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Corticostriatal response selection in sentence production: Insights from neural network simulation with reservoir computing

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ABSTRACT

Language production requires selection of the appropriate sentence structure to accommodate the communication goal of the speaker – the transmission of a particular meaning. Here we consider event meanings, in terms of predicates and thematic roles, and we address the problem that a given event can be described from multiple perspectives, which poses a problem of response selection. We present a model of response selection in sentence production that is inspired by the primate corticostriatal system. The model is implemented in the context of reservoir computing where the reservoir – a recurrent neural network with fixed connections – corresponds to cortex, and the readout corresponds to the striatum. We demonstrate robust learning, and generalization properties of the model, and demonstrate its cross linguistic capabilities in English and Japanese. The results contribute to the argument that the corticostriatal system plays a role in response selection in language production, and to the stance that reservoir computing is a valid potential model of corticostriatal processing.

1. Introduction

The goal of the current research is to present a model of sentence production based on the function of the primate corticostriatal system, extending our previous work on corticostriatal function in sentence comprehension. We situate this work in the context of related models, and background on the neuropsychology of corticostriatal function in sentence production, both of which are relevant to our proposed model. The transmission of meaning by language is one of the marvels of human cognition. Sentence production and comprehension are complementary, but asymmetric. In comprehension, it is possible to correctly extract only part of the message – for example only the thematic role assignment (who did what to whom). In production, the speaker must generate a specific linear string of words which communicates the intended meaning that in addition to thematic roles should include some notion of focus or importance, and other dimensions including time, mode and aspect (Klein, 2013). These dimensions can be considered in the larger context of phrasal semantics – meaning that can be communicated by the grammatical structure of the sentence (Dominey, 2005; Jackendoff, 2002). Here, we can consider a representation of the meaning of an event and its thematic roles in a predicate-argument structure, along with some indication of whether the focus is on the agent, object, recipient, etc. Our meaning representation is in a predicate-argument format, originally developed in the domain of describing object manipulation actions, e.g. "The ball was given to Jean by Marie" (Dominey & Boucher, 2005). There we adopted a representation with the predicate, corresponding to the action, and the arguments corresponding to the agent, the manipulated object, and the recipient. This resulted in our use of the PAOR – or predicate, agent, object, recipient-representation. Thus, our notion of object in the PAOR notation corresponds to the classic thematic role of patient. Both of these components (thematic roles, and focus) should be encoded in the phrasal semantics of the sentence. In comprehension, the reception of this sentence should allow the listener to reconstruct the intended meaning – the thematic roles and the focus structure constituting the speakers' construed meaning.[1] Part of the richness of language expressivity is the varying ability across languages to use word order as a mechanism for specifying the communicative focus and other aspects of phrasal semantics within the sentence, in addition to communicating "who did what to whom."

[1] We note that in the more general case of discourse and dialog, once the processing has begun, there is significant context which specifies some of the intended meaning. This potentially reduces the difficulty of production and comprehension.

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Our model can be considered in the larger context of models of language production, with those that focus on aspects of the word level processes of semantic retrieval, word repetition, and word production Roelofs (2014), or that may be more concerned with accounting for higher level behavior including alignment between speakers at multiple levels (e.g. alignment of grammatical structures, and situation models of the joint task that dialog participants are working on) that takes place during dialog (Pickering & Garrod, 2013). We are concerned with the production of sentences, multiple word utterances, that may have some degree of complexity including the use of embedded relative clauses. Takac, Benuskova, and Knott (2012) have modeled sentence production as a form of mapping from sensorimotor sequences to word sequences. They did not address issues of multiple non-canonical orders, relative clauses etc. Chang (2002) modeled sentence production using a dual path model that has one pathway for mapping message content to words and a separate pathway that enforces sequencing constraints, i.e. word order, based on Elman's simple recurrent network (SRN) (Elman, 1990, 1991, 1993). This model employs recurrent connections that are modified by back propagation of error. In order to simplify the difficult problem of assigning error to recurrent connections, the problem is simplified, by only taking one recurrent pass through the network into account for the learning, hence the term "simple". This model has been quite influential in cognitive science, including studies of language, e.g. (Christiansen & Chater, 1999; Elman, 1993) and sequence learning e.g. (Cleeremans & McClelland, 1991; Jiménez, Méndez, & Cleeremans, 1996; Servan-Schreiber, Cleeremans, & McClelland, 1991). Chang also set out to account for cross-linguistic differences, and thus demonstrated that the dual path model could account for word-order effects in English and in Japanese. Chang (2009) demonstrated that when the prominence of the thematic roles is expressed as part of the meaning, the model can appropriately learn different forms (e.g. active and passive) in English, and accommodate word scrambling in Japanese. The model was able to handle 50 different constructions with analogous structure in English and Japanese. This included 3 simple constructions, 9 sentential conjunctions, 6 phrasal conjunctions, 32 structures with relative clauses. In order to address relative clauses in more detail, Fitz, Chang, and Christiansen (2011) exploited the extended dual path model to accommodate multiple clauses. The meaning representation included three components: thematic roles (AGENT, PATIENT, RECIPIENT, etc.), concepts (lexical semantics), and event features to signal the number and relative prominence of event participants. Dell and Chang (2014) have recently applied their model of prediction and prediction error processing in sentence production to understanding aspects of aphasic production. Part of the goal of such modeling indeed should be not only to posit mechanisms of linguistic function, but also to establish links between linguistic function and the underlying neurophysiology.

The current research proposes a biologically inspired neural network model, in the reservoir computing framework, that learns to produce sentences. The link between reservoir computing and corticostriatal neurophysiology can provide useful insight into understanding aspects of higher cognitive function in human and non-human primates. Barone and Joseph (1989) observed PFC activity in macaque monkeys trained to perform a visuomotor sequencing task. For the first time, they observed PFC neurons that encoded a mixture of spatial and sequential rank selectivity. We modeled PFC as a network of leaky integrator neurons with fixed recurrent inhibitory and excitatory connections, and corticostriatal connections modifiable based on reward-related dopamine (Dominey, Arbib, & Joseph, 1995). This was the first instantiation of reservoir computing. The key notion is that the intrinsic dynamics of the fixed-connection reservoir provide an inherent capacity to represent arbitrary sequential structure. PFC neurons in the model displayed the same mixture of spatial location and sequence rank as observed by Barone and Joseph. We further demonstrated that in this configuration, PFC encodes task context, and striatum encodes action selection, again as observed in the primate (Dominey & Boussaoud, 1997), thus supporting the analogy between reservoir–readout and cortex–striatum. More recently the claim that cortex corresponds to a reservoir (based on dense local recurrent connections) has been supported by anatomy and physiology, and modeling (Nikolic, Hausler, Singer, & Maass, 2009; Rigotti, Rubin, Wang, & Fusi, 2010; Rigotti et al., 2013).

In this context, we attempt to determine if this approach to modeling the corticostriatal system can be applied to sentence production. We are particularly interested in the problem of how different word orders can be used to describe the same event, but with different focus. As will be described in more detail below, given a mental model with two events, and three arguments each, there is a small combinatorial explosion of the different ways that this meaning can be expressed in a sentence in English. The explosion is even greater in Japanese where there are fewer restrictions on word order.

When faced with this level of possible degrees of freedom, sentence production can take on an aspect of motor planning, in that the sequence of words to be produced is specific for a particular communicative goal, like a motor sequence trajectory may be specific for a particular action goal. The framework that we use to address this problem is based on the sequence processing capabilities of the corticostriatal system which plays a central role in the sequential organization of behavior, and action sequence selection (Hikosaka, Nakamura, Sakai, & Nakahara, 2002). In order to appreciate the functional significance of the corticostriatal system, one should recall that all of the primary and associative cortices including the language areas project to the striatum – the input nucleus of the basal ganglia (Alexander, DeLong, & Strick, 1986; Yeterian & Pandya, 1998). The integrity of the corticostriatal system is thus likely required both for language comprehension and production (Argyropoulos, Tremblay, & Small, 2013; Friederici & Kotz, 2003; Friederici, Kotz, Werheid, Hein, & von Cramon, 2003; Frisch, Kotz, von Cramon, & Friederici, 2003; Hochstadt, 2009; Hochstadt, Nakano, Lieberman, & Friedman, 2006; Kotz, Frisch, von Cramon, & Friederici, 2003).

We have previously examined how the corticostriatal system could implement aspects of the mechanism that learns to interpret sentences in language (Dominey, 2001, 2013; Dominey, Hoen, Blanc, & Lelekov-Boissard, 2003; Dominey & Inui, 2009; Dominey, Inui, & Hoen, 2009) where language is considered a structured inventory of grammatical constructions mapping sentence form to meaning (Goldberg, 1995, 2003). The model was based on the hypothesis that thematic role assignment (determining who did what to whom) can be determined by the order and position of closed class elements (grammatical function words and grammatical morphemes) (Dominey, 2001; Dominey & Inui, 2009; Dominey et al., 2003, 2009; Hinaut & Dominey, 2013). In this family of models, the input to the recurrent network was the sequence of activation of neurons coding the closed class words as they appeared in the sentence. This drove the recurrent network into a specific trajectory for each different sentence type. Learning in connections between the recurrent reservoir nodes and the output neurons allowed the output neurons to correctly decode the thematic roles for the open class words for input sentences. In the current research we invert this process, that is, we provide the input as activation of neurons coding the meaning of the desired sentence. Meaning is coded as the ordered set of open class elements, and their corresponding thematic roles, that we together refer to as the focus hierarchy. This drives the recurrent network through a specific trajectory of activation. We train the output connections to activate word-coding units in the appropriate order to generate the corresponding sentence to express the input meaning.

This model of language processing thus places strong requirements on the function of the corticostriatal system. Indeed we have proposed the notion of a corticostriatal language loop (Dominey, 2013) that would take its place in the set of functional loops initially proposed by Alexander et al. (1986). This is based on several modeling studies that link corticostriatal function to language comprehension (Dominey & Inui, 2009; Dominey et al., 2009), including predicting results in EEG, fMRI and aphasia that were subsequently confirmed (Dominey & Hoen, 2006; Dominey, Hoen, & Inui, 2006; Dominey et al., 2003; Hoen, Pachot-Clouard, Segebarth, & Dominey, 2006).

Thus, this model would predict that deficits in the corticostriatal system would have repercussions in language production. There is significant evidence for the role of the corticostriatal system in language that is derived from studies of healthy subjects with fMRI and EEG (e.g. (Friederici & Kotz, 2003)), and from studies of pathology including Parkinson's disease (Friederici et al., 2003), Huntington's disease (Teichmann et al., 2005) and subcortical aphasia (e.g. (Moro et al., 2001). The principal core aspect of subcortical aphasia is impaired generative language production. While the ability to read a sentence out loud is generally intact, the ability to generate a sentence given a verb is severely impaired (Mega & Alexander, 1994). The role of the fronto-striatal system in language production is highlighted by these authors: "We propose that the severity of the language profile reflects the extent of damage to frontal-striatal systems." (Mega & Alexander, 1994, p. 1827). Damage to the paraventricular white matter can produce this core deficit, underlying the importance of the intact corticostriatal system.

Mega and Alexander situate this subcortical aphasia in a historical context. They note that Luria and Tsvetkova (1967) described what they called "dynamic aphasia" as an impairment in "subjective generative grammar" producing a disturbance in the "transition from the initial thought to the 'linear scheme of the phrase'." They further consider more recent analysis suggesting that the problem is actually a language deficit in automatic access to or recruitment of proceduralized syntactic systems necessary for sentence construction" (p. 1828) (Mega & Alexander, 1994). Such proceduralized systems could reflect an extension of the procedural system for grammatical rules attributed to the corticostriatal system by Ullman (Ullman, 2001a, 2001b, 2004; Ullman et al., 1997). The core profile of deficits in the generation of syntactically rich language, not just in speech generation, following lesions in the dorsolateral striatum or its frontal connections provides additional support for this view.

Multiple phenomena may intervene in these pathologies, and some authors have challenged the role of the basal ganglia in subcortical aphasia (Nadeau & Crosson, 1997). Recent data from brain imaging in healthy subjects examined caudate and putamen activation in different conditions including sentence generation and sentence repetition (Argyropoulos et al., 2013). Their findings support the idea that it is primarily the caudate that contributes selection processes in sentence generation vs. repetition. A recent review of language production in Parkinson's disease notes impaired grammaticality and reduced syntactic complexity among the recurrent deficits (Altmann & Troche, 2011). Modeling can contribute to this discussion related to the functional role of the corticostriatal system in sentence production.

Our modeling approach extends our model of corticostriatal function from sentence comprehension to sentence production, and is based on the hypothesis that the corticostriatal system can learn to select appropriate sentence forms for expressing meanings, based on learning from matched meaning-sentence pairs. From a brain and language perspective, this is useful, as it makes a clear hypothesis about the functional role of the corticostriatal system in sentence production, as a form of grammatical construction selection. The challenges we face are the following: The system should be capable of learning meaning-to-sentence mappings, with little language specific processing. This includes the ability to process relative clauses. The system should demonstrate cross-linguistic capabilities, and we will thus consider the learning of grammatical constructions in English and Japanese. The model should also address language production deficits in the presence of striatal damage as observed in patients with Parkinson's disease (Altmann & Troche, 2011) and in patients as observed by Mega and Alexander (1994) with deficits in the generation of syntactically rich language following lesions in the dorsolateral striatum or its frontal connections. An additional objective of this work is to demonstrate that without modification of the recurrent connection weights the recurrent network still provides a foundation for representing the transformation between meaning and sentence structure. This is of interest because of the contrast with all other recurrent network models of language production which focus on modification of the recurrent network itself. Here we will demonstrate that a recurrent network with fixed recurrent connections can generate appropriate dynamics that can be used to learn to produce sentences via modifiable readout connections, in the reservoir computing framework (Dominey, 1995; Dominey et al., 1995; Jaeger & Haas, 2004; Lukosevicius & Jaeger, 2009; Maass, Natschlager, & Markram, 2002). This is important with respect to characterizing the minimal requirements for language universality. It demonstrates that without modification, the recurrent network is inherently capable of representing the grammatical structure of language.

It is now known that one of the fundamental properties of such reservoirs – or recurrent networks with fixed connections – is that they project the inputs into a high dimensional space, in which a multitude of non-linear combinations of the inputs (and their serial and temporal order) are represented (Antonelo & Schrauwen, 2012; Hermans & Schrauwen, 2012; Jaeger & Haas, 2004; Manjunath & Jaeger, 2013). Arbitrary functions of these representations can then be learned and read-out from the output neurons that are connected to the recurrent network by modifiable connections. Interestingly, it has been observed that neural representations in the cerebral cortex have these high-dimensional reservoir properties (Nikolic et al., 2009; Rigotti et al., 2010, 2013). This research will then attempt to contribute to the argument that, even without learning within the recurrent connections, the existing high dimensional dynamics allow a re-coding of language structure into a space where regularities are represented, and can be learned in a linear readout.

How does this notion of fixed connections in the recurrent network apply to the question of cross-linguistic competence? Our reservoir-based model of sentence production should function for different languages with no changes to the reservoir concept. That is, while the reservoir operates with fixed connectivity, it is in the readouts that language-specific changes are made.

2. Functional requirements for language production

We thus return to the question of the meaning-to-sentence transformation. In this context we consider that there is a mental model of a situation – an internal representation that can be formed via multiple methods including perception, hearing or reading a description (Johnson-Laird, 1980, 2004; Johnson-Laird, 2010), and that based on diverse attentional and discourse effects, a particular construal of that mental model is generated. The construal takes a specific perspective on the mental model, and can then be expressed in the generated sentence (Warglien, Gärdenfors, & Westera, 2012).

Consider a relatively simple example where the mental model represents an action where John gives a ball to Mary. This can be expressed in at least the 6 following ways:

(1) John gave the ball to Mary. Give(John^1, Ball^2, Mary^3)
(2) John gave Mary the ball. Give(John^1, Ball^3, Mary^2)
(3) The ball was given to Mary by John. Give(John^3, Ball^1, Mary^2)
(4) The ball was given by John to Mary. Give(John^2, Ball^1, Mary^3)
(5) Mary was given the ball by John. Give(John^3, Ball^2, Mary^1)
(6) Mary was given by John the ball. Give(John^2, Ball^3, Mary^1)

In these six cases, we can observe that all possible orderings of the arguments agent, object and recipient can be accommodated, each by a specific grammatical form. Each of these forms allows a different specification of the focus. Typically one considers a single element of focus. Thus sentences 1, 3 and 5 respectively focus on the agent (John), object (ball) and recipient (Mary). But we can consider a hierarchy of focus, that completely specifies the ordered set of arguments, thus allowing the distinction between 1 and 6, respectively. This corresponds to an extension of the primary and secondary topic of Givón (2001). Topicality is a cognitive dimension at the level of information structure related to the focus of attention on one or two important events or state participants during processing of multi-participant clauses. Subject and DO of clauses may be viewed as grammaticalized primary and secondary topics (Givón, 2001). In another model of information structure, Steedman envisages two orthogonal dimensions: theme/rheme and focus/background. Theme is the topic and rheme is the comment the utterance makes about the topic, and each can contain focus and background information (Steedman, 2000).

Given the dialog and discourse context, a speaker may wish to exploit these additional degrees of freedom. We now consider a more elaborate example in which a teacher gives an award to a student who is congratulated by the school principal, which thus employs the use of relative clauses.

Mental model: Give(teacher, award, student), Congratulate (principal, student).

This is a potentially richer and more complex mental model that can be construed in a number of ways that grows in a combinatorial expansion with the number of elements in the model. Here we enumerate some ways of construing this situation. While some of these sentences are syntactically challenging (e.g. 11–14 with fronted PPs), they allow us to examine the model's ability to handle variability in the sentences and meanings.

(7) The teacher gives the award to the student that the principal congratulates.
(8) The teacher gives the award to the student that was congratulated by the principal.
(9) The teacher to the student that the principal congratulates gives the award.
(10) The teacher to the student that was congratulated by the principal gives the award.
(11) By the teacher the award was given to the student that the principal congratulates.
(12) By the teacher the award to the student that the principal congratulates was given.
(13) To the student that the principal congratulates the teacher gives the award.
(14) To the student that the principal congratulates was given by the teacher the award.
(15) The award was given by the teacher to the student that the principal congratulates.
(16) The award was given by the teacher to the student that was congratulated by the principal.
(17) The award was given to the student that the principal congratulates by the teacher.
(18) The award was given to the student that was congratulated by the principal by the teacher.

Considering these combinatorial enumerations of how this situation can be construed thus helps to pose the problem of language production. That is, in language production, the system must accommodate the multiple possible construals of a mental model, and be capable of generating the corresponding sentences for expressing them. We thus define construal as a situation model or mental model combined with a focus hierarchy (Warglien et al., 2012). Given a specific construal the system should be capable of generating a sentence that expresses it. Note that in some expressive conditions the speaker may not care about the depths of the hierarchy and is concerned only with the first elements.

We must consider construal in the broader context of phrasal semantics, the meaning pole in the form-meaning characterization of grammatical constructions. In Jackendoff's characterization (Jackendoff, 2002) phrasal semantics can be considered to include three levels: The descriptive tier addresses the organization of conceptual functions, arguments and modifiers, including thematic role assignment. The referential tier identifies how constituents refer to conceptualized individuals in an ordered, indexed manner, with lists of indices that record the active referents in the discourse. This is related to our notion of the indexed or ordered set of open class items, and would include pronoun reference. The information structure tier characterizes distinctions including focus/presupposition, theme/rheme and old/new information, in the context of how the speaker intends to inform the listener in the context of the previous discourse. Our focus hierarchy is part of the information structure tier, and it also contains information in the descriptive tier, related to thematic role assignment. We previously demonstrated how our grammatical construction model addresses aspects of descriptive, referential and information structure in phrasal semantics for sentence comprehension (Dominey, 2005). In the current research we will see that this use of phrasal semantics can be extended for unambiguously characterizing the meaning pole of the form-meaning constructions to accommodate sentence production.

Given the variety of meaning to be expressed, we can now appreciate part of the potential difficulty of this aspect of the language production problem. We propose a model of sentence production whose operation is characterized by the following three postulates:

Postulate (1) Meaning is represented by thematic roles of the open class elements and their position in the sentence. This meaning is a subset of the information available in the descriptive, referential and information structure tiers of phrasal semantics.
Postulate (2) Meaning is coded by the constellation of closed class elements in the sentence.

Postulate 2 is closely linked to the cue competition model of Bates and MacWhinney which holds that a limited set of cues including word order, grammatical markers and prosody compete during language acquisition for specification of the grammatical structure of the language being learned (Bates & MacWhinney, 1987; Li & Macwhinney, 2013). We have extensively exploited the cue competition hypothesis in our work on sentence comprehension (Dominey, 2013; Dominey et al., 2003, 2009; Hinaut & Dominey, 2013).

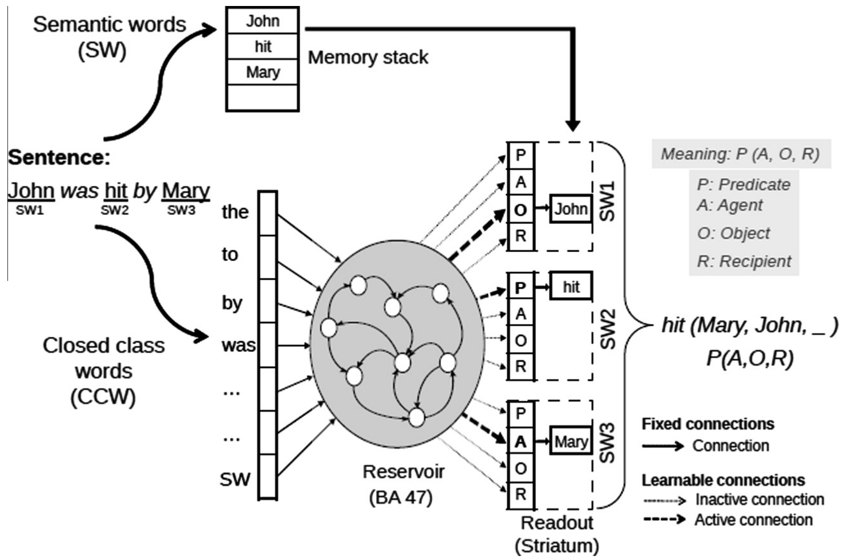

Fig. 1. Sentence comprehension model illustrating grammatical construction processing in the reservoir framework. Semantic and closed class words are separated on input. Semantic words (SW) are stored in a memory stack. Closed class words and a single input for all SWs are inputs to the reservoir (analogous to prefrontal cortex area BA47). During training, input sentences are presented word-by-word, and readout units (corresponding to striatum) are forced to the corresponding coded meaning (i.e. SW1-Object, SW2-Predicate, SW3-Agent). In testing, readout units code the predicted role(s) of each semantic word, forming the coded meaning. The meaning (i.e. hit(Mary, John, _)) can be reconstructed from the coded meaning, as SWs in memory stack are reassigned to the thematic roles (predicate, agent, object, recipient) identified in the read-outs, preserving their input order. The "_" indicates there is no recipient in the current example, as John is the Object. (From Hinaut and Dominey (2013)).

Postulate (3) The unique mapping between meaning and sentence form can be used to generate the appropriate sentence, given the meaning (via Postulate 2).

For sentence comprehension, by Postulate (2), when given a sentence, we use the closed class structure to retrieve the meaning, including the thematic roles. The focus structure is already there, in the ordering of the open class elements. For sentence production, by Postulate (3), given the meaning, we can generate the corresponding sentence, with its corresponding closed class structure. There is a form of symmetry between the meaning, and the closed class structure that supports it. Thus, no two sentences should have the same meaning, unless they are in fact the same sentence.[2] We must take care not to confuse meaning with the sequence of open class words. While sentences 19 and 20 have the same order of specific open class elements, the meanings are different, as are the focus hierarchies.

(19) John sent the letter to Mary [A P O R][3]
(20) John was sent the letter by Mary [R P O A]
(21) Mary sent the letter to John [A P O R]

According to our postulates, given the meaning (focus hierarchy and corresponding thematic roles), the language production system should be capable of producing the corresponding sentence. Concretely this means generating a sentence in which the open class elements follow the order specified in the focus hierarchy, and that the grammatical markers code the desired thematic roles. Again, note that 19 and 20 have the same order of open class elements, but different thematic roles for those elements, and thus different meanings, indicated by their different focus hierarchies. The goal of the system is to select and generate a sentence with appropriate word order for expressing the thematic roles of the event to be described, preserving the order of open class elements as expressed in the focus hierarchy.

3. Corticostriatal models for sentence comprehension and production

We have previously developed a model of sentence comprehension that takes sentences as inputs, and generates as output the thematic roles of the open class elements, and the corresponding focus hierarchy. This model is illustrated in Fig. 1.

We demonstrated that the model can reliably learn how patterns of closed class words in a sentence correspond to the thematic role labeling of the open class words in the sentence. Thus, as illustrated in Fig. 1, after training, when the model is given a new input sentence, activity in the recurrent network (reservoir) drives activation of the readout neurons that code the semantic labels of the ordered open class words. The system thus encodes the thematic roles of the expressed predicates (i.e. "who does what to whom") and preserves and represents the focus hierarchy in terms of the order of the open class words. This means that the system will respect the distinction between sentences like (20) and (21), representing correctly gave(Mary, letter, John) while maintaining the two distinct focus hierarchies.

The sentence production model will perform the opposite transformation (see Fig. 2). Given a coding of the thematic roles of the ordered open class elements, it will learn to produce the correct sentence. This means that it will generate a sentence that preserves the specified order of the semantic elements, while correctly specifying the grammatical closed class elements so as to correctly indicate the appropriate thematic roles. An initial version of this model was presented in (Hinaut, Petit, Pointeau, & Dominey, 2014) using only a limited set of constructions in a human–robot interaction context.

It is clear then that the focus hierarchy must be coded in the meaning. In a similar situation, Chang (2002) codes the meaning message in a binding-by-space method, where different event roles are represented by different banks of units. Each bank (or set) of units represented a slot in the message, and there were three role

[2] As we will see below when we address Japanese passives, this hypothesis is a straw-man that is likely to fail, but in ways that are principled and informative.

[3] The [PAOR] notation represents the focus hierarchy, with ordered Predicate, Agent, Object and Recipient.

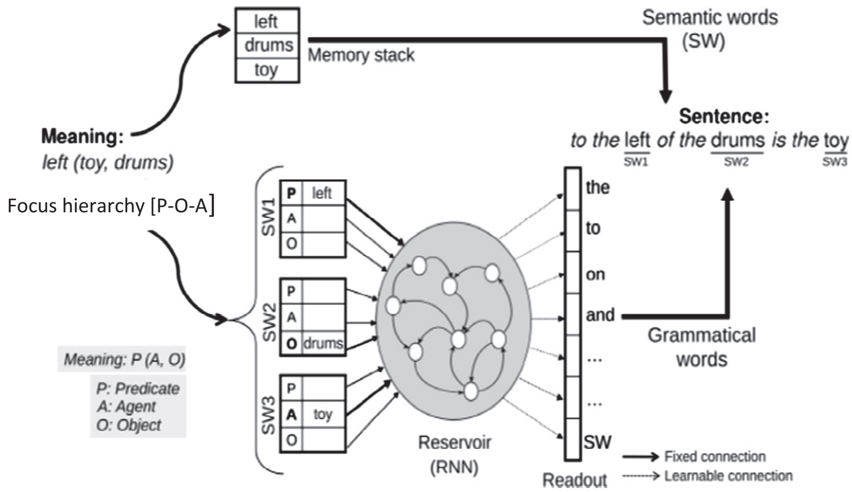

Fig. 2. Sentence production model. The input should express two aspects of the meaning: (1) meaning format (Predicate(Agent, Object) – left(toy, drums)) corresponding to relation *toy to the left of drums*, and (2) the focus hierarchy indicating [SW1 – Predicate, SW2 – Object, SW3 – Agent] which could be written in a compact way a [P-O-A]. The system must find a construction that allows this mapping of SWs to thematic roles.

slots (agent, patient, goal) and a slot for the action. These slots were populated by localist representations. Chang noted that certain types of messages (e.g. transitive motion) could be associated with two different constructions (John gave Mary the book, John gave the book to Mary). He allowed the active passive distinction for the transitive type. It should be noted that in (Chang, 2002) the concern is not to accommodate multiple word ordering nor relative clause structure. These issues were addressed in Fitz et al. (2011).

Here we illustrate meaning representations for two example sentences listed above from the corpus with the thematic role coding, and the focus hierarchy. The focus hierarchy consists of two vectors – one for the main clause, and one for the relative clause. Each vector is an ordered set of 8 items, each which can take on one of four roles (PAOR) which thus codes the thematic roles. Each of the 8 elements in the focus hierarchy corresponds to the 8 possible positions or indices of open class words in the sentence. Empty slots correspond to open class words in the sentence that do not participate in the coded clause. The thematic role is coded in a localist way, with one element for each of the four roles. In sentence (7) below, for example, the 4th open class element (indicated in bold) is the recipient of the first event and the object of the second (relative) event, as coded in the focus hierarchy.

(7) The teacher[1] gives[2] the award[3] to the student[4] that the principal[5] congratulates[6].
Predicate-argument: Gives(teacher award student), congratulates(principal student)
Meaning: [A-P-O-**R**-_-_-_-_] [_-_-_-**O**-A-P-_-_]
(18) The award was given to the student that was congratulated by the principal by the teacher.
Predicate-argument: Gives (teacher award student), congratulates (principal student)
Meaning: [O-P-R-_-_-A-_-_] [_-_-O-P-A-_-_-_]

3.1. Functioning of the model

As illustrated, the focus hierarchy consists of two vectors – one for the main clause, and one for the relative clause. Each vector is an ordered set of 8 items, each which represents an open class word, and can take on one of four roles (PAOR). The concatenating of this into a single input vector gives 2 (clauses) $*$ 8 (possible open class words) $*$ 4 (possible roles) = a 64 element vector. This is the input to the reservoir. The output corresponds to a sequential activation of the readout neurons where each corresponds to a possible closed class word and a single neuron representing open class words. During normal functioning of the model, presentation of the

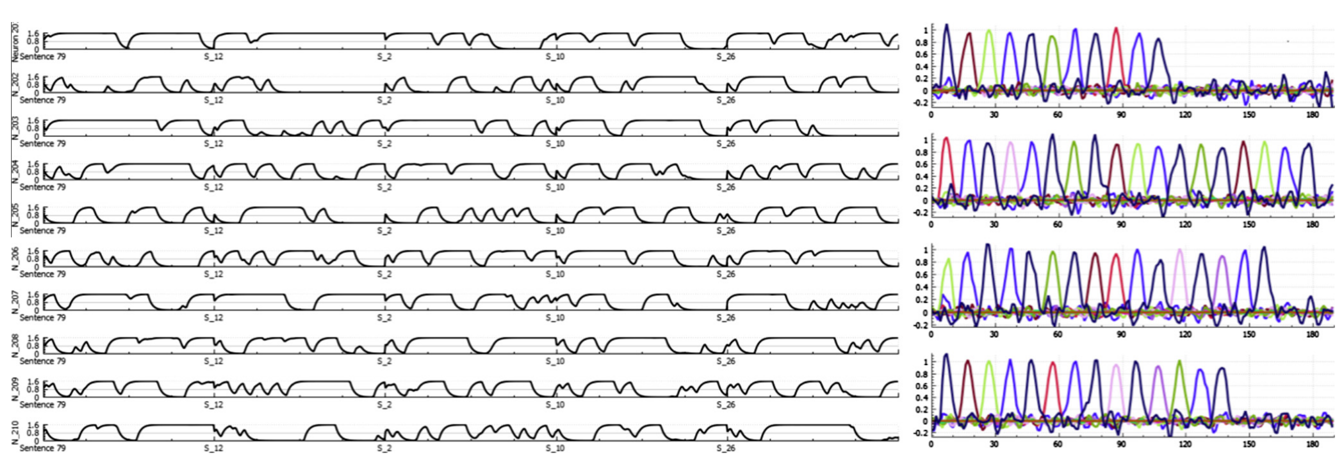

Fig. 3. Left – activation of example reservoir neurons during the processing of 5 sentences from 100 sentences trained with a network of 5000 neurons. Note how neurons respond differently for each sentence. Right – readout neuron activity as the model produces sentences from the corpus. Each colored trace indicates one readout neuron activation, with each readout neuron corresponding to a closed class word, and one neuron coding all open class words.

input focus vector will instigate a vector-specific activation in the reservoir which then becomes a dynamic pattern of activity. This can be observed in the left panel of Fig. 3. The system has been trained so that as specific patterns are traversed in this pattern trajectory, those patterns activate readout neurons. The succession of input driven patterns in the reservoir thus triggers the successive activation of the readout neurons that code the appropriate sentence. This can be observed in the right panel of Fig. 3.

3.2. Training

For performance optimization, training takes place in a form of batch processing which first involves generation of the input activation for the entire corpus. This is played into the reservoir, so that we can record the trajectories of activation in the reservoir for each input meaning for the whole corpus. Finally, we record the desired output activation for the entire corpus. These three sequences (input, reservoir activity, desired output) are thus time locked over the entire processing of the training corpus. The learning involves taking the trajectory of reservoir activation and the trajectory of output activation, and calculating the readout weight matrix W_{out} that minimizes the error between the Reservoir $* W_{out}$ and the desired output for each point in the trajectory. Details of the training methods are provided in (Hinaut & Dominey, 2013). In all simulations, performance is expressed in terms of the percentage of words in the correct order and correct position.

We now describe a series of experiments using different subsets of grammatical constructions from the 26 element and 462 element corpora used for studying sentence comprehension (Hinaut & Dominey, 2013). To demonstrate the cross-linguistic capabilities of the production model we also perform experiments with Japanese constructions used in (Dominey et al., 2006).

4. Experiment 1: Validation of model and parameter sensitivity

We first test the model with 500 neurons on a representative corpus of 10 different constructions from the 462 corpus. The model is trained and tested on the same constructions. Two key parameters control the temporal dynamics in the reservoir. The reservoir neuron leak rate specifies the rate at which activity in the individual recurrent neurons decays in time. The spectral radius is a more global property of the reservoir connection matrix that determines the effective time constant of the network, and the amount of non-linear interaction within the network. We perform a parameter search where we systematically vary the spectral radius and the neuron leak rate. As illustrated in Fig. 4, we see two phenomena of interest. First, there is a set of these parameters where the model performs well. Second, there is actually a fairly broad range of these parameters where the model performs well. This indicates that while somewhat sensitive to the parameters, the model has a robust range of parameter values where performance is good. This means that the performance is not a fragile, unstable property, but rather that it is robust within a reasonable parameter range.

We recall that in the comprehension reservoir study (Hinaut & Dominey, 2013), with 100 neurons the system was able to learn and generalize at 85% correct on a corpus of 26 constructions. Our simulations revealed that for production, 500 neurons are required to learn a corpus of 10 constructions. This poses the question of how the system will scale with increasing corpus size.

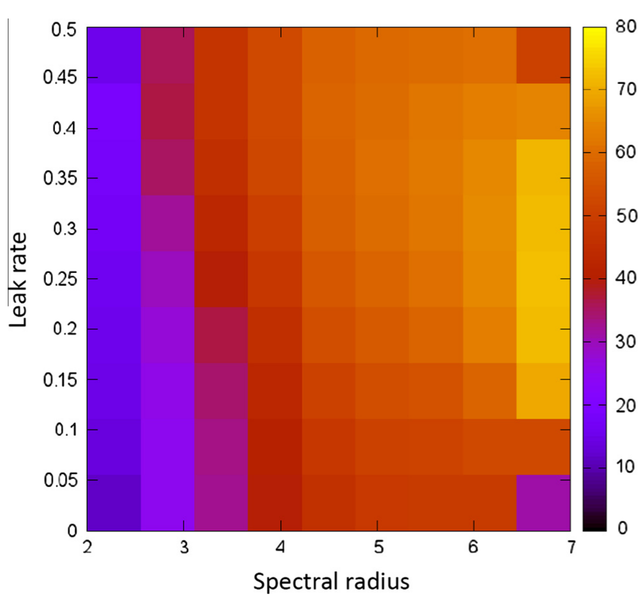

Fig. 4. Effects of reservoir parameters on production performance. Color scale indicated as percent correct.

5. Experiment 2: Effects of syntactic complexity and corpus size

5.1. Experiment 2.1

We first tested a larger corpus of 26 English constructions (Appendix B) that had been used in Hinaut and Dominey (2013). The training and testing set were the same. The experiments were performed with 10 instances that differ only in the seed value used to assign the random weights. With 1500 neurons the model learns to produce these sentences with no errors. In order to assess if there are systematic performance differences for different construction types, we examined partially "degraded" performance when 10 instances of a new model was tested with only 500 neurons. The 26 constructions in the appendix are presented in order, ranked by degree of complexity in terms of number of clauses, presence of passives and object-relatives, and length. Model performance was correlated with complexity, $F(1,24) = 32$, $p < 0.001$, $R^2 = 0.57$. We looked in more detail at four constructions that had either one or two clauses, and the presence or not of a passive in the first clause (constructions 3, 4 and 6, 7 from Appendix A). Performance was analyzed in a 2(clause) × 2 (active/passive) ANOVA. There was a trend to make more errors for the two clause vs. one clause construction (58% vs 67% correct) but this was not significant for 10 instances of the model $F(1,9) = 0.8$, $p = 0.39$. Passive constructions were more difficult than active (53% vs 72% correct respectively), and this effect was significant $F(1,9) = 11$, $p < 0.01$. There was no interaction. Performance in these degraded modes reveals the relative difficulty associated with the passive vs. active constructions. This is likely due to the lower frequency of passive clauses in the four sentence types we examined here, in which the agent is displaced from the head of the clause and of the focus hierarchy.

5.2. Experiment 2.2

We then set out to determine if the model could accommodate a larger corpus, with a greater variety of grammatical constructions. We determined that in order to learn a 120 sentence corpus, the system required 5000 neurons.

Fig. 5 illustrates the effects of the corpus size on the network performance. We see the progressive loss in performance as the number of sentences increases. Performance is measured by comparing word by word the expected sentence and the produced sentence. Each word should be in the correct position. Performance is

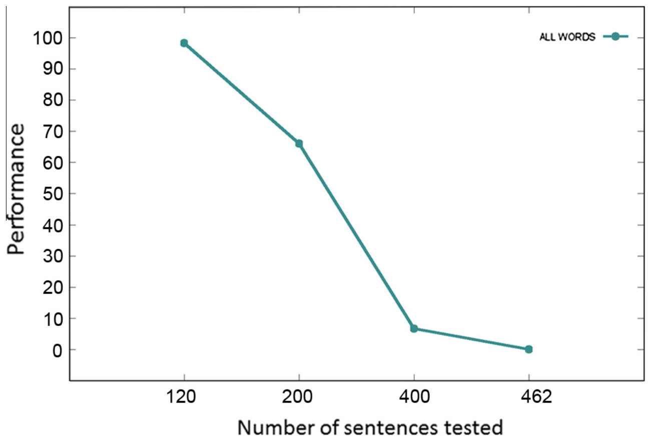

Fig. 5. Effects of corpus size on network performance for a network with 5000 neurons.

expressed in terms of the percentage of words in the correct order and correct position. We observe a clear reduction in performance as the number of sentences is increased. Note that each sentence corresponds to a distinct grammatical construction.

6. Experiment 3: Generalization based on corpus structure

If the model is able to learn these grammatical constructions for language production, we must ask about the nature of what is being learned. We can formulate two potential hypotheses about what is being learned.

6.1. Learning hypothesis 1: Learning general structure

According to this hypothesis, the model learns internal structure of the corpus, by mapping focus hierarchy to sentence form in a way that exploits the underlying grammatical structure inherent in the training corpus. If we remove that structure (by randomizing the order of words in the sentences or the PAOR elements in the meaning structures in training corpus) then the model should demonstrate reduced performance. That is, with the internal structure removed, the model will no longer be able to capitalize on this structure, even though each individual sentence-meaning pair is perfectly well-formed and learnable.

6.2. Learning hypothesis 2: Brute force memorization (over-fitting)

According to this hypothesis, the model memorizes each construction in the corpus as a distinct item, and thus the model does not benefit from any underlying structure in the corpus. Each element (sentence, meaning pair) is considered as a distinct item, and there is no underlying structure. Thus, if we remove the structure that would link one construction to another (by randomizing sentences or the meaning structures in the training corpus as mentioned above), while leaving each separate meaning-sentence pair well-formed, then the model should not be affected. That is, it will simply continue to memorize each construction, independent of the others.

6.3. Testing the two hypotheses

Thus in order to distinguish between these two hypotheses, that is, to determine if the model is simply memorizing each meaning-sentence mapping as an isolated case, vs. learning some underlying aspect of the grammar used to generate these mappings (i.e. generalizing over the grammatical structure in the corpus), we performed the following experiments. *Scrambled sentences:* A set of 120 sentences was selected randomly from the 426 element corpus from Hinaut and Dominey (2013) (provided in supplementary material). In the first experiment, starting with 0, and incrementing in successive steps of 30 sentences, we scrambled the order of words in the sentences, while leaving the PAOR representations intact. *Scrambled meanings:* In the second experiment we took a similar approach, but this time scrambling the elements in the PAOR meaning representations and leaving the sentences intact. Note that in this case, the structural regularities across the output sentences is preserved, but the grammatical link between meaning and sentence is lost, at the level of the corpus, but maintained for individual sentences. We predicted that if the model is exploiting the underlying structure, i.e. generalizing, then performance will degrade as this structure is progressively removed. The experiment is performed with a network of 5000 neurons. The results are illustrated in Fig. 6.

What we observe, both for scrambled sentences and scrambled meanings, is that when individual sentence-meaning pairs are left intact, but the relations between different pairs is destroyed, then learning is impaired. This allows us to reject hypothesis 2, and support learning hypothesis 1, which holds that the model is generalizing across the corpus.

7. Experiment 4: Larger corpora, larger reservoir

7.1. Experiment 4.1 learning

We further tested the system with progressively larger reservoirs. Because of the high computational requirements of these larger reservoirs, we were required to use high-performance computing resources, including parallel computing on the French National Institute of Nuclear and Particle Physics (IN2P3) computing grid. Likewise, in order to accelerate matrix computations involved in the training, we also benefitted from GPU matrix manipulation with CUDA, using the NVIDIA Corporation Tesla K40 GPU. Using a network of 18,000 neurons we achieved 99.8% correct performance with the 462 corpus.

7.2. Experiment 4.2 generalization

Again, in order to determine whether the system is overlearning these constructions, or actually learning the underlying grammatical structure, we examined whether the system would suffer a reduction in performance when the learning material is randomized in Experiment 4.2. As in the Experiment 3, we see in Table 1 that this is the case.

This demonstrates that with a fully unstructured corpus, where each sentence-meaning pair is well-formed, but there is no common underlying structure linking the different sentence-meaning pairs, then the model learning is reduced by up to 44%, though it can still learn to some extent. That is, it still produced 55% of the words in the correct order and position. However, when the grammatical structure that is common across the different sentence-meaning pairs is restored, then the model is at 99% correct. This indicates that the 44% improvement is due to a form of generalization across the corpus.

8. Experiments with Japanese

Another form of generalization involves testing exactly the same model with a different language. In Dominey et al. (2006) we demonstrated that our grammatical construction model based on the closed class hypothesis could operate equally well on English and Japanese. In Japanese, the grammatical markers –ga,

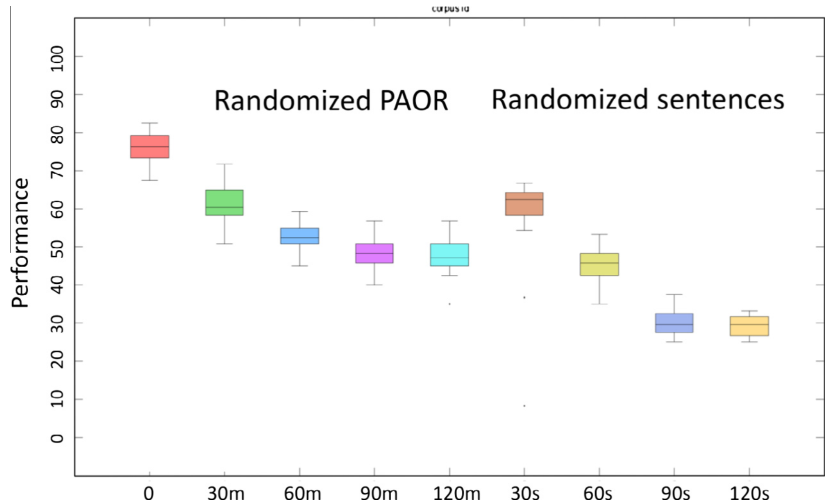

Fig. 6. Network performance with different forms of perturbation of the PAOR or sentence order. Leftmost trace – normal baseline performance when 0 perturbations were introduced. 30–120 m – progressive impairment in performance as more PAOR meaning representations are scrambled. 30–120 s – progressive impairment in performance as more sentences are scrambled. Since these modifications impact performance, the model is not simply memorizing each individual element, but rather, is exploiting the inherent grammatical structure common to all elements of the corpus.

Table 1
Performance of the reservoir on the 462 Corpus with 18,000 neurons as sentences are progressively randomized.

Proportion randomized	0/462	100/462	200/462	300/462	462/462
Percent correct	99.8	83.5	70.1	64.7	55.6

-wo, ni, -yotte, etc. serve as a form of case marker, and thus, allow the model to identify a unique pattern of these markers corresponding to a unique assignment of meaning. Here we present an example set of sentences and meaning that we used to test the sentence production model.

(22) Template: Predicate agent object recipient [focus hierarchy]; sentence
(23) tataita block circle [A-O-P]; block -ga circle -wo tataita
(24) tatakareta block circle [A-O-P]; block -ni circle -ga tatakareta
(25) tatakareta block circle [O-A-P]; circle -ga block -ni tatakareta
(26) tataita block circle [O-A-P]; circle -wo block- ga tataita

Looking at these four example sentences from our Japanese corpus, we see that each of the four has a distinct pattern of –ga, -wo, -ni particles. Thus, for comprehension, each of these sentences is distinct in terms of the pattern of closed class elements. In production, we will proceed in the opposite sense. That is, from focus hierarchy to sentence. Interestingly, however, here we face a serious problem. Sentences 23 and 24 have the same focus hierarchy [A-O-P], as do 25 and 26 [O-A-P]. Looking at 23 and 24, if we ask the model to learn these two constructions, it will fail, as the same focus hierarchy [A-O-P] is supposed to lead to the generation of two distinct sentences. This reveals a distinction between the nature of the focus hierarchy or meaning in Japanese and English, with respect here to the passive. In English, there is an explicit relation between the notion of "passive" and word order. The object is moved to the head of the sentence and becomes the subject. In Japanese, passive and word order are not coupled. The passive is explicitly marked, and the word order can remain unchanged. Thus in Japanese, it is possible to have grammatical forms for passive and active that have the same word order, and focus hierarchy. This induces us to introduce an additional element in the PAOR representation, which corresponds to a passive predicate, which we will label Q. In this way we have the following.

(23) tataita block circle [A-O-P]; block -ga circle -wo tataita
(24) tatakareta block circle [A-O-Q]; block -ni circle -ga tatakareta
(25) tatakareta block circle [O-A-Q]; circle -ga block -ni tatakareta
(26) tataita block circle [O-A-P]; circle -wo block- ga tataita

The complete corpus is specified in Appendix B. This modification to the representation of the focus hierarchy raises an important question and limitation: as additional languages and linguistic phenomena are investigated, will successive ad-hoc changes be required for the model? We believe that while changes will be necessary, they are not ad-hoc, and actually reveal pertinent aspects of the corresponding linguistic phenomena, which we will address in the discussion.

9. Japanese corpus results

9.1. Experiment 5.1 learning

We determined that with a reservoir with 500 neurons with a 24 element corpus, the model was able to correctly process the set of sentences. In Fig. 7 we observe reservoir neuron activation on the left, and readout neuron activation on the right, coding the output sentences. It is of interest to compare this figure to Fig. 3, illustrating the same activation, but in processing English sentences. What is interesting is that the essential aspects of the processing do not differ between the two languages. We also verified performance on the generalization test as indicated in Fig. 8.

9.2. Experiment 5.2 generalization

In Fig. 8 we illustrate network performance as we successively scramble sentences. We see the same profile of performance as observed in the English sentences. While each sentence-meaning pair is perfectly well-formed and learnable, the overall learnability of the corpus is reduced, when the grammatical structure that is common across different sentence-meaning pairs is removed.

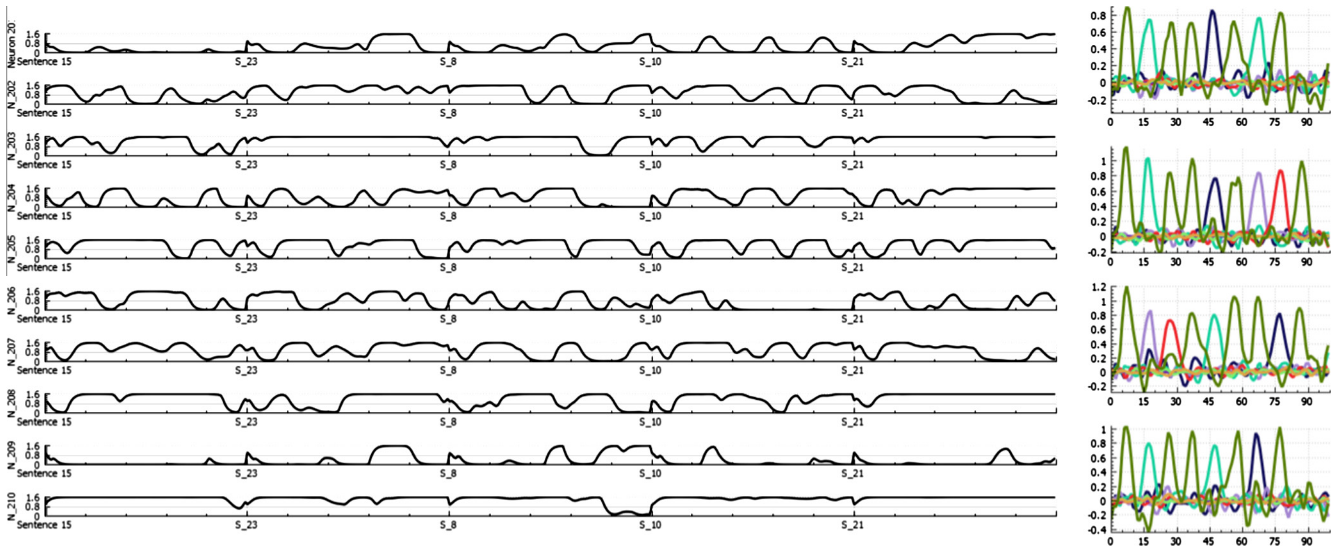

Fig. 7. Left – activation of example reservoir neurons during the processing of 5 sentences from 24 Japanese sentences trained with a network of 500 neurons. Note how neurons respond differently for each sentence. Right – readout neuron activity as the model produces sentences from the corpus. Each colored trace indicates one readout neuron activation, with each readout neuron corresponding to a closed class word, and one neuron coding all open class words.

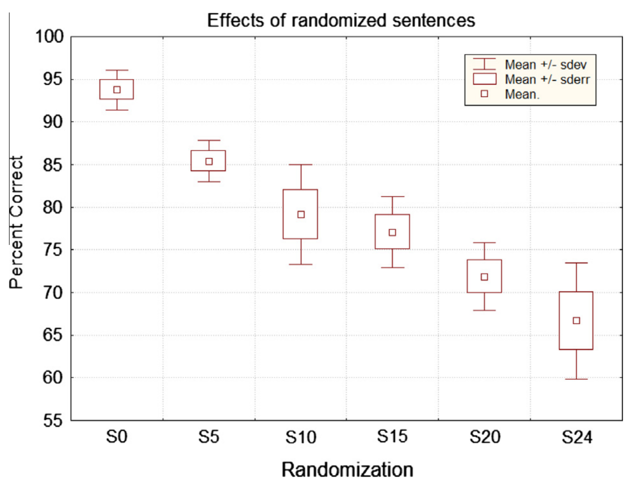

Fig. 8. Performance of the reservoir on the 24 construction Japanese Corpus with 380 neurons as sentences are progressively randomized. As sentence structure is progressively removed, the overall learning is progressively impaired. This indicates that the model is not memorizing individual sentence-meaning pairs, but learning structure that is common across sentence-meaning pairs.

10. Discussion

The objective of this research was to determine if a computational neuroscience model of the corticostriatal system could demonstrate language-learning capabilities for sentence production. The reason behind this objective was twofold: First, the implication of the corticostriatal system in language production has a long and rich history. The development of a neural network based on the corticostriatal system that can demonstrate language production capabilities can help to shed light on the functional neurophysiology of the corticostriatal system in language production. Second, we have observed the computational power of recurrent networks with fixed connections and modifiable readouts, and from a theoretical perspective, the demonstration that language production is in the class of tasks that can be performed by such systems is of particular interest. Indeed, this contributes to further understanding of aspects of the nature of the human language learning system.

One of the challenges of understanding language comprehension and production lies in conceiving a physiological mechanism with flexibility allowing the learning of any human language(s). In other words, what neural system could provide the necessary high degrees of flexibility in learning the mappings between meanings and sentences in arbitrary human languages? Recent advances in cognitive neuroscience and machine learning help provide an answer. Neural networks with fixed feedback (recurrent) connections display rich dynamics, due to the flow of information percolating through the system via the recurrent connections, and have been widely used in engineering applications, e.g. Jaeger and Haas (2004). It appears that the primate cortex exploits these properties (Nikolic et al., 2009). Neurophysiological data suggests that computations in PFC emerge from the concerted dynamics of large populations of neurons that have been well characterized in the domain of reservoir computing (Sussillo, 2014). In this context, Rigotti thus claims that reservoirs produce high dimensional neural representations with the desirable property of allowing simple readouts such as linear classifiers to implement a large set of input–output relations. Models that rely on such high dimensional representations can generate very rich dynamics and solve complex tasks (Rigotti et al., 2010, 2013).

We have proposed that in this context, cortex corresponds to the reservoir, and striatum the readout, even before these terms were coined (Dominey, 1995, 2013; Dominey & Ramus, 2000; Dominey et al., 1995, 2009; Hinaut & Dominey, 2013). The mapping of cortex to the reservoir and striatum to the readout makes sense at a gross level: cortex is characterized by massive local recurrent connectivity (Binzegger, Douglas, & Martin, 2009; Douglas, Koch, Mahowald, Martin, & Suarez, 1995), and the corticostriatal synapse is modified by reward-related dopamine (Calabresi, Picconi, Tozzi, & Di Filippo, 2007; Hollerman & Schultz, 1998; Ljungberg, Apicella, & Schultz, 1992). However, this is potentially an oversimplification. We know that there is plasticity in cortico-cortical connections (Buonomano & Merzenich, 1998), thus potentially playing a role in readout. The potential for a reservoir role for the striatum is less evident. The anatomical organization of the striatum is less appropriate for reservoir behavior with the dominance of GABAergic medium spiny neurons (Wise, Murray, & Gerfen, 1996; Yelnik, Francis, Percheron, & Tandéa, 1991).

Our work on simulation of the corticostriatal system in sentence comprehension leads to the proposal of a corticostriatal language circuit whose function can be characterized in the context of reservoir computing (Dominey, 2013). The current research extends this investigation to sentence production. The selection of the sentence form that will be generated during on line speech production must somehow be constrained, so that a specific choice is made. One way that this can occur is that the speaker has a specific meaning to communicate, and that meaning drives the selection/generation of the appropriate sentence structure. This issue has been faced in different cases of language production modeling. Fitz et al. (2011) noted that when active–passive and different relative forms interact, similar meaning messages could map to different sentences, leading to potentially redundant coding and interference between the multiple mappings. Indeed, it is to avoid these redundancies that we exploit a unique mapping. They used thematic roles (AGENT, PATIENT, RECIPIENT, etc.), concepts (lexical semantics), and event features to signal the number and relative prominence of event participants by binding them to their respective thematic roles. These event features correspond to our focus hierarchy. The crucial idea is that in order to select the proper sentence form, the desired meaning to be communicated must be construed. In our case this construal corresponds to generating the focus hierarchy in the PAOR format, where each of the PAOR roles is filled by an open class word.

In order to accommodate the passive voice verb form in Japanese, we were obliged to augment the PAOR meaning representation with an additional element for passive predicates. This raises the question: for each new language, will we be required to modify the meaning representation? The assumption in English is that for a given meaning (i.e. a given order of the thematic roles predicate, agent, object, recipient) there is one corresponding sentence. We discovered in Japanese that this is not the case, because the active–passive distinction can be made independent of the word order. Indeed, this raises an interesting question of language typology: are there languages where the same thematic roles and focus hierarchy can be maintained while expressing different distinctions with different sentences?

In fact, we were too hasty in considering that in English the PAOR representation uniquely specifies sentence forms. Consider examples:

(27) [R P O] The boy has been given the toy.
(28) [R P O] The boy was given the toy.
(29) [R P O] It is the boy that was given the toy.

Such examples indicate that the same thematic roles and focus hierarchy can generate sentences with different phrasal semantics. This indicates that some additional information must accompany the current meaning definition to unambiguously characterize the meaning so that it maps uniquely onto a single sentence. This additional dimension can come from different sources, and corresponds to the larger context of phrasal semantics. In dialog, speakers tend to align to one another, and such alignment is one such source that would constrain the form of sentences produced (Pickering & Garrod, 2004).

Comparing sentence comprehension to sentence production, we can observe that while 1000 neurons were sufficient to learn the 462 construction corpus for comprehension (Hinaut & Dominey, 2013), 18,000 neurons were required to learn this corpus for production. Why is production more difficult than comprehension? Sentence comprehension takes a dynamic input signal, and produces a single output signal that must be correct at the end of the sentence. In contrast, sentence production takes a static input, and must produce a rhythmic, ordered sequential output that must be correct throughout the entire output process. This passage from fixed input pattern to a dynamically structured output pattern is of higher complexity that the converse. Additionally, part of the problem is that we have here isolated the process of grammatical structure formation from the rest of language processing. It is more likely that production and comprehension interact and proceed in a more incremental manner (Pickering & Garrod, 2013).

The difference between comprehension and production was also observed in generalization. For comprehension, we observed that the 1000 neuron network displayed a robust capability to generalize to new grammatical constructions at 80% correct with the 462 corpus. In the production network we saw robust learning, but were not able to observe reliable generalization to new constructions. Learning was tested for English (Exp 1, 2.1, 2.2, and 4.1) and Japanese (5.1), with the model trained and tested on the same sentences in each experiment. Generalization was tested for English with the 120 corpus (Exp 3), the 462 corpus (Exp 4.2), and the Japanese corpus (Exp 5.2). We tested generalization by progressively reducing the grammatical structure in the training and testing corpus, and observed a progressive and corresponding decrease in learning. Each sentence remained well formed, but the grammatical relation between sentences was removed. Removing grammatical structure from the corpus resulted in impaired learning. This is evidence that the model generalizes across constructions in the corpus, thus exploiting the underlying grammatical structure within the corpus, rather than simply memorizing mappings from meaning vectors to output sequences.

In Fig. 6 we see that the randomization effect is more pronounced when randomizing the sentences, than when randomizing the meanings (the [PAOR]). We believe this is due to the following observations: when the sentences are randomized, the model must now generate a set of random output sequences, which is one thing that reservoirs are not good at. When the meanings are randomized, the output sequences all maintain the general form of grammatical word order, and there is some redundancy across the sentences/sequences (i.e. common subsequences). Thus, randomizing the meanings allows the model to continue to benefit from the common structure in the output sentences, and is thus less difficult than randomizing the sentences, which of course destroys this common structure.

Interestingly, the apparent difficulty in generalizing to new constructions in production is observed in child language learners. In language production, children first tend to re-use grammatical constructions that they have already been exposed to, and only later generalize to new constructions (Tomasello, 2000, 2003). Indeed, it has been proposed that there is a continuum between such formulaic holistic expressive forms at one extreme and purely creative generation of novel forms at the other (Wray & Perkins, 2000). Formulaic language is widespread, and has multiple advantages from reducing processing cost, to signaling membership in a social group where that formulaic expression is used (Wray & Perkins, 2000). Our two Learning Hypotheses are thus not mutually exclusive. A learner could at the same time learn underlying structure so as to become generative, and also, memorize certain constructions in a holistic manner.

In this re-use context, in a communicative setting, children would select from an inventory of constructions one that met their current communicative needs (Tomasello, 2003). This suggests an interesting link with action selection. The corticostriatal system has long been associated with action selection (Grahn, Parkinson, & Owen, 2009), in the selection of action schemas and subgoals, fundamental to goal-directed action. We can consider that communication is a form of goal directed action, and that language production involves the selection of appropriate construction schemas, based on the communicative goal. This is compatible with Ullman's conception of grammatical rules being implemented in the corticostriatal system (Ullman, 2001a, 2001b, 2004). We have previously postulated such corticostriatal language loops or circuits (Dominey, 2013; Dominey et al., 2009) for language comprehension and here we extend this to production. Chan, Ryan, and Bever (2013) have demonstrated that an anterior corticostriatal loop is involved in linguistic sequencing, and Altmann and Troche (2011) have used fMRI and dMRI to map out distinct cortico-striato-thalamo-cortical circuits in man that could form the anatomical substrate. In the context of these studies and those cited in the introduction, there is a clearly emerging view of the role of the corticostriatal system in language. The current research contributes to this argument by demonstrating how the corticostriatal system could implement a form of construction selection process for language production.

One common aspect to sentence production and comprehension is that when the corticostriatal system is lesioned, both the comprehension (Friederici et al., 2003) and production (Altmann & Troche, 2011; Mega & Alexander, 1994) of grammatical constructions with rich syntactic structure are impaired. We have previously demonstrated that degrading the function of the corticostriatal language comprehension system produces perturbation in complex syntactic forms (Dominey, 2002), and here we demonstrate a related link between impaired processing in the model, and a corresponding degradation of sentence generation as a function of complexity.

The current model accepts up to two clauses. The next step would be to allow the attachment of arbitrary number of clauses. We faced a similar situation in comprehension (Dominey et al., 2006). In the static version of the model, sentences with up to two clauses were considered as a consolidated construction, as we currently do with production. We then introduced an analyzer that detected phrase structure boundaries and initiated the creation of new clause representations. The same should be present here. That is, a rather complex meaning representation could be developed based on a graph of indexed or ordered predicate(agent, object, recipient) elements. Language production would consist in traversing and linearizing this structure so that it could be reconstructed by the listener. Interestingly, this places requirements on the conceptual system, which should be able to represent such compositional structures (Dominey, 2003).

We should recall that it is of interest that the current research demonstrates that with no learning in the recurrent connections, the recurrent network is able to generate a temporal pattern of activation that, via the trained readout connections, allows the system to produce sentences based on the static input meaning coding. This is actually quite remarkable. The observation that this learning fails when the structural regularity between each sentence and its meaning is preserved, but the global grammatical structure of the corpus is removed, demonstrates that the system is capturing the underlying common grammatical structure. That the same model can function for English and Japanese contributes to the robustness of the effect. While it is not the focus of this research, it is still worth noting that this language production capability further argues for the idea that the corticostriatal system can be conceptualized in terms of reservoir computing (Dominey, 2013).

Acknowledgments

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Appendix A. 26 Element English corpus

1. V1 N1 N2; [A-P-O-_-_-_-_-_-_][_-_-_-_-_-_-_-_-_]; the N1 V1 the N2
2. V1 N1 N2; [O-P-A-_-_-_-_-_-_][_-_-_-_-_-_-_-_-_]; the N2 was V1 by the N1
3. V1 N1 N2 N3; [A-P-O-R-_-_-_-_-_][_-_-_-_-_-_-_-_-_]; the N1 V1 the N2 to the N3
4. V1 N1 N2 N3; [O-P-R-A-_-_-_-_-_][_-_-_-_-_-_-_-_-_]; the N2 was V1 to the N3 by the N1
5. V1 N1 N2 N3; [A-P-R-O-_-_-_-_-_][_-_-_-_-_-_-_-_-_]; the N1 V1 the N3 the N2
6. V1 N1 N2, V2 N1 N4; [A-_-_-P-O-_-_-_-_][A-P-O-_-_-_-_-_-_]; the N1 that V2 the N4 V1 the N2
7. V1 N1 N2, V2 N1 N4; [O-P-A-_-_-_-_-_-_][_-_-A-P-O-_-_-_-_]; the N2 was V1 by the N1 that V2 the N4
8. V1 N1 N2, V2 N2 N4; [O-_-_-P-A-_-_-_-_][A-P-O-_-_-_-_-_-_]; the N2 that V2 the N4 was V1 by the N1
9. V1 N1 N2, V2 N2 N4; [A-P-O-_-_-_-_-_-_][_-_-A-P-O-_-_-_-_]; the N1 V1 the N2 that V2 the N4
10. V1 N1 N2, V2 N3 N1; [A-_-_-P-O-_-_-_-_][O-P-A-_-_-_-_-_-_]; the N1 that was V2 by the N3 V1 the N2
11. V1 N1 N2, V2 N3 N1; [O-P-A-_-_-_-_-_-_][_-_-O-P-A-_-_-_-_]; the N2 was V1 by the N1 that was V2 by the N3
12. V1 N1 N2, V2 N3 N2; [O-_-_-P-A-_-_-_-_][O-P-A-_-_-_-_-_-_]; the N2 that was V2 by the N3 was V1 by the N1
13. V1 N1 N2, V2 N3 N2; [A-P-O-_-_-_-_-_-_][_-_-O-P-A-_-_-_-_]; the N1 V1 the N2 that was V2 by the N3
14. V1 N1 N2 N3, V2 N1 N5; [O-P-R-A-_-_-_-_-_][_-_-_-A-P-O-_-_-_]; the N2 was V1 to the N3 by the N1 that V2 the N5
15. V1 N1 N2, V2 N3 N2 N5; [A-P-O-_-_-_-_-_-_][_-_-O-P-A-R-_-_-_]; the N1 V1 the N2 that was V2 by the N3 to the N5
16. V1 N1 N2 N3, V2 N1 N5; [A-_-_-P-O-R-_-_-_][A-P-O-_-_-_-_-_-_]; the N1 that V2 the N5 V1 the N2 to the N3
17. V1 N1 N2 N3, V2 N2 N5; [O-_-_-P-R-A-_-_-_][A-P-O-_-_-_-_-_-_]; the N2 that V2 the N5 was V1 to the N3 by the N1
18. V1 N1 N2 N3, V2 N3 N5; [A-P-O-R-_-_-_-_-_][_-_-_-A-P-O-_-_-_]; the N1 V1 the N2 to the N3 that V2 the N5
19. V1 N1 N2 N3, V2 N3 N5; [O-P-A-R-_-_-_-_-_][_-_-_-A-P-O-_-_-_]; the N2 was V1 from the N1 to the N3 that V2 the N5
20. V1 N1 N2 N3, V2 N4 N1; [A-_-_-P-O-R-_-_-_][O-P-A-_-_-_-_-_-_]; the N1 that was V2 by the N4 V1 the N2 to the N3
21. V1 N1 N2 N3, V2 N4 N3; [A-P-O-R-_-_-_-_-_][_-_-_-O-P-A-_-_-_]; the N1 V1 the N2 to the N3 that was V2 by the N4
22. V1 N1 N2, V2 N1 N4 N5; [A-_-_-_-P-O-_-_-_][A-P-O-R-_-_-_-_-_]; the N1 that V2 the N4 to the N5 V1 the N2
23. V1 N1 N2, V2 N1 N4 N5; [O-P-A-_-_-_-_-_-_][_-_-A-P-O-R-_-_-_]; the N2 was V1 by the N1 that V2 the N4 to the N5
24. V1 N1 N2, V2 N2 N4 N5; [A-P-O-_-_-_-_-_-_][_-_-A-P-O-R-_-_-_]; the N1 V1 the N2 that V2 the N4 to the N5
25. V1 N1 N2, V2 N1 N4 N5; [O-_-_-_-P-A-_-_-_][_-P-O-R-_-A-_-_-_]; the N2 that V2 the N4 to the N5 was V1 by the N1
26. V1 N1 N2, V2 N3 N1 N5; [A-_-_-_-P-O-_-_-_][O-P-R-A-_-_-_-_-_]; the N1 that was V2 to the N5 by the N3 V1 the N2

Appendix B. Japanese construction corpus

The format for constructions identical to that is Appendix A, in three parts – specification of the predicate-argument structure, the focus hierarch, and the sentence. In order to aid in readability we use concrete nouns and verbs, but the structure is the same as in Appendix A.

N. predicate agent object recipient (for first and second clause; [PAOR representation][]; sentence

The block hit the circle

1. tataita block circle; [A-O-P-_-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; block -ga circle -wo tataita
2. tataita block circle ; [O-A-P-_-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_] ; circle –wo block –ga tataita

The circle was hit by the block

3. tatakareta block circle; [O-A-Q-_-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; circle -ga block -ni tatakareta
4. tatakareta block circle ; [A-O-Q-_-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_] ; block –ni circle –ga tatakareta

The block gave the circle to the triangle.

5. watashita block circle triangle; [A-R-O-P-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; block -ga triangle -ni circle -wo watashita
6. watashita block circle triangle; [A-O-R-P-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; block -ga circle -wo triangle -ni watashita
7. watashita block circle triangle; [R-A-O-P-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; triangle -ni block -ga circle -wo watashita
8. watashita block circle triangle ; [O-A-R-P-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_] ; circle –wo block –ga triangle –ni watashita

The circle was given to the triangle by the block.

9. watasareta block circle triangle; [O-A-R-Q-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; circle -ga block -ni -yotte triangle -ni watasareta
10. watasareta block circle triangle; [A-O-R-Q-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; block -ni -yotte circle -ga triangle -ni watasareta
11. watasareta block circle triangle; [A-R-O-Q-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; block -ni -yotte triangle -ni circle -ga watasareta
12. watasareta block circle triangle; [R-O-A-Q-_-_-_-_-_][_-_-_-_-_-_-_-_-_-_]; triangle -ni circle -ga block -ni -yotte watasareta

The block that hit the circle pushed the triangle.

13. tatakareta circle block, oshita block triangle; [A-P-O-_-_-_-_-_-_][_-_-A-O-P-_-_-_-_]; circle -ni -yotte tatakareta block -ga triangle -wo oshita

The block was hit by the triangle that pushed the circle.

14. oshita triangle circle, tatakareta triangle block; [_-O-P-A-_-_-_-_-_][O-_-_-A-P-_-_-_-_]; block -ga circle -wo oshita triangle -ni -yotte tatakareta
15. oshita triangle circle, tatakareta triangle block ; [O-P-A-_-_-_-_-_-_][_-_-A-O-Q-_-_-_-_] ; circle –wo oshita triangle –ni –yotte block –ga tatakareta

The block that hit the circle was pushed by the triangle.

16. tataita block circle, oshita block triangle; [O-P-A-_-_-_-_-_-_][_-_-A-O-P-_-_-_-_]; circle -wo tataita block -ga triangle -wo oshita
17. tataita block circle, osareta triangle block ; [O-P-A-_-_-_-_-_-_][_-_-O-A-Q-_-_-_-_] ; circle –wo tataita block –ga triangle –ni –yotte osareta

The block hit the triangle that pushed the circle.

18. tataita block circle, osareta triangle block; [_-O-P-A-_-_-_-_-_][A-_-_-O-Q-_-_-_-_]; triangle -ni -yotte circle -wo tataita block -ga osareta
19. oshita triangle circle, tataita block triangle ; [O-P-A-_-_-_-_-_-_][_-_-O-A-P-_-_-_-_] ; circle –wo oshita triangle –wo block –ga tataita

The block that was hit by the circle pushed the triangle.

20. oshita triangle circle, tataita block triangle ; [_-O-P-A-_-_-_-_-_][A-_-_-O-P-_-_-_-_] ; block –ga circle –wo oshita triangle –wo tataita

The block hit the circle and the triangle.

21. oshita block triangle, tataita triangle block; [A-_-O-P-_-_-_-_-_][O-P-A-_-_-_-_-_-_]; block -ga sore -wo tataita triangle -wo oshita
22. oshita block triangle, tataita block triangle ; [A-_-O-P-_-_-_-_-_][A-P-O-_-_-_-_-_-_] ; block –ga sore –ga tataita triangle –wo oshita

The block and the triangle hit the circle.

23. tataita block triangle, tataita block circle; [A-O-_-P-_-_-_-_-_][O-_-O-P-_-_-_-_-_]; block -to triangle -ga circle -wo tataita
24. tataita block circle, tataita block triangle; [O-A-_-P-_-_-_-_-_][_-A-O-P-_-_-_-_-_]; circle -wo block -to triangle -ga tataita

hit = tataku, hit = tataita, be hit = tatakareru, was hit = tatakareta; give = ataeru, gave = watashita, be given = ataerareru, was given = watasareta; push = osu, pushed = tataita, be pushed = osareru, was pushed = osareta

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.bandl.2015.08.002.

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