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Who Plays Complex Music? 
On the Correlations Between Structural and Behavioral Complexity Measures in Sign Boolean Networks

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Abstract—Intuition tells us that highly complex structure should be strongly correlated with highly complex behavior. In this work, we show that, while complex behavior does require complex structure, the converse is not necessarily true. Indeed, structural complexity can be also used to implement robust behavior, or even a variety of different relatively simple behaviors. To obtain these results, we explored the spaces of sign Boolean networks (SBNs) containing 2, 3, and 4 nodes, and we used complexity measures introduced in our previous work to study the relationship between structural and behavioral complexities of these networks.

I. INTRODUCTION

When one observes a mechanical or an electronic device, or even a natural system that we consider complex, common sense suggests its function or behavior should be too. However this is not necessarily always the case. Complexity can also support robustness, or it can be allocated to obtaining multiple behaviors. Error correction, spatial probes and rovers, protein folding, gene regulatory networks, all need robustness, often based on redundancy but also on the re-usability of some functional parts [1]–[4]. Finally, a complex structure can carry out multiple different functions, neither of which is particularly complex nor robust. One wonders whether the unstructured protein p53 can be seen as an example of such a structure, since it may function as a relatively simple switch for multiple cellular processes [5], [6].

To properly consider the relation between the complexity of the structure of a system and its behavior, we rely on Sign Boolean Networks or SBNs. Boolean networks can be used to represent gene regulation, but can also be viewed as good abstraction of any system of interconnected entities whose states can actually be classified into “on” and “off” groups [7]–[11]. In this context, the behaviour of the modelled system can be reasonably associated with the entire asymptotic dynamics (attractors) of the Boolean network, or a part of it, i.e. limited to the dynamics of only few entities. Various aspects of dynamics can be precisely defined and measured for Boolean networks, such as the number of attractors—which may correspond in biological interaction systems to multiple behaviors, the average size of the basins of attraction—which can be viewed as a source of robustness, or the average complexity of the attractors themselves. SBNs are a particular class of Boolean networks, in which every node is a 0-threshold function, called signed Boolean function (SBF): the new state of an SBF is computed by comparing the weighted sum of its inputs to 0. This particularly homogeneous structure is very useful for formal analysis, as it allows for computing a natural measure of structural complexity by combining the individual complexities of the participating SBFs, capturing the local functionality, with the global complexity of their interactions, or the layout of the network. For a detailed discussion on the methodology for computing BN dynamics and the structural and dynamic complexity of SBNs we refer to [12]–[15].

In this paper, we consider the relationship between the structure and the behavior of SBNs. More precisely, we focus on the connection between the local (related to the SBFs themselves) and global (related to the connections between SBFs) structural complexities of SBNs and their number of attractors (i.e. multiplicity of behaviors), the average size of the basins of attraction (i.e. robustness), as well as the average complexity of the attractors (i.e. complexity of behaviors). Our goal is to investigate how these 3 observables of the dynamics are correlated with the structural complexity, e.g. to evaluate whether the most complex behaviors are observed in the most structurally complex SBNs. Considering the influence of structural complexity on various aspects of dynamic complexity helps understand the organisation of complex systems, of which the living organisms are a typical example. Intuitively, one would consider that structurally complex parts of an organism implement complex behaviors. In this work we suggest that this intuition may not always correspond to reality, as high structural complexity may also give rise to simpler but very robust behavior, or to multiple different behaviors, as illustrated in Figure 1. Furthermore, local complexity of individual SBFs and the global complexity of the layout of the SBN may have unequal contributions to the behavioral complexity.
**II. METHODOLOGY**

We computed the structural complexity of all sign Boolean networks (SBNs) of a given dimension \(d\) (60 SBNs for \(d = 2\), 31065 SBNs for \(d = 3\), and about \(3.6 \times 10^9\) for \(d = 4\)) by combining the local complexities of the individual SBFs with the global complexity of the network structure. In [13], we thought the local complexity of an SBF as related to its rarity—the inverse of the probability of randomly picking the \(d\) particular SBFs that compose the SBN according to a uniform probability distribution, and the global complexity of the layout as a centralization index, aggregating the centralities of the nodes of the SBN—the probabilities that they influence each other. For each of these networks, we also computed the complexity of their behaviors, according to the following reasoning.

SBNs feature a deterministic evolution, necessarily ending up in a cyclic attractor or in a stable state. Therefore, the significant part of the dynamics is described by the sequence of states corresponding to a period of the attractor. In addition, some nodes may be designated as observers, and the dynamics of the non-observer nodes may be discarded. In our work, we say that a binary sequence \(s \in \{0, 1\}^*\) is a behavior of an SBN if this binary sequence is generated by at least one node during exactly one period of the cyclic attractor. We sometimes refer to a behavior of an SBN as a music it plays, since Boolean networks seem to play repeated binary musics. Observing the music played by only a subset of nodes makes a lot of sense biologically speaking, because only a subset of variables defining an observed living system is generally accessible.

Since the behaviors we consider in our work are at most of length \(2^4\), we use the Coding Theorem Method (CTM) in conjunction with the Block Decomposition Method (BDM), both described in [16], to compute their complexities. CTM essentially consists in enumerating all small Turing machines and counting how many of them produce the given binary sequence. BDM consists in splitting a longer sequence into blocks, computing the complexity of every block using CTM,
and then aggregating individual block complexities to obtain
the complexity of the entire string. The combination of BDM
with CTM was shown to approximate well the Kolmogorov
complexity of the string.
For more details, we refer the reader to our previous
works [13]–[15].

III. RESULTS

We exhaustively explored the space of 2-, 3-, and 4-
node networks (\(d \in \{2, 3, 4\}\)) and measured their structural
complexity indices—average node centrality, average SBF
rarity, as well as behavioral complexity indices—the number
of attractors, average size of the basins of attraction, the
complexity of the exhibited behaviors. We also complemented
the structural complexity indices with the average number
of inputs of the SBFs (arity). We explored the spaces of 2- and 3-
node networks exhaustively, and the space of 4-node networks
by sampling every 100th equivalence class. Figure 2 shows a
number of 2D-histograms relating structural and behavioral
complexities of 3-node networks (\(d = 3\)). The appendix also
includes the histograms relating the same parameters for 4-
node networks (\(d = 4\)).

Figure 2 (A) shows that networks covering the entire
spectrum of centralities may generate simple behaviors. In fact,
there are more than \(10^3\) 3-node networks with centrality index
equal to 1, but whose behavior is very simple. On the other
hand, the higher the complexity of the behavior, the higher the
centrality needs to be. In particular, the majority of complex
behaviors (complexity > 250) are generated by networks with
centrality index equal to 1.

One remarks in Figure 2 (A) that networks of high centrality
tend to employ SBFs of lower rarity. Figure 2 (B) zooms in on
the relation between arity, rarity, and centrality. It follows from
this plot that rarer SBFs tend to have lower arity, and therefore
belong to SBNs of lower centrality. On the other hand, high-
centrality networks are moderately to highly frequent, and tend
to have higher average arity.

Figures 2 (C) and (D) both illustrate the strong connection
between the number of attractors of a network and the average
size of their basins of attraction. Indeed, since the size of the
state space is fixed (\(2^3 = 8\) states for 3-node networks), larger
basins of attraction imply fewer attractors. The distribution of
SBF rarity and SBN centrality in these plots is in accordance
with plot (B): more attractors with smaller basins of attraction
tend to employ rarer functions in networks of lower centrality,
while the largest basins of attraction employ moderately rare
functions in high centrality networks.

Figures 2 (E) and (F) focus on the connection between
the average number of attractors and behavioral complexity.
It follows that higher complexity requires fewer attractors,
and numerous attractors tend to produce simpler behavior on
average. Remarkably, however, there exist networks with 3
attractors which produce behaviors as complex as those of
some of the networks with 2 attractors. Average SBF rarity and
SBN centrality is distributed in these graphs as expected from
the previous histograms. In particular, attractors producing the
most complex behavior employ SBFs of moderate rarity, but
of high SBN centrality.

Figures 2 (G) and (H) complement the previous pair of plots
by highlighting the connection between the average size of
the basins of attraction and behavioral complexity. It turns
out that highly complex behavior is generally produced by
SBNs having attractors with larger basins, employing functions
of moderate rarity, but having quite high SBN centrality.
In fact, even moderately complex behaviors (of complexity
approaching 50 from below) tend to require high centrality,
while the arity of the SBFs involved in producing such
behaviors covers almost the whole spectrum. We recall that,
formally, the states of the attractor are part of the basin of
attraction; attractors associated with complex behavior may
occupy most of their respective basins of attraction. However,
it is also noticeable that some SBNs including rare SBFs (i.e.
with low arity), although having a low centrality, may display
quite important complex behaviors, for example those that
are shown in Figures 2 (G) and (H), and have a behavior
complexity of 80 and 4 states in their basin of attraction.

Finally, we explicitly remark that most of the values ap-
pearing in these histograms are average: SBF rarities, arities,
and centralities, as well as the sizes of the attractors and their
basins of attraction. This is why all figures include violin plots
showing the distribution of means and standard deviations of
the measures defining the colors. For example, in Figure 2, the
SBNs have average SBF rarity around 0.9, with low variation.
On the other hand, SBNs having large variations of SBF rarity
tend to employ relatively unrare SBFs, and are rather few.
The violin plot in (B) shows that the variations of centralities
in lower-centrality SBNs can be quite noticeable, while at the
same time, in higher-centrality SBNs all nodes tend to
have rather high centrality. In plots (C), (E), and (G), most
SBNs tend to employ functions with rarity around 0.8, with
negligible variations, except for SBNs containing lower-rarity
SBFs. The spectrum of centralities is on the other hand richer
in plots (D), (F), and (H). However, and in a remarkably
similar way to rarity, when SBNs already contain some SBFs
with high arity most of the SBN nodes tend to be of high arity
too.

IV. CORRELATIONS BETWEEN STRUCTURAL AND
BEHAVIORAL COMPLEXITY

The numerical data we present in the previous section give
a rather detailed picture of the connections between different
indices of structural and behavioral complexity. In particu-
lar, they show that while complex structure does sometimes
correlate with complex behavior, it is quite more frequent for
structural complexity to be invested into larger basins of attrac-
tion (higher robustness) or into more attractors (multiplicity
of behaviors). In this work we do not bring forward definitive
conclusions concerning the relationship between the structure
and the function of the networks, but the numerical data and
the observations we presented here lay down future research
directions which will make this relationship clearer and more
Fig. 2. Parameters of structural and behavioral complexities for $d = 3$. These histograms illustrate the connections between the structural complexities—centrality, rarity, and arity—and the number of attractors, the size of the basins of attraction, and the complexity of the behaviors, for all 3-node networks. Average values are shown. Each histogram is accompanied by a violin plot giving the distribution of the mean and the standard deviation of the corresponding measure. (A) shows that most networks produce simple behaviors, even the most structurally complex ones. (B) illustrates the relationship between rarity, arity, and centrality. (C) and (D) indicate that the number of attractors and the sizes of their basins of attraction are inversely related, and also show distributions of centrality and rarity. Finally, (E) and (F) show how rarity and centrality are connected to the number of attractors and the behavioral complexity, while (G) and (H) illustrate the relation with the size of the basins of attraction.
usable in the study of living systems. As an important example, it would be relevant to identify structural patterns leading specifically to high behavioral complexity, multiplicity of behaviors, and high robustness.

While the strategy of exhaustive exploration of the SBN space allows for making comprehensive observations, it is not necessarily representative of the networks which appear in concrete biological systems. For example, a gene in a regulatory network is typically influenced by a small number (< 10) of other genes (e.g. [17]), while neurons in neural networks tend to integrate many more inputs (often tens to hundreds, or even thousands in the case of Purkinje cells, e. g. [18]). Therefore, subspaces of the SBN space should instead be considered, based on the observed organisation of the systems of interest. In these subspaces, structural and behavioural complexity may be correlated differently, and new specific connections may emerge.

In this work, we focus on a particular set of structural and behavioral complexity measures, which are well suited for generic SBNs. Different new complexity measures may be introduced to capture the particularities of classes of SBNs sharing some properties with real-life networks. In fact, these measures should be stated explicitly as part of the modelling framework, and should be targeted towards a specific objective, as complexity is always a formal representation of a part of a question or problem.

Our observations have a number of methodological implications. One typically studies a complex living system part by part, trying to tackle its inherent complexity by identifying modules. Our work confirms the intuition that this approach is not always viable: Figures 2 (F) and (H) show for example that many behaviors, even the simplest ones, may be implemented in networks with high average node centrality. Finding modules in such structures may be hard or even impossible, as all nodes may contribute in some ways to all exhibited behaviours.

In fact, in many modelling scenarios, the actual structure is hard to identify correctly due to the complex interplay of different factors in the production of the behavior of interest. In these cases, one typically designs an ersatz structure, which is meant to represent the partially unknown mechanisms at a high level of abstraction. This is often the case with Boolean approaches, in which the structure of the network is derived from the observed time series (e. g., [17]). A finer-grained understanding of how structural complexity distributes into various aspects of behavioral complexity for the modelled networks may therefore help design better models.

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Fig. 3. Parameters of structural and behavioral complexities for $d = 4$. As in Figure 2 in the main text of the paper, these histograms illustrate the connections between the structural complexities—centrality, rarity, and arity—and the number of attractors, the size of the basins of attraction, and the complexity of the behaviors, for all 4-node networks. Average values are shown. Each histogram is accompanied by a violin plot giving the distribution of the mean and the standard deviation of the corresponding measure.