Kolmogorov Complexity and Chaotic Phenomena

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Abstract

Born about three decades ago, Kolmogorov Complexity Theory (KC) led to important discoveries that, in particular, give a new understanding of the fundamental problem: interrelations between classical continuum mathematics and reality (physics, biology, engineering sciences, ...).
Specifically, in addition to the equations, physicists use the following additional difficult-to-formalize property: that the initial conditions and the value of the parameters must not be abnormal. We will describe a natural formalization of this property, and show that this formalization in good accordance with theoretical physics. At present, this formalization has been mainly applied to the foundations of physics. However, potentially, more practical engineering applications are possible.

1 Introduction

Traditional mathematical approach to the analysis of physical systems implicitly assumed that all mathematically possible integers are physically possible as well, and all mathematically possible trajectories are physically possible. Traditionally, this approach has worked well in physics and in engineering, but it does not lead to a very good understanding of chaotic systems, which, as is now known, are extremely important in the study of real-world phenomena ranging from weather to biological systems.

Kolmogorov was among the first who started, in the 1960s, analyzing the discrepancy between the physical and the mathematical possibility. He pinpointed two main reasons why a mathematical correct solution to the corresponding system of differential or difference equation can be not physically possible:

- First, there is a difference in understanding the term "random" in mathematics and in physics. For example, in statistical physics, it is possible (probability is positive) that a kettle, when placed on a cold stove, will start boiling by itself. From the viewpoint of a working physicist, however, this is absolutely impossible. Similarly, a trajectory which requires a highly unprobable combination of initial conditions may be mathematically correct, but, from the physical viewpoint, it is impossible.

- Second, the traditional mathematical analysis tacitly assumes that all integers and all real numbers, no matter how large or how small, are physically possible. From the engineering viewpoint, however, a number like $10^{10^{10}}$ is not possible at all, because it exceeds the number of

particles in the Universe. In particular, solutions to the corresponding systems of differential equations which lead to some numbers may be mathematically correct, but they are physically meaningless.

Attempts to formalizing these restrictions have been started by Kolmogorov himself. These attempts are at present, mainly undertaken by researchers in theoretical computer science who face a similar problem of distinguishing between theoretically possible "algorithms" and feasible practical algorithms which can provide the results of their computations in reasonable time.

The goal of the present research is to use the experience of formalizing these notions in theoretical computer science to enhance the formalization of similar constraints in engineering and physics.

This research is mainly concentrated around the notion of Kolmogorov complexity. This notion was introduced independently by several people: Kolmogorov in Russia and Solomonoff and Chaitin in the US. Kolmogorov used it to formalize the notion of a random sequence. Probability theory describes most of the physicist intuition in precise mathematical terms, but it does not allow us to tell whether a given finite sequence of 0's and 1's is random or not. Kolmogorov defined a complexity $K(x)$ of a binary sequence x as the shortest length of a program which produces this sequence. Thus, a sequence consisting of all 0's or a sequence 010101... have a very short Kolmogorov complexity because these sequences can be generated by simple programs, while for a sequence of results of tossing a coin, probably the shortest program is to write print(0101...) and then reproduce the entire sequence. Thus, when $K(x)$ is approximately equal to the length $\mathrm{len}(x)$ of a sequence, this sequence is random, otherwise it is not. The best source for Kolmogorov complexity is a book [29].

The definition of $K(x)$ only takes into consideration the length $\mathrm{len}(p)$ of a program p. From the physical viewpoint, it is also important to take into consideration its running time $t(p)$, because if it exceeds the lifetime of the Universe, this algorithm makes no practical sense. This development is in line with Kolmogorov's original idea that some natural numbers which are mathematically possible (like $10^{10^{10}}$) are not feasible and thus, should not considered as feasible. Corresponding modifications are also described in the above book. We plan to show how to use the corresponding ideas in physics and engineering.

Specifically, these ideas lead us to the following improvements in comparison with the traditional mathematical approaches to science and engineering, approaches that do not take into consideration the difference between "inhuman" ("abnormal") and "human" ("normal") numbers:

- *Physically impossible events become mathematically impossible as well.* From the physical and engineering viewpoints, a cold kettle placed on a cold stove will never start boiling by itself. However, from the traditional probabilistic viewpoint, there is a positive probability that it will. Our new approach makes the mathematical formalism consistent with common sense: crudely speaking, the probability is so small that this event is simply physically impossible.

- *Physically possible indirect measurements become mathematically possible as well.* In engineering and in physics, we often cannot directly measure the desired quantity; instead, we measure related properties and then use the measurement results to reconstruct the measured values. In mathematical terms, the corresponding reconstruction problem is called the *inverse problem*. In practice, this problem is efficiently used to reconstruct the signal from noise, to find the faults within a metal plate, etc. However, from the purely mathematical viewpoint, most inverse problems are *ill-defined* meaning that we cannot really reconstruct the desired values without making some additional assumptions. We show that the only assumption we

need to make is that the reconstructed signal, etc., is "normal", and immediately, the problem becomes well-defined in the precise mathematical sense.

We also show that this idea naturally leads to an emergence of *chaos*, and it also helps to deal with systems that display chaotic behavior.

2 Main Idea: In Brief

One of the main objectives of science is to provide *guaranteed* estimates for physical quantities. In order to find out how estimates can be guaranteed, let us recall how quantities are estimated in physics:

- First, we must find a *physical law* that describes the phenomena that we are analyzing. For some phenomena, we already know the corresponding laws: we know Maxwell's equation for electrodynamics, Einstein's equation for gravity, Schroedinger's equations for quantum mechanics, etc. (these laws can be usually deduced from symmetry conditions [15, 8, 10]). However, in many other cases, we must determine the equations from the general theoretical ideas and from the experimental data. Can we guarantee that these equations are correct? If yes, how?

  There is an extra problem here. In some case, we know the equations, but we are not sure about the values of the *parameters* of these equations. If the theory predicts, e.g., that a dimensionless parameter is 1, and the experiments confirm it with an accuracy of 0.001, should we then use exactly 1 or 1 ± 0.001 for a guaranteed estimate? If the accuracy is good enough, then the physicists usually use 1. We may want to use 1 ± 0.001 to be on the safe side, but then, for other parameters of a more general theory (that in this particular theory are equal to 0) should we also use their experimental bounds instead of the exact 0 value? There are often many possible generalizations, and if we take all of them into consideration, we may end up with a very wide interval. This is a particular case of the same problem: when (and how) can we *guarantee* that these are the right equations, with the correct values of the parameters?

- Suppose now that we know the correct equations. Then, we need to describe how we will actually predict the value of the desired quantity. For example, we can get partial differential equations that describe how exactly the initial values $\phi(x, t_0)$ of all the fields change in time. Then, to predict the values of the physical quantity at a later moment of time t, we must do the following:

  - Determine the values $\phi(x, t_0)$ from the measurement results.
  - Use these values $\phi(x, t_0)$ to predict the desired value.

  The problem with this idea is that reconstructing the actual values $\phi(x, t_0)$ from the results of measurements and observations is an *ill-posed problem* [28] in the sense that two essentially different functions $\phi(x, t_0)$ are consistent with the same observations. For example, since all the measurement devices are inertial and thus suppress the high frequencies, the functions $\phi(x, t_0)$ and $\phi(x, t_0) + A \cdot \sin(\omega x)$, where ω is sufficiently big, lead to almost similar values of observations.

Thus, strictly speaking, if we do not have any additional restrictions on $\phi(x, t_0)$, then for every x, the set of possible values of $\phi(x, t_0)$ is the entire real line. So, to get a *guaranteed* interval for $\phi(x, t_0)$ (and hence, for the desired physical quantity), we need to use some additional information. The process of using this additional information to get non-trivial estimates for the solution of the inverse problem is called a *regularization* [28]. There are several situations where this additional information is available:

- If we are analyzing familiar processes, then we usually know (more or less) how the desired function $\phi(x, t_0)$ looks like. For example, we may know that $\phi(x, t_0)$ is a linear function $C_1 + C_2 \cdot x_1$, or a sine function $C_1 \cdot \sin(C_2 x_1 + C_3)$, etc. In mathematical terms, we know that $\phi(x, t_0) = f(x, C_1, \ldots, C_k)$, where f is a known expression, and the only problem is to determine the coefficients C_i. This is how, for example, the orbits of planets, satellites, comets, etc., are computed: the general shape of an orbit is known from Newton's theory, so we only have to estimate the parameters of a specific orbit. In such cases, the existence of several other functions $\phi(x, t_0)$ that are consistent with the same observations, is not a big problem, because we choose only the functions $x(t)$ that are expressed by the formula $f(t, C_1, \ldots, C_k)$. This is not, however, a frequent situation in physics, because one of the main objectives (and the main challenges) of physics is to analyze new phenomena, new effects, qualitatively new processes, and in these cases no prior expression f is known.
- In some cases, we know the statistical characteristics of the reconstructed quantity $\phi(x, t_0)$ and statistical characteristics of the measurement errors. In these cases, we can formulate the problem of choosing the maximally probable $\phi(x, t_0)$, and end up with one of the methods of *statistical regularization*, or *filtering* (Wiener filter is one of the examples of this approach).
- If we do not have this statistical information, but we know, e.g., that the average rate of change of $x(t)$ is smaller than some constant Δ (i.e., $\sqrt{\int \dot{x}(t)^2\, dt} \leq \Delta$), then we can apply regularization methods proposed by A. N. Tikhonov and others [28].
- In many cases, we do not have the desired statistical information. However, we may have some *expert knowledge*. For example, if we want to know how the temperature on a planet changes with time t, then the experts can tell that most likely, $x(t)$ is limited by some value M, and that the rate $\dot{x}(t)$ with which the temperature changes, is typically (or "most likely,", etc) limited by some value Δ, etc. We can also have some expert knowledge about the error, with which we perform our measurements, so the resulting expert's knowledge about the value of measured quantity y looks like "the difference between the measured value $\tilde{y}$ and the actual value y is most likely, not bigger than δ" (where δ is a positive real number given by an expert). The importance of this information is stressed in in Chapter 5 of [19]. The methods of using this information and their application to testing airplane and spaceship engines is described in [18, 16].
- In many case, we do not have any quantitative expert information like the one we described. In these cases, it is usually recommended to use some heuristic (or semi-heuristic) regularization techniques [28]. These methods often lead to reasonable results, but they do not give any *guaranteed* estimate for the reconstructed value $\phi(x, t_0)$.

There are two possible approaches to this problem:

- A *pessimistic* approach: that we will never be able to get guaranteed estimates. This approach is typical in *statistics*. For example, a well-known statistician R. A. Fisher says that a "hypothesis is never proved or established, but is possibly disproved, in the course of experimentation" ([11], p. 16). Strictly speaking, from this viewpoint, we cannot even say that a theory is *disproved* with a guarantee. Indeed, if, e.g., a theory predicts 1, and the measurement has led to 2, then, no matter how small the standard deviation of the measurement error can be, the probability that the difference is caused by the measurement error is non-zero, and so, it is possible that the theory is still correct.

- An *optimistic approach*, that most physicists hold, is that we *can* make guaranteed conclusions from the experiments. A disproved theory *is* wrong, and the chance that the measurement error has caused it is as large as having the cards in order after thorough shuffling, or a possibility to win the lottery every time by guessing the outcome: it is *impossible.*

In this paper, we will describe a formalization of the optimistic approach.

3 Main Idea in Detail

Physicists assume that initial conditions and values of parameters are not abnormal. To a mathematician, the main contents of a physical theory is the equations. The fact that the theory is formulated in terms of well-defined mathematical equations means that the actual field must satisfy these equations. However, this fact does *not* mean that *every* solution of these equations has a physical sense. Let us give two examples:

- At any temperature greater than absolute zero, particles are randomly moving. It is theoretically possible that all the particles start moving in one direction, and, as a result, the chair that I am sitting on starts lifting up into the air. The probability of this event is small (but positive), so, from the purely mathematical viewpoint, we can say that this event is possible but highly unprobable. However, the physicists say plainly that such an abnormal event is *impossible* (see, e.g., [6]).

- Another example from statistical physics: Suppose that we have a two-chamber camera. The left chamber if empty, the right one has gas in it. If we open the door between the chambers, then the gas would spread evenly between the two chambers. It is theoretically possible (under appropriately chosen initial conditions) that the gas that was initially evenly distributed would concentrate in one camera, but physicists believe this abnormal event to be impossible. This is a general example of what physicists call *irreversible processes*: on the atomic level, all equations are invariant with respect to changing the order of time flow $t \to -t$). So, if we have a process that goes from state A to state B, then, if at B, we revert all the velocities of all the atoms, we will get a process that goes from B to A. However, in real life, many processes are clearly irreversible: an explosion can shatter a statue, but it is hard to imagine an inverse process: an implosion that glues together shattered pieces into a statue. Boltzmann himself, the 19 century author of statistical physics, explicitly stated that such inverse processes "may be regarded as impossible, even though from the viewpoint of probability theory that outcome is only extremely improbable, not impossible." [2].

- If we flip a coin 100 times in a row, and get heads all the time, then a person who is knowledgeable in probability would say that it is possible, while an engineer (and any person

who uses common sense reasoning) would say that the coin is not fair, because it is was a fair coin, then this abnormal event would be impossible.

- In all the above cases, we knew something about probability. However, there are examples of this type of reasoning in which probability does not enter into picture at all. For example, in general relativity, it is known that for almost all initial conditions (in some reasonable sense) the solution has a singularity point. Form this, physicists conclude that the solution that corresponds to the geometry of the actual world has a singularity (see, e.g., [31]): the reason is that the initial conditions that lead to a non-singularity solution are abnormal (atypical), and the actual initial conditions must be not abnormal.

In all these cases, the physicists (implicitly or explicitly) require that the actual values of the fields must not satisfy the equations, but they must also satisfy the additional condition: that the initial conditions should *not* be *abnormal*.

The notion of "not abnormal" is difficult to formalize. At first glance, it looks like in the probabilistic case, this property has a natural formalization: if a probability of an event is small enough (say, $\leq p_0$ for some very small p_0), then this event cannot happen. For example, the probability that a fair coin falls heads 100 times in a row is 2^{-100}, so, if we choose $p_0 \geq 2^{-100}$, then we will be able to conclude that such an event is impossible. The problem with this approach is that *every* sequence of heads an details has exactly the same probability. So, if we choose $p_0 \geq 2^{-100}$, we will thus exclude all possible sequences of heads and tails as physically impossible. However, anyone can toss a coin 100 times, and this prove that some sequences are physically possible.

Historical comment. This problem was first noticed by Kyburg under the name of *Lottery paradox* [21]: in a big (e.g., state-wide) lottery, the probability of winning the Grand Prize is so small, then a reasonable person should not expect it. However, some people do win big prizes.

How to formalize the notion of "not abnormal": idea. "Abnormal" means something unusual, rarely happening: if something is rare enough, it is not typical ("abnormal"). Let us describe what, e.g., an abnormal height may mean. If a person's height is ≥ 6 ft, it is still normal (although it may be considered abnormal in some parts of the world). Now, if instead of 6 pt, we consider 6 ft 1 in, 6 ft 2 in, etc, then sooner or later we will end up with a height h such that everyone who is higher than h will be definitely called a person of abnormal height. We may not be sure what exactly value h experts will call "abnormal", but we are sure that such a value exists.

Let us express this idea is general terms. We have a *Universe of discourse*, i.e., a set U of all objects that we will consider. Some of the elements of the set U are abnormal (in some sense), and some are not. Let us denote the set of all elements that are *typical* (*not abnormal*) by T. On this set, we have a decreasing sequence of sets $A_1 \supseteq A_2 \supseteq \ldots \supseteq A_n \supseteq \ldots$ with the property that $\cap A_n = \emptyset$. In the above example, U is the set of all people, A_1 is the set of all people whose height is ≥ 6 ft, A_2 is the set of all people whose height is ≥ 6 ft 1 in, A_2 is the set of all people whose height is ≥ 6 ft 2 in, etc. We know that if we take a sufficiently large n, then all elements of A_n are abnormal (i.e., none of them belongs to the set T of not abnormal elements). In mathematical terms, this means that for some n, we have $A_n \cap T = \emptyset$.

In case of a coin: U is the set of all infinite sequences of results of flipping a coin; A_n is the set of all sequences that start with n heads but have some tail afterwards. Here, $\cup A_n = \emptyset$. Therefore, we can conclude that there exists an n for which all elements of A_n are abnormal. So, if we assume that in our world, only not abnormal initial conditions can happen, we can conclude that for some n, the actual sequence of results of flipping a coin cannot belong to A_n. The set A_n consists of all elements that start with n heads and a tail after that. So, the fact that the actual sequence does

not belong to A_n means that if an actual sequence has n heads, then it will consist of all heads. In plain words, if we have flipped a coin n times, and the results are n heads, then this coin is biased: it will always fall on heads.

Let us describe this idea in mathematical terms [9, 17]. To make formal definitions, we must fix a formal theory: e.g., the set theory ZF (the definitions and results will not depend on what exactly theory we choose). A set S is called *definable* if there exists a formula $P(x)$ with one (free) variable x such that $P(x)$ if and only if $x \in S$.

Crudely speaking, a set is definable if we can *define* it in ZF. The set of all real numbers, the set of all solutions of a well-defined equations, every set that we can describe in mathematical terms is definable.

Mathematical comment. This does not means, however, that *every* set is definable: indeed, every definable set is uniquely determined by formula $P(x)$, i.e., by a text in the language of set theory. There are only denumerably many words and therefore, there are only denumerably many definable sets. Since, e.g., there are more than denumerably many set of integers, some of them are this not definable.

A sequence of sets $A_1, \ldots, A_n, \ldots$ is called *definable* if there exists a formula $P(n, x)$ such that $x \in A_n$ if and only if $P(n, x)$.

Let U be a universal set. A non-empty set $T \subseteq U$ is called a *set of typical (not abnormal) elements* if for every definable sequence of sets A_n for which $A_n \supseteq A_{n+1}$ and $\cap A_n = \emptyset$, there exists an N for which $A_N \cap T = \emptyset$. If $u \in T$, we will say that u is *not abnormal*. For every property P, we say that *"normally, for all u, $P(u)$"* if $P(u)$ is true for all $u \in T$.

It is possible to prove that abnormal elements do exist [9]; moreover, we can select T for which abnormal elements are as rare as we want: for every probability distribution p on the set U and for every ε, there exists a set T for which the probability $p(x \notin T)$ of an element to be abnormal is $\leq \varepsilon$.

4 Applications

4.1 Restriction To "Not Abnormal" Solutions Leads To Regularization Of Ill-Posed Problems

An ill-posed problem arises when we want to reconstruct the state s from the measurement results r. Usually, all physical dependencies are continuous, so, small changes of the state s result in small changes in r. In other words, a mapping $f : S \to R$ from the set of all states to the set of all observations is continuous (in some natural topology). We consider the case when the measurement results are (in principle) sufficient to reconstruct s, i.e., the case when the mapping f is 1-1. That the problem is ill-posed means that small changes in r can lead to huge changes in s, i.e., that the inverse mapping $f^{-1} : R \to S$ is *not* continuous.

We will show that if we restrict ourselves to states S that are not abnormal, then the restriction of f^{-1} will be continuous, and the problem will become well-posed.

Definition. *A definable metric space (X, d) is called definably separable if there exists a definable everywhere dense sequence $x_n \in X$.*

PROPOSITION [14] **.** *Let S be a definably separable definable metric space, T be a set of all not abnormal elements of S, and $f : S \to R$ be a continuous 1-1 function. Then, the inverse mapping $f^{-1} : R \to S$ is continuous for every $r \in f(T)$.*

In other words, if we know that we have observed a not abnormal state (i.e., that $r = f(s)$ for some $s \in T$), then the reconstruction problem becomes well-posed. So, if the observations are accurate enough, we get as small guaranteed intervals for the reconstructed state s as we want.

Comment. To actually use this result, we need an *expert* who will tell us what is abnormal.

4.2 Every Physical Quantity is Bounded

PROPOSITION. *If U is a definable set, and $f : U \to R$ is a definable function, then there exists a number C such that if $u \in U$ is not abnormal, then $|f(u)| \le C$.*

If we use the physicists' idea that abnormal initial conditions and/or abnormal values of parameters are impossible, then we can make the following conclusions:

Special relativity. If as U, we take the set of all the particles, and as f, we take velocity, then we can conclude that the velocities of all (not abnormal) particles is bounded by some constant C. This is exactly what special relativity says, with the speed of light as C.

Cosmology. If we take the same state U, and as f, take the distance from the a particle u to some fixed point in the Universe, then we can conclude that the distances between particles in the Universe are bounded by a constant C. So, the Universe is *finite*. Similarly, if we take a time interval between the events as f, we can conclude that the Universe has a *finite lifetime*.

Why particles with large masses do not exist. If we take mass of the particle as f, then we can conclude that the masses of all particles are bounded by some constant C. This result explains the following problem:

- Several existing particle classification schemes allow particles with arbitrarily large masses [3]. E.g., in Regge trajectory scheme, particles form families with masses $m_n = m_0 + n \cdot d$ for some constants m_0 and d. When $n \to \infty$, we have $m_n \to \infty$.
- Only particles with relatively small masses have been experimentally observed (see, e.g., [33]).

These particles with large masses, that are difficult to wed out using equations only, can be easily weeded out if use the notion of "not abnormal".

Dimensionless constants are usually small. This is the reason why engineers and physicists can safely estimate and neglect, e.g., quadratic (or, in general, higher order terms) in asymptotic expansions, even though no accurate estimates on the coefficients on these terms is known [7]. In particular, such methods are used in quantum field theory, where we add up several first Feynman diagrams [4]; in celestial mechanics [34], etc.

4.3 Chaos Naturally Appears

Restriction to not abnormal also explains the origin of chaotic behavior of physical systems. In mathematical terms, chaos means, in particular, that after some time, the states of the system get close to the so-called *strange attractor*, i.e., a set whose sections are *completely disconnected set*.

Mathematical comment. A set S in a metric space X is called *completely disconnected* if for every $s_1, s_2 \in S$, there exist open sets S_1 and S_2 such that $s_1 \in S_1$, $s_2 \in S_2$, $S_1 \cap S_2 = \emptyset$, and $S \subseteq S_1 \cup S_2$.

In other words, every two points belong to different topological components of the set S. The relationship between this definition and typical elements is given by the following result:

PROPOSITION. *In a definable separable metric space, the set of typical elements is completely disconnected.*

So, if we assume (as physicists do) that abnormal states are impossible, then we immediate arrive at the chaotic dynamics.

5 How to Deal with Chaos?

We have shown that our ideas naturally lead to the emergence of a chaotic behavior. Since chaotic systems are difficult to analyze, this conclusion may sound negative.

However, as we will show, this same approach also helps us to deal with these problems because it shows us that a lot of mathematical complexity usually associated with chaos is caused by the inability to separate feasible from non-feasible. Once this separation is in place, the analysis becomes much simpler. Let us briefly describe what we mean.

First thing we do is – as we have done before – eliminate the contradiction between the traditional mathematical models and common sense. Specifically, one of the main characteristic properties of chaotic systems is their non-predictability, what Lorenz – the discoverer of the first chaotic system of differential equations – called the *butterfly effect*: something as light as a flap of butterfly wings can lead to a drastic change of temperature at a certain day a few years in the future. In more precise terms, this property can be described as follows: in order to predict the state $x(T)$ at a moment $T > 0$ with accuracy ε, we usually need to know the state $x(0)$ with the accuracy $\delta \ll \varepsilon$. For chaotic systems, $\delta \sim \varepsilon \cdot \exp(-C \cdot T)$ for some positive number C. Due to the exponential term, for reasonably large T, the accuracy δ becomes practically impossible. So, from the purely mathematical viewpoint, the prediction is possible, but in practice, it is not. What our approach does is eliminates the contradiction between common sense and mathematical description: when δ becomes small, eventually, it is not normal anymore, so prediction is not possible from the mathematical viewpoint either.

We cannot predict the exact behavior of the system, so all we can predict is its possible behaviors. How can we describe them? Here again, our approach helps. From the purely mathematical viewpoint, we have a continuous system with infinitely many different states, a situation difficult to describe and to understand. However, from the practical viewpoint, very close states cannot be distinguished from each other – same reason as why we cannot measure the initial state with the accuracy $\delta \ll 1$. Thus, from the practical viewpoint, we do not have to consider all infinitely many states, all we have to do is consider finitely many practically distinguishable ones. are only finitely many states, the consequent states $x(t_0)$, $x(t_0 + \Delta t)$, $x(t_0 + 2\Delta t)$, ..., cannot be all different – thus, two states at different moments of time must coincide: $x(t_0 + k \cdot \Delta t) = x(t_0 + l \cdot \Delta t)$ for some $k < l$. Since the system is deterministic, we can therefore conclude that the next states also coincide: $x(t_0 + (k+1) \cdot \Delta t) = x(t_0 + (l+1) \cdot \Delta t)$, $x(t_0 + (k+2) \cdot \Delta t) = x(t_0 + (l+2) \cdot \Delta t)$, ..., i.e., after the time $t_0 + k\Delta t$, the system becomes periodic with the period $(l-k) \cdot \Delta t$.

In other words, if we take the different between "normal" ("human") and "abnormal" ("inhuman") numbers into consideration, then every trajectory of a (seemingly chaotic) dynamical system becomes *periodic*. Periodic trajectories are relatively easy to analyze, easy to simulate – definitely much easier than the usual mathematical trajectories that wrap themselves around the system's strange attractors.

Details of this approach are given is [20].

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