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ORIGINAL ARTICLE

Template Construction Grammar: From Visual Scene Description to Language Comprehension and Agrammatism

Victor Barrès · Jinyong Lee

Abstract How does the language system coordinate with our visual system to yield flexible integration of linguistic, perceptual, and world-knowledge information when we communicate about the world we perceive? Schema theory is a computational framework that allows the simulation of perceptuo-motor coordination programs on the basis of known brain operating principles such as cooperative computation and distributed processing. We present first its application to a model of language production, SemRep/TCG, which combines a semantic representation of visual scenes (SemRep) with Template Construction Grammar (TCG) as a means to generate verbal descriptions of a scene from its associated SemRep graph. SemRep/TCG combines the neurocomputational framework of schema theory with the representational format of construction grammar in a model linking eye-tracking data to visual scene descriptions. We then offer a conceptual extension of TCG to include language comprehension and address data on the role of both world knowledge and grammatical semantics in the comprehension performances of agrammatic aphasic patients. This extension introduces a distinction between heavy and light semantics. The TCG model of language comprehension offers a computational framework to quantitatively analyze the distributed dynamics of language processes, focusing on the interactions between grammatical, world knowledge, and visual information. In particular, it reveals interesting implications for the understanding of the various patterns of comprehension performances of agrammatic aphasics measured using sentence-picture matching tasks. This new step in the life cycle of the model serves as a basis for exploring the specific challenges that neurolinguistic computational modeling poses to the neuroinformatics community.

Keywords Neurolinguistics · Computational model · Construction grammar · Visual scene description · Schema theory · Agrammatism · Language comprehension · Language production

Talking about the World: From Schema Theory to Template Construction Grammar

Linking the Eye and the Mouth

Understanding the language system requires understanding not only the processing of grammatical constraints but also how such processes are integrated with evolutionarily more conserved systems that support our sensory-motor interactions with the world. In this paper, we focus on the relation between vision and language. In a visual scene description task, a subject simultaneously gathers information from the image, fixating elements that become salient based on both bottom-up features and top-down hypotheses, and starts generating linguistic output based on relevant visual information. Under pressure to communicate she might start producing fragmented utterances while in more relaxed conditions the message might become composed of well-formed sentences packaging content collected through many fixations. Turning to comprehension, a patient suffering from brain lesions impairing her capacity to use grammatical cues can compensate in some cases by relying on her knowledge of the world to assign linguistic inputs to their correct semantic role and correctly identify what picture matches the sentence she has just heard. We offer a neurolinguistic computational framework that tackles such behavioral and neuropsychological data. Part 2 presents a computational model for generating flexible scene descriptions

V. Barrès (✉)
Neuroscience Graduate Program and USC Brain Project, University of Southern California, Los Angeles, CA, USA
e-mail: barres@usc.edu

J. Lee
Computer Science Department and USC Brain Project, University of Southern California, Los Angeles, CA, USA
e-mail: jinyongl@usc.edu

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from visually extracted semantic content. In Part 3, the model is conceptually extended to comprehension with a focus on the case of agrammatic aphasics. Taking a step back, Part 4 discusses more generally the role that neuroinformatics can play in bolstering neurolinguistic modeling efforts.

Introducing Schemas

We build on a version of *schema theory* (Arbib 1981) in which instances of *perceptual schemas* (enabling the recognition of specific objects, situations or events in the world, as well as parameters relevant to action) and *motor schemas* (akin to control systems for some course of action) compete and cooperate in the brain of an organism constantly engaged in an action-perception cycle through which it makes sense of, and interacts with, its changing environment. Distributed patterns of *cooperative computation* – competition and cooperation between schema instances – yield patterns of activity that commit the organism to one course of action rather than another. Schema theory provides a level of computational modeling that aims at facilitating later transfer to neural level implementation. It is both symbolic (whether or not a schema has been instantiated) and subsymbolic (the activity level and parameter values of current schema instances). It allows for the distinction between a feature implicit in the operation of a schema and the activation of a schema that makes that feature explicit. For example, the color of an apple may enter into recognizing an object's shape en route to identifying it as an apple whether or not it enters explicit awareness that the apple is red or green. An initial schema-based model becomes part of *neural* schema theory if it addresses data from lesion studies, brain imaging, or single-cell recording to help us understand how this behavior is mediated by the inner workings of the brain. In this paper, we extend earlier work (Arbib et al. 1987; Arbib and Lee 2008) applying schema theory to language processing.

The computational architecture of the VISIONS system (Draper et al. 1989; Hanson and Riseman 1978) for understanding visual scenes offered useful insights into cooperative computation. Low-level processes extract visual features that contribute "bottom-up" to an intermediate representation of a visual scene − including contours and surfaces tagged with features such as color, texture, shape, size and location. Perceptual schema instances then process different features of regions of the intermediate representation to form confidence values for the presence of objects like houses, walls and trees – and may initiate further processing "top-down" within the intermediate representation to resolve ambiguities. Cooperative computation between schema instances may yield a "winning coalition," with the suppression of previously active instances, which provides (at least for a while) the interpretation of the scene. The knowledge required for such interpretation is stored in *long-term memory (LTM)* as a *network of schemas*, while the state of the interpretation of a particular scene unfolds in *working memory (WM)* as a *network of (parameterized) schema instances* (Fig. 1). Note that this working memory is not defined in terms of recency (as in short term memory) but rather in terms of continuing relevance.

VISIONS provides an example of how a schema network can be used to model some portion of world knowledge (here objects, how to recognize them from low level perceptual features extracted from an image, and how they are related spatially to their parts or frequently associated objects) and how this knowledge can be retrieved on the basis of activation values of already instantiated schemas.

The HEARSAY-II speech understanding system (Lesser et al. 1975) also adopted the perspective of cooperative computation even though implemented on a serial computer. HEARSAY uses a dynamic global data structure called the blackboard, partitioned into surface-phonemic, lexical and phrasal levels. Processes called knowledge sources act upon hypotheses at one level to generate hypotheses at another. Arbib and Caplan (1979) discussed how the knowledge sources of HEARSAY, which were scheduled serially, might be replaced by schemas distributed across the brain to capture the spirit of "distributed localization" of Luria (e.g., 1973). Today, advances in the understanding of distributed computation and the flood of neurolinguistic neuroimaging and behavioral data call for a new push at neurolinguistic modeling informed by the understanding of cooperative computation. Using the visual world paradigm, psycholinguistic studies are able to present linguistic stimuli to a subject who is simultaneously looking at a visual scene while recording the subject's eye movements. Altmann and Kamide (1999), among others, showed how subjects could incrementally combine linguistic, visual, and world knowledge information during a comprehension task. Faced with visual display showing a cake, two toys, and a boy, the subjects were faster to fixate the cake upon hearing the verb "eat" in the sentence "the boy will eat …" than upon hearing the more general verb "move" in the sentence "the boy will move ….". For us the challenge is therefore to link language processes to the perception of "realistic" visual scenes while also accounting for the role of world knowledge. But first, we need to introduce construction grammar.

Construction Grammar

Construction grammar comes in varied forms (Bergen and Chang 2005b; Croft 2001; De Beule and Steels 2005; Dominey et al. 2006b; Goldberg 1995; Kay 2002; Kay and Fillmore 1999). What is common to these various efforts is that grammar is not based on a small set of purely syntactic rules but instead on *constructions* which, like items in the lexicon, combine syntactic, semantic and even in some cases phonological information. In the framework of construction grammar, *He kicked the bucket* is ambiguous because it has

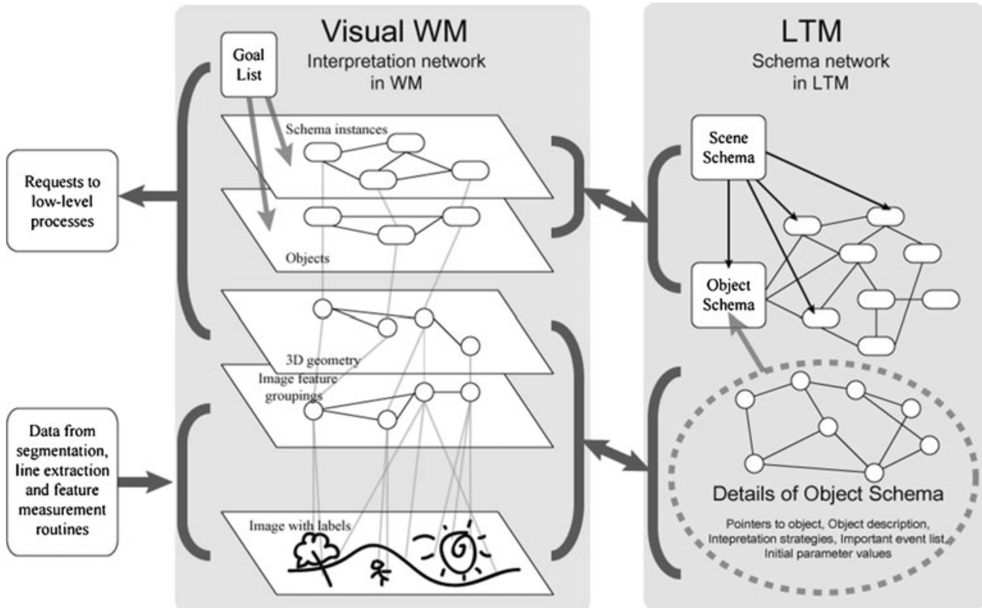

Fig. 1 The Visual Working Memory (WM) of VISIONS interprets the current scene by a network of parameterized instances of schemas from Long Term Memory (LTM). These schema instances are linked to the visual world via an intermediate database (here represented by the image feature groupings) that offers an updatable analysis of the division of the world into regions that are candidates for interpretation as agents and objects, possibly in relation with each other

two parsings. One yields an instance of the general formula *He X'd the Y* whose overall meaning varies with the meanings of *X* and *Y*. The other yields a term in which no substitutions can be made for *kick* and *bucket* and the meaning has no relation to those of *kick* or *bucket ("He died")*. As Hurford (2011, Chapter 4) notes, there is evidence that on hearing an idiom, both the overall meaning (e.g. die) and the meanings of the individual parts (e.g., kick and bucket) can be primed, suggesting redundant storage. This fits with our general view of competition and cooperation of schemas in that the initial activation of constructions for both parsings can have a priming effect even though just one eventually wins the competition determining our understanding of the sentence that contains the idiom.

In the *He X'd the Y* construction, the role of X and Y can be filled by almost any transitive verb (for X) and noun (for Y). Conversely, in the *kick the bucket* construction, some syntactic variation is possible but no substitutions may be made for *kick* or *bucket*. However, a core empirical foundation of construction grammar stems from closer analyses of constructions that revealed a continuum between rather syntactic and rather lexical constructions, with many constructions being sui generis in terms of the constraints they impose on their parts. For example, the constraints on Y and Z in the Goal-object construction *X'd Y with Z* as in "Sam filled the glass with water" and the Theme-object construction *X'd Z in Y* as in "Sam poured water in the glass" cannot be simply accounted for in terms of general syntactic classes. Indeed fill/drench/soak/saturate/infuse work with the Goal-object and not with the Theme-object construction and vice versa for pour/drip/dribble/spill. Such richness in constructional behavior is what led cognitive linguistics to adopt constructions to represent grammatical knowledge, abandoning the duality between lexicon and grammar, as well as between syntactic and semantic components.

Our goal is to show how language schemas can be defined as constructions and from there offer a neurocomputational model of language processing. Working within schema theory, the goal of our model is to show how cooperative computation of construction schemas can generate dynamic control structure for production and comprehension of language. Such a perspective distinguishes our approach from other implementations of construction grammars that have focused on the role of perceptuo-motor simulations in language comprehension (Bergen and Chang 2005a), diachronic language evolution in embodied robots (Steels and De Beule 2006), or language learning in a brain anchored connectionist implementation (Dominey and Boucher 2005; Dominey et al. 2006a). We share however with the latter two a focus on the language-vision interface.

Template Construction Grammar (TCG) as a Model of Visual Scene Descriptions: SemRep/TCG

We now introduce SemRep and TCG, building on the work of Arbib and Lee (2008) and Lee (2012) to provide a visually grounded version of construction grammar. What is worth stressing, however, is that our approach is not an attempt to *apply* directly a construction grammar formalism to computational neurolinguistics– rather, it is based on the realization that early approaches to a schema-theoretic linguistics (e.g., Arbib et al. 1987) can indeed be understood by interpreting the type of schemas that were then called *templates* as being examples of *constructions* as broadly construed within variants of construction grammar.

Arbib and Lee (2008) introduced *SemRep* as a hierarchical graph-like "semantic representation" designed to link the semantic content of sentences to the representation of visual scenes. SemRep is a representation abstracted from the schema assemblages such as those generated by VISIONS. Where the latter defines a "*cognitive structure,*" a SemRep defines the associated "*semantic structure*". However, the following discussion postulates an extended visual system in which actions objects are recognized as well as and relations (clearly, this depends on the set of schemas embedded within the system for visual scene perception).

A given scene can be perceived in many different ways; SemRep abstracts from the current pattern of schema activation a set of nodes and relations which constitute one possible semantic structure for the current scene. The properties of a recognized entity (an object or an action) are converted into a node linked to the perceptual schema instance in the schema assemblage while the semantics of a relationship between entities (including semantic roles for an action) are converted into an edge. Each node or relation is attached with a *concept* which may later be translated into words by the language system. However, concepts are not word labels but more abstract descriptors, allowing the same graph to be expressed in multiple ways within a given language. Consider the specific scene shown on the left of Fig. 2. Here, the concept DRESS could yield a variety of phonological forms such as "dress" or "frock." A SemRep expresses semantic relations but with no commitment to word choice, and can thus be the basis for description in any language once the appropriate grammar and lexicon are deployed. As Fig. 2 makes clear, a single scene can have many SemReps. Each SemRep encompasses one analysis which captures something of the agents, objects, actions and relationships that may be present in the one (possibly temporally extended) visual scene.

A schema instance in the visual analysis may be associated with a number of parameters, some of which (such as size, shape, orientation and location) may be relevant to possible interactions with what the schema represents and yet not be included in a verbal expression. We thus postulate that SemRep makes explicit very few parameters and can direct requests to Visual Working Memory when more information is required for explicit cognitive processing or verbal expression.

We now turn to the schema-based model of a grammar mapping the SemRep content onto verbal expression. Our version of construction grammar for language production, *Template Construction Grammar (TCG)*, was already introduced in Arbib and Lee (2008), and Lee (2012). TCG adopts two major policies common to all construction grammar frameworks: (1) each construction specifies a mapping between form and meaning, and (2) the systematic combination of constructions yields the whole grammatical structure. But TCG also provides two key additions: (1) The semantic structure of an utterance is given as a SemRep, and (2) each construction is viewed as a language schema and therefore endowed with all the dynamic properties of schemas. Such additions turn construction grammar into a dynamic system of representations that can enter into cooperative computations and flexibly map visual semantic content (SemRep) onto a verbal linguistic output.

A *construction* in TCG is defined by a triple (name, class, and template):

- *Name* is the name of the construction. It is not involved in processing and is only there for reference purposes.
- *Class* specifies the "category" of the result generated by applying the construction. It determines for which other constructions this result could serve as an input. In the examples considered here the class is chosen for simplicity as a conventional syntactic category, such as "noun" or "verb", for the head of the phrase which is returned on applying the construction. In general, though, the class of a construction is "syntactico-semantic" and based on usage. There is no a priori constraint on the number of classes

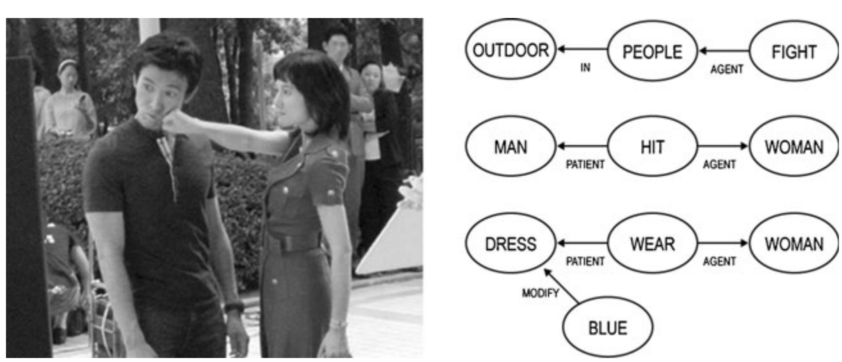

Fig. 2 Left: A picture of a woman hitting a man (original image from "*Invisible Man Choi Jang Soo*", Korean Broadcasting System). Right: Three example SemRep graphs that could be generated from the scene. Note: the words on the nodes are labels of convenience for yet-to-be-verbalized concepts. These SemReps might yield such sentences as "*a woman hits a man*", "*a woman is wearing a blue frock*", or "*people are fighting outside*"

(Croft 2001) - minimizing the number of categories does not seem useful from a neurolinguistic perspective since the brain codes great amounts of information, often in a redundant way.

- *Template* defines the form-meaning pair of a construction. It has two subcomponents, SemFrame and SynForm that correspond to the meaning and form part of the construction, respectively.
  - *SemFrame* (semantic frame) represent the meaning part of the construction. It is defined as the part of a SemRep graph that the construction will "cover". The SemFrame also specifies the "head" components which act as the representatives of the whole construction when forming hierarchy with other constructions.
  - *SynForm* (syntactic format) represent the form part of the construction. It consists of a series of words or morphemes, and *slots* which specify the classes of constructions that can fill them. A given slot represents non-phonological requirements imposed by the construction on its more schematic parts. It conveys construction-specific grammatical constraints that include both *semantic constraints* defined by the coupled SemRep element in the SemFrame, and *syntactic constraints* that are specified by the specific classes associated with the slot.

The lexical constructions at the bottom of Fig. 3 exemplify the way in which the concept associated with a single node or edge of the SemRep can ground the selection of a word to express that concept. The constructions at the top of Fig. 3 move up the hierarchy to cover larger and larger parts of the SemRep. Thus, the IN_COLOR construction has the interesting property that it must recognize the node for CLOTHING but only uses it to license the construction which yields utterances like *pretty woman in blue,* where the nodes for WOMAN and PRETTY have already been covered by another construction to yield the phrase *pretty woman* to fill the first slot in IN_COLOR, which is linked to the node HUMAN.

During production, a SemRep may yield one or more utterances as TCG finds ways to "cover" the relevant portion of the given SemRep with a set of "small" subgraphs, where each is chosen such that there is a construction available in the language considered to express the content of that subgraph. The SemFrame parts of the constructions' templates are used to select constructions that match whole or subparts of the SemRep graph, and can therefore participate in expressing some of its content. Thus, constructions are applied recursively, starting with lexical constructions, which have no slots (Fig. 3, bottom), and then by applying higher-level constructions (Fig. 3, top) in such a way that their SynForms match the results of earlier application of constructions (see Fig. 4 for an example).

In this section, we treat lexical constructions the same way we treat other constructions. However, this does not mean that lexical and more schematic constructions are neurologically equivalent: consider cases of double dissociation in language production between anomia (patient has difficulties in naming object or actions) and agrammatism (patient has difficulties producing syntactically correct utterances) (Goodglass 1976).

The scheme of VISIONS may therefore be lifted to a similar structure (Fig. 5) in which a Linguistic Working Memory (the Working Memory that keeps track of the state of the system resulting from the application of constructions to the current SemRep) provides the workspace for the operation of construction selection and attachment, thus providing a dynamic set of

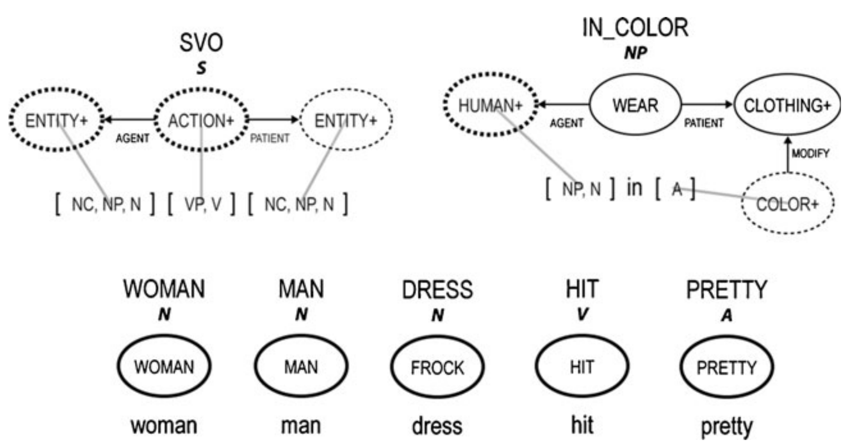

Fig. 3 Examples of constructions The name and class of each construction appears above it. Each construction includes a SemRep-like graph with either generic or specific labels on the edges and nodes, with each linked to a text or an empty slot. The node labels correspond to concepts, *not* words. Top: Higher-level constructions used to encode grammatical information. For each slot there may be restrictions as to what can serve as slot fillers. The head of each construction is marked with a thick-line (e.g. the node HUMAN in IN_COLOR). The node marked with a dashed-line (e.g. the ENTITY nodes in SVO) represents a "shared" element. A shared element can overlap with other elements (of other constructions) without conflict when covering a SemRep, allowing combination between constructions to happen at that overlapping area. Bottom: Constructions that correspond to elements in the lexicon, replacing a concept (small caps) with a word or, not shown here, phrase (lower case)

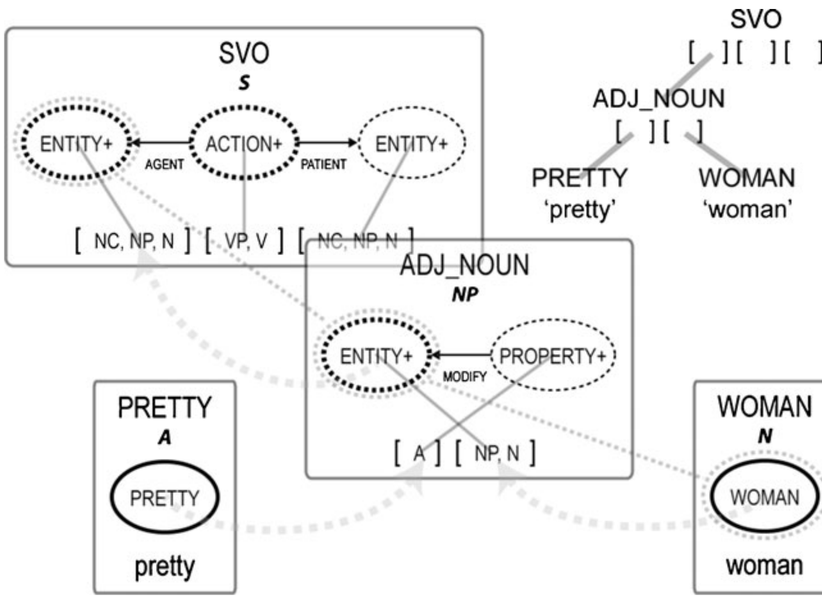

Fig. 4 An illustration of how a grammatical structure is built in TCG. When the semantics of the "head" components of a construction (represented as nodes with *thick lines*) is matched with the associated semantics of the slot that the construction fills in (e.g. ENTITY and WOMAN in combination of ADJ_NOUN and WOMAN construction) and the class of the construction is matched with one of the classes specified in the slot (e.g. N of WOMAN construction and [NP, N] of the second slot of ADJ_NOUN construction), syntactic combinations between constructions (represented by dashed-line arrows) are made. The head components of the combining constructions act as the "pivot" in the combination of the three constructions (WOMAN, ADJ_NOUN, and SVO) as they play a role as the representative components of the constructions that fill into the slot of other constructions (the ENTITY nodes are successively replaced by the WOMAN node through the syntactic linkage as represented by the dashed-line) – e.g. in forming the phrase *pretty woman*, the head node WOMAN and the associated construction becomes the head of the phrase, *woman*. Note that different constructions may compete and cooperate to cover a given SemRep which can thus give rise, in general, to different utterances

hierarchically organized construction structures with varying degrees of confidence.

Figure 5 shows two systems running in parallel. During production of a description, a number of constructions are activated simultaneously to build upon the unfolding SemRep. Constructions cooperate and compete with each other in order to produce a verbal description of a scene. The language system, which uses the linguistic working memory, applies constructions on SemRep hierarchically and reads off the resulting formed sentence or sentence fragments. The vision system concurrently interprets the scene and updates the SemRep. As Spivey et al. (2005) note, the visual environment can be treated as an external memory with eye movements being the typical access method. When necessary, the language system may generate requests for more details from the vision system. Constructions are applied based both on the "current" SemRep and on the state of the Grammatical WM, where there are a number of partially (or fully) created construction assemblages. The system produces utterances as soon as some threshold is reached. A speaker with a low threshold may produce "sentence fragments", while one with a high threshold may tend to talk in complete sentences. The sentence forming process is both: (1) incremental since new constructions are constantly being applied according to the current conceptual representation, SemRep, and (2) hierarchical since constructions may be applied atop other constructions to form a hierarchical organization anchored at its base directly on the SemRep abstracted from the visual processes.

In his thesis (Lee 2012) and in two companion papers, Jinyong Lee presents the implementation of TCG for visual scene description in considerable detail (Lee In preparation a) and then presents data on the utterances and eye movements of subjects as they describe complex natural visual scenes, showing how time pressure can "lower the threshold" resulting in fragmentary rather than well-formed utterances and explaining these results within the framework of the SemRep/TCG model (Lee In preparation b).

By making explicit how mechanisms for describing a scene using words parallel those for recognizing what is in the scene, Fig. 5 illustrates the claim that much is adapted or exapted from visual perception and motor activity to support the cognitive abilities involved in language processing. However much remains to be done in order to understand what extensions of the basic primate brain architecture were required to yield a language-ready brain (Arbib 2012).

Template Construction Grammar as a Model of Comprehension

We propose a conceptual extension of TCG as a model of language comprehension. Our goal is two-fold: (1) to incorporate

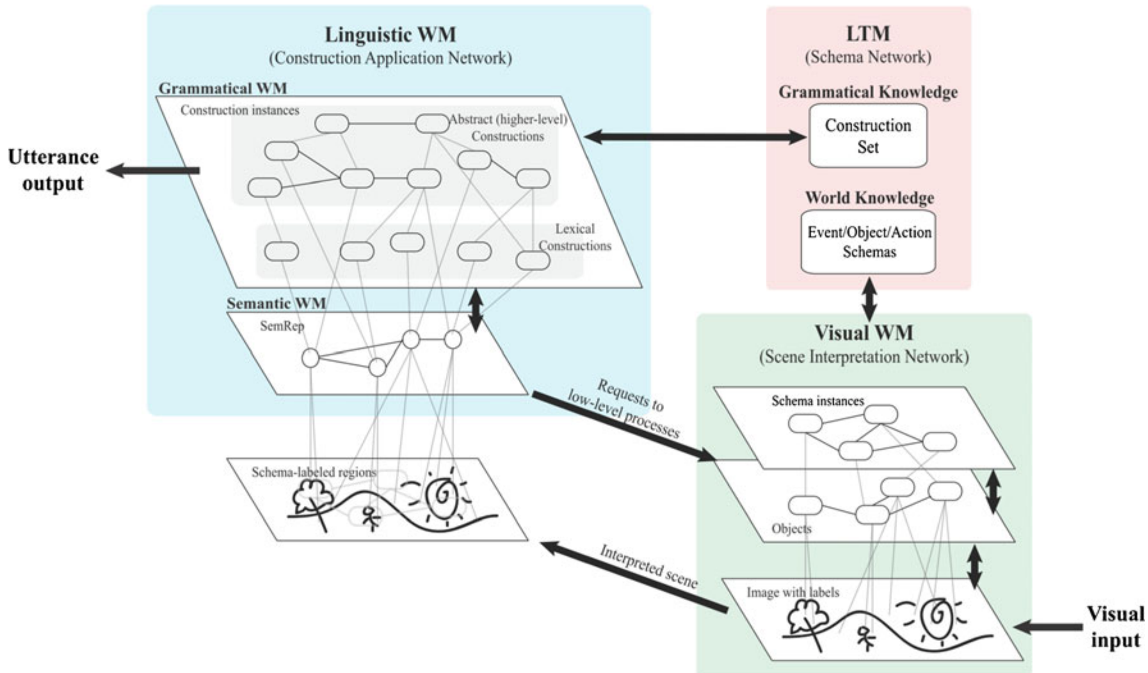

Fig. 5 The structure of our model of scene description. It echoes the interaction of Visual WM and Long Term Memory (LTM) in VISIONS (see Fig. 1), but incorporates the language system adding a Linguistic WM and Grammatical knowledge. Based on visual attention and communicative goals, the system extracts a SemRep in Semantic WM from the perceptual schemas active in Visual WM to capture key entities and relations from the scene, thus discarding many details from visual perception less relevant for verbal description. In Grammatical WM, TCG then can apply lexical constructions to associate nodes with words, and higher-level constructions to build either directly on nodes in SemRep or on an already partially completed construction assemblage. The Grammatical WM holds a hierarchical covering of the current SemRep by iterated applications of constructions from Long Term Memory – it provides not only a Working Memory for construction applications but also allows an utterance to be read off at any time. Just as VISIONS allows Visual WM to request more data from low-level processes, our model link the language system allows the SemRep to be updated by requesting information from the vision system when completion of an utterance requires further attention to the visual scene

the role that world knowledge plays in the incremental generation of semantic representations during comprehension, and (2) to do so in a way that accounts for neuropsychological data on comprehension performance in aphasic patients who display certain forms of agrammatism. We specifically focus on the performances of agrammatic aphasics in *sentence-picture matching tasks* during which the patient is asked to decide whether a sentence he hears matches a visual scene.

Comprehension Patterns of Agrammatic Aphasics

Agrammatic aphasics are patients suffering from brain lesions that result in the deterioration of their capacity to speak in a grammatically correct fashion. Their disfluent speech production patterns and agrammatism have historically been closely associated with Broca's aphasia, although there is no one-to-one link of symptoms with specific lesion sites (and in particular Broca's area). In contrast to a relatively unimpaired capacity to use the correct content words to carry out their message, agrammatic aphasics tend to omit function words, verbal inflections, etc. Caramazza and Zurif (1976) were among the firsts to show that agrammatic aphasics could also be impaired in their capacity to make use of syntactic cues during language *comprehension*. They found that Broca's aphasics were no different than normal subjects when asked to match a picture with canonical active sentences such as "the lion is chasing the fat tiger", but were no better than chance for center-embedded object relatives such as "the tiger that the lion is chasing is fat". However, performances of Broca's aphasics was restored to the level of normal subjects for object relatives when world knowledge cues were available to constrain the sentence interpretation as in "The apple that the boy is eating is red". This latter result led the authors to hypothesize a neuropsychological dissociation between two comprehension processes: a "heuristic" system based primarily on world knowledge information and an "algorithmic" system relying mainly on syntactic information. Sherman and Schweickert (1989) replicated the experiment while controlling for the possible combinations of syntactic cues, world knowledge plausibility and, importantly, picture plausibility.

Since this seminal work was published, it has been shown that agrammatic production does not necessarily entail agrammatic comprehension and that the comprehension performances of agrammatic aphasics appear quite heterogeneous.

Moreover, the very notion that agrammatism reflects the impairment of an identifiable function of a syntactic system (as in the Trace Deletion Hypothesis of Grodzinsky 2000) is strongly challenged by the diversity of comprehension performances. In their meta-analysis of 15 studies published between 1980 and 1993 that reported agrammatic aphasics' comprehension performances on sentence-picture matching tasks and included contrasts between active and passive constructions, Berndt et al. (1996) found that the 64 unique data sets (for 42 patients) could be clustered into three groups of approximately equal size, each reflecting a distinct comprehension pattern: (1) only active constructions are comprehended better than chance, (2) both active and passive constructions are comprehended better than chance, (3) both structures are comprehended no better than chance. So far none of the theories linking agrammatism to a specific deficit in syntax processing has been able to account for this variety in performances (for a discussion of the possible role that group selection played in generating this variety see (Berndt and Caramazza 1999; Zurif and Piñango 1999)). Rather than conclude that agrammatism does not constitute a useful neuropsychological syndrome for the understanding of the neural and cognitive structure of the language system (Caramazza et al. 2005) we suggest that this diverse set of lesion-behavior data points provides a good target for a new neurocomputational approach (including in particular the fact that Broca's aphasic patients, for whom the lesions tend to be localized in the left-anterior cortex, seem to display only the second pattern of comprehension (Grodzinsky et al. 1999), but we leave the problem of the neural anchoring of the model for subsequent work).

Importantly the second conclusion of Caramazza and Zurif (1976) regarding the role world knowledge plays alongside syntax is largely admitted as a non-controversial empirical fact confirmed by subsequent studies (Ansell and Flowers 1982; Kudo 1984; Saffran et al. 1998; Sherman and Schweickert 1989). We seek, then, to extend SemRep/TCG to provide a model of language comprehension that includes the possibility of selectively impairing various aspects of grammatical processing while leaving world knowledge processes involved in comprehension relatively unimpaired.

Light and Heavy Semantics

We cannot yet provide a comprehensive explanation of the heterogeneous performances of agrammatic aphasics but do show how a dynamic, schema-based model can be used as to study some key aspects of these data sets. The focus of TCG on the language-vision interface offers a platform well suited to simulate sentence-picture matching tasks. We adopt a two-route approach to comprehension, with a world knowledge route that may be left more or less intact while lesions are performed on a grammatical route. But first we discuss the necessity, following both our construction grammar approach and neurophysiological evidence, to distinguish theoretically between the roles of two different types of semantic constraints on the comprehension system.

We saw in Part 2 how TCG constructions combine both *form* (SynForm) and *semantic constraints* (SemFrame). This operationalizes the core tenet of construction grammar – that syntax and semantics are not dissociated into two different theoretical components (Croft and Cruse 2005). But the empirical results reviewed above demand that we distinguish the world knowledge preserved in agrammatic aphasics from construction-related semantic constraints. We thus coin the terms *heavy semantics* and *light semantics* for world knowledge and construction-based semantics, respectively. World knowledge, as we saw in Part 1, represents a source of information that plays a pervasive role in both visual scene and language comprehension and is *heavy* in terms of content since it spans motor and perceptual schemas but also conceptual abstract knowledge that we can acquire through the very use of language. Such knowledge of agents, objects, actions and more abstract entities that gets richer as we interact with the physical and social environment, contrasts with the *light* semantic content of constructions which develops through experiences of patterns of language *about* agents, objects, actions and more. The latter may vary from the highly abstract (as in noun versus verb providing a language-dependent syntactic elaboration of the semantic categories of objects versus actions) or strongly linked to sensory or motor experience as illustrated by the example of the IN-COLOR construction (see Fig. 3). For us, light semantics reflects this construction-related categorization, more or less abstracted from world knowledge in a usage-based language-laden way. It is "light" because only a few semantic features matter, and it cannot be refined and enriched by interacting with the world beyond the bounds set by a given language (although of course performances vary). Theoretical distinctions have been proposed by others that are closely related to ours (for example see Levin 1993; Mohanan and Wee 1999; Pinker 1989). Those however stem from linguistic analyses, while the light and heavy semantics distinction emerges from considerations related to neuropsychological data and computational brain theory. It will be the role of future work to analyze the relations between these different theoretical perspectives and in particular to discuss how to bridge between approaches like ours that go from the brain-up and those that work from language-down.

Kemmerer (2000a) reported a word-picture matching task that required discrimination between 3 verbs that differed only on the basis of semantic features relevant from a grammatical point of view such as "spill", "pour", and "sprinkle." One subject performed poorly on this word-picture matching task while performing well in a grammaticality judgment task involving the same verbs "slotted" into constructions that matched or not in terms of the "grammatical" semantic constraints e.g., "Sam spilled beer on his pants" vs. *"Sam spilled his pants with beer" (see Construction Grammar section in Part 1). Two other patients showed the opposite pattern of performance. This double dissociation has been replicated for the semantic constraints associated in English with prenominal adjective order ("thick blue towel" vs. * "blue thick towel") (Kemmerer 2000b; Kemmerer et al. 2009), those associated with the un-prefixation of verbs (buckle-unbuckle vs. *boil-unboil) (Kemmerer and Wright 2002), and for the body-part possessor ascension construction ("Sam hit Bill on the arm" vs. *"Sam broke Bill on the arm") (Kemmerer 2003). These empirical results, bringing a new light on the grammatical impairments that can result from brain lesions, demonstrate the need for our model to account for the possibility of selective impairments of heavy and light semantics in language comprehension.

Dynamic Interactions of World Knowledge, Linguistic, and Visual Information During Language Comprehension

While remaining centered on the question of modeling the language-vision interface, we conceptually extend TCG to account for the role of heavy semantics during comprehension with a SemRep now serving as the output of the comprehension system. Crucially, the final SemRep can emerge through cooperative computation from both linguistic information and world knowledge. The general architecture of the TCG comprehension model is described in Fig. 6.

Lessons from Agrammatism: A Two-Route Model for the Processing of Linguistic Inputs

In our initial work on scene description, the SemRep was generated and dynamically updated by the visual system, with construction assemblages controlling the flexible generation of utterances corresponding to all or part of the SemRep (see Part 2). In the TCG comprehension model, we enrich this dynamics by allowing the SemRep to be built and updated not only by the vision system, but also by two routes processing input utterances in parallel. These two routes, shown in Fig. 6, correspond to (1) the *heavy semantic route* that generates semantic representations from content words using world knowledge and (2) the *grammatical route* that puts grammatical knowledge to work, using grammatical cues and constraints (including light semantics) to map the surface content of the utterance input to a SemRep graph representing its semantic content. Therefore, the SemRep, during comprehension, becomes the locus of interaction between three sources of information: vision, grammar, and world knowledge that can enter into cooperative computations.

A key feature of the TCG comprehension model's architecture lies in the fact that each input word will have an effect on 2 different routes triggering two parallel processes to update the SemRep. For an input word W:

– *Route HS. Heavy semantic route*: If W is a content word, the heavy semantic route will allow W to create or verify an existing node in Semantic Working Memory by directly accessing its associated world knowledge content representation in long term memory. If W is a function word, it is ignored by the heavy semantic route that is blind to grammatical cues. Complementary to this data-driven instantiation of world knowledge, the heavy semantic route allows active SemRep nodes to query the world knowledge through a World Knowledge WM that builds plausible semantic relations between the nodes. For example, the word "eat" might not only instantiate a node for the concept EAT but also link it to a node for SOMETHING-EDIBLE. These world knowledge based hypotheses can then verify, modify, or enrich the structure (nodes and edges) of the SemRep subgraphs currently active in Semantic WM or yield nodes which compete for later resolution. Working incrementally, upon receiving W the heavy semantics route updates the state of the Semantic WM, which is composed of a cloud of competing and cooperating SemRep subgraphs (see for example Fig. 8 (t4)), on which the next word W' will be received, generating anticipations of what semantic content W' will bring.
– *Route G. Grammatical route*: Whether W is a content or a function word, it will result in the instantiation or verification of a construction, modifying the state of the construction assemblage in Grammatical Working Memory. In our previous production model the constructions are initially anchored on the SemRep through their SemFrame with the final utterance production resulting from the read out of the SynForms of the constructions alliances that won the competition. During comprehension, in contrast, the constructions are initially anchored on input words through their SynForm. At each time step, the unification of the SemFrames for the winning construction alliance provides the graph structure representing the current meaning associated with the word sequence received. Therefore, through the modification of the construction assemblage, the input W to the grammatical route will verify, update, or modify the SemRep graph structures in semantic working memory. By updating of the state of the semantic working memory upon receiving W, the Grammatical route, like the Heavy Semantics route, modifies the semantic context on which the next word W' will be received and generates anticipations. For the Grammatical route, such anticipations and context modification also extend to the Grammatical working memory: the updated construction assemblage following the reception of W generates new grammatical expectations for W'.

Following the principle of cooperative computation, the SemReps graphs active in semantic working memory are also

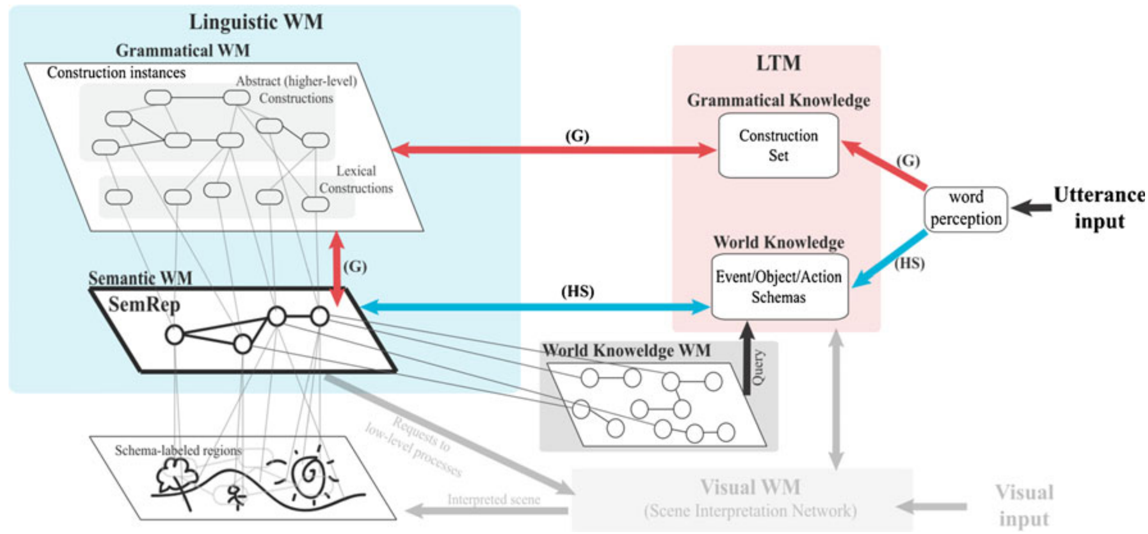

Fig. 6 TCG as a two-route model of language comprehension. The utterance input is fed in parallel to a grammatical route (G) that updates the SemRep indirectly through the creation of a construction schema assemblage in grammatical working memory and to a heavy semantic route (HS) that can generate SemRep nodes directly for content words but is not sensitive to grammatical cues. In addition, the heavy semantic route incorporates the possibility for the Semantic WM to query the world knowledge WM to generate hypotheses about the plausible relations between SemRep nodes. The currently relevant hypotheses are kept active in the World Knowledge WM where they cooperate and compete to update the SemRep. Thus the Semantic WM becomes the locus of a cooperative competition where the construction assemblage on the one hand and the world knowledge hypotheses on the other compete and cooperate at each time to update the SemRep. The Visual working memory remains a source of input for the SemRep as in the production model. (*WM* Working Memory, *LTM* Long Term Memory)

defined both in terms of their structure and in terms of the activation levels of their components (nodes and edges), activation levels that reflect the degree of confidence associated with a relation (edges) or with some semantic content (node). Any modification made by either the heavy semantics or the grammatical route on a SemRep subgraph is expressed in terms of a change in activation levels (that can result in piece of graph being discarded altogether if its activation level becomes too low). These can therefore register the competition and cooperation of both routes.

While it had been proposed that the architecture of the language system organizes the linguistic processes serially with syntax being processed first, yielding a syntactic tree from which meaning can be derived (Frazier and Fodor 1978; Friederici 2002), recent empirical studies tend to favor a "multi-stream" view of the language system (Osterhout et al. 2007) in which comprehension is the result of parallel processing pathways (with usually one of which is more semantic in nature and related to world knowledge while the other is more syntactic) interacting only at given interfaces (e.g. for models based on ERP data and related to the issue of the "semantic P600" see (Bornkessel and Schlesewsky 2006; Kim and Osterhout 2005; Kos et al. 2010; Kuperberg 2007), for eye-tracking experiments during reading see (Vosse and Kempen 2009) and for models based on direct comprehension tests see (Ferreira 2003)). In line with these approaches, our comprehension model sees the syntactic tree (the construction pyramid built in Grammatical WM) as a means to an end – namely to generate the appropriate SemRep – with the heavy semantic route (HS) and Grammatical route (G) competing and cooperating at each time step. In addition, by computationally grounding the comprehension process into the cooperative computation, TCG highlights the problem of determining when the computation should stop. A parsing can therefore be good-enough to support a semantic interpretation of the input without necessarily exploiting or satisfying all the syntactic constraints, a position that echoes the empirical findings of (Ferreira and Patson 2007) related to the notion of "good-enough comprehension".

The Heavy Semantic Route

The heavy semantic route (HS) can directly create SemRep nodes (or verify an existing node) for content words, without invoking constructions. In addition, active nodes in Semantic working memory can send queries to world knowledge that can in turn post hypotheses in the World Knowledge WM, exploiting the principle of the working memory system of VISIONS. In doing so, heavy semantics can restructure the semantic graph, modifying the edges, enriching the semantic content, and setting semantic expectations for future the linguistic inputs.

Following the conventions of schema theory, the state of world knowledge WM depends on competition and cooperation in a distributed network of schema instances representing world-knowledge. We propose to represent the heavy semantics content carried by world knowledge schemas using a graph structure similar to the one used for the SemRep. Heavy semantic content can capture knowledge about things (their perceptual properties, their use, events they participate in …), actions (the type of agents, things they usually involve and the role they play …), or events (who participates, where, in what actions…).

When queried, the schemas are instantiated in the world knowledge working memory where they remain as long as they continue to be relevant and are pruned out when their activation levels fall below threshold. Initially each world knowledge schema instance invoked is associated with an activation value that represents the degree of confidence in the hypothesis it represents. Those whose activation levels are large enough participate in updating the SemRep by posting their hypothesis in semantic memory where it will enter in cooperative computation with other hypotheses. The process can yield an increase in activation values within winning "alliances" and a decrease in activation values for the losers. The activation level of an unused schema instance slowly decays.

Figures 7 and 8 illustrate how the heavy semantic route can generate a semantic representation from the example input utterance "*The officer is chased by the thief in blue*". In Fig. 7 word inputs are noted on the left and are received sequentially. Content words are in bold and only they activate the semantic route. (All the words activate the grammatical knowledge but this route is not shown here; see below The Grammatical Route). At (t1) the words "*The officer*" are received and a node is directly created for the content word *officer*. This active OFFICER node in turn sends a query to world knowledge that instantiates two world knowledge schemas representing perceptual knowledge about officers: that they were blue uniforms, and knowledge about events they are involved in: they are the agents of actions that involve thieves as patients. The latter has a high initial activation value and updates the SemRep right away. At (t2) the words "*is chased*" are received and a CHASE node is created. The processing of the previous word has resulted in a SemRep that anticipates the reception CHASE and has already set OFFICER in the agent role and THIEF in the patient role. The CHASE node therefore simply tries to unify with the ACTION node. Since it is a good match, this unification link (dotted line) receives a good activation value and the general activation value of the OFFICER-ACTION-THIEF graph goes up since it has received some evidence of being correct.

In Fig. 8, at (t3) the words "*by the thief*" are received. A THIEF node is created that right away generates a high activation unification link with the already present THIEF node. This further boosts the general hypothesis that the officer is chasing the thief. An instance of a world knowledge event schema is invoked carrying the hypothesis that thieves steal objects. At (t4) the words "*in blue*" are received and a BLUE node is created. In world knowledge memory, the OFFICER-WEAR-UNIFORM-BLUE hypothesis was slowly decaying since it did not seem to be relevant. In presence of the BLUE node its activation value increases to a level high enough to enter semantic working memory and generate a possible unification link with the BLUE node. On the other hand, another hypothesis enters the competition, queried by the THIEF node, representing the general knowledge that THIEF wear cloth that can have attributes (including color). So the BLUE node also creates a link with this hypothesis, this link is stronger than the other one because of a recency bias.

This notion of *recency* bias is a crucial element in modeling comprehension (and this holds for constructions as well as world knowledge – consider, for example, the role of "dependency distance" in assessing language complexity as used, e.g., by Hawkins 1999). Just as in VISION an object creates context for what can be found in its immediate surroundings, here each content word serves as context for what occurs in their temporal vicinity. Here we focus on semantic context: *blue* occurs closer to *thief* than to *officer*. Two subgraphs therefore compete for the attachment of BLUE and the cooperative computation might not generate a clear winner. Note that in this example, the THIEF-STEAL-ENTITY has lingered with its activation decaying. If the sentence had continued with "…because he stole a diamond", the THIEF-STEAL-ENTITY hypothesis could have helped resolve the ambiguous anaphoric reference (since "he" could in theory refer to either the thief or the officer).

Relying on heavy semantics only, the final SemRep provides an interpretation of the input sentence "*the officer is chased by the thief in blue*" as "*The officer chases the thief*" with high confidence, but is at chance for the interpretation of whether "*the officer is wearing a blue uniform"* or "*the thief wears a blue outfit*", with the former favored by general world knowledge while the latter is favor by the temporal proximity of *thief* and *blue*.

This conceptual example illustrates how initial world knowledge hypotheses bias the interpretation of later inputs, while temporal proximity of inputs tend to result in bias towards linking them semantically. We can find a direct parallel of this incapacity to resolve the attachment of BLUE in the performance at chance of agrammatic aphasics on reversible sentences such as "*The lion that the tiger chased is fat*". Initial hypotheses would tend to favor the lion in the agent role of some action of which tiger would be the patient, but the proximity of *chase* with *tiger* relative to *lion* would favor an attachment of *tiger* as an agent of *chase*. Cooperative computation might not be able to break the tie other than through the action of noise, resulting in answers at chance.

The Grammatical Route

Contrary to the heavy semantics route, the grammatical route processes all word inputs (content and function words) and incrementally updates the SemRep indirectly by invoking

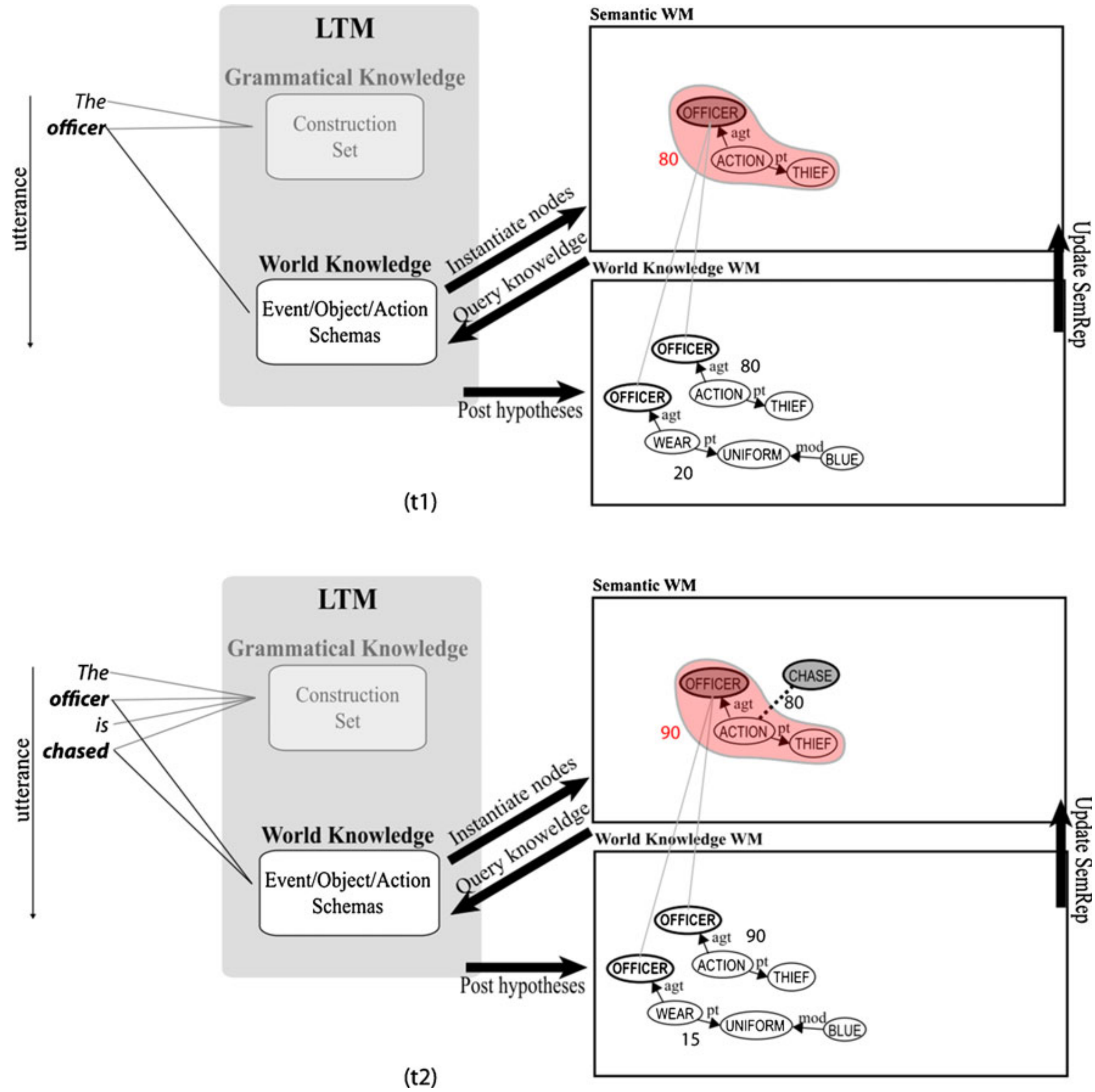

Fig. 7 Illustration of the comprehension process focusing on the heavy semantics route for the input utterance "*The officer is chased by the thief in blue*". The top and bottom sections of the figure represent the unfolding comprehension at time (t1: after hearing "officer") and (t2: after hearing "chased") respectively; Fig. 8 shows how processing unfolds as the remaining content words are heard. At each time, on the left, is represented the portion of the utterance that has been received so far. The content words are in bold; only they serve as inputs for the HS route. The mapping of all the words to the grammatical route through grammatical knowledge is shown but is not pursued here (see section The Grammatical Route). At each time, the state of the World knowledge Working Memory (World knowledge WM) is shown at the bottom right, while the state of the Semantic Working Memory (Semantic WM) is shown at the top right. Numbers indicates activation values. Colored regions of the SemRep graph in Semantic WM represent hypotheses generated from World knowledge WM

constructions in Grammatical working memory whose SynForms match either the perceived input words or some already activated construction instances. In grammatical working memory, constructions enter into cooperative computation to generate construction assemblages. Unifying the SemFrames of the participating constructions provides grammatically driven hypotheses for updating the SemRep by modifying the graph structure (adding nodes, edges, or modifying existing edges). The process of building the construction assemblage retains the key properties of cooperative computation described for production and exemplified in Fig. 4. The main difference is that during production constructions are invoked on the basis of their SemFrame and cooperate to generate utterances by unifying their SynForms.

Constructions represent learned pieces of grammatical knowledge, *which includes knowledge about light semantics constraints*. Construction assemblages represent therefore *form-meaning mapping hypotheses* linking input words sequences to their semantic representations, hypotheses that exclusively rely on grammatical knowledge (and not on world

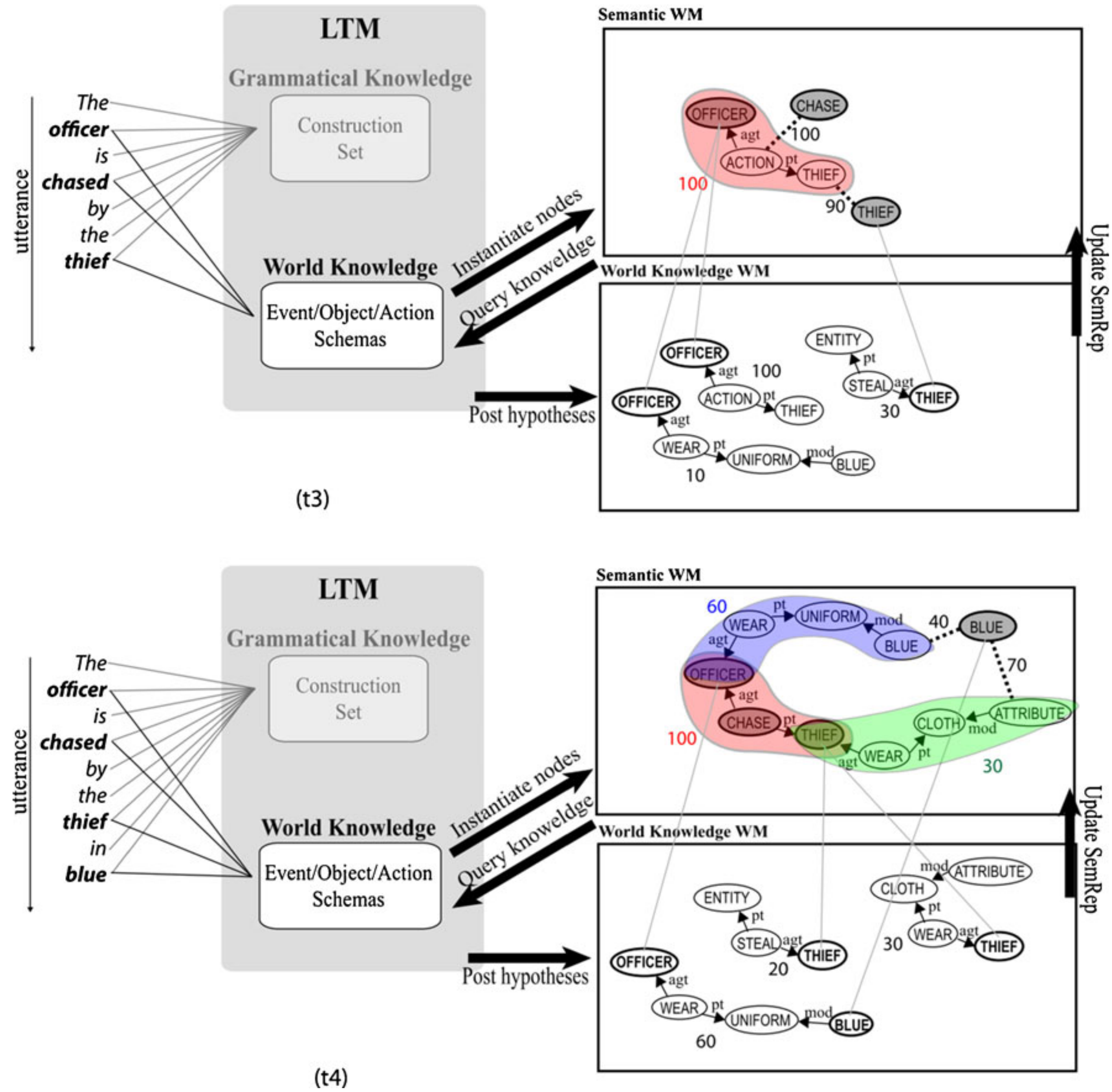

Fig. 8 Generating the SemRep from the heavy semantic route (Part 2). Continuation of Fig. 7 for time (t3: after hearing "thief") and (t4: after hearing "blue"). Details of the process are given in the text

knowledge). The activation value of an assemblage, reflecting how stable it is as well as its competition with other "alliances", codes the plausibility of the associated hypothesis. The cooperative computation process leading to the self-organization of form-meaning mappings can be seen as a distributed search of solutions that jointly satisfy the multiple local grammatical constraints learned and stored in grammatical knowledge as constructions.

Due to the incremental and cooperative nature of the computation, each new construction invoked in grammatical working memory serves as a context for further processing, generating expectations that will impact the grammatical processing of following inputs.

Figures 9 and 10 illustrate how the grammatical route can generate a semantic representation from the example input utterance "*The officer is chased by the thief in blue*", a process that – in normal subjects – occurs in parallel of the one described above for the heavy semantics route (see section The Heavy Semantics Route). The conventions used to represent the input words are the same as the ones used for the heavy semantics route. This time only the grammatical route is shown. In Fig. 9 at (t1) the words "*the officer*" are received. This results in the invocation in grammatical working memory of the **DET_the** construction whose SynForm matches *the* and of the word level **OFFICER** construction whose SynForm matches *officer.* Since the **OFFICER** construction matches the constraints of the second slot of the **DET_the** construction, the two form a first alliance that maps this initial word sequence to a SemRep OFFICER node. In addition, some higher level constructions enter the grammatical working memory since their first slots can link to the **DET_the** + **OFFICER** alliance. The **SVO** construction competes with

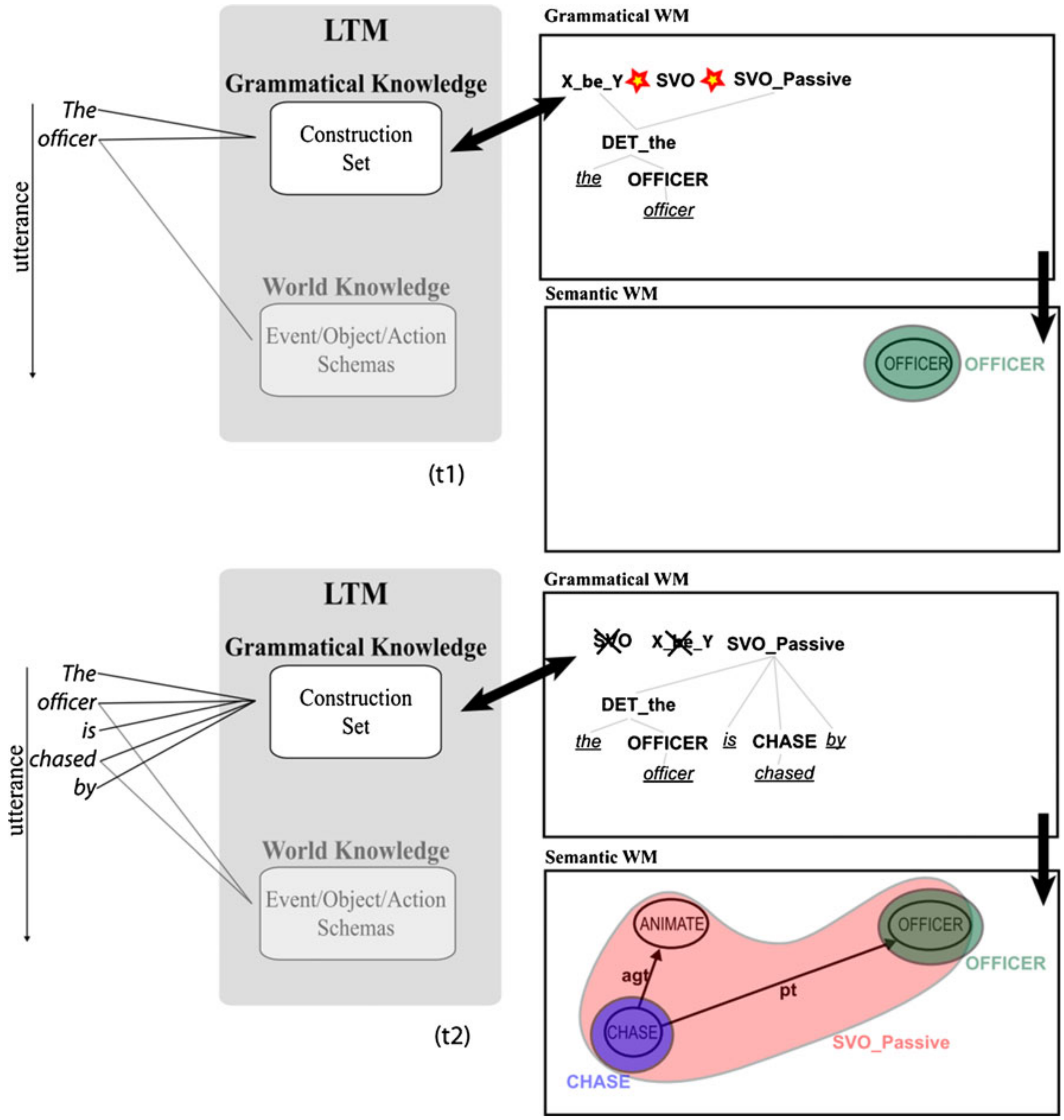

Fig. 9 Generating the SemRep from the Grammatical route (Part 1). Illustration of the comprehension process focusing on the grammatical route for the input utterance "*The officer is chased by the thief in blue*" (continued in Fig. 10). The top and bottom part of the figure represent the unfolding comprehension at time (t1) and (t2) respectively. At each time, on the left, is represented the portion of the utterance that has been received so far. All the words (content and function words) serve as input to the grammatical route through grammatical knowledge. The mapping of content words as inputs for the HS route is shown but not pursued here (see section The Heavy Semantics Route). At each time, the state of the Grammatical Working Memory (Grammatical WM) is shown at the top right, while the state of the Semantic Working Memory (Semantic WM) is shown at the bottom right. Colored regions of the SemRep graph indicate that they have been generated by reading out the form-meaning mapping of the construction whose name is noted next to the colored region. Details of the process are given in the text

X_be_Y (where Y is an attribute of X) and **SVO_Passive** compete, with **SVO** initially having the upper hand since it benefits from a higher initial activation due to its very frequent use in English, which makes it a highly plausible hypothesis. At (t2) the words "*is chased by*" are received. The past participle and preposition *by* only match the SynForm of **SVO_Passive** whose activation increases, causing it to win the competition against **SVO** and **X_be_Y.** The read out of the form-meaning mapping generated by the assemblage updates the SemRep with a CHASE node as well as an ANIMATE node representing its expected agent while the OFFICER node is now assigned the role of patient.

In Fig. 10, at (t3) the words "*the thief*" are received. The construction **DET_the** and **THIEF** are invoked, which form an assemblage whose attachment is already guided by the presence of a strongly activated alliance involving **SVO_Passive**. The new assemblage updates the content of the former ANIMATE

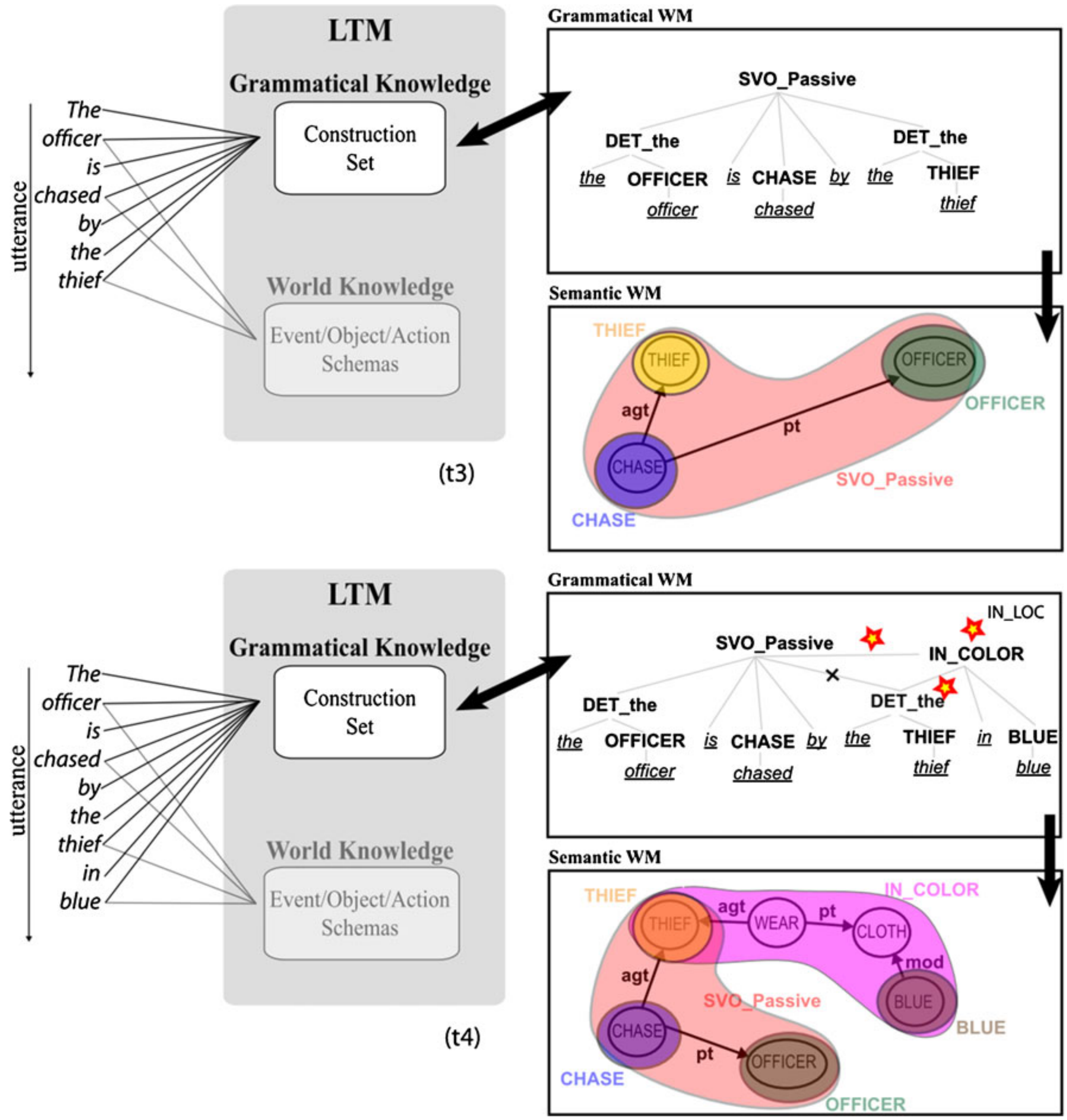

Fig. 10 Generating the SemRep from the grammatical route (Part 2). Continuation of Fig. 9 for time (t3) and (t4) (top and bottom respectively). Details of the process are given in the text

node which becomes a THIEF node, as a result of the attachment of the **DET_the** + **THIEF** assemblage to the last slot of the **SVO_Passive** construction. At (t4), the words "*in blue*" are received. Even if *blue* invokes more strongly the **BLUE** construction, *in* invokes both the **IN_LOC** construction and the **IN_COLOR** construction (shown in Fig. 3). If both have the general SynForm *in X*, the former requires X to be a location while the latter requires X to be a color. This difference in light semantics constraints will result in the BLUE construction matching only the slot of **IN_COLOR** which will win the competition with **IN_LOC**. A competition remains for the last slot of **SVO_Passive** between **DET_the** and **IN_COLOR**. Although the former was already linked to this slot, the alliance in which **DET_the** links to **IN_COLOR** and **IN_COLOR** to **SVO_Passive** is larger and therefore benefits from a higher activation value. This leads to the final form-meaning mapping updating the SemRep linking the THIEF node to a BLUE node through the **IN_COLOR** SemFrame.

Cooperative Computation Between Grammatical and Heavy Semantics Routes

The final SemRep in the previous section, generated by the grammatical route alone, accurately represents the semantic content of the input utterance, with thief assigned as the agent of the action of chasing the officer, and blue assigned as the color of the thief's outfit. However, in the case of grammatically ambiguous utterances the final output via route G alone may preserve competing form-meaning mapping hypotheses (e.g. *The man kicked the ball in the tree*, for which *tree* can be assigned as goal where the ball ends, or the location where the man is located when he performs the kick). It is the cooperative competition between the grammatical and the heavy semantics routes that can disambiguate this output. The heavy semantics route can provide the information that kicking rarely occurs in trees. Similarly, going back to our ambiguous example in the previous section "The lion that the tiger chases is fat", the grammatical route will break the ambiguous heavy semantics interpretation.

With this, let's see how our model postulates that the heavy semantic (HS) and grammatical (G) routes process the utterance inputs in parallel and enter into cooperative computation in semantic working memory to generate the SemRep. Figure 11 illustrates this cooperative computation process by showing the combined influences of the two routes on the SemRep for the input utterance used in the examples detailed above: "*The officer is chased by the thief in blue*". It describes the state of the system once all the input words have been received. The grammatical memory therefore contains the construction assemblage already described in Fig. 10 (t4) while the world knowledge working memory is as described in Fig. 8 (t4). If in this example we focus on (t4), we want to insist on the fact that the grammatical and heavy semantic routes do not independently proceed to completion but interact at each stage. The semantic working memory in this example however, contains SemRep graphs generated by both routes. This results in a more complex graph than in the preceding examples. Two different interpretations of the roles that THIEF and OFFICER play in the CHASE action are simultaneously part of the SemRep: the grammatical route assigns the role of agent to THIEF based on grammatical cues while the heavy semantics assign the role of agent to OFFICER. We note that the competition between the roles of patient and agent for OFFICER emerges as early as (t2). The attachment of BLUE to the outfit of either the officer or the thief is ambiguous from the point of view of the heavy semantics route while it is assigned as an attribute of the outfit of the officer by the grammatical route by the **IN_COLOR** construction.

The SemRep appears therefore as a locus of cooperative computation resulting in competition between incompatible semantic interpretations of the utterance input and in cooperation between the ones that supports each other. In our example, a competition is initiated early on between the grammatical route and the heavy semantic route for the assignment of the role that the OFFICER plays in the action. The grammatical route cooperates with the heavy semantic hypothesis that BLUE refers to the outfit of the thief but competes with the hypothesis that it refers to the outfit of the officer. This can result in the latter being pruned out, leaving only the correct interpretation present with a high activation value in semantic working memory. As for the assignment of roles in the CHASE action, the resolution depends on the activation values of each interpretation engaged in a winner-take-all competition. The activation values in turn depend on the cooperative computation process within each route, but we suggest that it can also depend on two other factors:

– The weight assigned to each route. For healthy subjects, the evidence gathered through the grammatical route probably weighs more in the competition than that gathered through the heavy semantics route. But in noisy or low attention conditions, or following a partial lesion of the path allowing the updating of the semantic working memory from grammatical working memory, the heavy semantics route could win the competition. The reduction of the weight assigned to the grammatical route in noisy and low attention conditions rests on the assumption that the grammatical route is more sensitive to noise and less automatic (requiring more sustained attention) than the heavy semantics route.
– The visual input presented. Since the SemRep is a semantic representation tied to visual perceptual schemas interpreting visual scenes, we can imagine – as in the visual world paradigm (see Part 1, Section 1) and the sentence picture matching task (see Part 2 Section 1 above on agrammatism) – a scenario where a scene depicting a thief and an officer is presented to the subject with variations in terms of who chases whom and in the color of the outfits. In this case, in addition to the topology of the SemRep, the visuospatial relations between nodes, as defined by their associated perceptual schemas, can serve as constraints in the competition. For example, if the image presents a thief with a blue outfit, then the BLUE node, through the visual system, links to the same spatial region as THIEF and this therefore would influence the competition in favor of having the BLUE node associated with the THIEF node.

Conceptual Account of Agrammatic Comprehension Performances in Sentence-Picture Matching Tasks

The empirical evaluation of comprehension performances in aphasics requires the use of experimental paradigms that let the neurologist or the researcher probe the interpretation of the sentence that the patients generate during the comprehension process. As we described in the previous section on agrammatism (Part 3 Sections 1 and 2), *sentence-picture matching tasks* are commonly used in aphasia battery tests or in neurolinguistics experiments. The patient listens to an utterance while or before being presented with one or multiple visual scenes. The task consists then for him to answer questions about these scenes. In the case of single scene presented the question can be "Does the scene match the utterance?"

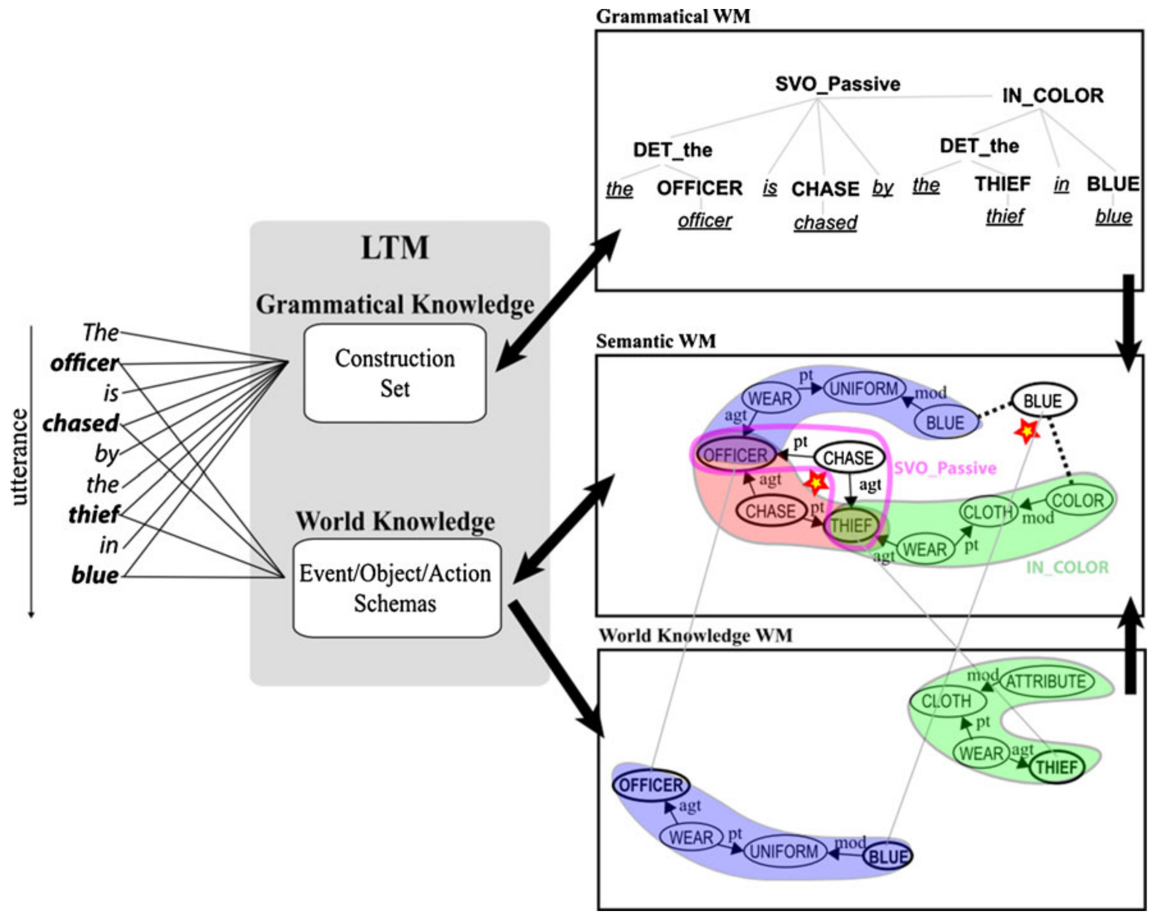

Fig. 11 The two routes are engaged in cooperative computation to generate the SemRep. The figure combines the final outputs of the comprehension process for the heavy semantics route (Fig. 8 (t4)) and for the grammatical route (Fig. 10 (t4)). The Semantic Working Memory appears as a locus of competition and cooperation between SemRep graphs representing the interpretations of the utterance input generated by each route. Details of the process are given in the text

which requires a yes or no answer. Alternatively, if multiple scenes are presented, the question can be "Which scene matches the utterance?" which requires the patient to point to the correct scene. In future work, we will apply TCG to this problem. Basically, the task tests the capability of the patient to determine whether there is a SemRep for the sentence that matches a SemRep for a given picture in orderto reach a yes/no decision. Alternative approaches could (i) use vision to generate SemReps for each scene, use TCG in comprehension mode to generate a SemRep from the target sentence, and test whether these match in some sense; or (ii) use TCG in production mode to generate a sentence describing the scene, and then test whether this matches the target sentence in some sense. This begs the question of whether the processing of visual scenes used in the sentence-picture task is segregated from the workings of the "language system" or whether the two cooperate throughout to reach a decision. The design of the experiments could be such that the effects of the visual scene presentation are counterbalanced and controlled at the level of multiple trials and/or subjects, leaving the possibility to specifically target the language system. However, the goal of computationally guided models is to simulate the behavior of a single individual performing a single trial of a sentence-picture matching task and cannot eschew the problem of incorporating the role of visual processes. The TCG models of comprehension and production allow us to revisit the experimental results on agrammatism focusing on (conceptual) simulation of a sentence-picture matching trial, limiting ourselves to tasks involving only one visual scene for which the subject has to decide whether or not it matches the utterance they hear.

Figure 12 provides four conceptual examples of sentence-picture matching trials illustrating the collaborative computation of the grammatical and the heavy semantics routes but also of the visual processes in generating the semantic representation associated with an utterance. In each panel, the top section represents the perceptual schemas active in visual working memory, the bottom section represents the state the construction assemblage in grammatical working memory, the left section represents instantiated world knowledge hypotheses in world knowledge working memory (the number indicates

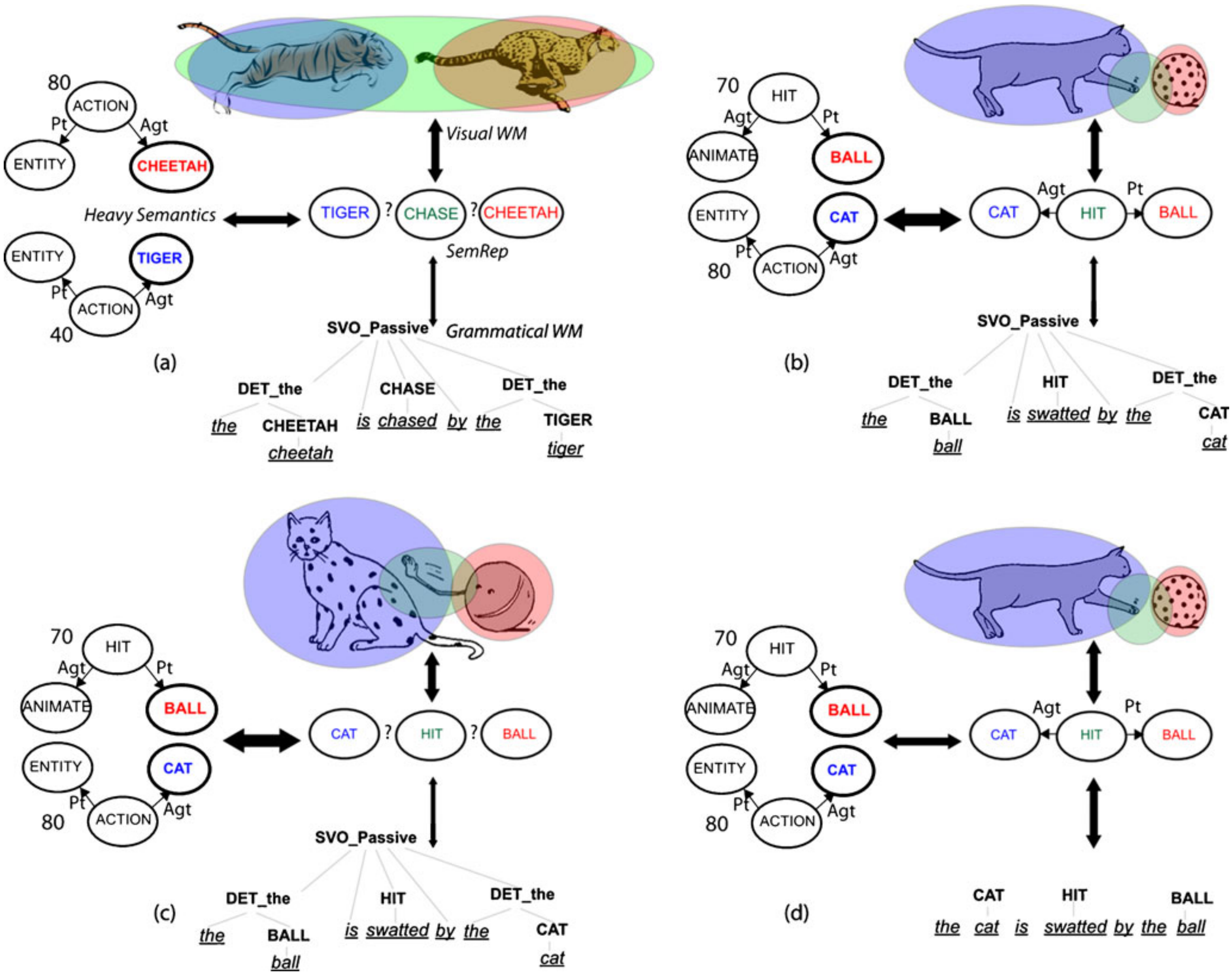

Fig. 12 Modeling the sentence-picture matching task with TCG employed in comprehension mode. In each panel, the top section represents the perceptual schemas applied to the visual scene. The bottom section represents the grammatical working memory maintaining a construction assemblage generated by the grammatical route. The left section represents the world knowledge working memory and currently active hypotheses. The middle section represents the SemRep built in semantic working memory, locus of collaborative computation between the three routes (indicated by *double arrows*). The thickness of the double arrows represents the weight assigned to the interpretation of each route in the collaborative computation of the SemRep. Lower weights can be due to partial lesions. In panel (d), the absence of construction assemblage represents the effect of lesions that would impair the processing capacities of the grammatical working memory. Details for each panel are given in the text

their activation level). At the center of each panel, all three routes converge to update the content of semantic working memory. For simplicity, we present in each panel a static snapshot of the system that illustrates a key property of the TCG comprehension model's dynamics in relation to modeling agrammatic comprehension. We assume that the utterance has been received to insist on the cooperative computation between routes rather than the incremental process of word by word comprehension (that has been described in the previous sections). We therefore also assume that all the nodes associated with content words have been instantiated, the three routes collaborating and competing for the assignment of relations between them (edges).

Figure 12(a) illustrates the situation in which an utterance neutral in terms of heavy semantics is received, "*the cheetah is chased by the tiger,*" while a visual scene that accurately matches its meaning is presented. The TIGER, CHEETAH and CHASE nodes are linked to their respective perceptual schemas, hypotheses in the world knowledge working memory, and to the respective **TIGER, CHEETAH** and **CHASE** constructions in grammatical working memory. The goal of the cooperative computation between routes is therefore to judge what roles to assign to the TIGER and CHEETAH nodes in relation to the CHASE action nodes. The thin arrow mapping the grammatical working memory to the SemRep simulates a partial lesion of this route resulting in a deficit in using the form-meaning mapping generated by the grammatical route to update the SemRep (see Fig. 12(d) for an alternative lesion simulation). The interpretation of the utterance input rests therefore essentially on the heavy semantics route. Since, from a heavy semantics perspective, it is just as likely to have either the cheetah or the tiger as the agent of the action, such situation can result in an at chance assignment of the agent and patient role. However, the fact that, in the passive construction, the CHEETAH node is created first, results in an earlier activation of the CHEETAH related world knowledge that could bias the assignment of the CHEETAH node as an agent, agent role confirmed by the then generated CHASE node. Once the TIGER node is created it would then fill in the patient role in the already quite highly activated and stable SemRep. Assuming some residual but weak capacity to assign roles based on grammatical processes, for an input in the passive voice, the weak assignment generated by **SVO_Passive** construction would compete with the heavy semantics "agent received first" hypothesis while, for the active voice, the weak **SVO** construction would cooperate with the similar heavy semantics "agent received first" hypothesis. Such an interpretation would explain the classic pattern of agrammatic comprehension for which patients are above chance for active sentences and at chance for passive sentences even when no world knowledge cues are apparently available. However, in our case, the explanation of the comprehension pattern is not found in a differential treatment of **SVO** and **SVO_Passive** constructions (one being "more lesioned than the other" or "harder to process") but emerges from the cooperative computation between routes.

In Fig. 12(b), the input utterance is "*The ball is swatted by the cat*". This example illustrates the case in which the heavy semantics route generates a unique highly plausible hypothesis that can collaborate with the weakened grammatical route and allow the system to generate the proper interpretation of the utterance input. Here the visual scene matches the meaning of the input and therefore all the processes converge to the same stable interpretation, compensating the lesion to the grammatical route. Figure 12(c) presents the situation in which for a similar input utterance, the visual scene presented does not match and is counterfactual with respect to our knowledge of the world (a ball swatting a cat). The hypothesis generated by the heavy semantics would cooperate with the output of the weakened grammatical route to generate a SemRep graph that this time enters in competition with the graph generated by the perceptual schemas active in visual working memory. This competition signals the mismatch between the utterance received and the visual scene.

Such examples of visual scenes in Fig. 12(b) and (c) are directly drawn from sentence-picture matching tasks used to test agrammatic comprehension (Sherman and Schweickert 1989). We see that the behavioral result of the sentence-picture matching trial rests on the complex interactions of three sources of information at the level of the SemRep. A bias towards one source of information or another can tip the cooperative computation in favor of one of the possible interpretations of the linguistic input. Discounting perceptual information while boosting the role of heavy semantics to compensate for the degradation of grammatical processing simulates the role world knowledge plays in agrammatic comprehension. However, the model puts at the forefront the fact that when using a sentence picture matching task, the impact of the perceptual content of such an image on the language comprehension system cannot be fully dissociated from that of the linguistic and heavy semantic content.

For the first three examples we have focused on possible lesions affecting the link between and an intact grammatical working memory and the semantic working memory. Such lesion that would keep the grammatical process per se intact but deteriorate its capacity to impact the semantic interpretation partially echoes the conclusions of Schwartz et al. (1987) who moved away from a purely syntactic explanation of agrammatism and hypothesized that the deficit resulted from an impaired participation of the extracted syntactic information in the thematic role assignment process. Figure 12(d) illustrates the fact that the degradation of the role of grammatical information on generating the SemRep could also be simulated by a lesion limiting the computational capacity of the grammatical working memory to process grammatical constraints. This hypothesis echoes the capacity approach to agrammatism developed by Miyake et al. (1994, 1995) who hypothesized that agrammatic comprehension is a result from a reduction, following brain lesions, of working memory resources available to compute the syntactic information contained in linguistic inputs. In this case, the connection between semantic and grammatical working memory remains intact, but the grammatical working memory is limited in the complexity of the construction assemblages it can build, a limitation that we illustrate here by allowing only word level construction to be invoked into working memory. Constructions invoked in grammatical working memory TCG are instances of schemas and therefore represent active processes mapping their SynForm to a SemFrame but also creating links between their slots and other constructions. Since these processes involve both detecting temporal sequences of inputs or constructions that match a SynForm or assessing the match between the light semantic constraints of a slot with possible construction inputs, reduced computational capacity of grammatical memory can be generated by a variety of lesion affecting parts or whole of the process of construction matching. In particular, specific lesion to the light semantic constraints matching can be simulated, lesions that would result in the deterioration of the grammatical working memory to build stable construction assemblages while the heavy semantics system remains intact.

To conclude we go back to the tripartite distinction found by (Berndt et al. 1996) in their meta-analysis of comprehension patterns for reversible sentences (agent and patient role for the entity described are equally plausible) in sentence-picture matching tasks. They found that about the same number of agrammatic aphasics were (1) at chance for both passive and active, (2) at chance only for passive and better than chance for active, or (3) better than chance for both. In our analysis of Fig. 12(a) we showed how the TCG model of comprehension can account for the comprehension pattern (2) as emerging from the cooperative computation between a weakened grammatical route and the heavy semantics route without assigning the deficit to a processing difficulty to specifically associated with the **SVO_Passive** construction. **SVO** and **SVO_Passive** are treated equally. The lesion deficit is assigned to the capacity to use the form-meaning mapping built in grammatical working memory to update the SemRep. Such deficit results in the equal deterioration of the capacity to use the grammatical cues associated with each one of these constructions to assign relations between nodes, deterioration that can be alleviated in the case of the **SVO** construction only thanks to the general heavy semantics hypothesis that tend to assign the role of agents to the first encountered content word (if it describes an animate entity that is usually involve in doing something). The model can explain the comprehension pattern (1) by making the hypothesis that patients showing degraded capacity to process both active and passive constructions for sentence-picture matching task could suffer from lesions affecting not only the grammatical route but also the heavy semantics route. This indeed would result in a difficulty to use the "agent received first" hypothesis efficiently. As for the comprehension pattern (3) it can be accounted for by allowing for only mild lesion of the grammatical route, allowing the grammatical constraints to weigh in the final role assignment.

Finally, the explanations of the comprehension patterns (1) and (2) by the TCG comprehension model entail the following predictions. Patients that show good performances for active constructions even in the case where no world knowledge cues can be used, should be significantly better for sentences of the type "*the tiger chases the cheetah*" in which the "agent received first" hypothesis applied, than for sentence of the type "*the ball hit the bat*" for which the heavy semantics would not instantiate hypothesis that would have BALL as an agent, removing the possibility of heavy semantics to early on help building anticipations of the relations that will link the nodes generated by the content words hit and bat.

Future Challenges

In TCG both production and comprehension involve building construction assemblages in grammatical working memory through cooperative computation. However, so far the model remains agnostic as to whether the construction instances stored in long term memory and invoked during production and comprehension are the same. Linguistic work on idioms has distinguished between encoding and decoding idioms (Makkai 1972). Indeed a hearer could figure out the meaning of an encoding idiom when she first encounters it although as a speaker she would not have guessed that these expressions are semantically correct (e.g. "answer the door") while one needs to learn the conventional meaning of a decoding idiom to be able to understand and use it (e.g. "he kicked the bucket" or "he pulled a fast one"). From a usage base perspective, such differences between encoding and decoding can be extended to all constructions with speakers having their own idiosyncratic encoding preferences at the word, idiom, and up to argument structure level, while decoding expectations are shaped by the landscape of input that the speaker receives. If the question of the relation of between the grammatical knowledge stored in long term memory for production and comprehension remains to be better analyzed in TCG, the fact that a single brain system supports both the encoding and decoding grammatical working memory finds support in recent behavioral (Kempen et al. 2012) and fMRI adaptation studies (Menenti et al. 2011; Segaert et al. 2012).

The empirical results gathered in the last 10 years by the various groups focusing on good-enough comprehension and for which, to our knowledge, no computational framework has been developed are yet another challenge that will need to be addressed by TCG (for a review see Ferreira and Patson 2007). These studies have used rephrasing empirical paradigm to more precisely study the semantic representations that subjects derive from garden path sentences (Christianson et al. 2001; Christianson and Luke 2011) revealing until then ignored semantic effects such as the fact that the semantic representations derived from the initial incorrect parse of a garden-path sentence lingers and can be maintained alongside the correct final semantic interpretation. The TCG framework could offer a way to directly simulate this rephrasing paradigm by coupling the comprehension and the production system through a SemRep which, since it emerges from cooperative processes, is not endowed with any requirement to optimally represent the semantic content carried by the linguistic input.

As a framework that tackles (so far separately) both production and comprehension, the next step in the development of TCG will be to integrate grammatical encoding and decoding from a computational perspective as well as in relation to possible shared neural substrates. In doing so, we will also need to expand our initial focus on agrammatic comprehension to account for the relation between the deficits in receptive and expressive aphasia. The integration of production and comprehension, linked to a deeper analysis of the interface between the language and visual system through the computational the exploration the neural processes underlying sentence-picture matching tasks, would make a step towards a computational neurolinguistic model of a brain that can perceive its environment, produce, and understand utterances about what it perceives and therefore interact with others

(Steels 1999). Such a step is crucial if we ever want to be able to build a brain theory of language processing that accounts for the essentially social and interactive aspect of language.

If the TCG model of comprehension has not so far been tested against real-time processing empirical results, it offers a computational framework that coarsely fits generally with these multi-stream approaches in terms of the general differentiation between a world knowledge and grammatical route (see above Lessons from agrammatism). Moreover TCG adds a quantitative perspective on the challenges that emerge from any attempt to understand brain systems in which computation is distributed while schema theory puts time at the core of the modeling effort. Indeed, we showed how the recency bias, capturing the fact that word serves as context for what occurs in their temporal vicinity, plays a crucial role in modeling comprehension (see above The Grammatical Route). However the question of the relation between the real-time processing, ie time as measured using neuroimaging techniques and especially EEG/MEG, and computational time remains a major challenge. So far this type of timing is out of reach for our model but to our knowledge this is general shortcoming of models that tackle higher level vision or language processes. Bridging the gap between neurocomputational models and real time EEG/MEG recording by allowing models (at the neural or schema level) to make clear causal contact with the measured data would allow computational neurolinguistic models to generate predictions that could be directly tested against neural timing data. As a first step in this direction, we proposed elsewhere to expand synthetic brain imaging methods to the modeling of ERP components (Barrès et al. 2013, see below). Conversely, EEG/MEG data can be used to constrain a model's parameter space and Dynamic Causal Modeling (David et al. 2006) offer a partial answer to this problem. However, linking computational neurolinguistic model to real-time data remains for a great part an open question, even though this issue is one of the main stumbling blocks hindering the establishment of clear linkages between the work of experimentalists and modelers.

Neuroinformatics Challenges Raised by Conceptual and Computational Neurolinguistics

We have introduced TCG as a model of utterance production and provided a conceptual extension of the TCG framework to account for deteriorated comprehension performances in agrammatic aphasics while focusing on the complex interactions between visual information and grammatical and world knowledge. We have argued for an approach to comprehension whose product is a semantic representation of the linguistic input. The production model has been implemented computationally and has offered useful psycholinguistic insights into on the verbal description of somewhat complex natural scenes. The extensions for TCG as model of comprehension have been presented conceptually in enough detail to show their relevance to the study of agrammatism and sentence-picture matching tasks. In this last section, we turn to the more general issues posed by developing databases and competing models that will support further progress in neurolinguistics, and not just for our own efforts in enriching the TCG framework. We also discuss possible federation with natural language processing resources, and the need to employ neuroinformatics to foster collaboration between researchers.

Empirical Data Management

Neurolinguistic modeling navigates among diverse types of data including fMRI, ERP, lesion, language acquisition, eye tracking, and connectivity data. Some are of generic use in cognitive neuroscience (e.g. fMRI) while others are more specific to neurolinguistics (e.g., lesion data related to aphasia). Table 1 provides a summary of the neuroimaging databases reviewed in this section. Table 2 focuses on connectivity databases and Table 3 on language-related databases.

fMRI is the main neuroimaging technique used in neurolinguistics to link brain regions to brain functions, just as in any other fields of cognitive neuroscience (Friederici 2002; Hagoort 2005; Hickok and Poeppel 2004). fMRI data management is relatively well developed compared to, for example, that for ERP data. fMRI databases benefit first of all from relatively standardized methods for reporting results in publications – usually in the form of a table with each row representing a clump of voxels for which a significant variation of BOLD activity has been measured between experimental and baseline conditions. The various columns correspond to the coordinate of activation reported either in the standard Talairach stereotaxic atlas (Talairach and Tournoux 1988) or MNI atlas (Montreal Neurological Institute, Evans et al. 1993), the p-, t- or z- values, and usually a name associated with the brain area where the activation is found taken from an existing nomenclature. BrainMap (Fox et al. 2005; Fox and Lancaster 2002) is one of the main databases for fMRI results. It is combined with statistical tools for meta-analysis of the data. The Activation Likelihood Estimation (ALE) method and toolbox supports statistical combination of fMRI results to extract patterns across many experiments (Laird et al. 2009). Vigneau et al. (2006) carried out a widely cited neurolinguistics oriented meta-analysis which provides an integrated perspective on language systems that could not be achieved through individual fMRI experiments. However it is interesting to note that the authors did not rely on an existing database to perform their analysis, but simply relied on extracting the stereotactic coordinates of peak activations from tables in manually selected papers, illustrating the work that remains to be done to make those databases more commonly used tools. The Surface Management System Database (SumsDB, Van Essen 2009) is an example of an MRI (rather than fMRI) oriented database for

Table 1 Neuroimaging databases

Name and URL	Scope	Notes
BrainMap http://www.brainmap.org/	Repository for human fMRI brain imaging data.	Brain imaging data are linked to a rich ontology for the description of experimental procedures. Provides statistical tools (activation likelihood estimation, ALE) for meta-analysis of coordinate based activation data.
SumsDB Surface Management System Database, http://sumsdb.wustl.edu/sums/index.jsp	Repository of brain-mapping data (surfaces & volumes; structural & functional data)	It accepts unpublished data (which however are not public) as well as published data. Provides tools for visualization (WebCaret).
BRAID Brain-Image Database http://www.rad.upenn.edu/sbia/braid/	Large-scale archive of normalized digital spatial and functional imaging data.	Is related to clinical use including lesion studies.
NEMO Neural ElectroMagnetic Ontologies, http://nemo.nic.uoregon.edu/wiki/NEMO	EEG and MEG ontology for ERP and ERF databasing.	Aims at providing statistical tools for analysis of the EEG and MEG activations patterns. So far, few entries are available.
MEG-SIM http://cobre.mrn.org/megsim/	Shared database for simulated and recorded MEG data.	Still at an early stage. The stated goal is to create "realistic simulated data sets in formats used by each of the 3 major MEG manufacturers. These can then be directly tested using various algorithms which include multidipole, spatiotemporal modeling, current reconstruction, minimum norm, and beam forming methods."

neuroanatomical data that also provides the possibility of storing private unpublished data.

fMRI databases, SumsDB, BrainMap as well as the model-oriented Brain Operation Database (Arbib et al. 2013), all provide visualization tools to compare the activation foci of various experimental results. Conceptual models in neurolinguistics however do not usually report the neural substrate of the processing modules they define in terms of quantitative stereotaxic coordinates but in terms of brain area nomenclatures based on more or less formal ontologies. In a classic conceptual model of language comprehension by Friederici (2002), brain regions are referred to using a mixed ontology of gyrus/sulcus neuroanatomical landmarks (e.g. left middle superior temporal gyrus) along with cytoarchitectonically defined Brodmann areas, neurolinguistics specific nomenclature (e.g. Broca's area), and functionally defined sensory areas (in this case the primary auditory cortex). This multiplication of nomenclatures and ontologies hinders the attempts to quantitatively compare the capacity of models to explain new empirical data. Such quantitative comparison should, in principle, be required for computational models and therefore their development should impose the creation of neuroinformatics tools to unify the nomenclatures or provide new standard ways of reporting hypothesized neural substrates. The reader will note, however, that our descriptions of TCG fail this requirement because the modules in the current version are not provided with hypotheses on neural localization.

Table 2 Connectivity databases

Name and URL	Scope	Notes
ConnectomeDB the Human Connectome Project http://www.humanconnectome.org/	NIH-funded large scale project to generate a database of the human brain connectome. It includes both anatomical white matter tracts defined by Diffusion Tensor Imaging, and functional connectivities based on resting state fMRI analysis.	Not yet available. Its development parallels an effort to develop quantitative tools to analyze the structure of anatomical and functional networks in the human brain.
CoCoMac Collations of Connectivity data on the Macaque brain http://cocomac.org	Systematic record of the known wiring of the macaque brain. The main database contains details of hundreds of tracing studies in their original descriptions.	The database contains only tracing studies. The development of MRI in non-human primates could lead to the development of MRI based connectivity databases for this species.

Table 3 Language related databases

Name and URL	Scope	Notes
Aphasia Bank http://talkbank.org/AphasiaBank/	Multimedia interactions for the study of communication in aphasia	This component of TalkBank system (talkkbank.org), is aimed at the improvement of evidence-based therapy for aphasia rather than at processing models of language in which the effects of brain lesions can be simulated.
Purdue ASL Database http://www2.ece.ohio-state.edu~aleix/ASLdatabase.htm	Database of American Sign Language (ASL) videos and transcriptions	Still very preliminary but could be scaled up.

ERP data provide timing data at the expense of localization, so that a model designed to address ERP data might involve modules which can simulate various events with appropriate timing but which have imprecise localization (and may indeed reflect the cooperative computation of diverse circuits). Thus part of the neuroinformatics challenge is to provide tools to integrate diverse phenomena related to a given neurolinguistic function, assess models which cover certain types of phenomena but not others, and then provide tools to support development of new models that, e.g., integrate the insights into lesion data from one model with the insights into timing data from another.

Electroencephalograms (EEG) and Event Related Potentials (ERP), and magnetoencephalograms (MEG) and Event Related Fields (ERF) provide a core data type of neurolinguistics. By offering a millisecond temporal resolution they uniquely suit the needs of neurolinguistics since one of the main characteristic of the language system is its capacity to process rapidly changing inputs (whether visual or auditory). Despite the importance of ERP data for neurolinguistics, no standard way to report ERP data has yet been developed. The number of electrodes for which the ERPs are reported vary and the scalp distributions of the potential are not necessarily provided. The extraction of quantitative data from such reports is arduous if not impossible – they serve more a role of visual support. Even when quantitative data are reported, the lack of standards is still an issue. For example, the timing of a component can be reported as time to peak, time to half-surface under the curve, or as onset time. Moreover, the meaning of an ERP data point often relies on a comparison with other ERP data point. For example the so called "semantic P600" component that is measured in response to certain type of semantic violation, takes its interpretation from the comparison with the classic P600 component associated with syntactic violations. It is the association of these two results that makes the "semantic P600" a challenge for neurolinguistics by suggesting close interactions between semantic and syntactic processing.

There have been few attempts to database ERP results. The Neural ElectroMagnetic Ontologies (NEMO) is one of the most developed of these attempts (Dou et al. 2007). It provides an ontology to report and store EEG raw data, ERP data, data provenance, and the cognitive and linguistic paradigms that were used to collect the data. Its main goal is quantitative data decomposition and analysis which certainly would be a great option for more standard treatment of EEG/ERP results. However since most important data collected over the past 30 years is incompatible with their framework, other tools are needed to tackle existing datasets.

Use of ERP data led to the development of computational tools to compute putative positions of the cortical sources of the ERP signal using *inverse models* (Wendel et al. 2009), but the problem is ill-posed – a given ERP pattern is compatible with diverse source distributions. We have proposed that computational modeling should extend Synthetic Brain Imaging (SBI) techniques (Arbib et al. 2000) to extract Synthetic ERPs, hypothesized EEG patterns of activity, from the activity of neural or schema levels computational models (Barrès et al. 2013). This *forward modeling* approach would enable the direct test of simulated ERP with empirically collected data. We also note the attempt by the MEG-SIM project (Aine et al. 2012) to provide a shared database for simulated and recorded MEG data in order to improve source localization comparison between models.

The linkage between structure and function is at the heart of many debates in neurolinguistics focusing on data on white matter tracts collected using Diffusion Tensor Imaging methods (DTI) or statistical correlation between BOLD activity between regions (for a review see Friederici 2009). Recently the Human Connectome Projects started to systematically collect both DTI and BOLD statistical correlation data to create a general database of human brain connectivity (ConnectomeDB) (Marcus et al. 2011; Sporns et al. 2005). Such a database should provide an increasingly powerful neuroinformatics tools for the brain based design of the architecture of neurolinguistic models.

A generally omitted option for anchoring neurolinguistic computational or conceptual models in the brain is the use of non-human primate oriented databases. Such databases could be used, at least partially, based upon ever more developed theories of the evolution of the neural systems supporting language processing. Their use however would require the existence of homology databases such as the Neurohomology Database (NHDB) which used to offer (it has not been maintained) tools to statistically map macaque and human brain anatomy(Arbib and Bota 2003). Links to macaque brain oriented databases would open the doors for neurolinguistics to develop computational models of neurophysiological recording datasets and of direct white matter tracts analysis as systematically reported in the Collations of Connectivity data on the Macaque brain (CoCoMac) (Bakker et al. 2012; Stephan et al. 2001).

Our work on the TCG model of comprehension has focused on aphasia and lesion data (though future work will indeed address fMRI and ERP data). Both aphasic patients' linguistic performances and lesion data in general have existing databases. However, most of them are designed as tools for clinical neurologists more than for neurolinguistics. This is the case for Aphasia bank (MacWhinney et al. 2011) which is part of the more general TalkBank project (MacWhinney 2007). For lesion studies, lesion sites can be reported using anatomical MRI and stored in brain imaging databases such as Brain-Imaging Database, BRAID (Letovsky et al. 1998). The diffuse and idiosyncratic nature of the lesions makes the generalization of statements based on such data difficult. Statistical analysis tools of lesion sites have started to develop in combination with the lesion databases (e.g., Chen et al. 2008). Extending the use of such databases and tools to neurolinguistics is one of the challenges we see for neuroinformatics.

Finally, TCG as a production model is related to empirical findings from eye-tracking experiments (see Lee In preparation b). In fact, a large number of psycholinguistic studies have used eye-tracking experiments since the seminal work of Tanenhaus et al. (1995). Using the visual world paradigm, and in addition to the investigation of the role of world knowledge in situated language comprehension briefly mentioned in Part 1, eye-tracking empirical results have been at the basis of conceptual models which emphasize semantic access and thematic role assignment (Mayberry et al. 2006), planning scope in spoken sentences (Gleitman et al. 2007), referential domains of spoken language (Chambers et al. 2004), and so on. However, there exist neither standardized databases nor generalized formats for the quantification of eye-tracking data. The lack of standards and available public resources results in eye-tracking experiments being analyzed at a small scale (with limited possibility for pooling data resources into larger scale meta-analyses) and visual stimuli being hand-crafted by each researcher with rather arbitrary representational formats which makes inter-experiment comparisons arduous.

Models Databasing, Updating and Integration

The field of neurolinguistics is characterized by both the predominance of conceptual models, and by the diversity of the existing computational models which span from natural language processing oriented symbolic systems to neural network models. This large population of conceptual models and the variety of computational model types makes databasing, updating, and integrating models a difficult challenge for neuroinformatics systems that would want to provide tools tailored for neurolinguistics. Table 4 provides links to two model oriented databases. For further discussion, see (Arbib et al. 2013).

Neurolinguistics and Natural Language Processing Resources

We end with a brief mention of the role natural language processing (NLP) oriented resources could play in neurolinguistic oriented neuroinformatics. Since the early 90s and the advent of statistical methods in NLP, the field has largely divorced from earlier Artificial Intelligence oriented models and from cognitive neuroscience. Its focus was switched to massive data analyses using ever more advanced statistical methods. Semantics was not considered an essential step anymore since many problems seemed to find their solution in statistical analysis of data at the level of lexical items or syntactic categories. This focus on low level features has had two main consequences: on the one hand the development of massive corpora of annotated text and of powerful

Table 4 Model oriented databases

Name and URL	Scope	Notes
BODB Brain Operation Database, http://nsl.usc.edu/bodb/	Linking processing models with summaries of empirical data	In addition to comparison of empirical data with simulation results, BODB accesses models via both a structural ontology (brain structures) and a functional ontology (brain operating principles, BOPs) and offers tools for model comparison
ModelDB http://senselab.med.yale.edu/modeldb	Documented code for models, primarily those implemented in the NEURON modeling environment	For each model, provides instructions on how to run it to get published results.

Table 5 NLP Databases and the challenges of their use in neurolinguistics

Name and URL	Scope	Integration challenges for neurolinguistics
WordNet http://wordnet.princeton.edu/	Natural Language Processing oriented hierarchical conceptual ontology.	Use this type of ontologies as a starting point to develop neurolinguistic oriented databases whose structure fits our empirical knowledge of world knowledge organization in the human brain.
VerbNet http://verbs.colorado.edu/~mpalmer/projects/verbnet.html	Public database version of the work of Levin on verb classes.	Refine these databases by distinguishing language specific semantics (light semantics) and world knowledge.
FrameNet https://framenet.icsi.berkeley.edu/fndrupal/	A database focusing on how words are used in context based on manually annotated text. It links words to the semantic *frames* they can invoke.	
Penn Treebank Project http://www.cis.upenn.edu/~treebank/	Database of text annotated for syntactic structure. Incorporate skeletal parses showing rough syntactic and semantic information. A *bank* of linguistic *trees*	The statistical focus in NLP has pushed for the generation of very large scale corpora. However, some crucial data types for neurolinguistics are not tackled by NLP that focuses on well-structured written text. Multimodal data, conversation data, or sign languages are usually ignored by NLP but important for neurolinguistics.

mathematical tools to analyze them, but on the other hand the rather limited resources available for semantic modeling. The computational tools and corpora are now readily available for neurolinguistic researchers. A Python implemented platform such as the Natural Language Tool Kit (NLTK) offers most of these tools and access to over 50 corpora in an easy-to-use interface.

Corpus based statistical analyses of affinities between words and constructions could offers a quantitative way to understand the “light semantic” constraints associated with constructions (Stefanowitsch and Gries 2003). Other databases such as VerbNet, WordNet, or FrameNet (Baker et al. 1998; Fellbaum 2010; Schuler 2005) also focus on organizing linguistic data based on semantic patterns (Table 5). These can help initiate

Table 6 New Neuroinformatics resources called for in this article

Scope	Notes
Event-related potential (ERP) data linked to linguistic and other cognitive tasks.	This requires a standard ontology for ERP recordings. One candidate is provided by the Neural ElectroMagnetic Ontologies (NEMO) project, http://nemo.nic.uoregon.edu/wiki/NEMO, that aims to create EEG and MEG ontologies and ontology based tools. A related issue is to develop standards for linking extracting components from ERP signals and linking them to a limited set of brain regions using, e.g., fMRI data.
NeuroHomology Database (NHDB) revisited	A new version of a defunct resource to integrate data on human brains and the brains of other species to establish homologies that support new hypotheses about detailed neurophysiological, neurochemical and genetic mechanisms that are hard to resolve from the human data alone.
Lesion database linked to MRI and experimental paradigm database.	The study of linguistic performances of brain damaged patients and the development of brain based models from this data would benefit from the creation of a lesion database similar in format to Brain Map. Crucially, such database should not be limited to aphasics or to other specific impairments as brain damage analysis would benefit from a better understanding of the loss of functions as whole rather than multiplying the smaller scopes analyses. An example of this would be the comparative analysis of aphasia and apraxia in a database to better understand the link between language and action systems.
Conceptual model ontology and database	To this day, no database exists that offers an ontology to store and compare conceptual models. BODB and ModelDB are both oriented towards computational models and the challenge would be more of integration rather than having one of these databases take over the role to store conceptual models.
EEG and MEG visualization tools and standardize head models for display.	Similar to the Talairach Daemon visualization tool (http://www.talairach.org/daemon.html) for tomographic imaging, a standard head for display of EEG and MEG results would benefit the neurolinguistic community both in terms of the ease of visual comparison, but also as it would provide a way to report EEG and MEG results in papers in more uniform table-like way as it has become standard for fMRI results (using Talairach or MNI coordinates).

computational neurolinguistic work tackling semantic issues but an effort to develop similar resources more specifically dedicated to the computational modeling for neurolinguistics are necessary. These resources would need to better fit our understanding of the organization of world knowledge in the brain but also of the link between such knowledge and linguistic forms. The lack of such tools hinders the creation of computational neurolinguistic models as the modelers tend to create their own resources, usually small scale and handcrafted, which makes model comparison difficult in the absence of shared standards.

It is important to note that the NLP oriented corpora still lack many of the important characteristics of language relevant to neurolinguistic research. For example, NLP corpora focus on text data extracted from the web, newspapers or books with little conversation data. The extraction of semantic ontology from massive text corpora correspond to a radically different approach than the more cognitive neuroscience perspective focusing on patterns extracted from the physical world with which an individual interacts. Finally, only a few languages are represented (with English being the dominant one). This problem is epitomized by sign languages which are at the center of many neurolinguistic debates (Poeppel et al. 2012). With the exception of the Purdue ASL Database (Wilbur and Kak 2006) that focuses on American Sign Language, sign languages are completely ignored by the NLP community.

Conclusion

The transformation of the TCG model of language production into a TCG model of comprehension to integrate new empirical data on language comprehension served as a case study to raise some of what we consider to be the specific challenges modelers face in the field of computational neurolinguistics, challenges we believe should be analyzed from the perspective of neuroinformatics. Table 6 offers a view of the neuroinformatics resources needed to support the collation of neurolinguistic data and the summarization of that data into forms that can enter into the design and testing of neurolinguistic models.

Neuroinformatics offers researchers in neurolinguistics the possibility to turn many of the difficulties they encounter regarding data management, model comparison, and collaboration, into scientific challenges. We hope that this article will help foster the communication between these two scientific communities that are too often unaware of one another.

Information Sharing Statement

All the data used or mentioned in this article can be accessed by using the bibliographic references or URLs provided.

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