



The Unified Theory for Prediction in Complex Systems

A Framework for Thinking, Analysis
and Increasing Relative Certainty

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2026

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Author's Preface

Since time immemorial man has sought to glimpse beyond the horizon of time. He studied the sky to understand the weather, the sea to predict storms, the land to estimate the harvest, the movement of people to understand a society, and the markets to detect change even before it was fully formed.

Is the future a completely random space, or is it influenced by structures, connections and laws that we do not yet fully understand?

Complex systems sometimes seem unpredictable because they include a large number of components working at the same time. Each change may affect another change, and each result may become a new factor within the system. Data, expectations, behavior, cycles, environmental conditions and human decisions intertwine and create a reality that cannot be explained by a single variable.

But complexity is not necessarily the absence of legality. Sometimes it indicates that the legality has not yet been identified, that the data is still incomplete, that the relationships between the variables have not yet been deciphered, or that the system is being examined at a level of observation that is not suitable for it.

This book offers a framework for studying complex systems and predicting their behavior. It does not guarantee absolute certainty, nor does it assume that every phenomenon is fully predictable. Its goal is ambitious but measured: to systematically increase predictability, expand relative certainty and reduce decisions based solely on guesswork.

The framework grew out of the meeting between engineering thinking, systematic investigation of failures and processes, and dealing with systems in which a result sometimes becomes clear only after it has occurred. She seeks to reverse the direction of the investigation: instead of describing reality in retrospect, try to identify the structures emerging within it in real time.

The theory presented here is based on the concept that data is not just numbers. They are a language. Every figure is a sign; Every relationship between data carries meaning; And every complex system tells a story through the changing relationships between its components.

To read this story, gathering information is not enough. The data must be sorted into families, examine their characteristics, perform transformations, identify cycles, understand groups and interrelationships, and examine how different insights intertwine. From this process, thinking modules adapted to the

researched field are built, and on top of them a super model works that examines the agreements, gaps and changes between the insights.

This is not just a method of prediction. This is a way of thinking about uncertainty. Instead of seeing randomness as the end of a verse, the theory proposes to see it as a starting point for investigation: a sign that there may be missing data, connections that have not yet been identified, cycles that have not yet been deciphered, or a system level that has not yet been examined.

The journey begins here.

Opening: The Wind Around an Aircraft Wing

When an airplane moves through the air, the flow around its wings does not always look orderly. Sometimes vortices, pressure changes, splits in the flow and fast movements that are difficult to follow are created around the wing. At first glance, the phenomenon may seem random: as if every vortex is formed without regularity, and every change is unpredictable.

But the flow does not occur in a vacuum. It is affected by the shape of the wing, the angle of attack, the speed of the aircraft, the air density, the temperature, the pressure, the environmental conditions and vortices created earlier. Each component affects other components, and each change may change the conditions under which the other changes occur.

The system is very complex, but not necessarily without legality. The difficulty in predicting the flow does not necessarily stem from the lack of physical laws, but from the fact that we do not always have all the initial conditions, all the environmental data and the full calculation capacity needed to describe the system with full accuracy.

This example does not prove that there is no randomness in nature. It emphasizes a more important principle: some of what appears to be random may be the result of partial understanding, partial measurement, or an incomplete computational model.

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The same principle may also exist in other systems. In the capital market, a single price movement may seem random, but it can be related to reality data, expectations, participant behavior, groups, cycles, resource flows, and broader interrelationships. In sports, one outcome may seem unpredictable, but it can be related to load, fitness, decisions, playing style, team structure and environmental conditions.

In systems where humans are involved, interests, incentives, fears, partial information, policies, mutual reactions and behavioral changes are also added. These do not eliminate the possibility of prediction. They require a wider observation, a more precise handling of the data and a deeper understanding of the relationships between the components.

Hence the guideline of the book: randomness is not the end of prediction. It is a sign that the system is not yet fully understood. When a phenomenon appears to be random, one must ask what

we still do not know, what data is missing, what interrelationships have not yet been examined, whether the right level of observation has been chosen, and whether there is a structure hidden beneath the noise that we have not yet been able to read.

The unified theory for prediction in complex systems seeks to build an orderly way to deal with these questions. It starts with the raw data, but does not stop there. It examines it through the data family to which it belongs, through possible transformations, through the relationships between it and other series, through groups, cycles, changes in the structure of the system and interweaving between thought modules.

The purpose of the process is not to create false certainty. Its purpose is to gradually increase the ability to predict, expand the relative certainty and reduce the scope of decisions based on guesswork only.

CHAPTER 1

Principles of Prediction in Complex Systems

Complexity, Perceived Randomness and the Readability of the System

A Complex System Is Not a Collection of Parts

A complex system is not just a large system. It is a system in which many components work simultaneously, influence each other and respond to changes that occur within it. Sometimes a small change in one component creates a cumulative effect on an entire group; Sometimes the same effect repeats and changes the component from which it started. Therefore, it is not enough to examine each component separately. The interrelationships and the structure that connects them must be understood.

Complexity intensifies when the system involves time, memory, repeated responses, expectations, capacity limitations, or human participants. In such systems, yesterday's figure is not just a description of the past. It may influence today's decisions and the conditions under which tomorrow's outcome will be obtained.

Therefore prediction in a complex system is not a search for a single number that will provide an answer. It is an attempt to understand the fabric in which numbers, decisions, relationships and environmental conditions take on meaning.

Perceived Randomness Versus Uncertainty

When we find it difficult to explain a phenomenon, the natural tendency is to call it random. However, a distinction must be made between actual randomness, if it exists, and perceived randomness: a situation where the result appears to be illegitimate because the information is incomplete, because the relationships are not visible, or because the model we are using is too narrow.

The theory does not seek to decide the philosophical or physical question of whether each phenomenon can be fully deciphered. She offers a working assumption: in many systems, some of the apparent randomness stems from measurement limits, excess noise, lack of data, regime change, or a misunderstanding of the correct system level. Therefore randomness is not a term to end the discussion; It is a sign of the direction in which the investigation should be deepened.

The goal is not to eliminate uncertainty. The goal is to separate what we don't know yet from what we can't know, and to improve the first part as much as possible.

Convergence and Difficulty

Predictability increases when relatively independent families of data tell a similar story. When reality data, expectations and behavior point to the same structure, convergence occurs. Convergence is not absolute proof; It is a situation where several different testimonies reinforce each other and reduce the space of competing explanations.

On the other hand, when the data diverges, when groups work in contradictory directions, or when the same letter takes on a different meaning according to the context, the level of difficulty increases. Difficulty is not necessarily a failure of the system. It is information in itself: it indicates that an expansion of the research field, an examination of another group, an examination of cycles or a change in the structure of assumptions is required.

A simple rule follows from this: the smaller the convergence, the greater the probability of being in a more complex prediction space; As the convergence increases, the ability to read the system more stably increases.

Capacity and Generativity

Capacity is the ability of a system to accommodate a load, change or disturbance without losing its operational structure. A system close to its limits may be more sensitive to small changes. A system with a wider operating range may respond in a more measured manner. Capacity is therefore not just an operational figure; is a condition that affects the stability of a process.

Fertility is a complementary concept. It describes the degree of ability of a certain situation to produce possible scenarios, ramifications and changes. The higher the fertility, the more possibilities the system may develop. Fertility is not just a side measure; It is a layer of interpretation that changes the weight we give to other signals. In a particularly fertile space, a wider convergence is required before a single letter is given high meaning.

Capacity and fertility are intertwined. A system with reduced capacity and high productivity may enter a space where difficulty increases rapidly. A system with wide capacity and low fertility may be more readable, although this is no guarantee as to the direction of the result.

White Swan and Black Swan

In this theory, a white swan and a black swan do not necessarily describe a good or bad event, an increase or decrease. They describe the quality of the prediction space. A white swan is a situation where the level of perceived randomness is lower, the connections between the data are relatively clear and the system is more stable to read. A black swan is a situation in which the perceived randomness is high, the level of difficulty increases and the ability to predict weakens without appropriate tools, algorithms and systemic understanding.

The Black Swan is not necessarily a single event. It can be a region in the prediction space where previous assumptions are not sufficient. Even then there is no need to abandon the prediction. Clarity may not be found in the unit under consideration but in a wider group, network, cycle or regime.

From here the theory moves to the next stage: if the system speaks through data, one must learn how to read their language.

CHAPTER 2

The Language of Data

From Raw Data to Systemic Meaning

Data Are Not Numbers Alone

A single figure is a sign. It may be accurate, but it still doesn't tell the story. Its meaning is created from the place where it appears, from its relationship with other series, from the sequence of time and from the question we wish to ask.

You can think of data as a language. A data field is a letter. Several fields that connect to each other form a word. Continuous relationships between groups of data form a sentence. And only when the sentences are read in a broad context, it is possible to understand the story that the system tells.

The most common mistake is to interpret data out of context. An increase can express strengthening, but also an overreaction. A decrease can express weakening, but also a temporary adjustment. The figure itself is not enough; It is the context that gives it meaning.

The Three Families of Data

To avoid mixing up different types of information, the theory divides the data into three basic families. The first family is the reality family: the data describing the actual state of the system. These can be performance, resources, loads, outputs, results, failures, revenues, inventory or any other measure that reflects the floor of truth of the investigated field.

The second family is the family of expectations. It describes what participants, researchers, clients, managers or audiences believe will happen. Expectations may appear in forecasts, plans, estimates, sentiment, commitments or operating assumptions. They are not reality, but they influence it because they direct decisions.

The third family is the behavior family. It describes what the system components actually do: actions, choices, flows, resource use, responses, policy changes or traffic patterns. Sometimes the gap between what exists, what is expected to happen and what is actually done is the most important source of insight into the entire system.

Data Quality and Its Treatment

Before calculating, one must ask what the nature of the data is. Is it up to date? Is the source reliable? Is it complete? Is it measured by the same method over time? Are there gaps, delays, changes in definition or source biases? The quality of the prediction cannot exceed the reading quality of the data on which it is based.

The raw figure is always saved. It is the floor of truth to which one can return when a certain interpretation turns out to be wrong. But next to the raw data, additional representations can be created, which allow to see structures that were not clear before. This operation is called data transformation.

Transformation is not falsification of the data but a deliberate change of its reading form. For example, a series in which a value increases, remains almost unchanged and then decreases, can also be examined as a simple directional representation: 1, 0, 1-. The new representation does not replace the original intensity of change, but it makes it possible to examine a sequence, a change in momentum, a cyclical pattern or a transition between states.

Simplification, Weights and Cyclicity

Each data series can have several representations: raw value, rate of change, ratio to average, threshold exceeded, relative ranking, direction of movement, rate of change, or cyclical state. Simplification is not an end in itself. Its purpose is to produce another point of view on the same phenomenon.

After the transformation, it is possible to examine weights, relative values, segment boundaries and domain intrusions. One can ask if a value repeated a previous pattern, if it approached a limit that was significant in the past, if it went out of a known range or if the relationship between two series has changed. Cycles are also not considered a magic sign; It is a way to examine whether the current behavior resembles repeated structures or deviates from them.

At every stage one must beware of simulated convergence. Some indicators can appear to have broad support, even though they are derived from the same source or the same basic figure. Therefore, the language of data requires not only the accumulation of information, but also a test of the independence of the sources and the meaning of the connections between them.

Controlled Complexity

More data is not necessarily more understanding. Data systems can become so complex that they produce noise, duplication, and hidden dependencies between metrics. The theory calls for controlled complexity: enough layers to see the system, but not so many layers that the central structure disappears.

The question is not how much data has been collected, but which data changes the readability of the system. Each data field should justify its place: does it add meaning, does it improve the distinction between alternatives, does it fit into the appropriate data family, and can its contribution be examined over time.

Once the data has been given a language, it is necessary to understand where it operates. For this purpose, the theory moves from the single series to the network.

CHAPTER 3

The System as a Network

Units, Groups, Cyclicity and Regime

From the Unit to the Network

A single unit does not work alone. A company, group, component, department, actor, machine or service station operates within a relational environment. Sometimes the unit's behavior is better explained by its place in the network than by its internal data alone.

Therefore the prediction is not performed on an isolated object. It is carried out on a network of relationships. When a unit becomes dim, it is not necessary to stop predicting. Sometimes the field of research must be expanded: to the group to which it belongs, to tangential groups, to a supply chain, to an operational environment or to the wider circulation.

Expanding the field is not a search for simplicity. Sometimes the broad field is more complex. But it may be richer in references, and therefore more readable than the single point.

Groups as an Investigative Structure

A group is not just a list of items with a common label. It is a research structure in which internal relationships are examined: who leads, who follows, who disconnects, whether change spreads between components, and whether the direction seen from the outside is supported by the breadth of the group or only by a small number of prominent units.

A unit can belong to several groups at the same time. It may be part of an industry, operational, technological, behavioral or research group built for the purpose of testing a hypothesis. The multiple affiliation is not a defect. It makes it possible to see gaps: a unit can appear strong in one context and weak in another. The gap itself may be information.

When several units within a group begin to show a similar change, it must be examined whether it is a group organization or a local merger. When an entire group changes its relationship to other groups, the wider system may begin to change.

Interactions Between Groups

The most important part is not only the state of the groups but the interrelationship between them. One group can influence another, compete with it for resources, lead it, be dragged behind

it or serve as a bridge between two different spaces. When such relationships change, so does the meaning of the information within each group.

In financial systems, one can think of a transition of attention and capital between groups. In operational systems it is possible to think about the transfer of load, demand or resources between units. In engineering systems, one can think of mutual influence between components, environmental conditions and loads. The principle is the same: it is not enough to check what happens inside a component. Check what passes between components.

Network traffic is not definitive proof of a particular cause. It is a sign that must be examined in a broad context. When several data families, groups and time cycles indicate the same relative change, the possibility increases that the system is indeed changing its relational structure.

Cyclicity and Regime

Every system lives in time. Therefore the current situation is not enough; The movement from which it was created must also be understood. A cycle describes possible sequences of organization, expansion, maturity, weakening, adaptation and renewal. It

is not a rigid template that every system must go through, but a reading framework that allows you to ask what stage the process is in and what has changed in relation to the previous stage.

A regime is the broad operating condition within which the cycle takes place. It is not just a direction. It expresses a situation in which the relations of forces, weights and reactions in the system take on a certain character. In the same regime, a particular letter may be significant; In another regime, the same signal can be weak, misleading or irrelevant.

Therefore, a given does not carry a fixed meaning. Its meaning depends on the question in which cycle and regime it was created, how the group behaves, and what connections exist between it and the other components of the network.

Multilevel Reading

The system as a network requires a constant transition between levels: from the unit to the group, from the group to the network, from the network to the regime, and then back to the unit. This is not a mechanical zoom in and out. It is about a conscious choice of the level of observation at which the data begins to take on meaning.

When one level does not provide an answer, it is not necessary to conclude that the system is unpredictable. The question may have been asked at too narrow a system level. This is how the context for the next chapter is created: a process is not only examined according to its state at a given moment, but according to the way in which it originates, receives continuity or changes its trend.

CHAPTER 4

Emergence, Continuity and Trend Reversal

Reading Processes Over Time

Emergence: When the Structure Begins to Change

A new process does not always appear at a sharp and clear moment. Sometimes it starts as a small gap between components, as a response that no longer fits the previous pattern, as a new relationship between groups or as a subtle change in the way the system responds to the same conditions. At this stage there is still not necessarily a clear trend, but a new structure is beginning to emerge.

The term genesis is more accurate than absolute terms such as birth. It describes a gradual change in which the system moves away from the previous structure, but is not yet necessarily consolidated into a new structure. Emergence can be the beginning of strengthening, weakening, regime change, reorganization or any other direction.

Not every anomaly is a creation. A complex system produces fluctuations and local results, some of which disappear. Emergence begins when the change takes on a context: it persists, connects to additional data, spreads to a group or changes relationships in a system.

Continuity: When the Process Gains Support

Becoming alone is not enough. A process can appear and disappear. Therefore the next question is whether the new structure receives continuity. Continuity is not just continuous movement in the same direction. It is the existence of systemic support for the process: relationships that remain consistent, a group that begins to participate, data that continues to connect, or a wider cycle that does not contradict the development.

A process may continue to be seen externally even when its internal support weakens. Therefore, only time and direction should not be examined. It must be examined whether the structure that supported the process is preserved, strengthened or expanded. Are more units in the group responding? Are the gaps narrowing or increasing? Are tangential groups supported? Does the regime still allow the same interpretation?

Continuity is not automatic approval. It is a research phase in which the structure's durability must be continued to be tested, the conditions that may break it and the alternatives that are beginning to appear around it.

Trend Reversal: When the Story Changes

A process does not have to end abruptly. Sometimes it loses coherence, changes shape, splits or is replaced by another structure. That is why it is better to talk about a change in trend and not about the death of the process. A change of trend is not just a reversal of direction. It is a change in the relationships that supported the previous process.

The change sometimes begins before the external result is clear. A unit can continue to look strong, but the group weakens. A group can continue to advance, but the number of units supporting it is reduced. Expectations can grow, while the data of reality or behavior no longer support the same intensity. In such situations, the previous story is still visible, but its internal structure begins to change.

Not every correction is a trend change. A system can stop, adapt or experience temporary volatility and still maintain the central structure. The question is not only whether there has been a

change, but whether there has been a change in the relationship between the unit, the group, the network, the cycle and the regime.

The Three States as a Single Continuum

Emergence, continuity and change of trend are not three closed cells. They are a sequence of reading. At every moment one must ask: Does the previous structure still explain the data? Is a new structure starting to form? Does the new structure receive support? And are the assumptions we relied on before still valid?

The transition between the modes does not have to be uniform in every area. In an engineering system, it can manifest itself in a change in the pattern of loads or failures. In an economic system it can appear in relations between groups, expectations and behavior. In a social system it can manifest itself in changes in incentives, norms and results. Therefore, the examination method will be defined later by thinking modules adapted to the field.

However, the principle remains constant: forecasting is not just looking for a situation, but a process. And to decide if a process deserves attention, one must examine how predictable it is in relation to a certain question.

CHAPTER 5

Predictive Capacity, the Space of Opportunity and Decision

From Understanding the System to Choosing Among Alternatives

Predictive Capacity Is a Property of the Question

The important question is not only what is expected to happen, but to what extent it is possible to predict what the question is about. Predictability is not a fixed property of an object. It is a variable property of the research field, of the time span, of the level of the system and of the available data.

It may be difficult to predict the exact movement of a unit in a short time, but its relative position within a group can be better understood. It may be difficult to identify the exact time of a transition, but it is possible to recognize that the regime is changing and that old trends are losing their validity. Therefore there is no absolute predictability; There is a prediction in relation to a defined question.

When the predictability of a certain layer is low, it does not mean that you should stop exploring. The test field must be expanded to layers, groups and neighboring systems. Sometimes the system itself becomes opaque, while its environment continues to transmit information of higher predictive value.

Measuring Relative Clarity

Predictability increases when there is a convergence between the data families, when the connections between the groups are legible, when the cycles and the regime do not contradict the story, and when the level of difficulty and fertility make it possible to give meaning to the signals. It decreases when the sources diverge, when the regime changes rapidly, when the group loses coherence or when there are many alternatives that cannot be preferred between them.

This is not a magic score. Predictability is a cumulative assessment of tissue quality. It can be high in relation to one direction and low in relation to another direction; high in one range and low in another; Clear in one group and dim in another. The purpose of the measurement is not to produce simulated certainty, but to know where the system can be read in a more responsible way.

In this sense, predictability is a navigational mechanism. It directs the researcher to the field where it is appropriate to delve deeper, to the signals that require reinforcement, and to the cases in which the basic assumptions must be reexamined.

The Space of Opportunity

Not every possibility is an opportunity. A possibility is a thing that may happen; An opportunity is a relatively prioritized possibility within a set of goals, time, constraints and alternatives. It is not necessarily a positive event, nor is it necessarily a call to immediate action.

A space of opportunity can justify continued investigation, changing the focus of attention, transferring resources, waiting, avoiding or choosing between courses of action. It is created when a certain option fits better with the information, with the system conditions and with the defined goal, compared to the other alternatives.

Predictability and opportunity space are not the same thing. The ability to predict makes it possible to understand; The opportunity space allows to prefer. Even a very readable system does not always present a superior practical alternative, nor does an

attractive option become an opportunity when the level of difficulty is too high or when the conditions are not fit for purpose.

Decision Among Alternatives

A decision is a conscious choice between possible alternatives. It is not automatically derived from a single prediction, nor does it amount to action or inaction. A decision can mean continuing an examination, changing the research framework, partially allocating resources, waiting or choosing a certain alternative over another.

In order to decide correctly, a goal must be defined. The same information can lead to different decisions according to the time frame, capacity, safety conditions, resource limitations or the type of desired result. Therefore, it is impossible to talk about a good decision out of context. The good decision is the one that prefers a certain alternative over the other alternatives, under the conditions defined at that time.

Capacity saving is also an alternative. When there is insufficient priority, conservation of time, attention, capital, personnel or other resources is not a lack of resolution; is a decision to

maintain responsiveness. A system that leaves no room for reaction may lose its freedom of choice precisely when the structure changes.

Decision Is Updated

Complex systems change, so decisions also need to be re-examined. A process that was better yesterday can lose its priority tomorrow. An alternative that seemed secondary can be strengthened. New information can change the interpretation of previous information. The decision is not the end of thinking; It is an action point within a learning cycle.

The guiding principle is simple: one should not choose an option because it seems good in itself, but because it is relatively better in relation to the goal, time, constraints and alternatives. To realize this principle, a thinking architecture is required that allows data, formulas and insights to work together.

CHAPTER 6

Thinking Modules, Interweaving and a Meta-Model

From the Isolated Datum to Systemic Insight

Domain-Adapted Thinking Modules

The theory does not offer one fixed formula for predicting any system. A financial, engineering, operational, security, sports or social system may be just as complex, but it speaks a different data language. Therefore, one list of modules, tests or thresholds should not be determined in advance to suit each field.

Instead, the theory suggests building dedicated thinking modules. A thinking module is a focused framework for examining a particular question within a system: it can organize data, examine relationships, identify change, compare alternatives, test cycles or evaluate the operating conditions of a process.

The modules change according to the field, but the principle of operation is preserved. Each module starts with the data relevant to the family to which it is connected, examines the characteristics of the series, activates transformations and produces insights that can be interwoven with other modules.

From the Datum to the Submodule

The first step is the raw data. It is joined by the characteristics of the series: the update rate, the range of values, noise, continuity, gaps, response speed, the reliability of the source and the relationship to the data family. A transformation is then carried out, when it is required, to examine the phenomenon in additional forms.

One series can be examined as a value, as a change, as a direction, as a relation to the average, as an exception, as a border crossing or as part of a cycle. This is where submodules are created. One module can test persistence; Another can examine cycles; A third can examine a change in the ratio between two series; And a fourth can examine whether a phenomenon spreads within a group or between groups.

The submodules are not separate islands. The result of one of them can change the test weight in another module. For example, detecting periodicity may change the way outliers are examined, and disparity between data families may require further examination of the behavior within a group.

The Interweaving of Formulas

In a complex system, a single formula does not just produce a result. It can change the operating conditions of another formula. This is the principle of interweaving. Instead of calculating indicators separately and then adding them flat, we will examine how one result changes the weight, meaning or threshold of another result.

A principle formula can be written like this: the meaning of a data is determined as a function of the raw value, the transformation made on it, its connection in the data family, the stage of the cycle, the level of difficulty and its interrelationships with other groups and series. It is not a final formula but a mental structure: the given does not work alone.

The weights, thresholds and cut-off limits do not have to be fixed. They can be examined over time, adapted to the field, check for border crossings, identify cyclical patterns and examine when a certain formula adds meaning and when it just reproduces noise. This is how an interwoven algorithm is built: formulas within formulas, modules influencing each other and repeated test loops.

The Meta-Model and Downward Feedback

A supermodel runs above the submodules. His job is not just to collect scores or summarize data. He looks at the relationships between the insights: whether several modules detect a similar change, whether the data families support or contradict each other, whether a process is visible only in one series or spreads to a wider network, and whether a local change begins to take on systemic significance.

The super model is not just a summary stage. It returns information downwards. When it detects a gap, contradiction or new pattern, it can trigger another examination cycle in the submodules, change priorities, request further validation or indicate the need for a different transformation of the data.

This is how a cyclical movement is created: data, transformation, submodules, interweaving, supermodel, feedback, and reexamination. The prediction is not a one-time event; It is a learning system of observation, interpretation, testing and correction.

Human-Dependent Systems and Other Systems

In systems where humans are involved, a significant part of the perceived randomness may arise from decisions, incentives, partial information, mutual reactions, policy changes and group

behavior. Systematic observation of human results, within a legal, authorized and ethical framework, can enrich the investigation. Trading graphs, sports tables, government data, operational processes and management systems are examples of spaces where human results leave traces that can be examined.

In systems that do not depend on a person, such as physical, engineering or natural systems, there are sometimes hidden variables, measurement limitations, tiny effects or high computational complexity. The theory does not claim that every random phenomenon can be controlled or fully deciphered. She suggests continuing to test whether what seems random is really unstructured, or whether it indicates a level of understanding, observation or calculation that has not yet been completed.

In this way the randomness becomes a guideline. It indicates where understanding is lacking, where additional information is required, and where the next layer of legality may be found.

Afterword: A Window into a Higher Level of Prediction

The unified theory for predicting complex systems is not satisfied with describing reality after it has occurred. Its purpose is to build a new way of reading reality before it is fully formed.

It starts with the raw data, but does not stop there. It breaks down the data into families, performs transformations, examines series, identifies cycles, compares groups, activates sub-modules, interweaves formulas and insights, and uploads all the information to a super model that looks at the system as a whole.

This is how there is a transition from looking at individual data to understanding the structure behind them; From the reaction to the event to the identification of its origin; From a guess to an established prediction; And from relying on a single sign to a convergence of layers of information, relationships and cycles.

The purpose of the theory is not to guarantee absolute certainty, because complex systems always include hidden variables, changes in conditions and uncertainties. But its purpose is clear: to systematically increase the ability to predict, expand the level of relative certainty and reduce the scope of decisions based on guesswork only.

The more correctly the data is handled, the more suitable the thinking modules are to the field under study, and the more precise the interweaving between the modules, the deeper insights can be generated, the earlier the distinction between noise and structure, and the closer to a higher level of prediction.

The vortex around the plane's wing does not disappear. The complexity does not disappear either. But when our ability to read deepens, a greater part of the unclear becomes explorable, assessable and predictable. The future does not have to remain an opaque space. It can gradually become a space where understanding is deeper and relative certainty is higher.

End of the Edited Manuscript

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