Extending Cognitive Architectures with Semantic Resources

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Abstract. This paper presents an integrated modeling framework where the learning and knowledge retrieval mechanisms of the ACT-R cognitive architecture are combined with a semantic resource. We aim to extend ACT-R with a scalable knowledge model, in order to support sub-symbolic processes with consistent, general high-level declarative representations. Design principles, methodology and implementation examples are provided.

Keywords: cognitive architecture, ACT-R, ontology, computational semantics

1 Introduction

In attempting to design systems capable of Artificial General Intelligence, two substantially different approaches have been attempted. The first, historically, has focused on the mechanisms of intelligence, taking the form of general problem-solving programs [1] or architectures (i.e., [2], [3]). The second, partly arising from the limitations of the first, emphasized the knowledge of the system, especially common-sense knowledge, as the source of intelligence (e.g., [4]). Those approaches have encountered substantial successes in their own rights, but have up to now not achieved the ultimate goal of AGI. Moreover, both approaches have largely downplayed the other: systems that focus on mechanisms tend to treat knowledge as something to be engineered in ad hoc, task-specific ways, while those that focus on knowledge rely on narrowly tailored mechanisms to access and leverage their content, often raising unsustainable computational requirements in the process.

In this paper, we argue that those approaches are complementary, and that both of their central aspects, mechanisms and knowledge, need to be addressed systematically in a comprehensive approach to AGI. Moreover, those two components strongly constrain each other, with learning mechanisms determining which knowledge can be acquired and in which form, and specific knowledge content providing stringent requirements for mechanisms to be able to access them effectively [5]. In the rest of this paper, we introduce each approach, sketch out a general framework for combining them, and then discuss an application of that framework to the problem of recognizing visual actions.

2 Cognitive architectures as knowledge systems

Cognitive architectures are examples of the first class of intelligent system: they attempt to capture computationally the invariant mechanisms of human cognition, including those underlying the functions of control, learning, memory, adaptivity, and perception and action. In this paper we will focus on one particular cognitive architecture: ACT-R [6]. ACT-R is a modular system: its components include perceptual, motor and declarative memory modules, synchronized by a procedural module through limited capacity buffers. ACT-R has accounted for a broad range of cognitive activities at a high level of fidelity, reproducing aspects of human data such as learning, errors, latencies, eye movements and patterns of brain activity. Declarative memory (DM) plays an important role in the ACT-R cognitive architecture. At the symbolic level, ACT-R models perform two major operations on DM: 1) accumulating knowledge chunks learned from internal operations or from interaction with the environment and 2) retrieving chunks that provide needed information[1]. The ACT-R theory distinguishes 'declarative knowledge' from 'procedural knowledge', the latter being conceived as a set of procedures (production rules) which coordinate information processing between its various modules[2]: according to this framework, agents accomplish their goals on the basis of declarative representations elaborated through procedural steps (in the form of *if-then* clauses). This distinction between declarative and procedural knowledge is grounded in several experimental results in cognitive psychology regarding knowledge dissociation; major studies in cognitive neuroscience implicate a specific role of the hippocampus in "forming permanent declarative memories" and the basal ganglia in production processes (see [6], pp. 96-99, for a general mapping of ACT-R modules and buffers to brain areas and [7] for a detailed neural model of the basal ganglia's role in controlling information flow between cortical regions).

3 Hybrid semantics for declarative memory

Although discontinuously popular among AI scholars, this separation between declarative and procedural knowledge has also been an important issue for AI over the years. In 1980 John McCarthy first realized that, in order to enable full-fledged reasoning capabilities, logic-based intelligent systems need to incorporate "re-usable declarative representations that correspond to objects and processes of the world" [9]. Along these lines, Pat Hayes developed an axiomatic theory for *naïve physics* [10] and John Sowa acknowledged the relevant role played by philosophy in defining a structured representation of world entities [11], i.e. an 'ontology'[3]. There have been

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[1] Both chunk learning and retrieval are performed through limited capacity buffers that constrain the size and capacity of the chunks in DM.

[2] In the ACT-R theory, these procedures based on condition-action structures are considered as units for skill acquisition ([6], p. 26).

[3] This was the genesis of using the word 'ontology' in AI. Ontology, 'the study of being as such' – as Aristotle named it –, in fact originated as a philosophical discipline.

numerous (and often alternative) attempts to define 'ontology' in Computer Science[4]. According to Guarino, "an ontology" is a language-dependent cognitive artifact, committed to a certain conceptualization of the world by means of a given language[5] (see [14] for formal details). Besides the *protocol layer*, where the syntax of the communication language is specified, the ontological layer contains the *semantics* of that language: if concepts are described in terms of lexical semantics, ontologies take the simple form of *dictionaries* or *thesauri*; when ontological categories and relations are expressed in terms of axioms in a logical language, we talk about *formal ontologies*; if logical constraints are then encoded in a computational language, formal ontologies turn to *computational ontologies*[6]. This research area finds application in a growing variety of cases: from database integration to security analysis, from enterprise modeling to the expansive vision of the Semantic Web [15]. In particular, the Semantic Web community is making massive efforts towards the development of scalable ontology-driven technologies as, for example, the "Linked Open Data"[7] best practice suggests.

In this paper we focus on a rather new field of application, namely integration between computational ontologies and cognitive architectures. In our context computational ontologies should be appropriately re-defined here as "computational specifications of declarative conceptual structures". In particular we aim at extending ACT-R with a scalable, reusable knowledge model that can be applied across a wide range of tasks. Considering the state of the art[8], most research efforts have focused on designing methods for mapping large knowledge bases to the ACT-R declarative module. Here we commit on taking an integrated approach: instead of tying to a single ontology, we propose to build a *hybrid computational ontology*[9] that combines different semantic dimensions of declarative representations. Our project consists in linking partitions of distinctive lexical databases like WordNet [21] and FrameNet [22] with a suitable computational ontology of actions and events.

Four general issues justify our methodological approach:

1. Meaning is multi-dimensional, i.e. it depends on natural language, cognitive phenomena, contextual information (*human-understandability specifications*);
2. Meaning is computable insofar as semantics is expressed in terms of knowledge representation languages (*machine-understandability*);
3. Event-types correspond to verbs in the lexicon, and WordNet is the broadest source of lexical information available in an electronic format;
4. FrameNet schematically represents the conceptual patterns underlying event

[4] See [12] for a detailed reconstruction. The original definition is considered Gruber's: "formal specification of a shared conceptualization" [13].

[5] Guarino distinguishes between 'Ontology' as a discipline (with the capital 'o') from 'ontologies' as engineering cognitive artifacts.

[6] E.g., Ontology Web Language (OWL). OWL is based on description logics; description logics are *decidable* fragment of First-Order Logic (http://www.w3.org/TR/owl-features/).

[7] http://linkeddata.org/

[8] For ACT-R see [16], [17], [18], for SOAR see [19].

[9] The adjective "hybrid" is used to emphasize the heterogeneity of theories and resources we are adopting for the purposes of the project. For a general survey on hybrid semantic approaches see [20]. For the sake of readability we will henceforth omit the mid-adjective "computational".

verbs, providing detailed information of roles and fillers for basic action types.

The following sections describe the fundamental features of an integrated cognitive model for high-level visual recognition of motor actions to support visual machine learning with solid symbolic representations in the domain of basic human actions.

4 HOMinE & ACT-R: an integrated cognitive model

We address the perspective of an integrated cognitive model oriented to visual intelligence (HOMinE - Hybrid Ontology for 'Mind's Eye' project[10]), outlining methodological aspects and backbone structure of required components. Some distinctive mappings to the ACT-R cognitive architecture are also considered: we show how the modular dynamic structures of ACT-R can benefit from augmenting declarative memory with a multi-layered semantic resource, where lexical and ontological knowledge are properly encoded.

4.1 Design and implementation of HOMinE

WordNet (WN) is a semantic network of *synsets* ("sets of synonym terms")[11], whose arcs are fundamental semantic relations[12]. Over the years, there has been an incremental growth of the lexicon (the latest version, WordNet 3.0, contains about 117K synsets), and substantial enhancements of the entire architecture, aimed at facilitating computational tractability (accordingly, some OWL conversions have been implemented[13]). HOMinE's core layer is based on a partition of WN related to verbs of motion, such as "walk", "touch", "haul", "kick", "chase", etc. In order to find the targeted group of relevant synsets, we basically started from two pertinent top nodes[14] of the semantic network of verbs:

1. {01835496} move#1**,** travel#1, go#1, locomote#1 (change location; move, travel, or proceed) "*How fast does your new car go?*"; "*The soldiers moved towards the city in an attempt to take it before night fell*"; - <verbs.motion>
2. {01850315} move#2, displace#4 (cause to move or shift into a new position or place, both in a concrete and in an abstract sense) "*Move those boxes into the corner, please*"; "*The director moved more responsibilities onto his new assistant*" - <verbs.motion>

As one can easily notice, the synset move#1 denotes a change of position accomplished by an agent or by an object (with a sufficient level of autonomy), while move#2 is about causing someone or something to move (both literally and

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[10] http://www.darpa.mil/i2o/programs/me/me.asp

[11] Life_form#1 stands for synset {life_form, organism, being, living_thing}, which is identified in the database with a specific code (in this example, {05217061}). Every synset (node of the network) is associated to a gloss (e.g., "the characteristic bodily form of a mature organism").

[12] The most important is synonymy; WN also uses hyponymy (sub-class-of), meronymy (part-of), antonymy (opposite-of), troponymy (like hyponymy, but only for verbs), causation, etc.

[13] E.g., http://www.w3.org/TR/wordnet-rdf/

[14] Aka *Unique Beginners* (see [21], Chapter 1].

figuratively). After extracting the sub-hierarchy of synsets related to these generic verbs of motor action, we have introduced a top-most category "movement-generic", abstracting from the two senses of "move" (see **Figure 1**). These operations have been performed on Protégé-OWL (release 3.4.4), the most widely used platform for creating computational ontologies in the context of semantic technologies[15]. More precisely, in order to extract and modify the designated WN partition we used the OntoLing[16] plug-in, a tool that supports semi-automatic population of ontologies. OntoLing allows importing lexical knowledge structures in the form of RDF(S)[17] properties, *de facto* enabling semantic compatibility with ontological knowledge patterns[18]. As far as lexical databases are augmented with axioms and property restrictions based on OWL primitives, the resulting *hybrid ontologies* can support logical inferences: this feature is central for our project, since we plan to further develop HOMinE to enable automatic reasoning capabilities[19].

FrameNet (FN) is the additional semantic layer of HOMinE's integrated cognitive model. Besides wordnet-like frameworks, a computational lexicon can be designed from a different perspective, for example focusing on *frames* (to be conceived as orthogonal to domains). Based on Fillmore's frame semantics (see i.e. [23]), FN aims at documenting "the range of semantic and syntactic combinatory possibilities (valences) of each word in each of its senses" through corpus-based annotation. Different frames are evoked by the same word depending on different contexts of use: the notion of "evocation" helps in capturing the multi-dimensional character of knowledge structures underlying verbal forms. For instance, if you point to the **bringing** frame, namely an abstraction of a state of affairs where *sentient agents (e.g., persons) or generic carriers (e.g. ships) bring something somewhere along a given path*, you will find several "lexical units"[20] evoking different roles (or frame elements - FEs): i.e., the noun 'truck' instantiates the "carrier" role in the frame **bringing**[21]. In principle, the same Lexical Unit (LU) may "evoke" distinct frames, thus dealing with different roles: 'truck', for example, can be also associated to the **vehicle** frame ("the vehicles that human beings use for the purpose of transportation"). FN contains about 12K LUs for 1K frames annotated in 150000 sentences.

Computational lexicons largely differentiate upon the explicit linguistic features they expose, which may vary in format, content granularity and grounding [24]. WN and FN are based on distinct models, but one can benefit from the other in terms of coverage and type of information conveyed. Accordingly, we have analyzed the "evocation" links between the motion verbs we have extracted from WN and the related FN frames: those links can be generated through "FN Data search", an on-line navigation tool used to access and query FN[22]. Our study led to a conceptual

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15 http://protege.stanford.edu/

16 For more information see http://ai-nlp.info.uniroma2.it/software/OntoLing/

17 RDF(S) stands for Resource Description Framework Schema.

18 OWL syntax builds on top of RDF(S) and extends its expressivity.

19 Protégé has a default inference engine, so-called "Pellet": http://clarkparsia.com/pellet/. We are also exploiting SWRL (Semantic Web Rule Language) to express IF-THEN rules.

20 Generically abbreviated with LUs - they correspond to terms in WN synsets.

21 The sentence is "The truck *bringing* coal to crushing facility at western surface coal mine".

22 See http://framenet.icsi.berkeley.edu/index.php

enrichment of lexical declarative structures for basic motor action types: starting from WN synset information, and using FN data, we could identify typical roles (and fillers) of those verbs. This process of extension becomes crucial if one considers the evident isomorphism holding between the elements of ACT-R chunks, namely slots and associated values and elements of frames, i.e. frame elements (roles) and fillers (LUs). The FN semantic layer of HOMinE is still under development: a complete implementation in Protégé will be extremely important for enabling logical reasoning (along the lines of [25]). In parallel, we have started to build an ACT-R model for action recognition, suitably expanding its declarative memory by means of HOMinE's semantic layers: in regards to this integration, section 4.2 shows a functional example.

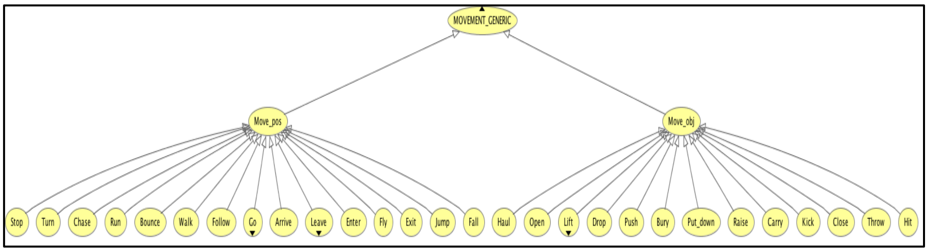

Fig. 1. HoMinE's backbone taxonomy of fundamental motor actions

4.2 Mapping HoMinE to ACT-R

Hybrid ontologies are "computational specifications of declarative conceptual structures": this definition highlights the role of semantic resources in cognitive architectures. From a methodological viewpoint, it is important to understand how this role is actually played in concrete use cases.

Mapping HOMinE to ACT-R requires some preliminary analysis of the basic structures involved. Chunks are the building blocks of ACT-R declarative memory, while ontologies are based on so-called "categories" ("*object*", "*event*", "*attribute*", "*value*", etc.) and "relations" ("*participation*", "*part-of*", "*dependence*", etc.) [26]. Let's consider the following chunk types and chunk instances:

```
(chunk-type car color) (c1 ISA car color red[23])
(chunk-type race duration) (r1 ISA race duration 1hour)
```

One can think of ontological categories as mapping to different elements of chunks: objects/events mapping to chunk types (e.g., *car*/*race*), attributes to slots of chunks (e.g., *color*/*duration*), and values to fillers of slots (e.g., *red*/*1hour*). Relations (e.g., *has_color*/*has_duration*) remain implicit, although they essentially "glue" together those pieces of declarative knowledge (e.g., *car – has_color – red*; *race –*

[23] A specific red nuance (individual), not to be confused with the abstract property "redness", which is a sub-type of "color".

has_duration – 1hour). Alternatively, we can observe that ontological relations can be represented as chunk types as well: e.g., we could have defined *has_duration* as a chunk type with slots *event* and *duration*, with *race* and *time* as filler:

```
(chunk-type has_duration event duration)
(r1 ISA has_duration event race duration 1hour)
```

The category *race* would then become filler of the slot *event*. This potentially variable matching between ontological knowledge and declarative representations reflect the fact that chunks are originally seen as units of memories, without any strong ontological constraint: in fact, anything that is introduced in declarative memory is a chunk, no matter whether an object, an event, an attribute, a value or a relation. The shift from chunk type to filler addresses the potential of alternative representations of categories in ACT-R. Conversely, from the viewpoint of *hybrid ontologies*, representing relations as chunk types becomes an important requirement: relations enable OWL-based inference engines[24] and definitely demand for an explicit counterpart in the declarative memory of the cognitive agent to make the integration effective. The ACT-R architecture also supports "inheritance"[25] from a single chunk type ("single inheritance"), so that different levels of specialization for slot and values are supplied. "Single inheritance" is a central feature for automatic reasoning over ontologies, since it helps prevent logical inconsistencies and internal incoherence of models (which are typically correlated to "multiple inheritance"). HOMinE discards "multiple inheritance" too, maintaining full compatibility with the ACT-R architectural choice.

Chunks are goal-driven, namely they represent the knowledge a person is expected to manipulate to solve a problem. We consider here an experimental setting where the task is to identify motor actions occurring in a simple scenario ("visualized" on a screen window, in natural language). The goal is accomplished when the cognitive model outputs the conceptual structure of the detected action: in terms of the current version of HOMinE, we assume that 1) the output coincides with correct recognition of the evoked frame 2) input sentences are fed by machine learning visual classifiers that parse the scene and return basic linguistic descriptions[26]. Let's consider three sample sentences presented to the ACT-R cognitive model augmented with HOMinE: (a) John **opens** the **door**; (b) John **opens** the **bag**; (c) John **opens** the **sack**.

Following the typical schema for sentence processing and representation in ACT-R (starting with [27]), our model parses the screen, reads sentences and encodes related chunks accordingly[27]. Afterwards, the actual retrieval of HOMinE declarative representations starts: the model first attempts a straightforward retrieval of frames evoked by the verb "open". In this version we purposely customized the model to always fail this operation. The main reason behind this choice is that an adequate

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[24] Ontological relations correspond to OWL object-properties and data-type properties.

[25] The notion of inheritance corresponds to "IS-A" in Computer Science and "hyponymy" in (computational) lexical semantics.

[26] For the sake of simplicity, visual pattern recognition algorithms and tools are considered as a black box in this paper: we are just focusing on the output labels they provide to ACT-R.

[27] For reasons of space, we just present an overview of the model here.

cognitive model should not contain all the information about verb-frame association, as much as we commonly agree that persons can't perfectly memorize 1K frames evoked by 12K LUs[28]. In order to overcome the failure of direct evocation, we implemented two competing productions, namely "retrieve-frame-from-hypernym" and "retrieve-frame-from-object". The first production searches for the superordinate verb of the one visualized on the screen, navigating upwards the taxonomy of WN: if the superordinate synset is associated to a frame, then the production retrieves that frame, otherwise "retrieve-frame-from-object" is fired. Note that the heuristics of "retrieve-frame-from-hypernym" is inspired by the algorithm implemented in [28], according to which WN synsets can be associated to FN frames by assigning suitable weights to WN relations. In particular, digging out frames through hyperonymy chain implies a penalization, since the evoked frame is associated to the input verb only because of the inheritance from the super-ordinate[29]. The production "retrieve-frame-from-object" fires as a further method to foster frame evocation. The rationale is to search for distinctive instances of frame elements in sentences; then, it is quite trivial for FEs to propagate evocation up to frame(s) they are member of. In our example, declarative memory contains information about the evocation between "door" and "bag" as filler of *object* slot in the following evocation chunk types:

```
(e7  ISA evocation object bag  frame-element entity)
(e8  ISA evocation object bag  frame-element container)
(e9  ISA evocation object bag  frame-element goal)
(e10 ISA evocation object door frame-element barrier)
```

Moreover, since *container*, *goal* and *barrier* appear in the structure of the following chunks, related frames for (a) and (b) are retrieved.

(f3 ISA frame name manipulation fe1 agent fe2 **entity**)
(f4 ISA frame name closure fe1 agent fe2 **container**)
(f5 ISA frame name bringing fe1 carrier fe2 **goal**)
(f7 ISA frame name openness fe1 theme fe2 **barrier**)

When the production "retrieve-frame-from-object" fires, we discover that (a) evokes the frame "openness" and that (b) may evoke, in principle, three different frames, respectively "manipulation", "closure" and "bringing". In order to prompt a choice within these frames, spreading activation can be exploited through the ACT-R sub-symbolic computations [6]. Spreading of activation from the contents of slots in the imaginal buffer triggers the evocation of frame-related chunks to the context of the perceived scene. Finally, by setting a high similarity parameter between *bag* and *sack*, whenever the model perceives *sack*, it will make reference to the *frame(s)* evoked by *bag* through the ACT-R mechanism of "partial matching", which allows the semantics

[28] Future versions of the model will provide a more accurate account, allowing for successful retrievals of the most frequent frames (with frequency measured on annotated corpus sentences), as well as failure to access information symbolically present in memory because of sub-symbolic (statistical) factors.

[29] In the current version of the model, the penalization is reflected *a priori*, setting up a low activation threshold of the chunk for the input verb.

of similarity between chunks to be reflected in the retrieval process [29].

5 Conclusions

This paper presented the general framework of integration between the ACT-R cognitive architecture and semantic resources. In particular, we considered the task of high-level visual recognition of motor actions, outlining how HOMinE ontological features can augment ACT-R declarative representations. Future work will be devoted to enhance both the semantic layer and the cognitive model: the former will be improved by adding grounding axioms to WN and FN structures; the latter will be extended in terms of experimental settings, task complexity and sub-symbolic parameterization. Finally, we also aim at importing WN and FN data-structure into symbolic ACT-R declarative memory structures as well as using statistical natural language processing techniques to constrain their sub-symbolic parameters.

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References

1. Newell, A.; Shaw, J.C.; Simon, H.A. (1959). Report on a general problem-solving program. Proceedings of the International Conference on Information Processing. pp. 256-264.
2. Anderson, J. R. (1983). The Architecture of Cognition. Cambridge, MA: Harvard University Press.
3. Newell, 1990, Unified Theories of Cognition, Harvard University Press.
4. Douglas B. Lenat, Mayank Prakash, Mary Shepherd. CYC: Using Common Sense Knowledge to Overcome Brittleness and Knowledge Acquisition Bottlenecks. Artificial Intelligence, 6 (4), pp. 65-85.
5. Anderson, J. R. & Lebiere, C. L. (2003). The Newell test for a theory of cognition. Behavioral & Brain Sciences 26, 587-637.
6. Anderson, J.R., Lebiere, C.: The atomic components of thought. Erlbaum, Mahwah, NJ (1998)
7. Anderson, J.R.: How Can the Human Mind Occur in the Physical Universe? Oxford University Press, New York (2007)
8. Stocco, A., Lebiere, C., & Anderson, J.R. (2010). Conditional Routing of Information to the Cortex: A Model of the Basal Ganglia's Role in Cognitive Coordination. Psychological Review 117(2) 541-574.
9. McCarthy, J.: Circumscription – A Form of Non-Monotonic Reasoning. Artificial Intelligence. 5, 13, pp. 27–39 (1980)

10. Hayes, P.J.: The Second Naive Physics Manifesto. In: Hobbs, J. R., Moore, R.C. (eds.) Formal Theories of the Common-sense World, Ablex, Norwood, pp. 1–36. (1985)
11. Sowa, J. F.: Conceptual Structures. Information Processing in Mind and Machine, Addison Wesley, Reading (1984)
12. Smith, B., Welty, C.: Ontology: Towards a new synthesis. In: Welty, C., Smith, B. (eds.) Formal Ontology in Information Systems. ACM Press, Ogunquit, Maine, pp. iii-x (2001)
13. Gruber, T.R.: A Translation Approach to Portable Ontology Specifications. Knowledge Acquisition, 5, pp. 199–220 (1993)
14. Guarino, N.: Formal Ontology and Information Systems. In: Guarino, N. (ed.) Formal Ontology in Information Systems, IOS Press (1998)
15. Berners-Lee, T.: The Semantic Web. Scientific American, May (2001)
16. Ball, J., Rodgers, S., Gluck, K.: Integrating ACT-R and Cyc in a large-scale model of language comprehension for use in intelligent agents. In: *Papers from the AAAI Workshop*, Technical Report WS-04-07, Menlo Park, AAAI Press, pp. 19-25 (2004)
17. Douglass, S., Ball, J., Rodgers, S.: Large declarative memories in ACT-R. In: Proceedings of the 9th International Conference of Cognitive Modeling (paper 234), Manchester, United Kingdom (2009)
18. Best, B. J., Gerhart, N., Lebiere, C.: Extracting the Ontological Structure of OpenCyc for Reuse and Portability of Cognitive Models. In: Proceedings of the 17th Conference on Behavioral Representation in Modeling and Simulation (2010)
19. Emond, B.: WN-LEXICAL: An ACT-R module built from the WordNet lexical database. In: Proceedings of the Seventh International Conference on Cognitive Modeling, Trieste, Italy, pp. 359-360, (2006).
20. Huang, C.R., Calzolari, N., Gangemi, A, Lenci, A., Oltramari, A., Prevot, L. (eds.): Ontology and the Lexicon. Cambridge University Press, (2010)
21. Fellbaum, C. (ed.): WordNet - An Electronic Lexical Database. Cambridge, Massachusetts. MIT Press (1998)
22. Ruppenhofer, J., Ellsworth, M., Petruck, M.R., Johnson, C.R., and Scheffczyk, J.: FrameNet II: Extended Theory and Practice. International Computer Science Institute (2006)
23. Fillmore, C.J.: The case for case. In: Bach, E., Harms, T. (eds.) Universals in Linguistic Theory. Rinehart and Wiston, New York (1968)
24. Pazienza, M.T., Stellato, A.: An open and scalable framework for enriching ontologies with natural language content. In: Huang, C.R., Oltramari, A., Buitelaar, P., Fellbaum, C., Lenci, A. (eds.) Ontologies and Lexical Resources – Workshop at Linguistic Resources and Evaluation Conference, Genoa (2006)
25. Ovchinnikova, E., Vieu, L., Oltramari, A., Borgo, S., Alexandrov, T.: Data-driven and Ontological Analysis of FrameNet for Natural Language Processing. In: Proceedings of 7th International Conference on Language Resources and Evaluation, La Valletta, Malta (2010)
26. Gangemi, A., Guarino, N., Masolo, C., Oltramari, A: Sweetening WordNet with DOLCE. AI Magazine, 24(3), Fall 2003, pp. 13-24 (2003)
27. Anderson, J.R.: Retrieval of propositional information from long-term memory. Cognitive Psychology, 5, pp. 451-474 (1974)
28. Burchardt, A., Erk, K., Frank. A.: A Wordnet detour to FrameNet. In: Schrder, B. Bernhard, F., Schmitz, H.C., Wagner, P. (eds.) Sprachtechnologie, mobile Kommunikation und linguistische Resourcen. Volume 8 of Computer Studies in Language and Speech, Peter Lang, Frankfurt am Main, pp. 408–421 (2005)
29. Budiu, R. & Anderson, J. R. (2004). Interpretation-Based Processing: A Unified Theory of Semantic Sentence Processing. Cognitive Science 28, 1-44.