Identity and its Robustness According to Second Person Descriptions

Taichi Haruna [a,*], Yukio-Pegio Gunji [a,b]

[a] Graduate School of Science & Technology, Kobe University, Nada, Kobe, 657-8501, JAPAN

[b] Department of Earth & Planetary Sciences, Faculty of Science, Kobe University

*Corresponding author. Tel.: +81 78 803 5759; fax: +81 78 803 5759.

E-mail address: cheetha@kcc.zaq.ne.jp (T. Haruna).

Abstract

Identity expressed in terms of second person descriptions is addressed in relation to robustness, and a simple computational model is proposed for preserving identity. Robustness is enhanced in the model by means of computational rules for chaotic cellular automata. The robustness enhancement mechanism is explained qualitatively.

keywords: identity, robustness, context, second person

PACS codes: 87.10.+e, 87.15.Aa

1 Introduction

In recent years, the notion of robustness has been considered as an alternative concept going beyond that of stability in complex systems research. In particular, Jen summarizes the aspects of robustness in common with, and differing from stability [1]. Robustness, in common with stability is "defined for specified features of a given system, with specified perturbations being applied to the system" and is "concerned with the persistence, or lack thereof". On the other hand, robustness differs from stability in that it includes "interplay between organization and dynamics", "costs and benefits of robustness", "notions of function, creativity, intentionality, and identity" and so on. These concepts are traditionally considered outside the scope of stability theory. Of these concepts, the subject of this paper is the notion of identity in relation to its robustness.

Let us consider the robustness of the identity Volkswagen 'Bug' (a nick name referring to a type of a car) [1], and suppose that design changes to the 'Bug' constitute a specific perturbation. The company itself has never called the car a 'Bug'. The official name of the car is 'Type 1', and only the general public uses the name 'Bug'. The identity 'Bug' is sustained by these people's act of calling the car a 'Bug'. Now the question relating to robustness is that if the design of the 'Bug' is changed, do people stop calling it a 'Bug'? (This question is purely academic since the production of the 'Bug' was stopped in 2003.)

Identity can be defined for at least two spatially or temporally different entities or events. In the above example, the identity relates to the type of car before a design change, and the type after that the change. The criterion reflecting whether they are the same is the use of the name 'Bug'. But who determines this criterion? The answer is of course that we do so ourselves, as external observers. As external observers we distinguish the identity of the car type according to whether people keep calling it a 'Bug'. A person may call the car a 'Bug' as their heart dictates. The act of *calling* has its own context. This is in principle irrelevant to any external observer's definition of identity. The confirmation of the identity by external observers is always post-hoc.

The identity 'Bug' is constructed in a bottom-up manner. In principle, the identity of any object can be seen as a product of bottom-up construction [2]. This is the second person description of an object. The robustness of an identity can only be addressed if it is described in the second person. In this paper we demonstrate how to address the robustness of an identity according to a second person description by a computational model. In particular, we are concerned with the identity of a bit sequence following rules for cellular automata.

Cellular automata modeling is one of the simplest multi-agent systems modeling natural phenomena. Each cell computes its state based on information from its local neighborhood. At the same time however, a single rule for computing the states of all cells is assumed by an external observer. This characteristic of cellular automata is appropriate for our purpose, since it attempts to clarify the relationship between an external observer's definition of the identity of a system and global patterns generated by the actions of local agents.

Any description of a natural phenomenon consists of both nomothetic parts and idiographic parts [3]. Nomothetic parts are laws governing the phenomenon. Idiographic parts are its initial and boundary conditions (or more generally, contexts). The former is emphasized more than the latter in existing scientific work. Such existing work is aimed at providing third person descriptions of nature. The history of science proves that these descriptions are very useful for the prediction, control or modification of nature. However, faced with the complexity of the world, trying to understand how such complexity can be recognized in terms of robust unities involves first investigating the mutual relationships between nomothetic and idiographic aspects. Any natural law works effectively only if some concrete context is specified in which it is applicable. Contexts constrain the application of natural laws. The complexities found in nature include considerable interplay between laws and contexts. Second person descriptions which emphasize context should thus be adopted primarily. The robustness of the identity of a complex system is a unique problem under this approach.

This paper is organized as follows. In Section 2 we discuss identity in terms of person. In particular, we compare the notion of identity under a second person description with that under a third person description. In Section 3 we propose a computational model of the identity preservation process based on second person descriptions. In Section 4 we describe our results regarding the responses of the proposed model to perturbations. In Section 5 we present a mechanism for enhancing robustness under the proposed model. Finally, concluding remarks are stated in Section 6.

2 Identity under Second Person and Third Person Descriptions

What is the difference between second person descriptions and third person descriptions? We regard it as the relationship between meaning and context [2]. With third person descriptions, there is only one context determining the meaning of each object in a system. The meaning of an object is determined according to a context provided by an external observer. The identity of a system is thus guaranteed by an external observer who describes the system as a single entity (Figure 1(a)). The robustness of a system's identity therefore cannot be addressed, in the sense that the identity of a system does not exist within the system itself. Note that the identity of a system must be defined by an external observer who gives a criterion for the identity, whether or not it is described in the third person.

With second person descriptions there is a local context associated with each object which determines the meaning of the object (Figure 1(b)). Both the meaning of an object and the context in which the meaning is determined are only defined locally and temporarily within a system. Meanings refer to how objects are interrelated under the contexts to which they belong. Contexts refer in general to initial and boundary conditions. They constrain how the laws of interaction governing a system work. In our cellular automata model below, contexts constrain how a cell reads it inputs. Under third person descriptions, interactions between objects occur under a single context specified by an external observer. Under second person descriptions however, each interaction between objects has its own unique local context. These interactions under local contexts generate a global pattern. External observers need only to see this pattern to distinguish identities. The identity of a system under a second person description must be perpetually maintained from within the system. Thus from an external observer's point of view, there must exist an identity preserving process. Under second person descriptions the robustness of the identity of a system may be addressed by focusing on the process preserving the identity.

As a simple example, let us consider the identity of a bit sequence. As a third person description, the identity of a bit sequence can be defined by Hamming distance. Given two bit sequences $s = \{s_n\}_{0 \leq n < N}, t = \{t_n\}_{0 \leq n < N}$, their Hamming distance is defined by

$$h(s,t) = \sum_{n=0}^{N-1} |s_n - t_n|$$

where $|a - b| = 0$ if $a = b$, and $|a - b| = 1$ otherwise. Since h is a metric, $s = t$ if and only if $h(s,t) = 0$. The identity of a bit sequence is provided by the Hamming distance that we, as external observers, define. This is the third person description of the identity of a bit sequence.

The notion of context does not explicitly appear in the third person description. By contrast, the notion of context must be introduced in the second person description since it is explicitly involved in the process for determining the value of a bit. Here we prepare a finite number of bit sequences $c^m = \{c_n^m\}_{0 \le n < N}$ $(m = 0, 1, 2, \cdots, M-1)$ as contexts. Given a bit sequence $s = \{s_n\}_{0 \le n < N}$, a context c^{m_n} is associated with each bit s_n of s. How should c^{m_n} be selected? Suppose that only the bits within a R-neighborhood of the n-th bit are relevant for the determination of the local context c^{m_n}. Since the identity of the bit sequence must be preserved insofar as possible from the perspective of the external observer, the difference between the third person description and the second person description must be as small as possible. c^{m_n} is thus defined as c^m which minimizes the *local Hamming distance*

$$h_{n,R}(c^m, s) = \sum_{i=n-R}^{n+R} |c_i^m - s_i|.$$

Since there are only a finite number of contexts we have $h_{n,R}(c^{m_n}, s) \neq 0$ in general. Hence $c_n^{m_n} \neq s_n$ can hold for some n. If s is transformed by some computational procedure such as the rules of cellular automata then the results of the computation for the third person description and the second person description may differ. If the number of contexts is one then the second person description is identical to the third person description. The third person description is a special second person description with a single context. Our computational model in the following sections can thus be seen as a generalization of standard cellular automata. In other words, it can be said that all usual cellular automata are based on a third person description.

In the next section we propose a computational model for the identity preservation process according to cellular automata rules.

3 A Computational Model Based on Second Person Descriptions

In this section we propose a formal model of the identity preservation process based on second person descriptions. For the sake of simplicity, we consider only rules for onedimensional cellular automata with nearest neighbor interactions. In order to construct a computational model that can be simulated on a personal computer, we make the following two assumptions. The first assumption is that there are a finite number of contexts for the determination of a cell's input. The second assumption is that a cell's context is determined by the local Hamming distance defined in the previous section. The procedure for the time evolution of the proposed model is based on the idea described in the previous section.

The details of the algorithm are as follows (Figure 2). Each cell has two radii. One is the *interaction radius* r for the rules of the cellular automata. In this paper we fix $r = 1$. The other is a *reference radius* R. This is used to determine a context for a given cell. The context of the i-th cell at time t is determined as follows. The bit sequence output by the previous computation is given. N contexts are prepared in advance, where N is finite and is an arbitrarily chosen positive integer. In the computer simulation below we fix $N = 20$. The initial condition is determined by a random bit sequence. Local Hamming distances around the i-th cell are employed for the pattern matching with respect to the reference radius. The context with the smallest local Hamming distance is chosen for the calculation of the state of the i-th cell in the next step. If there is more than one such context then one of them is chosen arbitrarily. The next state of i-th cell is obtained by applying a given rule to the i-th site of the chosen context. The new value for the i-th site of the chosen context is also obtained as an output of the computation. The values for the i-th sites of the other contexts remain unchanged.

In Figure 2, context 2 is chosen because it has the minimum local Hamming distance around the i-th cell. However, it is not equal to zero. The patterns around the i-th cell differ from context 2 for the given bit sequence. The input for the i-th cell is 101 for the given bit sequence. In context 2 however, it is 100. We describe such an input reading as *unusual*. If the input patterns for a given bit sequence and the chosen context are the same it is instead known as *usual*. Despite deterministic cellular automata rules, binary sequences are updated as if they were computed by stochastic rules, due to the unusual interpretation of the input. In the next section we will see how much they differ with respect to robustness.

4 Results

In this section we examine the robustness of the computation in the proposed model. We consider a computation according to rule 90 ($001, 011, 100, 110 \rightarrow 1$; otherwise 0). As is well known, the computation of rule 90 is unstable and not robust to small perturbations. This is usually demonstrated by calculating difference patterns (DP) [4]. A DP is the evolution of small perturbations to an initial arrangement. Since rule 90 has the following property, the perturbations propagate at the maximum velocity +1: if a_{i-1}^t or a_{i+1}^t is flipped then a_i^{t+1} is also flipped. Rule 90 was selected because of this simple mechanism for responding to perturbations. The results shown below all concern rule 90, although any class 3 or class 4 rule will behave in a similar way.

We show the results for the proposed model in Figure 3. 20 contexts were prepared for this case. The size of system is 150. The first 100 time steps are shown. For each reference radius R, the pictures on the left hand side show the time evolution of the bit sequence and the pictures on the right hand side show the evolution of the DP superimposed on the context. Cells in different contexts are colored differently, from yellow to black. DPs are given by randomly flipping 10 cells at the center at $t = 0$. The calculation of DPs is performed under the assumption that perturbations outside of the interaction radius are not relevant to the determination of context, *i.e.*, the context of a cell in the perturbed system is reviewed only if one of the states of the cells in its interaction neighborhood is different from the state of the corresponding cell in the unperturbed system. Otherwise, the context of a cell in the perturbed system is the same as that of the corresponding cell in the unperturbed system.

The patterns generated by the proposed model seem to be chaotic as is usual for rule 90. However, the propagation speed of perturbations varies according to R. For small or large R, fast propagation of initial perturbations occurs. The propagation speed is the slowest (Figure 4) when $R = 4$. At this point the robustness to initial perturbations is enhanced. For small R, cells perpetually change their contexts. For large R clusters of cells are generated with the same context. A few of them become dominant after a sufficiently long time. There is no difference from the usual rule 90 with respect to outputs in a cluster since each cell can read its input correctly. For an intermediate value of R like

$R = 4$, small size context clusters are perpetually generated and destroyed. The dynamics of such clusters may be related to the enhancement of robustness since the propagation of perturbations can only be interrupted at the cluster boundaries.

In the next section we explain the enhancement of robustness.

5 A Mechanism for the Enhancement of Robustness

The enhancement of robustness observed in the previous section can be understood as a balance between the invariance and variance of contexts. In this section we present a qualitative explanation using graphs.

Let β be the rate of context change when a cell contacts the front edge of a DP. In the practical calculation below, β is estimated from the frequency of context changes in cells that contact left or right edges of DPs during the first 100 time steps sampled over 200 trials. All the other quantities appearing below (δ, d_0, d_1 and s) are also based on the first 100 time steps of 200 trials. Let d_0 be the average displacement of a DP per unit time when the context remains the same at the front edge of the DP. The usual value for rule 90 is $+1$. Let d_1 be the average displacement of a DP per unit time when the context changes at the front edge. Let δ be the size of the DP after a time step τ. Then we have the trivial relationship

$$\delta = (1 - \beta)d_0\tau + \beta d_1\tau.$$

If the average growth rate of the DP s is constant, then $s = \delta/\tau$ for any sufficiently large τ. The following relationship may be obtained

$$s = (1 - \beta)d_0 + \beta d_1.$$

Figure 5 shows that this relationship holds for $\tau = 100$. s can be divided into a part with invariant context, $(1 - \beta)d_0$, and a part with varying context, βd_1.

$(1 - \beta)d_0$ is almost constant for $1 \le R \le 4$ (Figure 6(a)). For $R \ge 4$ it increases monotonically. βd_1 on the other hand, is monotonically decreasing until $R = 4$ (Figure 6(d)), and almost constant thereafter. This explains the minimum point in Figure 4(b) appearing at $R = 4$.

This may be further explained as follows. β is monotonically decreasing with respect to R (Figure 6(c)). High d_0 values for large R can be explained by the formation of large context clusters (Figure 6(b) and Figure 7(b)). High values of d_0 and d_1 for small R are on the other hand due to the high percentage of usual input readings (Figure 6(b), (e) and Figure 7(a)). The smaller the value of R, the easier the pattern matching. For large R, the percentage of usual input readings reduces when the future context differs from the current context of a cell (Figure 7(a)). This is because cells refer to many other cells that are irrelevant for input reading when they select their future context. This results in small or negative values of d_1 when R is large, since the flipping property of rule 90 is broken.

6 Concluding Remarks

In this paper we proposed a formal model of an identity preserving process based on second person descriptions. We presented a mechanism for enhancing robustness in the model, which seeks a balance between invariance and variance among contexts.

The measurement process is largely concerned with how context constrains the laws governing a system. The identification process discussed in this paper, while merely an example, is a measurement process that operates between cellular automata and an external observer. An external observer's identifications of the states of cells constrains how they read their inputs. Identity considered according to second person descriptions gives rise to a unique problem for the measurement process.

The identity considered in terms of a second person description can be seen as a kind of collective concept [5]. It glues fragmentary aspects of itself identified by local contexts. The foundations of this gluing process are described as quantum in [2] and material causes in [6]. The fragments to be glued may be mutually inconsistent. The notions of quantum and material causes provide a means for the dissolution of inconsistencies on one hand, but the dissolution process itself can generate new inconsistencies. We believe that such vague points of view can yield a new understanding of identity.

References

[1] E. Jen, Stable or robust? What's the difference? Complexity 8 (2003) 12-18.

[2] K. Matsuno, A. Nemoto, Quantum as a heat engine—the physics of intensities unique to the origins of life. Physics of Life Reviews 2 (2005) 227-250.

[3] S. Salthe, Evolving Hierarchical Systems. Columbia University Press, New York, 1985.

[4] S. Wolfram, Theory and Application of Cellular Automata. World Scientific, Singapore, 1986.

[5] R. Paton, Process, structure and context in relation to integrative biology. BioSystems 64 (2002) 63-72.

[6] Y.-P. Gunji, T. Haruna, K. Sawa, Principles of biological organization: Local–global negotiation based on "material cause". Physica D 219 (2006) 152-167.

Figure Captions

Figure 1. Images showing a third person description (a) and a second person description (b). In the third person description the meanings of the objects in the system are defined according to a context provided by an external observer. In the second person description a local context is associated with each object. Local contexts are glued together in order to provide an identity for the system.

Figure 2. The algorithm corresponding to the proposed model is shown schematically. The context of a cell is determined by a local pattern matching operation between the bit sequence and possible contexts.[[OK as edited?]] Each cell changes its state under the context chosen.

Figure 3. Results of computer simulation of the proposed model. For each R the picture on the left hand side shows the time evolving bit sequence pattern. A white cell indicates 0 and a black cell indicates 1. All of the results show chaotic patterns similar to the usual rule 90. In the pictures on the right hand side, the contexts to which cells belong are indicated by a gradation from yellow to black. DPs are superimposed on contexts and colored red.

Figure 4. (a) The average size of DP at each time step. The growth is linear for all values of R. (b) The growth rate of DPs, which is the slope of each line in (a). At $R = 4$ the growth rate of DPs is minimized.

Figure 5. Decomposition of the growth rate of DPs into two parts. One is the context invariant part ($(1-\beta)d_0$), and the other is the context varying part (βd_1).

Figure 6. Graphs of quantities $(1-\beta)d_0$, $1-\beta$, d_0, βd_1, β, and d_1 with respect to R are shown in (a), (b), (c), (d), (e) and (f), respectively. A qualitative explanation for the shapes of these graphs is given in the main text.

Figure 7. (a) The usual rate that inputs are read when the context of a cell remains unchanged (square) and when the context changes (circle). (b) Average cluster size, which is monotonically increasing with respect to R.

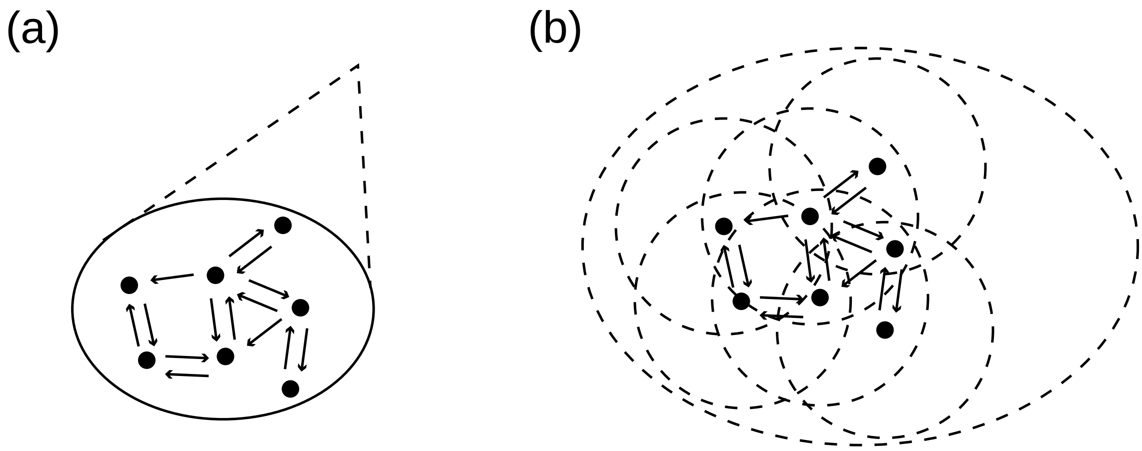

Figure 1.

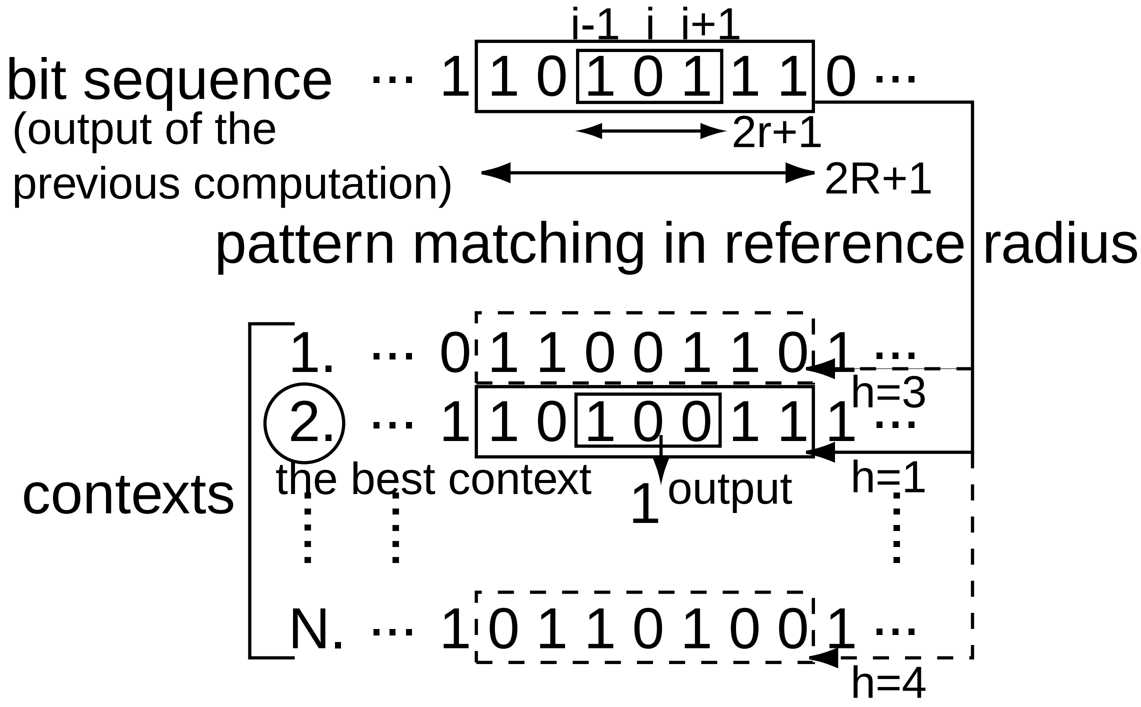
i-1 i i+1
bit sequence
(output of the
previous computation)
··· 1 1 0 1 0 1 1 1 0 ···
2r+1
2R+1
pattern matching in reference radius
contexts
1. ··· 0 1 1 0 0 1 1 0 1 ···
h=3
2. ··· 1 1 0 1 0 0 1 1 1 ···
h=1
the best context
1 output
N. ··· 1 0 1 1 0 1 0 0 1 ···
h=4

Figure 2.

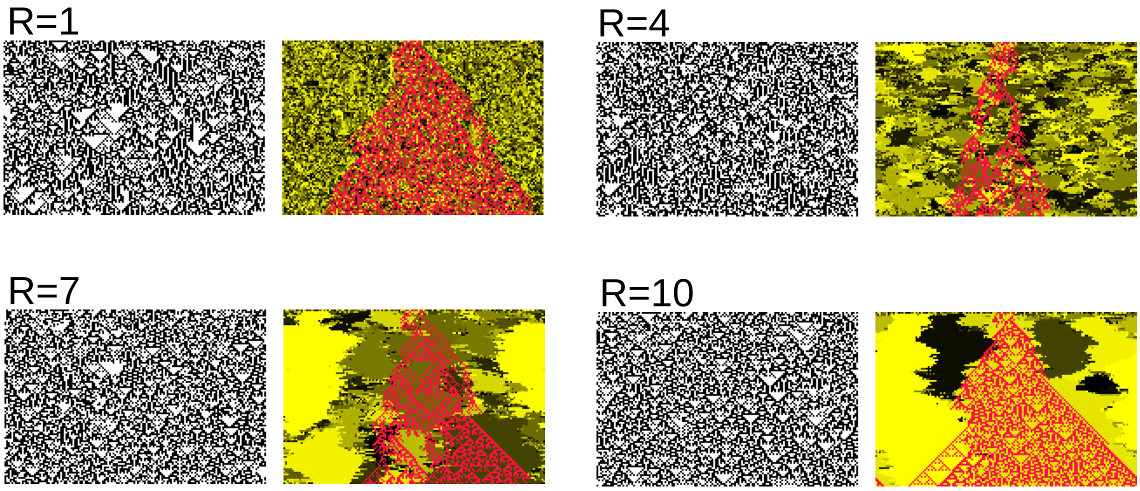

Figure 3.

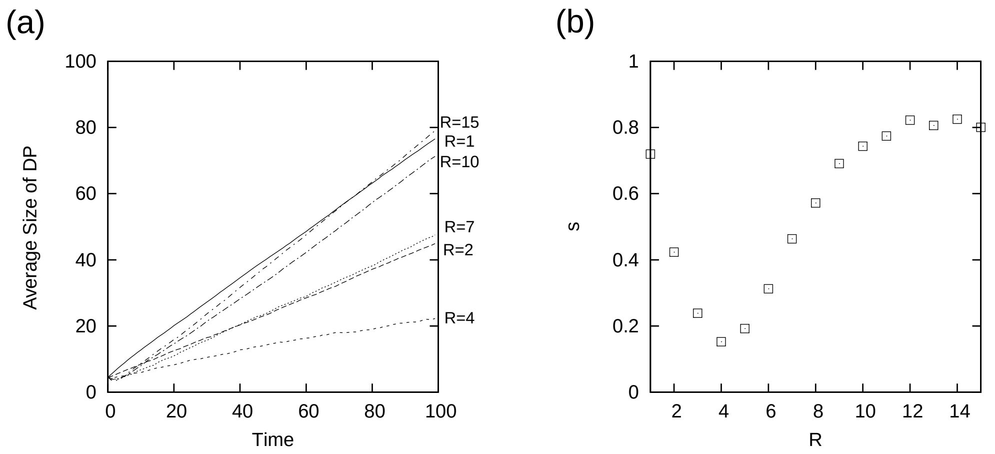

Figure 4.

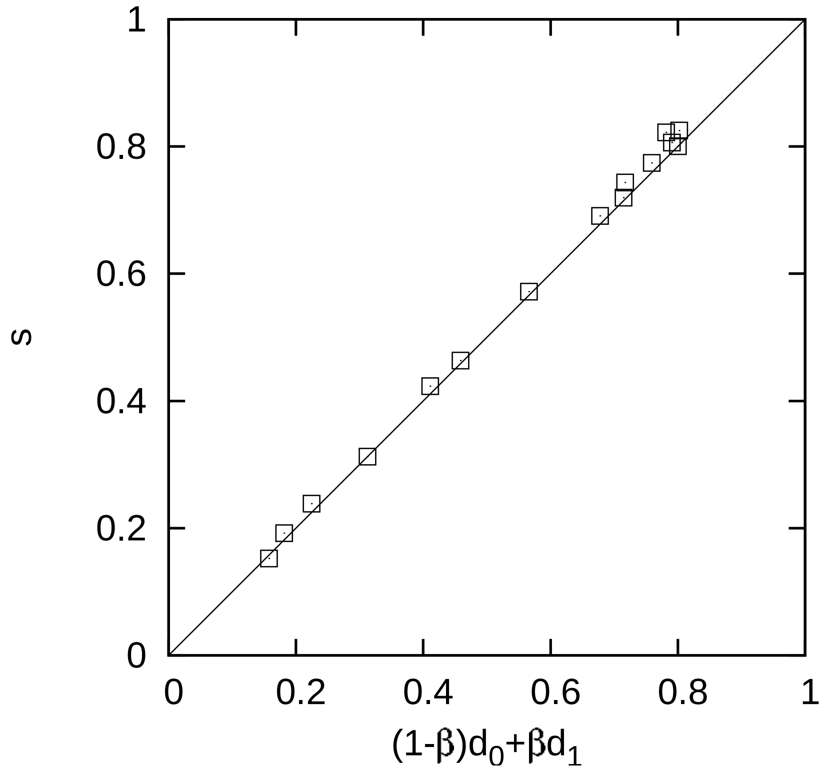

Figure 5.

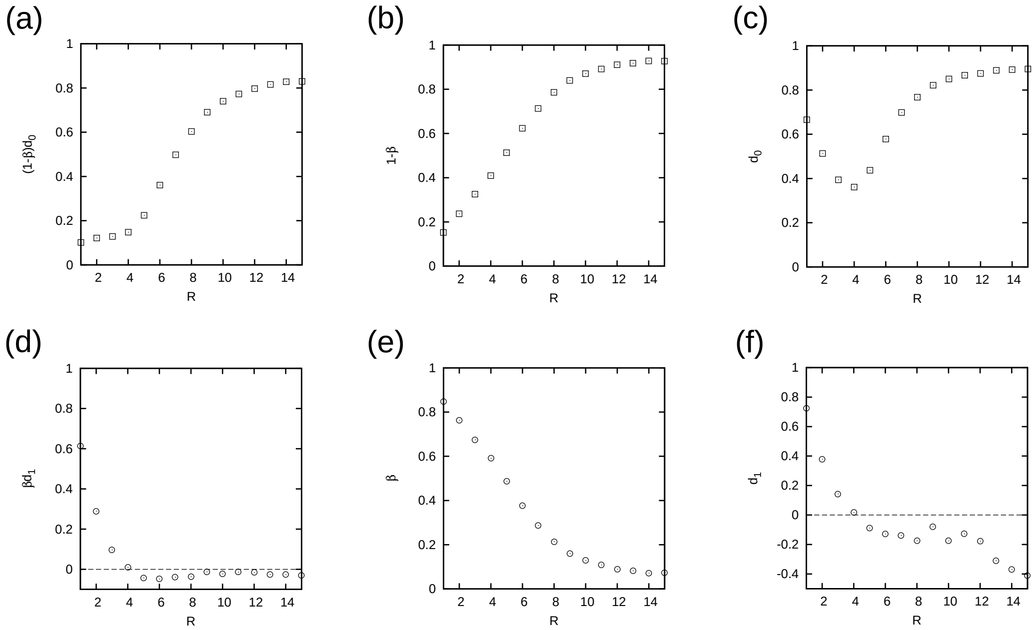

Figure 6.

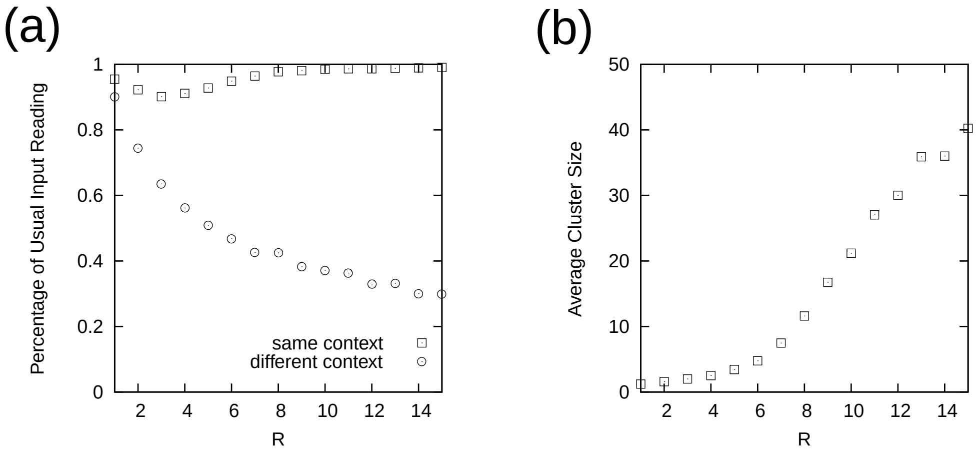
(a)
Percentage of Usual Input Reading
same context
different context
R
(b)
Average Cluster Size
R

Figure 7.