can pass on to the FOR a suggested new rule for further processing.

A FOR can, moreover, create new DFO objects within itself. It can create, for example, copies of any of its member DFOs, and it can also modify the new copies in any way permitted by the DFO rule sets. One of the methods of a DFO can be a request for a new "strategy" to be used by the FOR in which the DFO is embedded. The FOR can request from its own higher-level FOR that a copy of itself be made, with the new strategy replacing one of its own rules. The requesting FOR can then be either preserved or destroyed. Since the newly created FOR is an exact copy of the requesting FOR, except for the requested changes, the general rule is to destroy the old FOR.

This QR feature gives rise to a flexible and adaptive processing model in which DFOs can interact, as well as be created or destroyed. Their interaction may in turn produce new DFOs. Here the QR model is similar again to subatomic physics, where particles can also interact and produce other particles, or be annihilated.

A DFO can request its own annihilation by its FOR. It would do this when its processing tasks are complete (or determined to be futile). For example, a DFO that is used for object recognition would request its own annihilation when it has passed its best guess up to its FOR, and there is no further need for it.

On a conceptual level, a DFO may be seen as attempting to resolve a particular query, such as whether a given set of inputs matches some template for object recognition. Competing DFOs within the same FOR may be attempting the same task, and the FOR may determine that it is satisfied, simply extinguishing the sub-DFOs. DFO results may be passed on as probabilities, and when a probability passed upward during an ongoing computation reaches a given threshold (such as 90%), the FOR may be sufficiently satisfied to stop the other sub-DFO objects, releasing resources for other computations.

9. DFOs and Locality

DFOs are, from their own perspective, local. That is, they are self-contained objects that communicate with a higher-level process only through very structured mechanisms. However, the ability to have the same DFO in more than one FOR makes the model globally nonlocal. Information may be passed through a DFO in both directions, so that two different FOR objects can potentially communicate.

It is entirely possible for a DFO to be operating on one piece of computing hardware (including the "wetware" of some portion of the brain) and to be passing messages to its FOR, which is operating on an entirely different piece of computing hardware. The DFO model accommodates parallel computing technologies.

For DFO structures that have been metricized, as described above, the objects are distributed in some space. These spaces represent, in fact, a sophisticated model of conventional space-time, in which case the DFOs represent objects in space-time. As such, they are subject to and obey well-defined rules, which preserve both the metric nature of the space and the desired space properties, based on a particular DFO space.[9]

The general principles that follow from the previous discussion include:

- QR systems are conceptual objects constructed by making models of observation.
- QR objects and systems are structured and may, in appropriate cases, be viewed as distributed in some space-time.
- Although DFOs are local from their own viewpoint, QR systems are nonlocal in time or in their position in space-time. Nevertheless, they are subject to stringent transformational rules imposed by their frame of reference.
- QR systems can be distributed and can take advantage of parallelism.
- QR objects (DFOs) are building blocks or models of reality.

10. Cognitive and Practical Consequences

We have described the first steps toward building a model of human cognition, personality, and social behavior, based on DFO structures. It is important to realize that such a model is currently in its developing stage—we have merely described some of its conditions of possibility. When fully developed, the QR model would be useful, for example, in analyzing the most complex aspects of human behavior and in bringing sociological predictions to an acceptable level of accuracy.

Applications may include QR systems concerned with early detection and possible prevention of ecological disasters, global health hazards and epidemics, wars and political terrorism, stock market crashes, or severe socioeconomic crises and conflicts. They may also include diagnosing irresponsible and dangerous human behavior, such as unsound or irresponsible governing on all levels. Finally, QR may become an effective tool in elaborating and testing new scientific hypotheses and new technologies in a wide variety of fields, as well as in creating new global research and learning systems. Some of these applications are already in various stages of development and will be presented in future papers.

Notes

1. We would also like to thank Mihai I. Spariosu, who has been working with us both on the philosophical context of QR and on some of its practical applications in global learning and research.
2. More precisely, there are as many "realities" as there are observers whose frames of reference have different transformational rules. The differences in observation by each observer will differ by the amount determined by the different transformational rules. In relativistic motion, for example, there are as many different 'realities' regarding the length of an object as there are observers whose motion relative to that object differs. Of course, these different realities are all related to each other by the equation given above.
3. This is not a claim that the human brain is (only) a computing device. It is merely the recognition that the human brain is a device capable of some sophisticated computations.
4. The game of marbles is a set of electromagnetic interactions since only the electrons in the shells of the atom actually interact. The electrons in one marble repel those of the other, causing one marble to fly off when another one hits it.
5. Neither is a subatomic particle, actually. Subatomic particles viewed within very short time spans may change form, turn into one another, and so forth, in accordance with laws governing their interactions, including self-interaction.
6. For the mathematically inclined, it is more precise to say the set of integer numbers.
7. Again for the mathematically inclined, functional operators (functors) are developed, and the "field" is actually a field of operations over the functors.
8. From a viewpoint inside the DFO, we have added dimensions.
9. Again for the mathematically inclined, the functions that a DFO can execute may be viewed as operators on the space-time within it. A cover can be defined which is the set of such functions, and it is often useful to speak of the properties of that cover. Indeed, the behavior of the DFO itself may be, in appropriate cases, determined by the function space that can be so derived.