The AAAI 2017 Spring Symposium on
Computational Construction Grammar and Natural Language Understanding
Technical Report SS-17-02

Dynamic Construction Grammar and Steps Towards the Narrative Construction of Meaning

Peter Ford Dominey[1], Anne-Laure Mealier[1], Gregoire Pointeau[1], Solene Mirliaz[1,2], Mark Finlayson[3]

1. Univ Lyon, Université Lyon 1, Inserm, Stem Cell and Brain Research Institute U1208, 69500 Bron, France 2. ENS Rennes, France 3. FIU SCIS, Miami, FL USA
peter.dominey, anne-laure.mealier, Gregoire.pointeau<@inserm.fr>, solene.mirliaz@ens-rennes.fr, markaf@fiu.edu

Abstract

Dynamic construction grammar (DCG) is a neurcomputational framework for learning and generalizing sentence-to-meaning mappings. It is inspired by the cue competition hypothesis of Bates and MacWhinney, and learns regularities in the ordering of open and closed class words and the corresponding mapping to semantic roles for the open class words. The structure of meaning is a crucial aspect of these form to meaning mappings. Here we describe the DCG framework, and the evolution of meaning representations that have been addressed. The first and most basic meaning representation is a predicate-argument form indicating the predicate, agent, object and recipient. We developed an action recognition system, that detected simple actions and used naïve subjects' narration to train the model to understand. The DCG comprehension model was then extended to address sentence production. The resulting models were then integrated into a cooperative humanoid robotic platform. We then demonstrated how observed actions could be construed from different perspectives, and used the production model to generate corresponding sentences. In order to allow the system to represent and create meaning beyond the single sentence, we introduce the notions of narrative construction and narrative function word. In the same way that grammatical function words operate on relations between open class elements in the sentence, narrative function words operate on events across multiple sentences in a narrative. This motivates the need for an intermediate representation of meaning in the form of a situation model that represents multiple events and relations between their constituents. In this context we can now begin to address how narrative can enrich perceived meaning as suggested by Bruner.

Dynamic Construction Grammar

The dynamic construction grammar model is a neuro-computational implementation of concepts developed in the Bates and MacWhinney cue competition model (Bates and MacWhinney 1987; Li and Macwhinney 2013) of language. The principal inspiration from cue competition is that, across languages, a limited set of cues are available for encoding grammatical structure necessary for determining who did what to whom.

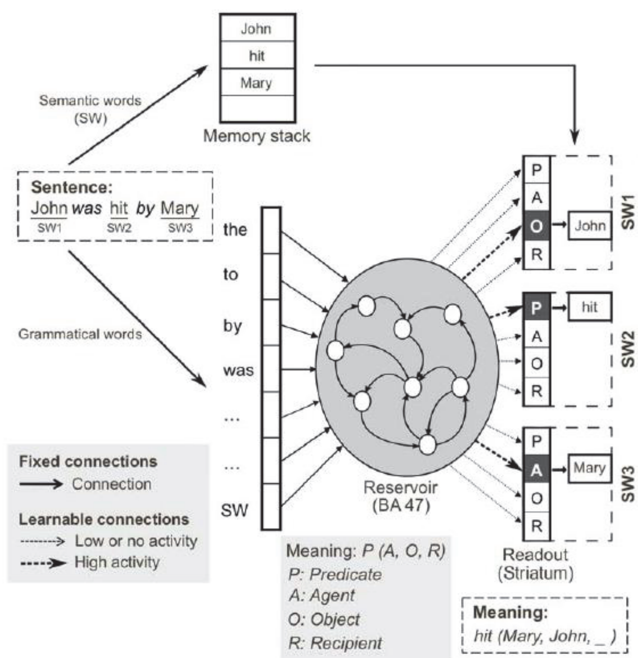

Figure 1. Grammatical construction comprehension. Input sentences are separated into open (semantic) and closed class (grammatical words). Grammatical words stimulate the recurrent reservoir. Learnable connections between reservoir and readouts that indicate for each ordered semantic word its semantic role in the construction. Each Semantic word (SW) can participate in two phrases, so the Predicate,

Amongst these cues are word order and grammatical morphology, in the form of free or bound grammatical morphemes. Free grammatical morphemes can be referred to as grammatical function words or closed class words, reflecting the notion that they are part of a fixed, closed class. In contrast, semantic words including nouns, verbs, and adjectives are part of a more open evolving class and can thus be referred to as open class words.

The DCG project thus set out to develop a neurophysiologically motivated system that could explain certain aspects of sentence comprehension based on the notion that thematic role assignment (determining who did what to whom) is encoded by a combination of word order and grammatical function word placement.

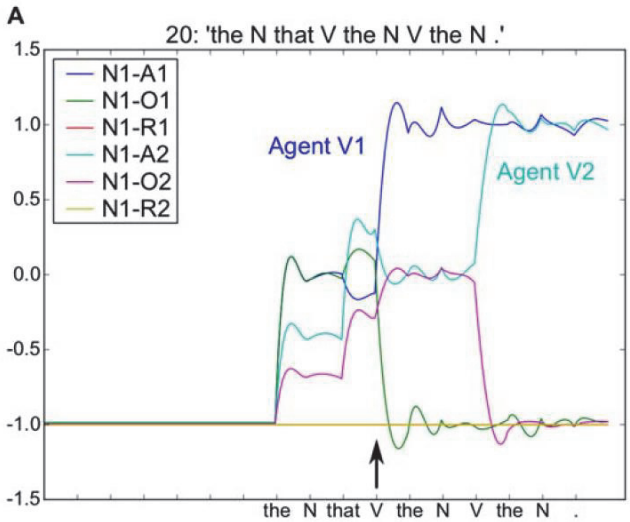

Figure 2. Dynamic predictive activation of readout neurons that code semantic roles as words are presented in real time. In this example, colored lines correspond to readouts that code the roles (Agent, Object, Recipient) in the first (1) or second (2) event for the first noun in the sentence. Successive words are presented at each tic mark. Note that as certain grammatical words arrive, the predicted meaning is updated. The system thus entertains a dynamic representation of multiple parallel parses.

The task that we set out to model is a task of thematic role assignment used by neurologist aphasiologist David Caplan and colleagues for assessing agrammatical aphasia in stroke patients (Caplan, Baker et al. 1985). The task assesses syntactic comprehension, that is, the ability to perform thematic role assignment using purely syntactic or grammatical cues. Subject are read aloud sentences, such as “The elephant was shown to the monkey by the giraffe.” They are then presented with visual images of an elephant, a monkey and a giraffe, and asked to indicate, by pointing, which was the agent of the action, the object and the recipient. The strange use of these animals yields an interpretation task where there are no semantic cues to thematic role assignment.

This task can be considered in the context of behavioral sequence processing: a sentence is presented as a sequence of words, and the response is a sequence of outputs corresponding to indication of the agent, the object and the recipient of the action, in that order. Dominey and colleagues (Dominey, Arbib et al. 1995) developed a model of sensorimotor sequence processing, where recurrent connections in the prefrontal cortex encode the spatiotemporal structure and history of the input sequence, and modifiable corticostriatal connections bind these states to behavioral responses. The fixed recurrent connections provide a dynamical state system that is ideally suited for representing temporal structure, hence the name temporal recurrent network (Dominey and Ramus 2000). An extension of the corticostriatal model to allow the system to work on sequences of variables coded in a working memory allowed the system to address more abstract sequences (Dominey, Lelekov et al. 1998) and artificial grammars (Dominey, Inui et al. 2009). We referred to this extension as the abstract recurrent network (ARN) and demonstrated that the resulting TRN and ARN system could simulate the initial state of the infant in language acquisition (Dominey and Ramus 2000) corresponding to sensitivity to the serial structure of syllables (Saffran, Aslin et al. 1996), the prosodic structure of different language classes (Nazzi, Bertoncini et al. 1998), and the abstract structure of sound sequences (Marcus, Vijayan et al. 1999).

At this point, we realized that the ATRN model could be used to solve the thematic role assignment task of Caplan. Separating open and closed class words, the open class words would be stored in the working memory, indexed by their order in the sentence, and the closed class words would activate the recurrent network, thus creating a dynamic representation of the sentence structure. The system would then be trained to produce an output sequence where the first output element would be the position of the open class word corresponding to the agent, then the object, then the recipient. We observed that the ATRN model could learning the Caplan task, predict agrammatic aphasic performance, and predict ERP responses in healthy subjects (Dominey, Hoen et al. 2003). The model thus implements a form of grammatical construction as form to meaning mapping (Goldberg 1995), where the sentence is the form component, and a predicate-argument representation of the thematic roles is the meaning component.

Neural Dynamics

The dynamic recurrent network that results from fixed connections that model the prefrontal cortex has a rich temporal dynamics that is not found in recurrent networks where the temporal history is cut off to allow learning in the recurrent connections (Pearlmutter 1995). This creation of a dynamic network with fixed recurrent connections (Dominey 1995; Dominey, Arbib et al. 1995) was the first instance of reservoir computing (see Lukosevicius and Jaeger 2009) that was subsequently developed independently by Jaeger (Jaeger 2001; Jaeger and Haas 2004) and Maass (Maass, Natschlager et al. 2002). Interestingly, because of the neural dynamics in the recurrent network and the trained readout connections, activity in the readout neurons is dynamic and predictive, as illustrated in Figure 2. In this context one can appreciate the dynamic aspect of DCG.

During training, as the input sentence is presented word by word, the reservoir traverses a dynamic trajectory of activity. For each sentence in the corpus, the meaning of each semantic word is specified as either the Predicate (verb), Agent, Object, or Recipient (PAOR) role in the first and (optional) second phrase of the sentence. To further understand Figure 2, consider the sentence "the ball that hit the block destroyed the pyramid". Figure 2 illustrates the readout neurons that code the role of "ball", as either Predicate (verb), Agent, Object or Recipient (the PAOR neurons in Fig 1). During training, we force the readout neurons that code Noun 1 (which is also Semantic Word 1 (SW1) in Figure 1) to Agent for the first and second phrase in the sentence, and apply a learning algorithm that links reservoir activity states to activation of these readout neurons (See Hinaut & Dominey 2013 for details). Note that in Fig 1, the PAOR neurons for the second phrase are not illustrated, for simplicity. After training, presentation of a sentence with the same structure leads to the neural activation in Fig. 2, indicating that "ball" is the agent in the two phrases.

As soon as "the" comes in, multiple possibilities for the roll of "ball" (the first Noun, and first SW) are activated. This includes the hypothesis that N1 (which has not even been seen yet) fills the R1 slot. After "that" comes in the hypothesis that N1 is O1 is the highest. This is because of other sentence patterns where this is a possibility such as "the dog that the cat bit chased the boy" (see Hinaut & Dominey 2013).

The activation of the readout neurons illustrates that the model is entertaining multiple parses of the sentence in real time, and that these probabilistic parses are confirmed or rejected as subsequent disambiguating words arrive. The neural activity thus reflects the statistics of the training corpus. The model is thus clearly situated in a usage-based approach to language acquisition (Tomasello 2000; Tomasello 2003). For both comprehension (Hinaut and Dominey 2013) and production (Hinaut, Lance et al. 2015), the DCG model is able to learn large corpora, and then to demonstrate generalization to novel constructions.

Generalization to untrained constructions

Using more efficient linear regression methods from reservoir computing for learning the mappings from neurons in the recurrent network (prefrontal cortex) to the readout (striatum) allowed the training of the reservoir network for sentence comprehension on much larger corpora of grammatical constructions. The corpora consist of matched pairs of sentences, and the corresponding meanings, coded in terms of the assignment of open class elements to their semantic role in the sentence. In this context, Hinaut and Dominey (2013) demonstrated that the trained model was able to correctly process novel constructions that were not present in the training corpus. This includes the understanding of complex constructions corresponding to sentences such as "The dog bit the cat that chased the boy" and "The dog bit the cat that was chased by the boy."

This generalization is based on the principal that information that characterizes the grammatical regularities is inherent in the training examples in the corpus. Exposure to a sufficiently rich and demonstrative corpus allows the system to generalize to new sentences that are consistent with the structure of the corpus.

A similar generalization capability was observed for sentence production (Hinaut, Lance et al. 2015). The DCG sentence production model essentially reverses the flow of information in the comprehension model. A predicate-argument representation of meaning is presented as the input, and the model learns to generate the corresponding sequence of open an closed class words to express the meaning. The notion of different construals of meaning becomes important here, when we consider two sentences like:

a. The award was given to the student that the principal congratulates by the teacher.
b. The teacher gives the award to the student that the principal congratulates.

These two sentences describe the same events, but with a different focus or information structure. Thus, in order to be able to generate such sentences, the DCG sentence generation model requires that this information structure is available in the input. This requirement is achieved by using the same representation as in the output structure illustrated in Figure 1. That is input specifies for the ordered semantic words the roles they play in the coded events.

Language and Meaning in Robotic Interaction

Our work in language comprehension is inspired by the "miniature language acquisition" challenge set by Feldman and colleagues (Feldman, Lakoff et al. 1990). We developed a system that could recognize simple actions performed by human subjects, who narrated their actions at the same time. These paired sentence-event corpora were used to train a variant of the DCG model, and then the test was to see if the trained system could answer questions about future observed actions (Dominey and Boucher 2005; Dominey and Boucher 2005). Given the success of this first approach, we proceeded with the full DCG models, integrated into a real-time interaction system for the humanoid robot iCub (Hinaut, Petit et al. 2014; Mealier, Pointeau et al. 2016), where language comprehension allowed the robot to understand complex commands like "Before you push the guitar point to the violin," in a setup where the human and the humanoid robot iCub interact in a shared physical space as illustrated in Figure 3. Likewise, language production was used by the robot in order to describe spatial scenes that were generated by the human placing objects in different configurations as illustrated in Figure 3.

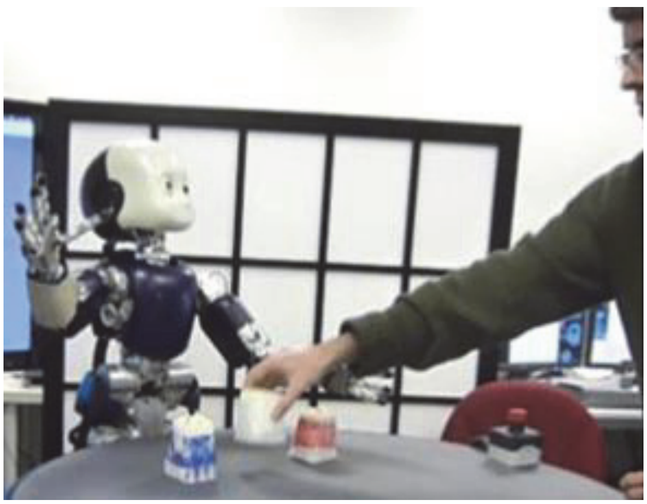

Figure 3. Human placing objects in a spatial configuration for the iCub to describe using the DCG sentence production model (from (Hinaut, Petit et al. 2014)).

Depending on the context, the iCub could say "The trumpet is to the right of the guitar" or "To the right of the guitar is the trumpet" to describe the same scene. This introduces the notion that the same scene can be construed in different ways.

Performance on data from naïve subjects

In order to demonstrate the flexibility of the system, we invited naïve users to describe scenes that took place in the shared space, and then we used the resulting sentences to generate corpora to train the comprehension model. The use of data from naïve subjects was quite interesting, as they used sentence formulations that we had not considered when generating our training data. Examples of novel sentences types that were successfully learned and generalized with ah leaving-one-out procedure are illustrated in Figure 4.

(5) Point the triangle **before** grasping the circle
(20) Put the cross to the left **before** grasping the circle
(92) Point to the cross **twice**
(198) **Before you** grasp the cross **please** grasp the triangle
(214) **Before** pushing the triangle to the middle **please** push the cross to the right
(230) Grasp the circle and then point to **it**
(245) Touch the triangle then move **it** to the left
(260) The cross touch **it**
(268) Point to the circle **after** having grasped **it**
(313) Point cross **two times**
(340) **Before** grasp circle point triangle

Figure 4. Examples of sentences generated by naïve subjects, and successfully learned and generalized by the DCG comprehension model.

Construals of Meaning

The variability that we see in the way that people describe the same events illustrates the notion of construal. Construal refers how one perceives, comprehends and interprets the world around them (Feldman 1987). Gardenfors and colleagues develop the idea that the same physical event can be construed from the perspective of the force that causes the event, or the result of the event.

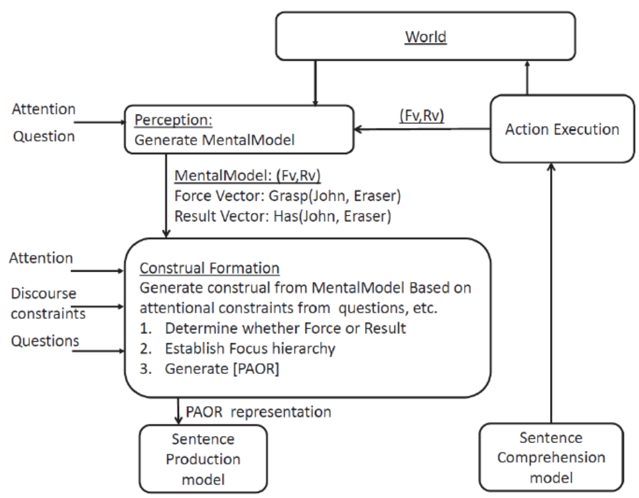

Figure 5. Meaning construal system. DCG comprehension model allows system to understand human action commands, and then to generate different construals (in terms of the underlying force or result) of these meanings in response to questions from the user

Correspondingly, the same event can be described with verbs that map onto the respective force or result vector (Warglien, Gärdenfors et al. 2012). We thus extended the cognitive system framework developed for the iCub, as illustrated in Figure 5, to include the capacity to associate with different physical events the force and result vectors, and to allow the system to choose which construal to make, based on the attentional context that is created when the user asks questions. Asking a question about "what did you do" is associated with the force or cause of the event. In contrast, questions about "what happened" are associated with the result vector (Mealier, Pointeau et al. 2016).

Narrative Construction

One of the limitations of the sentence-meaning mapping in DCG is that it is limited to single sentences. Data from human electrophysiology demonstrates that humans are able to keep a form of situation model in active memory so that information that was provided several sentences in the past is used in the on-line interpretation of new sentences (Hagoort and van Berkum 2007). More generally, human discourse tends to construct articulated semantic representations that go beyond a single sentence, forming a situation model (Kintsch 1974; Kintsch 1988; Zwaan and Radvansky 1998) or mental model (Johnson-Laird 1983) of the described events. As stated by Lakoff and Narayanan (2010), "Narrative exploits the rich structure of human event and action representation. Encoding this structure is necessary for representing, reasoning about the form and content of narratives."

We are developing a system where a situation model is assembled by linking event representations that are based on the PAOR attributes in Figure 1, and organized around an event structure with Initial state, Goal, Action, Result and Final state – IGARF. These events are linked with narrative relations (causal, temporal, intentional) from successive sentences in the narrative. This involves an extension of the notion of grammatical construction to narrative construction. This in turn involves the introduction of the notion of narrative function words. In analogy to the way in which grammatical function words operate on relations between open class words in a sentence, narrative function words operate on relations between events in a situation model (Mealier, Pointeau et al. submitted). Narrative function words including "because, since, then, so, before, after" allow the construction of relations between events in order to construct and enrich a situation model representation of meaning.

The major issue we had to resolve concerned how the DCG model could accommodate multiple sentences that are linked by their narrative structure and contribute to the construction of a coherent meaning representation. The solution was to extend the meaning pole of the DCG model. As illustrated in Figure 6, the DCG models have the meaning pole that continues to contain a representation of the events described in the sentence. In addition to coding the predicate-argument representation of the events, the meaning component is supplemented with an optional representation of the narrative context as coded by a narrative function word. This is indicated as narrative Relations in Figure 6. For example, in the sentence "I gave you the giraffe because I knew you wanted it", the meaning component represents standard predicate-agent-object-recipient (PAOR) the two events gave(I, you, giraffe, and the narrative relations component indicates the narrative function word that is now linked to these events. This link is then added to the situation model, as illustrated.

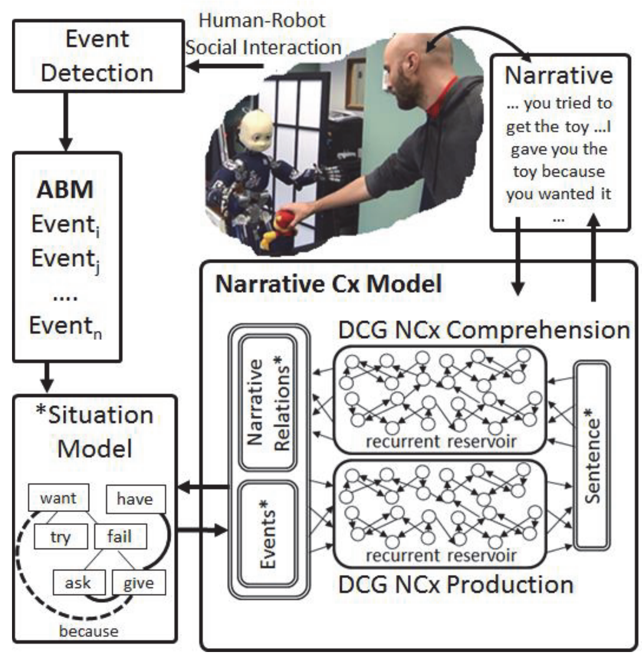

Figure 6. DCG in narrative enrichment. Human-robot cooperative interaction generates events, coded in the ABM, and transcribed into the situation model. Narrative input maps events into events in the SM, and allows enrichment of the SM via narrative relations (like "because") that are coded by narrative function words. See text for details.

From a developmental perspective, the idea is that the child or robot will live a particular experience. This is coded in the ABM, and then in a first version of the situation model. Incoming narrative will enrich the representation in the situation model, precisely by introducing these narrative relations (Bruner 1990; Bruner 1991). Our initial proof of concept demonstrates the feasibility of this approach, whereby multiple sentences can be understood in the context of a DCG model where the meaning pole is supplemented with a context or narrative relation component that allows the meaning of sentences to be embedded into the graph structure of a situation model.

Discussion

We present Dynamic Construction Grammar as a neurocomputational approach to integrating ideas from the cue competition model into a system that can perform semantic role labeling in sentence comprehension, and can generate well-formed sentences based on labeled semantic roles as input for sentence production. The DCG framework has been applied to sentence comprehension and production. It has been demonstrated to display generalization properties, including the ability to understand new construction that were not used in training for the comprehension model. Because of the dynamic nature of the recurrent network that encodes the internal input driven state of activation, the model displays real-time dynamic behavior. This can be seen as activation traces in the trained output neurons which represent multiple parallel parses as the sentences is processed word-by-word.

A characteristic feature of DCG is that there is very little language-specific structure within the dynamic reservoir system. The only language specific aspects are the coding of closed class words as input or output neurons for the comprehension and production models respectively, and the coding of meaning as semantic roles for the ordered open class words. Because the model relies on learning, there is a strong need for extensive training corpora. One way to avoid generating labeled corpora by hand is to exploit human-robot interaction systems where language and labeled meaning can be generated automatically.

Of course, there is a price to pay for this "lean" approach. Perhaps one of the most striking weaknesses is that verb morphology is not coded – verbs are handled as semantic words, period. One might think that a second, weakness is that because they are processed as semantic words, verbs lose their role in item-based constructions. Actually, we hypothesized that during development, some open class words may actually be bound into the construction, like a closed class word for our model (Dominey 2006). When considering a sentence like "John sneezed the napkin off the table", it is debatable whether the corresponding construction "SW1 SW2 the SW3 off the SW4" captures the notion that a construction can introduce meaning beyond that provided by the lexical items.

DCG can be contrasted with several alternate models of construction grammar. Embodied construction grammar (ECG) maps sentence form to meaning and includes a rich representation of meaning in terms of the execution of simulations that among other advantages allow inferences to made (Bergen and Chang 2005) This framework has been developed in a rich context that has also been extended to narrative processing (Lakoff and Narayanan 2010). Template construction grammar (TCG) has been developed in a context of visual scene parsing that generates the semantic representation part of the form to meaning mapping, and the lexical sequence that defines the form part (Arbib and Lee 2008). Part of the motivation for TCG is to establish deeper links to the evolution and neurophysiology of the language system (Arbib 2012). Fluid construction grammar (Steels and De Beule 2006; Steels 2011) was developed to allow open ended grounded dialog, building on formal and computational linguistics. A central motivation is the creative or fluid aspect of language including the invention of new forms to express meaning.

The narrative construction

The most challenging aspect of language processing concerns the integration of multiple sentences into a coherent narrative. From our classic grammatical construction approach, one sentences maps onto one meaning, and so the requirement on the meaning representation is limited to what can be expressed in a single sentence. In the context of narrative, this is no longer the case: meaning must be a more elaborated representation that can address multiple events and diverse relations between them. This has been developed as the notion of situation model or mental model, and significant effort has been dedicated to addressing how multiple sentences are integrated into a situation model representation (Johnson-Laird 1983; Kintsch 1988; Zwaan, Langston et al. 1995; Zwaan and Madden 2004; Johnson-Laird 2010).

Interestingly we find that the notion of grammatical construction extends in a rather elegant way to narrative construction. Grammatical constructions map sentence form to meaning. Narrative constructions map multiple sentences to a composed meaning in the form of a situation model. Grammatical function words specify relations between open class words and their semantic roles. Narrative function words specify relations between events and their constituent elements at the level of the situation model. We should note that the notion of narrative function word has previously been proposed (Norrick 2001). Second, we do not claim that the presence of narrative function words creates narrative, nor that narrative requires narrative function words. Rather, we claim that there is a class of function words that operate at the level of events and relations between them in a situation model.

We have taken a first step towards extending the DCG model into the domain of narrative, with the notion of narrative construction. This can be considered a very early step in the development of the narrative capability – in particular where adult narrative can be used to enrich event representations in the developing child (Fivush 1994; Nelson and Fivush 2004).

In the context of computational narrative Finlayson has demonstrated how machine learning can extract culturally relevant plot structures from folktales (Finlayson 2012). Such plot structures as *villainy* or *revenge* can be recognized based on underlying structure in the framework of analogical story merging. This will have significant impact in understanding how high cognitive representations such as cultural norms are transmitted and represents a much higher level of sophistication than what we have started to address in the current research.

In this context it is worth noting how Bruner considered that narrative is a vehicle for making meaning, including understanding the behavior of others as folk psychology (Bruner 1990). Gallagher and Hutto (2008) have further addressed how this might work in more detail in the narrative practice hypothesis, and our future research will attempt to model how narrative patterns can provide for aspects of folk psychology.

DCG takes a stance on issues of learnability and learning in language acquisition, and it takes a stance on the neurophysiological bases of these language related functions. Future research should attempt to determine whether these stances are to be validated. Also, because of its flexibility and learning, DCG is beginning to be seen as a useful component of natural language interaction systems for robots. This too remains a potentially fruitful avenue for future research.

Acknowledgement

This research was supported by the FP7-ICT project What You Say Is What You Did (WYSIWYD).

References

Arbib, M. A. (2012). How the brain got language: The mirror system hypothesis, OUP USA.

Arbib, M. A. and J. Lee (2008). "Describing visual scenes: Towards a neurolinguistics based on construction grammar." brain research **1225**: 146-162.

Bates, E. and B. MacWhinney (1987). Competition, variation, and language learning. Mechanisms of language acquisition. B. MacWhinney and E. Bates. Hillsdale, NJ, Erlbaum**:** 157-193.

Bergen, B. and N. Chang (2005). "Embodied construction grammar in simulation-based language understanding." Construction grammars: Cognitive grounding and theoretical extensions: 147-190.

Bruner, J. (1991). "The narrative construction of reality." Critical inquiry: 1-21.

Bruner, J. S. (1990). Acts of meaning, Harvard University Press.

Caplan, D., C. Baker, et al. (1985). "Syntactic determinants of sentence comprehension in aphasia." Cognition **21**(2): 117-175.

Dominey, P. (2006). "From holophrases to abstract grammatical constructions: insights from simulation studies." Constructions in Acquisition, E. Clark and B. Kelly, Eds. Stanford: CSLI Publications: 137-162.

Dominey, P. and J. Boucher (2005). "Developmental stages of perception and language acquisition in a perceptually grounded robot." Cognitive Systems Research **6**: 243-259.

Dominey, P. F. (1995). "Complex sensory-motor sequence learning based on recurrent state representation and reinforcement learning." Biol Cybern **73**(3): 265-274.

Dominey, P. F., M. A. Arbib, et al. (1995). "A Model of Corticostriatal Plasticity for Learning Oculomotor Associations and Sequences " J Cogn Neurosci **7**(3): 25.

Dominey, P. F. and J. D. Boucher (2005). "Learning to talk about events from narrated video in a construction grammar framework." Artificial Intelligence **167**(1-2): 31-61.

Dominey, P. F., M. Hoen, et al. (2003). "Neurological basis of language and sequential cognition: evidence from simulation, aphasia, and ERP studies." Brain Lang **86**(2): 207-225.

Dominey, P. F., T. Inui, et al. (2009). "Neural network processing of natural language: II. Towards a unified model of corticostriatal function in learning sentence comprehension and non-linguistic sequencing." Brain & Language **109**(2-3): 80-92.

Dominey, P. F., T. Lelekov, et al. (1998). "Dissociable processes for learning the surface structure and abstract structure of sensorimotor sequences." J Cogn Neurosci **10**(6): 734-751.

Dominey, P. F. and F. Ramus (2000). "Neural network processing of natural language: I. Sensitivity to serial, temporal and abstract structure of language in the infant." Language and Cognitive Processes **15**(1): 40.

Feldman, C. F. (1987). Thought from language: the linguistic construction of cognitive representations. Making sense: the child's construction of the world. J. Bruner. London, Methuen & Co.**:** 131-146.

Feldman, J. A., G. Lakoff, et al. (1990). Miniature language acquisition: A touchstone for cognitive science. 12th Ann Conf. Cog. Sci. Soc., Cambridge, MA, MIT Press.

Finlayson, M. A. (2012). Learning Narrative Structure from Annotated Folktales, Massachusetts Institute of Technology.

Fivush, R. (1994). "Constructing narrative, emotion, and self in parent-child conversations about the past." The remembering self: Construction and accuracy in the self-narrative: 136-157.

Gallagher, S. and D. Hutto (2008). "Understanding others through primary interaction and narrative practice." The shared mind: Perspectives on intersubjectivity: 17-38.

Goldberg, A. (1995). Constructions: A Construction Grammar Approach to Argument Structure. Chicago, University of Chicago Press.

Hagoort, P. and J. van Berkum (2007). "Beyond the sentence given." Philos Trans R Soc Lond B Biol Sci **362**(1481): 801-811.

Hinaut, X. and P. F. Dominey (2013). "Real-time parallel processing of grammatical structure in the fronto-striatal system: a recurrent network simulation study using reservoir computing." PLoS One **8**(2): 1-18.

Hinaut, X., F. Lance, et al. (2015). "Corticostriatal response selection in sentence production: Insights from neural network simulation with reservoir computing." Brain and language **150**: 54-68.

Hinaut, X., M. Petit, et al. (2014). "Exploring the acquisition and production of grammatical constructions through human-robot interaction with echo state networks." Front Neurorobot **8**.

Jaeger, H. (2001). "The" echo state" approach to analysing and training recurrent neural networks-with an erratum note'." Bonn, Germany: German National Research Center for Information Technology GMD Technical Report **148**.

Jaeger, H. and H. Haas (2004). "Harnessing nonlinearity: predicting chaotic systems and saving energy in wireless communication." Science **304**(5667): 78-80.

Johnson-Laird, P. N. (1983). Mental models: Towards a cognitive science of language, inference, and consciousness., Harvard University Press.

Johnson-Laird, P. N. (2010). "Mental models and human reasoning." Proc Natl Acad Sci U S A **107**(43): 18243-18250.

Kintsch, W. (1974). "The representation of meaning in memory."

Kintsch, W. (1988). "The role of knowledge in discourse comprehension: a construction-integration model." Psychol Rev **95**(2): 163-182.

Kintsch, W. (1988). "The role of knowledge in discourse comprehension: a construction-integration model." Psychological review **95**(2): 163.

Lakoff, G. and S. Narayanan (2010). Toward a Computational Model of Narrative. AAAI Fall Symposium: Computational Models of Narrative.

Li, P. and B. Macwhinney (2013). "Competition Model." The Encyclopedia of Applied Linguistics.

Lukosevicius, M. and H. Jaeger (2009). "Reservoir computing approaches to recurrent neural network training." Computer Science Review **3**(3): 22.

Maass, W., T. Natschlager, et al. (2002). "Real-time computing without stable states: a new framework for neural computation based on perturbations." Neural Comput **14**(11): 2531-2560.

Marcus, G. F., S. Vijayan, et al. (1999). "Rule learning by seven-month-old infants." Science **283**(5398): 77-80.

Mealier, A.-L., G. Pointeau, et al. (2016). "Construals of meaning: The role of attention in robotic language production." Interaction Studies **17**(1): 41-69.

Mealier, A.-L., G. Pointeau, et al. (submitted). "Narrative Constructions for the Organization of Self Experience: Proof of Concept via Embodied Robotics " Frontiers in Psychology: Language.

Nazzi, T., J. Bertoncini, et al. (1998). "Language discrimination by newborns: toward an understanding of the role of rhythm." J Exp Psychol Hum Percept Perform **24**(3): 756-766.

Nelson, K. and R. Fivush (2004). "The emergence of autobiographical memory: a social cultural developmental theory." Psychological review **111**(2): 486.

Norrick, N. R. (2001). "Discourse markers in oral narrative." Journal of pragmatics **33**(6): 849-878.

Pearlmutter, B. A. (1995). "Gradient calculations for dynamic recurrent neural networks: A survey." Neural Networks, IEEE Transactions on **6**(5): 1212-1228.

Saffran, J. R., R. N. Aslin, et al. (1996). "Statistical learning by 8-month-old infants." Science **274**(5294): 1926-1928.

Steels, L. (2011). Design patterns in fluid construction grammar, John Benjamins Publishing.

Steels, L. and J. De Beule (2006). A (very) brief introduction to fluid construction grammar. Proceedings of the Third Workshop on Scalable Natural Language Understanding, Association for Computational Linguistics.

Tomasello, M. (2000). "The item-based nature of children's early syntactic development." Trends Cogn Sci **4**(4): 156-163.

Tomasello, M. (2003). Constructing a language: A usage based approach to language acquisition. Boston, MIT Press.

Warglien, M., P. Gärdenfors, et al. (2012). "Event structure, conceptual spaces and the semantics of verbs." Theoretical Linguistics **38**: 159-193.

Zwaan, R. A., M. C. Langston, et al. (1995). "The construction of situation models in narrative comprehension: An event-indexing model." Psychological science: 292-297.

Zwaan, R. A. and C. J. Madden (2004). "Updating situation models." J Exp Psychol Learn Mem Cogn **30**(1): 283-288; discussion 289-291.

Zwaan, R. A. and G. A. Radvansky (1998). "Situation models in language comprehension and memory." Psychol Bull **123**(2): 162-185.