We Can Always Reduce a Non-Linear Dynamical System to Linear – at Least Locally – But Does It Help?

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We Can Always Reduce a Non-Linear Dynamical System to Linear – at Least Locally – But Does It Help?

Orsolya Csiszár, Gábor Csiszár, Olga Kosheleva, Vladik Kreinovich, and Nguyen Hoang Phuong

Abstract Many real-life phenomena are described by dynamical systems. Sometimes, these dynamical systems are linear. For such systems, solutions are well known. In some cases, it is possible to transform a nonlinear system into a linear one by appropriately transforming its variables, and this helps to solve the original nonlinear system. For other nonlinear systems – even for the simplest ones – such transformation is not known. A natural question is: which nonlinear systems allow such transformations? In this paper, we show that we can always reduce a nonlinear system to a linear one – but, in general, it does not help, since the complexity of
finding such a reduction is exactly the same as the complexity of solving the original
nonlinear system.

1 Formulation of the problem

Dynamical systems are ubiquitous. One of the main objectives of science is to
predict the future state of different systems. The state of a system can be described
by the values \(x_1, \ldots, x_n\) of different quantities that characterize this system. In many
cases, the current state of the system uniquely determines the rate \(\dot{x}_i\) with which
each of the values changes:

\[
\dot{x}_i = f_i(x_1, \ldots, x_n), \quad 1 \leq i \leq n. \tag{1}
\]

Such a system of differential equations is known as a dynamical system.

For a dynamical system, the current state of the system uniquely determines its
state at any future (or past) moment of time; see, e.g., [1, 2]:

In many cases, we have linear dynamical systems. In many practical situations,
the changes are relatively small. In such cases, for all moments of time, the values
\(x_i\) are close to their initial values \(x_i^{(0)}\). In such cases, it is convenient to describe
the state of the system by the differences \(y_i \overset{\text{def}}{=} x_i - x_i^{(0)}\) for which \(x_i = x_i^{(0)} + y_i\) and, thus,
\(\dot{x}_i = \dot{y}_i\). In terms of these differences, the equations (1) take the form

\[
\dot{y}_i = f\left(x_1^{(0)} + y_1, \ldots, x_n^{(0)} + y_n\right). \tag{2}
\]

Since the values \(y_i\) are relatively small, we can safely ignore terms that are quadratic
or of higher order in terms of \(y_i\). For example, if \(y_i \approx 10\%\), then \(y_i^2 \approx 1\%\), which is
much smaller than \(y_i\). Thus, we can expand the right-hand side of the formula (2)
in Taylor series in terms of \(y_i\) and keep only linear terms in this expansion. In this
case, the right-hand side of the system (2) becomes linear in \(y_1, \ldots, y_n;
\]

\[
\dot{y}_i = a_i + \sum_{j=1}^{n} a_{i,j} \cdot y_j, \tag{3}
\]

for some coefficients \(a_i\) and \(a_{i,j}\). Such dynamical systems are called linear.

Linear systems are easy to solve. There are known formulas for solving linear
systems.

Namely, in the absence of the constant terms \(a_i\), the general solution to this sys-
tem is a linear combination of the terms \(t^k \cdot \exp(\lambda \cdot t)\), where:

• \(\lambda\) is an eigenvalue of the matrix \(a_{i,j}\), and
• \(k\) is a non-negative integer which is smaller than the multiplicity of this eigen-
value.
A simple modification of this formula – in most cases, by adding constants – takes care of the general case of (3).

**Sometimes, we can reduce a non-linear system to a linear one.** In some cases, the differences $y_i$ are not small, so we have to consider the original nonlinear dynamical system (1). For such systems, there is no general way to solve it other than to solve it numerically. However, in some cases, it is possible to reduce a nonlinear system to a linear one and thus, to get an explicit solution.

A known example – for which such a reduction is possible – is the following system:

\[
\begin{align*}
\dot{x}_1 &= a \cdot x_1, \\
\dot{x}_2 &= b \cdot (x_2 - x_1^2).
\end{align*}
\]

In this system, the first equation (4) is linear, but the second (5) is nonlinear.

This system can be reduced to a system of linear equations if we add the third variable $x_3 = x_1^2$. In this case, the second equation (5) becomes linear:

\[
\dot{x}_2 = b \cdot x_2 - b \cdot x_3,
\]

and for the derivative of $x_3$, we have

\[
\dot{x}_3 = \frac{d}{dt}(x_1^2) = 2 \cdot x_1 \cdot \dot{x}_1.
\]

Substituting the expression (4) for $\dot{x}_1$ into this formula, we get

\[
\dot{x}_3 = 2 \cdot x_1 \cdot (b \cdot x_1) = 2b \cdot x_1^2.
\]

By definition of $x_3$ as $x_1^2$, this implies that for the rate of change of the third variables, we also have a linear equation

\[
\dot{x}_3 = 2b \cdot x_3.
\]

**For other nonlinear equations, such a reduction is not known.** Let us consider the simplest possible nonlinear dynamical system.

- The more variables, the more complex the system, so the simplest system should have a single variable $x_1$ – and thus, the dynamical system consists of a single differential equation $\dot{x}_1 = f_1(x_1)$. To find the simplest of such systems, we need to select the simplest possible nonlinear function $f_1(x_1)$.
- The simplest possible functions are linear, and the simplest nonlinear functions are quadratic. The simplest-to-compute quadratic function is simply the expression $x_1^2$ that can be computed by a single multiplication. So, the simplest possible nonlinear system is the equation

\[
\dot{x}_1 = x_1^2.
\]
For this system – as well as for other differential equations with quadratic right-hand sides – no reduction to linear systems is known.

**Natural questions.** For some nonlinear systems, there is a known reduction to linear ones, and this reduction helps solve the system. This fact leads to the following two natural questions:

- which nonlinear systems can be reduced to linear ones? and
- if such a reduction is possible, can it help solve the original nonlinear system?

**What we do in this paper.** In this paper, we provide answers to both questions. Namely, we show:

- that every nonlinear system can be reduced to a linear one – at least locally, but
- that this does not help us solve the original nonlinear system – finding this reduction is as complicated as actually solving the system.

**2 Our Answers**

**Notation.** As we have mentioned, in general:

- once we know the equations (1) and we know the state \( x = (x_1, \ldots, x_n) \) of the system at some moment \( t_0 \),
- we can uniquely determine its state at any other moment of time (at least locally, i.e., for times \( t \) sufficiently close to \( t_0 \)).

Since the system (1) does not explicitly include time, the transition between the state at moment \( t_0 \) and the state at moment \( t \) depends only on the difference \( t - t_0 \). Let us denote the state at moment \( t \) corresponding to the state \( x \) at moment \( t_0 \) by \( T_{t-t_0}(x) \). The components of the state \( T_{t-t_0}(x) \) will be denoted by \( T_{t-t_0,1}(x), \ldots, T_{t-t_0,n}(x) \). In these terms, the state \( x = (x_1, \ldots, x_n) \) is transformed into the state

\[
(z_1, \ldots, z_n) = (T_{t-t_0,1}(x_1, \ldots, x_n), \ldots, T_{t-t_0,n}(x_1, \ldots, x_n)).
\]

Clearly, if we let the system evolve for time \( t \) and then again for time \( t' \), this is equivalent to letting it evolve for time \( t + t' \), i.e., we have

\[
T_{t+t'}(x) = T_{t'}(T_t(x)).
\]  

**How to reduce a nonlinear system to linear: idea.** Let us consider the cases when the values of the last variable \( x_n \) are close to some number \( x_n^{(0)} \). In general, unless the system is degenerate and the value \( x_n \) does not change at all, the value \( x_n \) changes with time. For each tuple \( (x_1, \ldots, x_{n-1}, x_n^{(0)}) \), we can look for the time \( \tau \) at which the value \( x_n \) is equal to \( x_n^{(0)} \), i.e., at which
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\[ T_{\tau,n}(x_1, \ldots, x_n) = x_n^{(0)}. \]  \hspace{1cm} (9)

To find the unknown time \( \tau \), we have one equation (9) with one unknown \( \tau \). In general, if the number of equations is equal to the number of unknowns, the system has a unique solution – at least locally. Thus, we can always find such time \( \tau \).

**Towards the resulting reduction.** Now, instead of the original variables \( x_1, \ldots, x_n \), we can use the new variables \((y_1, \ldots, y_n)\) in which:

- the value \( y_n \) is equal to the time \( \tau \) determined by the formula (9), and
- the values \( y_1, \ldots, y_{i-1}, y_{n-1} \) are equal to

\[ y_i = T_{\tau,j}(x_1, \ldots, x_n). \]  \hspace{1cm} (10)

How will the variables \( y_i \) change with time? Due to formulas (9) and (10), we have

\[ (y_1, \ldots, y_{n-1}, x_n^{(0)}) = T_{\tau}(x_1, \ldots, x_n), \]

i.e., since \( \tau = y_n \), we have

\[ (y_1, \ldots, y_{n-1}, x_n^{(0)}) = T_{y_n}(x_1, \ldots, x_n). \]  \hspace{1cm} (11)

Thus, to describe \( x \) in terms of \( y \), it is sufficient to trace the changes of the state \((y_1, \ldots, y_{n-1}, x_n^{(0)})\) back in time for the period \( \tau = y_n \):

\[ (x_1, \ldots, x_n) = T_{-y_n} (y_1, \ldots, y_{n-1}, x_n^{(0)}). \]  \hspace{1cm} (12)

In time \( t \), the state \( x \) turns into \( T_{t}(x) \). By applying the transformation \( T_{t} \) to both sides of the formula (11) and taking into account the formula (8), we get

\[ T_{t}(x_1, \ldots, x_n) = T_{-y_n-t} (y_1, \ldots, y_{n-1}, x_n^{(0)}). \]  \hspace{1cm} (13)

Thus, by definition of the y-state, the y-state corresponding to \( T_{t}(x) \) has the form \((y_1, \ldots, y_{n-1}, y_n - t)\). Thus, with time:

- the new variables \( y_1, \ldots, y_{n-1} \) do not change at all, and
- the variable \( y_n \) linearly decreases with time.

So, we indeed have the desired reduction. Let us summarize it.

**Resulting reduction.** For each state \( x = (x_1, \ldots, x_n) \), let us define the new variables \( y = (y_1, \ldots, y_n) \) as follows: \( y_n \) is the solution to the equation

\[ T_{y_n,n}(x_1, \ldots, x_n) = x_n^{(0)}, \]  \hspace{1cm} (14)

and for all \( i < n \), we have

\[ y_i = T_{y_n,i}(x_1, \ldots, x_n). \]  \hspace{1cm} (15)
For the new variables, the dynamical system has the following form:
\[ \dot{y}_1 = \ldots = \dot{y}_{n-1} = 0, \quad \dot{y}_n = -1. \]  
(16)

From the new variables \( y_i \), we can get back to the original variables \( x_i \) by using the formula (12).

**Example: derivation.** Let us illustrate our reduction on the example of the simplest nonlinear dynamical systems \( \dot{x}_1 = x_1^2 \). This system is easy to solve. Indeed, we start with the original equation:
\[ \frac{dx_1}{dt} = x_1^2. \]
We then separate the variables by multiplying both sides by \( dt \) and dividing both sides by \( x_1^2 \). This results in:
\[ \frac{dx_1}{x_1^2} = dt. \]
If we integrate both sides of this equation, we get
\[ -\frac{1}{x_1} + C = t, \]
where \( C \) denotes the integration constant. Thus,
\[ \frac{1}{x_1} = C - t, \]
and so,
\[ x_1(t) = \frac{1}{C - t}. \]  
(17)

Let us describe the corresponding function \( T_t(x_1) \) that describes the transition from the state at moment 0 to the state at moment \( t \). At moment 0, the formula (17) leads to
\[ x_1(0) = \frac{1}{C}, \]
so
\[ C = \frac{1}{x_1(0)}. \]
Substituting this value \( C \) into the formula (17), we conclude that
\[ x_1(t) = \frac{1}{\frac{1}{x_1(0)} - t} = \frac{x_1(0)}{1 - x_1(0) \cdot t}. \]
Thus,
\[ T_t(x_1) = \frac{x_1}{1 - x_1 \cdot t}. \]  
(18)
Let us take $x_1(0) = 1$. Then, the value $y_1$ should be determined by the equation (14) which, in this case, has the form

$$\frac{x_1}{1 - x_1 \cdot y_1} = 1,$$

hence $x_1 = 1 - x_1 \cdot y_1$, so $x_1 \cdot y_1 = 1 - x_1$, and

$$y_1 = \frac{1 - x_1}{x_1} = \frac{1}{x_1} - 1. \quad (19)$$

For the new variable $y_1$, the dynamical system takes a linear form: $\dot{y}_1 = -1$.

Once we know new state $y_1$, we can reconstruct the original state $x_1$ by using the formula (12), which in this case takes the form

$$x_1 = T_{-y_1}(1) = \frac{1}{1 - 1 \cdot (-y_1)} = \frac{1}{1 + y_1}. \quad (20)$$

**Example: summary.** For the nonlinear system $\dot{x}_1 = x_1^2$, we can take the new variable

$$y_1 = \frac{1}{x_1} - 1$$

for which

$$x_1 = \frac{1}{1 + y_1}.$$  

For this new variable, the dynamical system has the form $\dot{y} = -1$.

**Does this reduction help solve the original nonlinear system?** Not really, since the reduction uses the solution $T_t(x)$ of the system.

**But can we have a reduction that does help solve the system?** Not really:

- if we know the solution, then, as we have shown, we can easily find the appropriate reduction;
- vice versa, if we know a reduction to a linear system, then, since solutions to linear systems are known, we can easily find the solution to the original nonlinear system.

Because of this, the complexity of finding a reduction to a linear system is exactly the same as the complexity of solving the original nonlinear system.

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References
