Computational Irreducibility and the Predictability of Complex Physical Systems

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Using elementary cellular automata (CA) as an example, we show how to coarse grain CA in all classes of Wolfram’s classification. We find that computationally irreducible physical processes can be predictable and even computationally reducible at a coarse-grained level of description. The resulting coarse-grained CA which we construct emulate the large-scale behavior of the original systems without accounting for small-scale details. At least one of the CA that can be coarse grained is irreducible and known to be a universal Turing machine.

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Can one predict the future evolution of a physical process which is described or modeled by a computationally irreducible (CIR) mathematical algorithm? For such systems, in order to know the system’s state after (e.g.) $1 \times 10^6$ time steps, there is no faster algorithm than to solve the equation of motion a million time steps into the future. Wolfram suggested that the existence of CIR systems in nature is at the root of our apparent inability to model and understand complex systems [1–4].

Complex physical systems that are CIR might therefore seem to be inherently unpredictable. It is tempting to conclude from this that the enterprise of physics itself is doomed from the outset; rather than attempting to construct solvable mathematical models of physical processes, computational models should be built, explored, and empirically analyzed. This argument, however, assumes that infinite precision is required for the prediction of future evolution. Usually coarse-grained or even statistical information is sufficient: indeed, a physical model is usually correct only to a certain level of resolution, so that there is little interest in predictions from such a model on a scale outside its regime of validity.

In this Letter, we report on experiments with nearest neighbor one-dimensional cellular automata (CA), which show that because in practice one seeks only coarse-grained information, complex physical systems can be predictable and even computationally reducible at some level of description. The implication of these results is that, at least for systems whose complexity is the outcome of very simple rules, useful approximations can be made that enable predictions about future behavior.

Cellular automata are dynamical systems composed of a lattice of cells. Each cell in the lattice can assume a value from a given finite alphabet. The system evolves in time according to an update rule that gives a cell’s new state as a function of values in its finite neighborhood. CA were originally introduced by von Neumann and Ulam [5] in the 1940’s as a possible way of simulating self-reproduction in biological systems. Since then, CA have attracted a great deal of interest in physics [4,6–8] because they capture two basic ingredients of many physical systems: (1) they evolve according to a local uniform rule. (2) CA can exhibit rich behavior even with very simple update rules. For similar and other reasons, CA have also attracted attention in computer science [9,10], biology [11], material science [12], and other fields. In early work [1–3,13], Wolfram proposed that CA can be grouped into four classes of complexity. Class 1 consists of CA whose dynamics reaches a steady state regardless of the initial conditions. Class 2 consists of CA whose long time evolution produces periodic or nested structures. CA from both of these classes are simple in the sense that their long time evolution can be deduced from running the system a small number of time steps. On the other hand, classes 3 and 4 consist of “complex” CA. Class 3 CA produce structures that seem random. Class 4 CA produce a mixture of random structures and periodic behavior. For a review on CA classification see Refs. [3,4,9]. There is no generally agreed upon algorithm for classifying a given CA. The assignment of CA to these four classes is somewhat subjective and, we will argue, may need to be refined. Based on numerical experiments, Wolfram hypothesized [1,3,13] that most CA from classes 3 and 4 are CIR.

There is no unique way to define coarse graining, but here we will mean that our information about the CA is locally coarse grained in the sense of being stroboscopic in time, but that nearby cells are grouped into a supercell according to some specified rule (as is frequently done in statistical physics). A system which can be coarse grained is compactable since it is possible to calculate its future time evolution (or some coarse aspects of it) using a more compact algorithm than its native description. Note that our use of the term compactable refers to the phase space reduction associated with coarse graining and is agnostic as to whether or not the coarse-grained system is reducible or irreducible. Accordingly, we define predictable to mean that a system is computationally reducible or has a computationally reducible coarse graining. Thus, it is possible to calculate the future time evolution of a predictable system (or some coarse aspects of it) using...
an algorithm which is more compact than both the native
and coarse-grained descriptions.

In order to quantify the implications of looking at
coarse-grained information only, we have systematically
attempted to coarse grain the 256 nearest neighbor
one-dimensional binary CA that were the subject of
Wolfram’s investigations [3,6]. The outcome, described
in detail below, is surprising: we found that many CA can
be coarse grained and that in some cases CIR CA are
coarse grained by computationally reducible ones. In
other words, even though microscopically a given system
might be CIR, its coarse-grained dynamics can be com-
 pactable and predictable.

We start by defining a simple procedure for coarse
graining a CA. Other constructions are undoubtedly pos-
sible. For simplicity we limit our treatment to one-
dimensional systems with nearest neighbor interactions.
Generalizations to higher dimensions and different inter-
action radii are straightforward. Let \( A = (a(t), S_A, f_A) \) be
a cellular automaton defined on an array of cells \( a(t) = \{a_n(t)\}_{n=-\infty}^{\infty} \). Each cell accepts an alphabet of \( S_A \) symbols,
\( a_n(t) \in \{0 \cdots |S_A - 1| \} \). The values of the cells
evolve in time according to the update rule \( a_n(t+1) = f_A(a_{n-1}(t), a_n(t), a_{n+1}(t)) \), where \( f_A : \{S_A\}^3 \rightarrow \{S_A\} \) is
the transition function. The update rule is applied simulta-
neously to all the cells and we denote this application by
\( a(t+1) = f_A(a(t)) \).

Our goal is to find a modified CA \( B = (b(t), S_B, f_B) \) and
an irreversible coarse-graining function \( b = C(a) \), which
are capable of a coarse-grained emulation of \( A \). For every
initial condition \( a(0) \), \( B \) and \( C \) must satisfy

\[
C(f_A^{T_n}a(0)) = f_B C(a(0)).
\]

Namely, running the original CA for \( T \) time steps and
then coarse graining is equivalent to coarse graining
the initial condition and then running the modified CA \( T \)
time steps. The constant \( T \) is a time scale associated with
the coarse graining.

To search for explicit coarse-graining rules, we define
the \( N \)th block version \( A^N = (a^N, S_A^N, f_A^N) \) of \( A \). \( S_A^N \) =
\( \{S_A\}^N \) and each cell in \( A^N \) represents a block of \( N \) cells in
\( A \). Cell values are translated between \( A \) and \( A^N \) according
to the base \( S_A \) value of \( N \) cells in \( A \). The transition
function \( f_A^N : \{S_A^N\}^3 \rightarrow \{S_A^N\} \) is computed by running \( A \)
for \( N \) time steps on all possible initial conditions of
length \( 3N \). In this way \( A^N \) computes in one time step \( N \)
time steps of \( A \). Note that \( A^N \) is not a coarse graining of \( A \)
because no information was lost in the cell translation.

Next we attempt to generate the coarse CA \( B \) by
projecting the alphabet of \( A^N \) on a subset of \( \{0 \cdots |S_A - 1| \} \). This is the key step where information is being lost,
a manipulation which distinguishes between coarse-
graining and emulation blocking transformations [3,4].
The transition function \( f_B \) is constructed from \( f_A^N \) by
projecting its arguments and outcome:

\[
f_B[\bar{x}_1, \bar{x}_2, \bar{x}_3] = f_A^N[\bar{x}_1, \bar{x}_2, \bar{x}_3],
\]

Here \( \bar{x} = P(x) \) denotes the projection operation. This
construction is possible only if

\[
f_A^N[\bar{x}_1, \bar{x}_2, \bar{x}_3] = f_A^N[\bar{y}_1, \bar{y}_2, \bar{y}_3], \quad \forall (x, y | \bar{x}_i = \bar{y}_i).
\]

Otherwise, \( f_B \) is multivalued and our coarse-graining
attempt fails for the specific choice of \( N \) and \( P \).

In cases where the above conditions are satisfied, the
resulting CA \( B \) is a coarse graining of \( A^N \) with a
time scale \( T = 1 \). For every step \( a_N^N(t+1) = f_A^N[a_{N-1}^N(t), a_N^N(t), a_{N+1}^N(t)] \) of \( A^N \), \( B \) makes the move

\[
b_n(t+1) = f_B[b_{n-1}(t), b_n(t), b_{n+1}(t)]
\]

\[
= f_A^N[a_{N-1}^N(t), a_N^N(t), a_{N+1}^N(t)] = a_N^N(t+1),
\]

where we have used Eq. (3) in the last step. \( B \) therefore
satisfies Eq. (1) with \( P \) as the coarse-graining function.
Since a single time step of \( A^N \) computes \( N \) time steps of \( A \),
\( B \) is also a coarse graining of \( A \) with a coarse-grained
time scale \( T = N \). The coarse-graining function \( C \) in this
case is composed of the translation from \( A \) to \( A^N \) followed
by the projection operator \( P \). Analogies of these operators
have been used in attempts to reduce the computational
complexity of certain stochastic partial differential equa-
tions [14,15]. Similar ideas have been used to calculate
critical exponents in probabilistic CA [16,17].

It is interesting to notice that the above coarse-graining
procedure can lose two very different types of dynamic
information. To see this, consider Eq. (3). This equation
can be satisfied in two ways. In the first case

\[
f_A^N[\bar{x}_1, \bar{x}_2, \bar{x}_3] = f_A^N[\bar{y}_1, \bar{y}_2, \bar{y}_3], \quad \forall (x, y | \bar{x}_i = \bar{y}_i),
\]

which necessarily leads to Eq. (3). \( f_A^N \) in this case is
insensitive to the projection of its arguments. The distinc-
tion between two variables which are identical under
projection is therefore irrelevant to the dynamics of \( A^N \)
and by construction to the long time dynamics of \( A \). By
eliminating irrelevant degrees of freedom (DOF), coarse
graining of this type removes information which is re-
dundant on the microscopic scale. The coarse CA in this
case accounts for all possible long time trajectories of the
original CA and the complexity classification of the two
CA is therefore the same.

In the second case Eq. (3) is satisfied even though
Eq. (5) is violated. Here the distinction between two
variables which are identical under projection is relevant
to the dynamics of \( A \). Replacing \( x \) by \( y \) in the initial
condition may give rise to a difference in the dynamics
of \( A \). Moreover, the difference can be (and in many
occasions is) unbounded in space and time. Coarse
graining in this case is possible because the difference
is constrained in the symbol space by the projection
operator. Namely, projection of all such different dynamics results in the same coarse-grained behavior. Note that the coarse CA in this case cannot account for all possible long time trajectories of the original one. It is therefore possible for the original and coarse CA to fall into different complexity classifications.

Coarse graining by elimination of relevant DOF removes information which is not redundant with respect to the original system. The information becomes redundant only when moving to the coarse scale. In fact, “redundant” becomes a subjective qualifier here since it depends on our choice of coarse description. In other words, it depends on what aspects of the microscopic dynamics we want the coarse CA to capture. In a sense, this is analogous to the subtleties encountered in constructing renormalization group transformations for the critical behavior of antiferromagnets [18,19].

We now give specific examples of coarse-graining CA. In the sequel, CA rules are numbered using Wolfram’s notation [3,6]. Figures 1(a) and 1(b) shows a coarse graining of rule 146 by rule 128. Rule 146 produces a complex, seemingly random behavior which falls into the class 3 malization group transformations for the critical behavior of antiferromagnets [18,19].

FIG. 1. Examples of coarse-graining transitions. (a) and (b) show coarse-graining rule 146 by rule 128. (a) shows results of running rule 146. The top line is the initial condition and time progress from top to bottom. (b) shows the results of running rule 128 with the coarse-grained initial condition from (a). (c) and (d) show coarse-graining rule 105 by rule 150. (c) shows rule 105 and (d) shows rule 150.

FIG. 2. Coarse-graining transitions within the family of 256 elementary CA. Only transitions with a cell block size $N = 2$, 3, and 4 are shown. An arrow indicates that the origin rules can be coarse grained by the target rules and may correspond to several choices of $N$ and $P$. As a second example we show a transition between rules with a comparable complexity. Figures 1(c) and 1(d) shows a coarse graining of rule 105 by rule 150. $N = 2$ in this example and $P(x) = 1$ only when $x = 0, 3$.

The coarse-graining procedure we described above is not constructive, but instead is a self-consistency condition on a putative coarse-graining rule with a specific block size $N$ and projection operator $P$. In many cases the coarse graining fails and one must try other choices of $N$ and $P$. Can all CA be coarse grained? If not, which CA can be coarse grained and which cannot?

To answer these questions we tried systematically to coarse grain Wolfram’s 256 elementary rules. We applied the coarse-graining procedure to each rule and scanned the $N, P$ space for valid solutions. In this way we were able to coarse grain 240 out of the 256 CA [20]. These 240 coarsenable rules include members of all four classes. Many elementary CA can be coarse grained by other elementary CA. Figure 2 shows a map of the coarse-graining transitions that we found within the family of elementary rules. Only coarse grainings with $N \leq 4$ are shown due to limited computing power. Other transitions may exist with larger $N$. We observe that rule complexity never increases along the map’s transitions, i.e., coarse graining introduces (at least here) partial order among CA rules.
As mentioned above, we were unable to coarse grain 16 elementary rules. 12 out of the 16 are the class 3 rules 30, 45, 106 and their symmetries. The other four are the class 2 rule 154 and its symmetries. We do not know if our inability to coarse grain these 16 rules comes from limited computing power or from something deeper.

Coarse-graining transitions can also exit the elementary CA family. This happens whenever the alphabet of the coarse CA consists of more than two symbols. One such example which is of special importance is rule 110. Rule 110 is interesting because this class 4 CA is universal [3] in the Turing sense [21] and is therefore CIR [13]. It is capable of emulating all computations done by other computing devices in general and CA in particular.

We found several ways to coarse grain rule 110. Using \( N = 6 \), it is possible to project the 64 possible states onto an alphabet of 63 symbols. A more impressive reduction in the alphabet size is obtained by going to larger values of \( N \). For \( N = 7, 8, 9, 10, 11 \) we found an alphabet reduction of \( 6/128, 22/256, 67/512, 181/1024 \), and \( 463/2048 \), respectively. We expect this behavior to persist for larger values of \( N \).

Another interesting coarse graining of rule 110 that we found is the transition to rule 0. Rule 0 has the trivial dynamics where all initial states evolve to the null configuration in a single time step. The transition to rule 0 is possible because the cell combination “01010” is not generated by rule 110 and can appear only in the initial state. Coarse graining by rule 0 is achieved using \( N = 5 \) and projecting “01010” to 1 and all other five cell combinations to 0. This example is important because it shows that even though rule 110 is CIR it has a predictable coarse-grained dynamics (however trivial). To our knowledge rule 110 is the only proven CIR elementary CA and therefore this is the only example of irreducible to reducible transition between elementary rules that we found.

We did find other complex, potentially CIR rules that can be coarse grained by reducible CA. Rules 18, 54, 126 and their symmetries are coarse grained by rule 0. As we showed above, rule 146 and its symmetries can be coarse grained by rule 128 in a nontrivial way. We do not know if these rules are CIR for lack of proof. Nevertheless, nontrivial irreducible to reducible transitions can in principle exist. Consider, for example, the CIR CA generated by the product of rules 110 and 128. Let the CA alphabet be \( \{a, b\} \times \{0, 1\} \), where the letters evolve according to rule 110 and the digits according to 128. We can recover the reducible, coarse-grainable rule 128 by projecting the alphabet onto \( \{0, 1\} \).

The fact that CIR rules can be coarse grained and that they have predictable coarse-grained dynamics shows that CIR is not a good measure of physical complexity. As in the case of rule 110, a CIR system may still yield an efficient predictable theory, provided that we are willing to ask coarse-grained questions. It seems that a better classification of physical complexity is related to what classes of projection operator are required to coarse grain the system: local, real space projections, or more complex nongeometric projections?

In summary, we have found that many CA, including CIR ones can be locally coarse grained in space and time. In some cases CIR systems are predictable, if coarse-grained information only is required.

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[7] Physica (Amsterdam) D issues No. 10 and No. 45 are devoted to CA.
[20] For a given \( N \) we often found several possible \( P \)'s, capturing different coarse-grained aspects of the origin CA.