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A Saddle Point Finding Method for Lorenz Attractor through Business Machine Learning Algorithm

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Abstract

Cancer has a long-time history in our human health experience. Practically, one-fifth of the disease was caused by virus infection. Thus, it is important for us to understand the virus-cancer infection mechanism. Statistically, we may perform the necessary causality regression analysis in such situation to build up the corresponding model just like my previous case in influenza-weather infection. In the present research, I will interact the systems of differential equations (Lorenz System) with my HKLam theory and figure out the recursive result that we may get. Then we may go ahead for the corresponding policy generated from the dynamic programming that can solve the Markov Decision Process. In addition, we may apply the HKLam theory to the chaotic time series and compare the model with machine learning one for a better selection while otherwise failure is explained. Finally, I will also discuss a novel mathematical method in determining the saddle point in Lorenz attractor together with the gradient descent. The aim is to find the equilibrium for the Lorenz attractor with given initial conditions. It is hope that the mathematics-statistics interaction together with the causal regression (Artificial Intelligence) model may finally help us fight against those diseases like virus-infected cancer or others.

Keywords: Artificial intelligence • Markov decision process • Saddle point • Algorithm

Introduction

Cancer has been a serious disease in our medical history and human is now trying to conquer it. Indeed, the most advanced and recent research show that different virus plays a significant role in the formation of various cancer diseases. In the following content, I shall outline the feasible causal (regression) analysis (or the artificial intelligence modelling) for the cancer formation under the corresponding virus attack. According to Joyce, et al., [1], alcohol can induce Hepatitis C Virus (HCV)-hepatocellular carcinoma (HCC) that causes the DNA methylation of repetitive elements. These elements may include long interspersed nuclear element-1 (LINE-1) and all elements (Alu). Joyce's research team further concludes that HCV inflection has a strong highly connection with the loss of DNA methylation in the specific REs. This event is then implicating molecular mechanisms in the liver cancer development.

Literature Review

If one is investigating the DNA methylation in a deeper aspect, Cho et al., [2] find that tobacco smoking may change the transcription and methylation states of extracellular matrix organization-related genes. I want to remark here that, tuberculosis (TB) virus may increase the risk of the lung cancer that is highly related to the smoking. In such case, DNA methylation patterns will be changed and hence altered the transcription states of genes. To be more precise, proteins will bind to methylated DNA. These DNA will then form complexes with the proteins that formulated during the process of deacetylated of histones. Therefore, when DNA is undergone the process of methylation, the nearby histones will also deacetylated. The outcome is the compounded inhibitory effects on transcription. Similarly, demethylated DNA will not cause the attachment of deacetylated enzymes to the histones and hence this event will allow DNA to keep their status to be acetylated and more mobile, thus promoting transcription to be happened.

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Next, when the transcription that indirectly caused by virus happens, lipidomics among cells may occur [3]. As a return, this event could obviously lead to the problem of lipid metabolism and hence cause the metabolic health issue. Snaebjornsson et al., [4] even told us that by altering lipid metabolism, one may even develop a possible therapeutic window for cancer treatment. Thus, with reference to my paper in causal (regression) analysis as shown in [5], one may deduce the following causality domino effects for the possible cancer formation mechanism:

Virus infection → DNA methylation → transcription occurs → lipidomics → metabolic problem cancer formation

Then with the suitable bio-informatics cancer data, one may follow the procedure as stated in my previous mentioned paper to establish the wanted Hayes Process model [6] (or the A.I. model) for such type of virus leading cancer formation mechanism. To go in depth, one may further perform the heterogeneous analysis together with the spatial one for the cancer formation mechanism etc. Indeed, it is no doubt that other disease infection mechanism like the COVID-19 can also be modeled by the same or similar methods if we can find out the infection details inside our body cells from experiments etc.

Results

The butterfly effects in our world's climate and public health

In the traditional chaos theory, the butterfly effect [7] always refers to the sensitive dependence on initial conditions. That is the small change in one state of the initial conditions of a deterministic nonlinear system will produce a large difference in the later state. Historically, the term came from the mathematician and meteorologist Edward Lorenz. He discovered that the time of formation together with the path taken of a tomada could be influenced by some minor perturbations. One of the cases is a distant butterfly flapping its wings several weeks earlier. Similarly, Lorenz also noted that when he tried to round the initial condition data value of his weather model, the result would not be the same as the unrounded weather model. Hence, he concluded that a small change in the initial conditions had created a significantly different outcome. Hence the Butterfly Effects occur in the most case of weather (or climate) prediction from the so-called Lorenz system which is a set of system equations [7]. It can be interacted with my HKLam Theory that will be shown later in this research paper. Other than weathering model, one may also construct the corresponding SIR Mathematical (or the compartmental) model in epidemiology where S is the stock of susceptible population, I is the stock of infected, R is the stock of removed population. According to Stephen et al., [8] in the case of Hepatitis B virus infection, we may employ the following phenomenological model (for another interaction with my HKLam Theory) as shown below:

$x'(t)=\lambda - dx - \beta\nu x$ equation (A)

$y'(t)=\beta\nu x - ay$ equation (B)

$\nu'(t)=ky - \mu\nu$ equation (C)

where x, y and ν are numbers of uninfected liver cells, infected cells and free virions, respectively;

λ represents the (constant) rate where the uninfected liver cells produced, dx means the linear term of maintaining tissue homeostasis in the face of hepatocyte turnover. During infection, healthy liver cells are assumed to become infected at a rate $\beta\nu x$, where β is the mass action rate constant describing the infection process. Infected liver cells are killed by immune cells at rate ay and produce free virons at rate ky, where k is the so-called 'burst' constant. Free virons are cleared by lymphatic and other mechanisms at rate $\mu\nu$ where μ is a constant. In the present paper, I will just focus in the interaction between HKLam Theory and the Lorenz system only.

What is "chaos"?

From the process of creating heaven and earth in the Bible, we know:

"The ground is empty and chaotic, the abyss above is dark, and the spirit of God is running on the water."

Additionally, we can take a review from the Kellert's book [9]:

Qualitative definition

What Stephen Kellert (Stephen Kellert) did define chaos theory is "a qualitative study of unstable non-periodic behaviour in deterministic nonlinear dynamic systems". This chaos definition may conform it to belong to just an attribute of nonlinear dynamical systems (although in some part of his book, Kellert mentioned quite ambiguous about chaos in a mathematical model quantitatively or even a real-world system). In other words, chaos can be defined to be an attribute in terms of mathematical models. According to Kellert's definition, there are two key characteristics and they are instability and aperiodicity [10]. Unstable system usually refers to the SDIC or the Sensitive Dependence on Initial Conditions. Non-periodic behaviour implies that the system variables will not repeat any value once more. Thus, in a nonlinear dynamic system, chaos can be viewed both as an unstable and non-periodic behaviour.

Quantitative definition

Suppose X (0) and y (0) are the two initial conditions for two individual different trajectories [11]. Then, we define the weakly sensitive dependencies (WSD)-as a system that characterizes by J(x(t)),

When $\exists\ \varepsilon>0$, it has the properties of low sensitivity to former described initial conditions, such that

$\exists\ \varepsilon>0$, $\forall x(0)$, $\forall\delta>0$, $\exists t>0$, $\exists y(0)$, with the following inequalities hold:

$|x(0)-y(0)|<\delta$ and $|J(x(t))-J(y(t))|>\varepsilon$.

The basic idea is that:

No matter the propagator how close x(0) is approaching to y(0); the trajectory starting from y(0) will still be separated from x(0) by a "ν" distant. On the contrary, WSD does not abstractly specify the divergence rate (that may be compared with the linear divergence). Or one may need to specify the number of points around x(0) that will finally produce different trajectories a set of arbitrary measures, such as zero.

However, chaos is usually characterized with the sensitive dependence:

$\exists\lambda$ such that for almost all points $\boldsymbol{x}(0)$,

$\forall\delta>0\exists t>0$ such that for almost all points $\boldsymbol{y}(0)$ in a small neighbourhood (δ) around $\boldsymbol{x}(0)$,

we always have:

$$|\boldsymbol{x}(0)-\boldsymbol{y}(0)|<\delta \text{ and } |\boldsymbol{J}(\boldsymbol{x}(t))-\boldsymbol{J}(\boldsymbol{y}(t))|\approx|\boldsymbol{J}(\boldsymbol{x}(0))-\boldsymbol{J}(\boldsymbol{y}(0))|e\lambda t,$$

where the "almost all" caveat means all points in state space with the exception that it is not true for a set of measure zero. Here, λ is considered as the largest global Lyapunov exponent and is taken to be the average rate of divergence of neighbouring trajectories. In addition, λ issues a forth from some small neighbourhood which is centered around $\boldsymbol{x}(0)$. Exponential growth is implied if $\lambda>0$(converged when $\lambda<0$). In general, the growth cannot go continuously until infinity. If the system is bounded in space together with momentum, limits exist and this can help us determine how far the nearby trajectories will diverge from one another [11].

Lorenz attractor

The Lorenz system is indeed consisting a set of system differential equations which is first under the investigation of Edward Lorenz. When one is applying certain parameters and initial values, the chaotic solutions will then appear. Or in particular speaking, the Lorenz attractor is actually a set of chaotic answers to the prescribed Lorenz system. In our usual meaning, the "butterfly effect" may stem from our real-world implications of the Lorenz attractor. In other words, for any physical system, without the perfect knowledge of the initial conditions (such as the situation of minuscule disturbance to the air as the result of a butterfly flapping its wings), our intention does to predict its future course will face a failure. This event shows that physical systems may be actually deterministic and is in fact still be inherently unpredictable when the quantum effects are ignored. The shape of the Lorenz attractor has been shown as Figure 1, when plotted graphically by the software R, can be seen to resemble like a butterfly.

When we are talking about the aperiodic properties of the Lorenz Attractor, we may refer it as the chaotic time series. According to Kose et al [12], we can forecast the series through Vortex Optimization Algorithm. In such case, the chaotic time series will be divided into the training stage and the testing one in the prediction process. This event is just like the business machine learning process in the study of influenza-weather prediction, Lam, 2020 [13]. That is we may modify the techniques in Lam, [13] for the business software R to the present prediction in chaotic time series. In reality, the programming code will be left to those professional R programmers as this event is out of the scope the present paper. This author will only pinpoint the similar idea that lies behind. To go a further step, one may employ the likelihood and Bayesian prediction for the chaotic system. This author wants to note that my HKLam theory does create a bridge (a linear transformation) for the connection between the Chaos non-linear part and the regression (or the approximation) for the linear part. The theory can thus be applied in the prediction (from the approximated model) of the chaotic system or the chaotic time series. In practice, there is a simple method to detect chaos in nature that is developed by Toker et al., [14]. We may establish the approximated model *via* HKLam theory and perform the necessary prediction when the system is chaotic with reference to the aforementioned methods described in the former part of this section.

Practically, we may have the following algorithm in establishing the best model for a chosen chaotic time series prediction:

1. Use a periodic chaos packages to determine whether chaotic time series

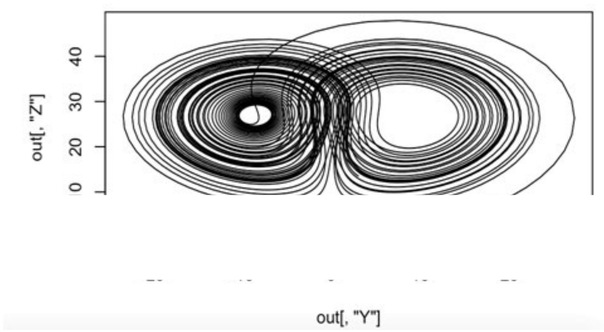

Figure 1. Lorenz Attractor that appears in form of chaos about the world climate-plotted from R-studio software.

exists;

2. Transform the chaotic time series into Markov Chain matrix through the stochastic process and apply HKLam theory to obtain the wanted regression approximation model (RAM) for prediction;

3. From the Chaotic time series to establish the machine learning model (MLM) by training and testing for another prediction;

4. Compare both of the models-(RAM and MLM), select the best model and explain for the failure;

5. Both of the above prediction methods constitute a kind of philosophy.

Once if we extend the above algorithm for various different sets of strange attractor parameters, we may find a series of model for the other types of attractor. Practically, these different set of parameters may be obtained by the numerical analysis method such as the secant one if we have the elementary seed attractor parameters. Indeed, the most common seeded attractor's parameters will be used as an example in the later section of this paper.

Interaction between Lorenz system and HKLam theory

In fact, the Lorenz differential system (or other differential equation models like the SERI) can be expressed in terms of a matrix. In addition, it is feasible that these matrices are capable of written by HKLam's (Net-Seizing) theorem. The following is one of the examples:

$$\begin{pmatrix} -\sigma & \sigma & 0 \\ -z+p & -1 & 0 \\ 0 & x & \beta \end{pmatrix}\begin{pmatrix} L \\ T \\ 1 \end{pmatrix}$$ =Linear regression of causal domino (LRA 1) (equation 1)

$$\begin{pmatrix} -\sigma & \sigma & 0 \\ -z+p & -1 & 0 \\ 0 & x & \beta \end{pmatrix}$$ =Linear regression expression (LRE 2) (equation 2)

(LRE 2) $\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$ =(LRA 1)

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}\begin{pmatrix} L \\ T \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}$$

$$\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$$

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}$$

$$\begin{pmatrix} L \\ T \\ 3 \end{pmatrix}$$

$$\begin{pmatrix} L \\ T \\ 4 \end{pmatrix}$$

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}$$

$$\frac{\partial}{\partial\theta}J_{\theta 3}=\frac{1}{m_3}\sum_{i=1}^{m_3}\left[\left(f_\theta\left(z_k\right)-v\right)z_k\right]=\frac{dz}{dt}$$

$$\sigma\frac{1}{\left(y-z\right)}\frac{1}{m_1}\sum_{i=1}^{m_1}\left[\left(h_\theta\left(X_i\right)-u\right)x_i\right]$$ (equation 3)

$$p=\frac{1}{x}\left(\frac{dy}{dt}+y\right)+z$$

$$p=\frac{1}{x}(\frac{1}{m_2}\sum_{j=1}^{m_3}\left[\left(g_\theta\left(y_j\right)-v\right)y_j\right]+y)+z$$

$$\beta\frac{1}{z}(xy-\frac{dz}{dt})=\frac{1}{z}(xy-\frac{1}{m_3}\sum_{i=1}^{m_3}\left[\left(f_\theta\left(z_k\right)-v\right)z_k\right])$$

Substitute $\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$ in equation (3) back into equation (1) and continues this (in fact which is initially an infinite and) recursive process (such that this is a kind of mathematical formalism) until the linear transformation $\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$ is found in the pre-calculated optimal approximation for a given set of values (ϭ1, þ1, β1) in the Lorenz attractor. In this case, we have got the wanted real values of the linear transformation $\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$ at that a particular given set of valued point; say (ϭ1, þ1, β1). Conversely, if there are sufficiently large amount of $\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$s, we can estimate back the corresponding true values of (ϭ2, þ2, β2) and get the optimal values in the Lorenz attractor. Hence, in terms of weather management, we can determine the consequence risks behind. Thus, we may associate with the most feasible warnings and give in advance by applying some suitable decision theories. In such case, we are actually using the HKLam Theory to net-seize those changes in our earth-weathering butterfly effect (or the Lorenz attractor). Similar cases happen in other differential equation models such as in the viruses mutation in micro-biology (cancer research) together with the spread of other viruses (influenza and COVID-19 for example) in our public health.

Take for some case studies, let's consider a set of values for (ϭ=10, þ, β=8/3, z=1, x=1) and interact with one of the regression model equation in Lam March, 2020 [15], we may get:

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}\begin{pmatrix} L \\ T \\ 1 \end{pmatrix}$$ =(4.3685.53+26.71*wind-2.185 wet test-2054.05 * temperature equation(1')

Approximate the matrix by a linear regression, we also have:

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}$$ =AX+ε0

equation (2')

Thus, by equating the above two equations, we get:

(AX+ε0) $\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$ =(4.3685.53+26.71*wind-2.185 *wettest-2054.05 * temperature; or

$\begin{pmatrix} L \\ T \\ 2 \end{pmatrix}$ =$(AX+\varepsilon_0)^{-1}$ * [(4.3685.53+26.71*wind-2.185 *wettest-2054.05 * temperature] equation (3')

Let B=(4.3685.53+26.71*wind-2.185 *wettest-2054.05 * temperature

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}[(AX+\varepsilon_0)^{-1} * B]=B$$

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}=B * [(AX+\varepsilon_0)^{-1} * B]^{-1}$$

Continue the above process for the second time, we get:

$B * [(AX+\varepsilon0)^{-1} * B]^{-1}\begin{pmatrix} L \\ T \\ 3 \end{pmatrix}=B$

$B * [(AX+\varepsilon_0)^{-1} * B]^{-1}=A'X+\varepsilon'_0$

$$(A'X+'_0)\begin{pmatrix} L \\ T \\ 4 \end{pmatrix}=B$$

$$\begin{pmatrix} L \\ T \\ 4 \end{pmatrix}=(A'X+'_0)^{-1\,*}B$$

$$B^{*}[(AX+\varepsilon_0)^{-1\,*}B]^{-1\,*}\ [(A'X+\varepsilon'_0)^{-1\,*}B]=B$$

$$B^{*}[(AX+\varepsilon_0)^{-1\,*}B]^{-1}=B^{*}[(A'X+\varepsilon'_0)^{-1\,*}B]$$

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}=B^{*}[B^{*}[(AX+\varepsilon 0)^{-1\,*}B]^{-1\,*}B]$$

$$=B^{2}[(AX+\varepsilon 0)^{-1}]^{-1}$$

if we assume $(A^{*}B)^{-1}=B^{-1*}A^{-1}$ and the communicative, distributive properties of matrix multiplication.

If furthermore, the Lorenz matrix can be QR decomposed, then we may have:

$$\begin{pmatrix} -10 & 10 & 0 \\ -1+p & -1 & 0 \\ 0 & 1 & 8/3 \end{pmatrix}=B^{2}[(QR)^{-1}]^{-1}$$

Obviously, the above sample Lorenz matrix (with assumed parameters) shows that we can always express it as the formative and recursive format by the linear regression approximation.

In general, the formative recursion computing can be solved by 5 steps process:

Find out the simplest possible input;

Play and visualize around with examples;

Relates hard cases to simpler cases;

Generalize the pattern;

Write computer code by combining recursive pattern with the base case;

Practically, for the computer recursive problem like the one as Lorenz-HKLam interaction above, we may solve it through the 5 steps process. Moreover, for the computer halting problem, may we hope to solve it by installing a backup system which can monitor all of the recursive process? The backup will automatically solve the problem by the above 5 steps before any restarting of the major system. Hence, the recursive halting one is now completely settled down. In fact, the five steps can be extended into our dynamic programming which may include reductions of the (recursive) problem, shortest path finding etc. Every details of the dynamic programming can be found elsewhere in the web and the major concerns of this paper are the computational method about the interaction between differential systems and regression approximation (or HKLam Theory).

Lorenz system and fast saddle point finding approximation algorithm

Furthermore, from the Lorenz system, we know:

= (y-x)--(1)

= x-y-xz------------------------------------(2)

=xy – z-------------------------------------(3)

Suppose that we want to get the best-fit regression line to predict the value of u_i, v_j, w_k based on the given input value x_i, y_j, z_k with respect to the domino regression function $h_\theta(x_i)$, $g_\theta(y_j)$, $f_\theta(z_k)$ then according to gradient descent in linear regression (with the cost functions), we have:

$$\frac{\partial}{\partial\theta}J_{\theta 1}=\frac{1}{m_1}\sum_{i=1}^{m_2}\left[\left(h_\theta\left(X_i\right)-u\right)x_i\right]=\frac{dx}{dt}\text{------------------}(1)^{*}$$

$$\frac{\partial}{\partial\theta}J_{\theta 2}=\frac{1}{m_2}\sum_{j=1}^{m_2}\left[\left(g_\theta\left(y_i\right)-v\right)y_i\right]=\frac{dy}{dt}\text{------------------}(2)^{*}$$

$$\frac{\partial}{\partial\theta}J_{\theta 3}=\frac{1}{m_3}\sum_{i=1}^{m_3}\left[\left(f_\theta\left(z_k\right)-v\right)z_k\right]=\frac{dz}{dt}\text{------------------}(3)^{*}$$

If we compare the system {(1), (2), (3)} and $\{(1)^{*}, (2)^{*}, (3)^{*}\}$, we get:

$$\sigma\frac{1}{(y-z)}\frac{1}{m_1}\sum_{i=1}^{m_1}\left[\left(h_\theta\left(X_i\right)-u\right)x_i\right]\text{----------------------------------}(1)^{**}$$

$$p=\frac{1}{x}\left(\frac{dy}{dt}+y\right)+z \text{ where } x\neq 0$$

$$p=\frac{1}{x}\left(\frac{1}{m_2}\sum_{j=1}^{m_3}\left[\left(g_\theta\left(y_j\right)-v\right)y_j\right]+y\right)+z\text{----------------------------}(2)^{**}$$

$$\beta\frac{1}{z}\left(xy-\frac{dz}{dt}\right)=\frac{1}{z}\left(xy-\frac{1}{m_3}\sum_{i=1}^{m_3}\left[\left(f_\theta\left(z_k\right)-v\right)z_k\right]\right)\text{--------------}(3)^{**}$$

Now, it is clear that ϭ, Ƿ and β can be expressed as the linear regressions of functions $h\theta(x_i)$, $g\theta(y_j)$, $f\theta(z_k)$ and x, y, z etc. Moreover, one can collect all of the inflection points of the Bayesian Optimization functions (in one set say A) together with the true functions (in another set, say B). Instead of a slow point-wisely gradient descent algorithm, we may first select one of the inflection points in set A. Next, we join the maxima or minima to the part of the approximated function (in quadratic appearance). Then we introduce algorithmic and dialectic mathematics proof, which can accelerate the convergent rate in a faster way (as opposed to the aforementioned gradient descent) and find the corrected optimal (or the intersection) point. Hence, when my HKLam theory is interacting with the Lorenz system, the above is the best method to find the wanted optimized point (or the saddle) for them. This is how we can compute the equilibrium from the interaction between the system and theory. Therefore,

by controlling different values of ϭ, Ƿ and β, we may get different linear regression functions correspondingly. In addition, we may shift from one saddle point

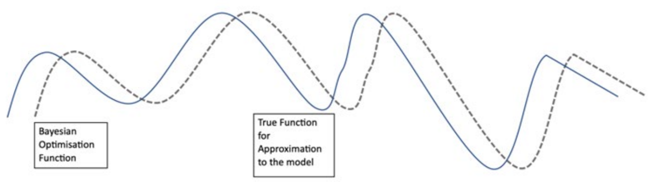

Figure 2. Using the Bayesian optimization function to approximate the model of the true function.

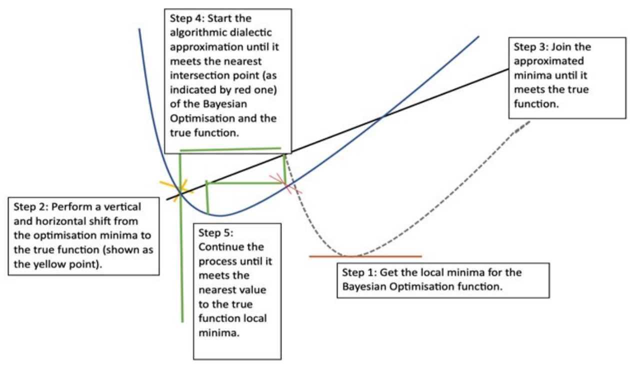

Figure 3. Steps in finding the true local minima and the intersection (optimal) point (of the HKLam Theory and Lorenz system) between the Bayesian Optimization function and the model of the true function. In fact, the present method (modified from fixed-point algorithm)'s convergent rate is clearly much faster than the point-wise Gradient Descent Algorithm.

to another until we find the best optimized one (Figures 2 and 3).

The following is the corresponding R programming code for a comparison between fixed-point algorithm and the gradient descent algorithm through the polynomial regression:

```
Library (tidy verse)
Library (caret)
theme_set (theme_classic())
data ("XXXXXX", package="MASS")
set.seed (123)
training.samples<-XXXXXX$medv%>%
  createDataPartition (p=0.8, list=FALSE)
train.data<-XXXXXX [training.samples, ]
test.data<-XXXXXX [-training.samples, ]
model<-lm (medv~ (lstat, 5, raw=TRUE), data=train.data)
predictions<-model %>% predict (test.data)
data.frame (RMSE=RMSE (predictions, test.data$medv),
R2=R2 (predictions, test.data$medv))
Ggplot (train.data, aes (lstat, medv) )+geom_point()+stat_smooth (method=lm, formula=y~poly(x, 5, raw=TRUE))
#Fixed-point Algorithm#
f<-function(x)
{fit=lm(medv poly(lstat, 5, raw=TRUE), data=train.data)}
x=0
x=f(x)
temp=0
err=1
temploop<-readline(prompt="Enter the number of iteration:")
n=temploop
for (i in 1:temploop)
if (err>0.00001){
temp=x
x=f (x)
print (i)
print ("th Iteration:    ")
print (x)
err=(x-temp)/x
if (err<0) err=0-err
i=I+1
print(i)
print(x)
```

According to Mustapha [16], we may find the corresponding gradient-descent algorithm and the Steepest Descent one will be find in Carathéodory [17]. Then we may proceed to the bayesian distributed stochastic descent.

Bayesian Distributed Stochastic Gradient Descent

For the further advance in the saddle point finding, may we apply the co-vector concept in the gradient descent algorithm? The following is part of the segment code of the gradient descent in R [18]:

```
W<-c(0.1, 0.2); b<-0.3; learn<-0.1
x<-matrix(c(0, 0, 1, 1, 0, 1, 0, 1), now=4)
Y<-c(0, 1, 1, 1)
F<-function(w, x, b) w%*% t(x)+b
Step<-function(x) ifelse(x<0, 0, 1)
For (I in 1:10) {
F1<-f(w, x, b)
w<-w-c(sum(learn * 2 * (pmax(0, F1)-y) * step(F1) * x[,1]),
sum(learn * 2 * (pmax(0, F1)-y) * step(F1) * x[,2]))
b<-b-sum(learn * 2 * (pmax(0, F1)-y) * step(F1))
…
(f(w, x, b)>0.5)=as.logical(y)
…
```

Indeed, the exact R programming implementation is out of the scope of the present paper since this author is NOT a professional programmer.

If we consider those convectors as a network of graph, then the problem of finding the saddle point or the equilibrium in the Lorenz attractor is immediately reduced into a shortest path problem. In such a way, we are indeed transforming the problem into a mathematical graph shortest path searching one. The problem can be solved this by the Dijkstra's Algorithm. Lastly, from the equilibrium saddle point, we may substitute back the local minimum to the approximation polynomial and the process continues recursively in a formative way but we may still solve the problem by dynamic programming algorithm such as those of the divide and conquer one etc.

In a brief, we may build various models from different set of parameters as the one mentioned in the previous section about the time series representation of the attractor. Then we may have a collection of different saddle points or the equilibrium according to the new fixed point method applied in this section for these models. Next, by comparing these equilibrium values, we can find the ultimate or the true value of the saddle (or the equilibrium) point for the investigated and continually varying strange attractor (in terms of different types of attractor) like the weathering such that one can obtain the most stabilized equilibrium. Certainly, all of the above algorithm may require a professional programmer to implement while this author is NOT. For our daily usage, we may also apply the above similar principles during the case in some types of vaccine production such as that cancer virus that will be evolved to become less toxic. In particular, for the case of COVID-19 virus, we may estimate the number of mutation cycles according to the general principles of strange attractor equilibrium finding method such that the virus becomes less harmful. In practice, Konishi [19] has just discovered that the mutation among minks can lead to some more human-friendly subtype COVID-19 virus and thus may be used for our future vaccine like the smallpox. This author wants to remark that there are reports about the co-infection of both COVID-19 and Epstein-Barr viruses in patients while the later may be responsible for the cause of several cancers. Thus, this author believes that the causality regression model method may help us have a fully understanding for the correlated infection mechanism between these two viruses. Hence this may help us develop the best fitted EBV-caused cancers drugs or vaccine.

Discussion

One of the most important applications of the so-called "Gradient-Descent" is their usage in daily life for finding the singularity such as the nature one-black-hole. In fact, from the Levent et al. [20-27], they have discovered that the Hessian of the loss function in deep learning is indeed degenerating. Practically, we may be able to look beyond the basins if we can further explore the energy landscape of the loss functions. This event may reduce our problem into singularity and minimal surface. Indeed, the black-hole can be viewed as the Gabriel's Trumpet. It may be well quantized according to one of my paper.

Another thing to do is to find the low energy paths between solutions. Then one may know which kind of flatness in such landscapes. Indeed, by understanding these energy paths, one may further compute and predict the black-hole evaporation phenomenon.

Furthermore, when one is trying to handle the recursive or the Markov (chained or intuitionism) Decision Process, one may settle down the issue by a dynamic programming. Indeed, the Markov Decision Process is useful for the study of optimization problem through a suitable dynamic programming algorithm (or it can solve the MDP with finite states and action spaces). Moreover, from the MDP, we may construct a framework to solve most of the reinforcement learning problem which is one of the branches in machine learning. I remark that in practice, the goal of a MDP is to find a good "policy" for a decision maker [21, 28-30]. One may usually refer dynamic programming (DP) as a collection of algorithms using to compute optimal policies when there is a perfect model of the environment as a Markov decision process (MDP) [22, 31-34].

Conclusion and Applications

All in all, we may interact the chaos or the Lorenz system by my HKLam theory. Then we may form the wanted recursive or the Markov Decision Process and solve this model by dynamic programming in order to generate a suitable policy when making a decision. At the same time, we may also find the saddle point (or the equilibrium of the Lorenz attractor) when we are performing the regression approximation to Lorenz system by gradient descending. Or the interaction (regression approximation) between the Lorenz system and HKLam theory can even be extended into various fields (like the subject philosophy), Markov Chain Model in geography suggested by a Russian mathematician Markov, for example. This author believes that there are still plenty of rooms existing in the matters of interacting (approximating) the Lorenz (or similar differential systems) from my HKLam theory especially in some other scientific area for those researchers to have their future investigations.

References

1. Zheng, Yinan, Ryan A. Hlady, Brian T. Joyce and Keith D. Robertson, et al. "DNA Methylation of Individual Repetitive Elements in Hepatitis C Virus Infection-Induced Hepatocellular Carcinoma." *Clin Epigenetics* 11, no. 1 (2019): 1-13.
2. Cho, Young-Dan, Pil-Jong Kim, Hong-Gee Kim and Yang-Jo Seol, et al. "Transcriptomics and Methylomics in Chronic Periodontitis with Tobacco Use: A Pilot Study." *Clin Epigenetics* 9, no. 1 (2017): 1-9.
3. Hussain, Iqtadar, Amir Anees, Ali Hussain AlKhaldi and Abdulmohsen Algarni, et al. "Construction of Chaotic Quantum Magnets and Matrix Lorenz Systems S-boxes and Their Applications." *Chin J Phys* 56, no. 4 (2018): 1609-1621.
4. Jonsson, Isak, and Bo Kågström. "Recursive Blocked Algorithms for Solving Triangular Systems-Part I: One-Sided and Coupled Sylvester-Type Matrix Equations." *ACM Trans Math Softw* 28, no. 4 (2002): 392-415.
5. Shun, Carson Lam Kai. "Students' Digital Equality and Scholarly Outcomes". *Sch J Phys Math Stat,* (2020).
6. Omer, Jérémy, and Michael Poss. "Time-Dependent Shortest Paths with Discounted Waits." *Networks* 74, no. 3 (2019): 287-301.
7. Imura, Hidefumi. "Understanding the Global Climate System." *Environ Syst Res* 2013, pp. 29-43.
8. Gourley, Stephen A, Yang Kuang, and John D. Nagy. "Dynamics of a Delay Differential Equation Model of Hepatitis B Virus Infection." *J Biol Dyn*, no. 2 (2008): 140-153.
9. Kellert, Stephen H. In the wake of chaos: Unpredictable order in dynamical systems. University of Chicago press, 1994.
10. Benhabib, Jess, ed. Cycles and chaos in economic equilibrium. Princeton University Press, 1992.
11. Broer, Henk, and Floris Takens. *Dynamical systems and chaos*. Springer Science & Business Media 172, (2010).
12. Kose, Utku, and Ahmet Arslan. "Forecasting Chaotic Time Series via anfis supported By Vortex Optimization Algorithm: Applications on Electroencephalogram Time Series." *Arab J Sci Eng* 42, no. 8 (2017): 3103-3114.
13. Lam Kai Shun "Forecast the Prediction or Predict the Forecast-a Precise view of Investigating Butterfly Effects" *Sch J Phys Math Stat* 7, 10:3 07-322.
14. Toker, Daniel, Friedrich T. Sommer, and Mark D'Esposito. "A Simple Method For Detecting Chaos In Nature." *Commun Biol* 3, no. 1 (2020): 1-13.
15. Lam Kai Shun,"Evaluation of the Weather-Influenza Pattern with a Regression Model Approximation to Causality." *Sch J Phys Math Stat* 7, 12 (2020): 398-412.
16. Lam, Kai Shun. "A Saddle Point Finding Method For Lorenz Attractor Through Business Machine Learning Algorithm." *Available at SSRN* 3837055 (2021).
17. Mustapha, Aatila, Lachgar Mohamed, and Kartit Ali. "An Overview of Gradient Descent Algorithm Optimization in Machine Learning: Application in the Ophthalmology Field." *In International Conference on Smart Applications and Data Analysis*, (2020): 349-359.
18. Jastrzębski, Stanislaw, Zachary Kenton, Devansh Arpit and Nicolas Ballas, et al. "Width of Minima Reached by Stochastic Gradient Descent is Influenced by Learning Rate to Batch Size Ratio." *In International Conference on Artificial Neural Networks*, (2018) pp. 392-402.
19. Sagun, Levent, Leon Bottou, and Yann LeCun. "Eigenvalues of the Hessian in DEEP learning: Singularity and Beyond." *arXiv preprint arXiv*:1611.07476 (2016).
20. Ahiska, S. Sebnem, Samyuktha R. Appaji, Russell E. King, and Donald P. Warsing, et al. "A Markov Decision Process-Based Policy Characterization Approach for a Stochastic Inventory Control Problem with Unreliable Sourcing." *Int J Prod Econ* 144, no. 2 (2013): 485-496.
21. Delgado, Karina V, Leliane N. De Barros, Daniel B. Dias, and Scott Sanner, et al "REAL-time Dynamic Programming for Markov Decision Processes with Imprecise Probabilities." *Artificial Intelligence* 230 (2016): 192-223.
22. Carlberg, Carsten, Stine Marie Ulven, and Ferdinand Molnár. Nutrigenomics: how Science Works. Springer, 2020.
23. Berliner, L. Mark. "Likelihood and Bayesianprediction of Chaotic Systems." *J Am Stat Assoc* 86, 416 (1991): 938-952.
24. Regalia, Phillip. Adaptive IIR Filtering in Signal Processing and Control. Routledge, 2018.
25. Horton, Nicholas J., and Ken Kleinman. Using R and RStudio for Data Management, Statistical Analysis, and Graphics. CRC Press, 2015.
26. Ge, Jinghuan, Fang, Enyin, and Tian, Dongwen Tian. "Data Control Method for Printing Quality Based on Polynomial Regression." *In Advanced Graphic Communication, Printing and Packaging Technology,* (2020): pp340-345.
27. D'Auria, Riccardo, and Mario Trigiante. From Special Relativity to Feynman Diagrams. Springer International, 2011.
28. Misra, Jayadev. "A Walk over the Shortest Path: Dijkstra's Algorithm Viewed as Fixed-Point Computation." Inf Process Lett 77, no. 2-4 (2001): 197-200.
29. Shun, Carson Lam Kai. "Teaching and Learning Mathematical Philosophy Through Infinity." 2016.
30. Collins, Lyndhurst, Roy Drewett, and Rob Ferguson. "Markov Models in Geography." *Journal of the Royal Statistical Society: Series D* 23, no. 3-4 (1974): 179-209.
31. Chakrabarti, Anirikh, Mathieu Membrez, Delphine Morin-Rivron and Jay Siddharth, et al. "Transcriptomics-Driven Lipidomics (TDL) Identifies the Microbiome-Regulated Targets of Ileal Lipid Metabolism." *NPJ systems biology and applications* 3, no. 1 (2017): 1-15.
32. Snaebjornsson, Marteinn Thor, Sudha Janaki-Raman, and Almut Schulze, et al. "Greasing the Wheels of the Cancer Machine: the Role of Lipid Metabolism In Cancer." *Cell Metab* 31, no. 1 (2020): 62-76.
33. Hayes, andrew f. Introduction to Mediation, Moderation, And Conditional Process Analysis*:* A Regression-Based Approach. Guilford publications, 2017.
34. Carathéodory, Constantin. Advances in Convex Analysis and Global Optimization: Honoring the Memory of c. Caratheodory (1873-1950). Springer Science & Business Media 54, 2001.

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