Tree-like Dispositional Dependency Structures for non-propositional Semantic Inferencing.

On a SCIP approach to natural language understanding by machine*

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Abstract

Arguing for the semiotic modeling *of natural language understanding by machine is to follow a procedural stance of approach focusing on processes of* meaning constitution. *These can be typified in pragmatic* situations *of performative* language games *which may be analyzed empirically, described formally, and simulated computationally. In doing so, graph theoretical tools have been employed and new tree structures developed which allow both, to restrict the relational manifold in high-dimensional vector space structures computed as fuzzy word meaning representations, and to visualize semantically motivated relevancies emerging from such restrictions as reflexive, non-symmetric, and (weakly) transitive dependency relations among them. As a basal, context-sensitive form of reorganizing distributionally represented fuzzy entities, the tree like* dispositional dependency structures (DDS) *serve as a non-propositional format for conceptual associations and semantic inferencing by machine, as opposed to propositional reasoning based on truth-functional constraints. After a short introduction into* semiotic cognitive information processing (SCIP) *and the text analyzing and meaning representational formalisms employed,* DDS *tree generation will be discussed, and some examples be given to illustrate the algorithms'* semantic inferencing *potential as computed from and performed on a sample of German newspaper texts.*

1 Introduction

In view of *semiotic processes* like understanding natural language sign structures the modeling enterprise is aggravated by the lore of thinking in traditional terms of (modern) linguistics, cognitive psychology, and artificial intelligence approaches. These tend to replicate computationally what is believed to be known about (fragments of) human processing instead of developing computational models which might (or might not) correspond to some of that knowledge, but whose functional results are equivalent (perhaps inferior, or even superior) to very obvious human processing capabilities[1]. Arguing for computational models in this sense is to ask for a genuinely procedural extension to cognition and cognitive modeling, trying to avoid rather than employ traditional conceptualizations for a chance to find possible solutions to problems differently posed. In other words, sentence *parsing* and *generation*, knowledge based *interpretation*, rule based *inferencing*—to name only the most salient—can be viewed as very particular abstractions (and models derived) of humans' general capabilities to employ signs and to constitute meanings that can be understood. It may be argued that these abstractions—however seminal in many respects—have impeded rather than advanced adequate computational modeling of e.g. discourse understanding, language and knowledge acquisition, adaptive learning and knowledge modification, dynamic reasoning with fuzzy, associative, and uncertain concepts, etc. that human beings normally are able to perform with ease.

Due to the centrality of *semiosis*, and its pivotal role in natural language understanding, the concept of *Semiotic Cognitive Information Processing* systems (SCIPS) was developed [18] to simulate the process of sign and/or meaning constitution by machine without (necessarily) replicating these processes as enacted by humans. The modeling of processes of *meaning constitution* as typified in pragmatic *situations* [1] of performative *language games* [22] basically follows an ecological systems theoretical approach [5], placing an information processing *system* into an *environment* whose *structural coupling* [4] is mutually achieved by processes of (material, energetic, informational) mediation between them. The generality of this concept lends it-

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[1]To illustrate the point by an example taken from engineering: the phenomenon of flying—observed in nature as airborne locomotion which (most) birds are capable of—has not been modeled by replicating nature's solution (flapping wings), but simulated by technologically quite different means (propeller, jet engine) in aircrafts which surpass birds' capacities in many respects.

self easily to accommodate hierarchically structured restrictions on recursive modes of processing [20]. Thus,

- ▷ *data processing* is defined as manipulation of data according to predefined rules, and may be distinguished from
- ▷ *information processing* which comprises the interpretation of data according to given and pre-established codes;
- ▷ *cognitive information processing* will be called any information processing whose interpretations are not codified but have to be derived from sets of principled structures and according to certain mechanisms either internal or external to the processing system and described as its knowledge; and finally
- ▷ *semiotic cognitive information processing* will be restricted to such cognitive or knowledge based information processing whose knowledge—internal or external to the system—is not just made available but is instead acquired, structured, represented, and/or modified by the system's own processing according to its capabilities and intrinsic principles.

Semiotic cognitive information processing (SCIP) capabilities appear to serve a double purpose, as a means of structuring an *environment* as perceived by an (artificial or natural) information processing *system*, and as a means of representing this structure in order to communicate it to other systems. In allowing not only for an (internally) representational processing whose states may provide stimuli for further action, but also for the (externalized) representations of the course or states of such processing in forms of agglomerated *sign structures*, this is roughly what understanding natural language translates to in a *semiotic* system-environment situation.

2 Modeling Language Understanding

The dramatic increase of computational power and symbol manipulation means has changed the fundamentals of many scientific disciplines, creating even new ones. Apparently, it has left linguistically oriented disciplines, even new ones, adhere to seemingly well grounded and traditionally dignified concepts (like *phrase* and *sentence*, *predicate* and *proposition*, *grammatical correctness* and *formal truth*, etc.) in describing natural language structures. Considering our as yet very limited understanding of natural language understanding, it may well be suspected that some of the problems encountered are due to inadequate conceptions and corresponding representational formats employed in depicting and manipulating linguistic entities (elements, structures, processes, and procedures) considered to be of interest or even essential to the understanding of the communicative use of natural languages by humans.

2.1 Different Approaches

An earlier attempt [21] to classify model constructions as produced in cognitive science had distinguished three types of modeling approaches: the *cognitive*, the *associative*, and the *enactive*. Whereas the first two approaches draw on the traditional rationalistic paradigm of mind-matter-duality—*static* and unable to adapt the former, *dynamic* and able to learn the latter—by assuming the existence of *external* world structures and an *internal* representations of it, the third type does not. Instead of assuming an external world and the systems' internal representations of it, some unity of mutual relatedness (*structural coupling*) is considered to be fundamental of—and the (only) condition for—any abstracted or acquired duality in concepts of the external and internal, object and subject, reality and any experience of it which might evolve. Considering the importance that the notions of formatting and representation (both internal and external to an information processing system) have gained in tracing processes on the grounds of their observable or resulting structures, it appears to be justified to add a fourth type, the *semiotic* [19]. It is focused on the concept of *semiosis* and may be characterized by the process of *enactment* too, complemented, however, by the representational impact. This is considered fundamental to the distinction of e.g. *cognitive processes* from their *structural results* which—only due to some traces these processes leave behind—may emerge in forms of *knowledge*. Its different representational modes comply with different forms of activation that allow for the distinction of *internal* or *tacit* knowledge (i.e. *memory*) on the one hand, and of *external* or *declarative* knowledge (i.e. symbolic representations like *language structures*) on the other.

According to the above types of cognitive modeling, *computational semiotics* can be characterized as aiming at the dynamics of meaning constitution by simulating processes of multi-resolutional representation [6] within the frame of an ecological *information processing* paradigm [18]. When we take human beings to be *systems* whose knowledge based processing of represented *information* makes them *cognitive*, and whose sign and symbol generation, manipulation, and understanding capabilities render them *semiotic*, we may do so due to our own daily experience of these systems' outstanding ability for representing results of cognitive processes, organizing these representations, and modifying them according to changing conditions and states of system-environment adaptedness.

2.2 Computational Processing

Computational systems for natural language processing are based upon relevant findings in computational linguistics (CL) and artificial intelligence (AI) research. Operational systems for natural language analysis and generation by machine require correct structural descriptions of input strings and their semantic interpretations. By and large, this is provided—for different languages differently—by rule based representations of (syntactic and lexical) *linguistic knowledge* and of (referential and situative) segments of domain specific *world knowledge* which grammar formalisms and deductive inferential mechanisms can operate on. This kind of *cognitive* (or *knowledge-based*) language processing (using monotone logics, symbolic representations, rule-based operations, sequential processing, etc.) and the statics of its representational structures were challenged—although for differing reasons—by connectionist and empirical approaches. These were particularly successful in simulating dynamic properties of cognitive natural language processing (based on the theory of dynamic systems, sub-symbolic or distributed representation, numerically continuous operations, parallel processing, etc.). New insights were gained into the wealth of structural patterns and functional relations as observed in *very large language corpora*[2] of communicative natural language performance as specified by models of quantitative and statistical analyses (based on probability and possibility theory, stochastic and fuzzy modeling, numerical mathematics and non-monotone logics, strict hypothesizing and rigorous testing, etc.). Language regularities and structures which are empirically traceable but may not easily be identified within the categorial framework of established linguistic concepts[3], were discovered by the empirical study of *performative* language phenomena providing valuable new insights and explanations because of a broader coverage of language material, and due to the new methods complementary to those of *competence* centered linguistics. Moreover, empirical approaches allow for quantitative-statistical as well as fuzzy-theoretical model constructions which promote a more *semiotic* understanding of the functioning of language signs as used by interlocutors in communicative interaction.

2.3 Information Systems View

Following a systems theoretical paradigm of information processing and accepting the cognitive point-of-view (implying that information processing is knowledge based), human beings appear to be not just natural information processing systems with wider cognitive abilities. Instead, they have to be considered very particular cognitive systems whose outstanding plasticity and capability to adapt to changing environmental conditions is essentially tied to their use and understanding of natural languages in communicative discourse. It seems that language faculty expands their learning potential well beyond experimental real-world experience into realms of experiencing hypothetical reality in virtual environments (*Gedankenexperimente*) for better real-world adaptation. The basic idea of model construction in terms of such an ecological theory of information [18] is that the processing structure of an information system is conceived as a correlate of those structures which such a system has to be able to process in order to survive. For cognitive models of natural language processing the system theoretical view suggests to accept natural language discourse as analyzable and empirically accessible evidence for tracing such processes, and to hypothesize about their procedural modeling. Thus, natural language discourse might reveal essential parts of the particularly structured, multi-layered information representation and processing *potential* to a system analyzer and model constructor in rather the same way as this potential is accessed in order to be constrained by an information processing system in the course of understanding.

3 SKIP Systems

Other than value attributing procedures that reorganize input data computationally according to predefined symbolic structures of intermediate representations (as hypothesized by *competence* theoretical linguistics and realized in cognitive CL models) *semiotic cognitive information processing* (SCIP) systems [17] will have to, and can in fact, be distinguished sharply as sets of procedures whose computations will transform structured input data according to its immanent regularities to yield new, structural representations emerging from that computation (as hypothesized by*performative* linguistics and realized in procedural models of *computational semiotics* [16]).

3.1 Constraint Exploration

Structural linguists have given substantial hints on how language items come about to be employed in communicative discourse the way they are. They have identified the fundamental and apparently universal constraints[4] that control the multi-level combinability and formation of language entities by distinguishing the restrictions on linear aggregation of elements (*syntagmatics*) from restrictions on their selective replacement (*paradigmatics*). This distinction allows within any sufficiently large set of strings of natural language discourse to ascertain syntagmatic regularities of element aggregations on level n whose characteristic dis-

[2]The Trier *dpa*-VLLC comprises the complete textual material, i.e. 720.000 documents of approx. 180 millions ($18 \cdot 10^7$) running words (*tokens*) from the *basic news real service* of 1990–1993 which the Deutsche Presseagentur (*dpa*), Hamburg, deserves thanks to have left the author with for research purposes. It is this corpus which provides the performative data of written language use for the current (and planned) *fuzzy*-linguistic projects at our department.

[3]Phenomena like linear short-distance/long-distance orderings (*Nah-* and *Fern-Ordnung*) of performative language entities (e.g. co-occurences) easily represented and processed as numerical expressions of correlation values with any precision, are cases in point here. Although observable results of structuring principles, they have continuously been overlooked by rule based approaches whose representational means comply more adequately with agglomerative orderings (*constituent-* and *phrase-structure*) as represented and processed by familiar grammar formalisms.

[4]The distinction of *langue–parole* (DE SAUSSURE) and *competence–performance* / *I-language–E-language* (CHOMSKY) in modern linguistics is grounded in the possibility to abstract (formally representable) *linguistic entities* from (empirically observable) *language phenomena*. The discovery of principles of combinatorial constraints responsible for regular string formation in natural languages gave rise not only to *segment* strings of language discourse and to *categorize* classes of types of linguistic entities, but also to distinguish and construct different levels of language description and linguistic analysis.

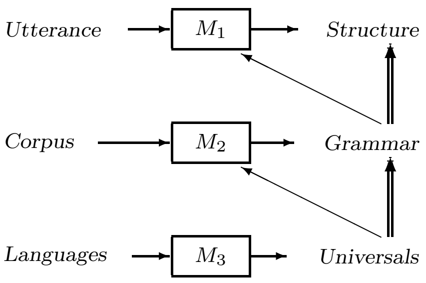

Figure 1

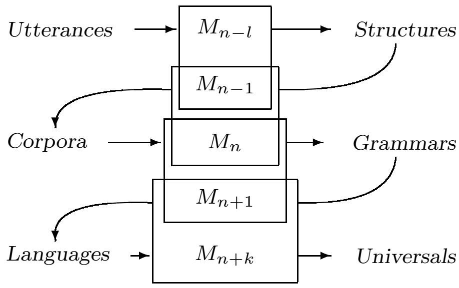

Figure 2

Schemata of model hierarchy of *cognitive linguistic* strata of mechanisms (BIERWISCH) as compared to model tiling of *computational semiotic* coverage of procedures (RIEGER) for the analysis and representation of (abstracted and observable) language phenomena.

tributional patterns or paradigms gain functional status on level $n+1$ for higher aggregation. The distinction of these representational levels and their identification with functional results introduced elsewhere [2] [19] is tantamount to the categorial constraints applied when identifying regularities with rules. Fully deterministic if-then rules will result in a rather coarse three-level hierarchy of categorial description (*Fig.* 1) whereas probabilistic or possibilistic dependencies produce a continuous, multi-level covering of distributional representations (*Fig.* 2). These model hierarchies distinguish cognitive *linguistic* from *semiotic* procedures whose computations transform structured input data according to its immanent regularities. Their output yields new structural representations emerging from computational processes. The elements they produce are value distributions or vectors of input entities whose structural properties are depicted by adjacencies of the new elements (and their structural relatedness) constituting multi-dimensional (metric) space structures (*semiotic spaces*). Their elements may also be interpreted as *fuzzy sets* allowing set theoretical operations being exercised on these representations which exhibit granular properties [23] and do no longer require categorial type (*crisp*) definitions of concept formation. Computation of letter (*morphic*) vectors in *word space*, derived from n-grams of letters (*graphemes*) [19] as well as of word (*semic*) vectors in *semantic space* [8], [9] derived from word-type correlations of their tokens in discourse have illustrated the operational flexibility and fine granularity of vector notations [15] to identify regularities of semiotic meaning constitution in language performance which traditional linguistic categories fail to represent.

3.2 Visualizing Vector Representations

Returning to the ecological systems theoretical view applied to information processing, we will focus on the problem of visualizing results of computational procedures developed to model and simulate semiotic processes whose numerical representations—by definition—do not have an immediate interpretation. We may concentrate on the level of *semantic* meaning constitution as various techniques formerly applied to analyze, scrutinize, and visualize the structuredness

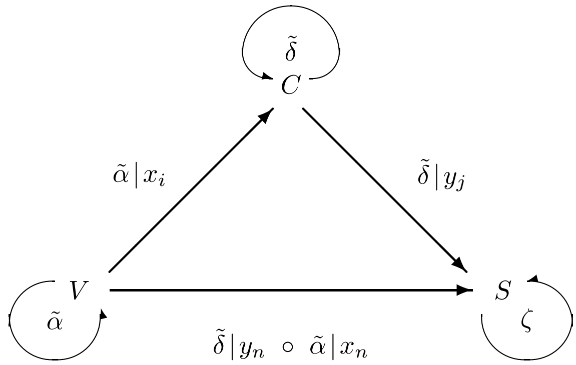

Figure 3: Morphisms of fuzzy mapping relations $\tilde{\alpha}$ and $\tilde{\delta}$ from structured sets of vocabulary items $x_n \in V$, via corpus points $y_n \in C$, to labeled meaning points $z_n \in S$.

of vectoral representations [10] [11] [12] [13] [14] have been able to demonstrate the definite non-contingency of *meaning points* z in *semantic space* S, ζ. Therefore, a short introduction to illustrate its conception as based upon the measurement of differences of usage regularities in VLLC of situated or *pragmatically homogeneous* texts will suffice.
For a vocabulary $V = \{x_n\}, n = 1, \ldots, i.j. \ldots, N$ of lexical items, their meanings $z_n \in \langle S, \zeta \rangle$ are re-constructed as a composite function $\tilde{\delta}\,|\,y_n \circ \tilde{\alpha}\,|\,x_n$ of the difference distributions

$$\tilde{\delta}\,|\,y_n : C \to S; \{z_n\} =: S \tag{1}$$

and the grounding usage regularity distributions

$$\tilde{\alpha}\,|\,x_n : V \to C; \{y_n\} =: C \tag{2}$$

The empirical measures employed to specify intensities of co-occurring lexical items are centered around a modified correlational coefficient

$$\alpha(x_i, x_j) = \frac{\sum_{t=1}^{T} (h_{it} - e_{it})(h_{jt} - e_{jt})}{\left(\sum_{t=1}^{T} (h_{it} - e_{it})^2 \sum_{t=1}^{T} (h_{jt} - e_{jt})^2\right)^{\frac{1}{2}}}; \qquad -1 \leq \alpha(x_i, x_j) \leq +1 \tag{3}$$

where $e_{it} = \frac{H_i}{L} l_t$ and $e_{jt} = \frac{H_j}{L} l_t$, computed over a text corpus $K = \{k_t\}; t = 1, \ldots, T$ having an overall length $L = \sum_{t=1}^{T} l_t; 1 \leq l_t \leq L$ measured by the number of word-tokens per text form the vocabulary

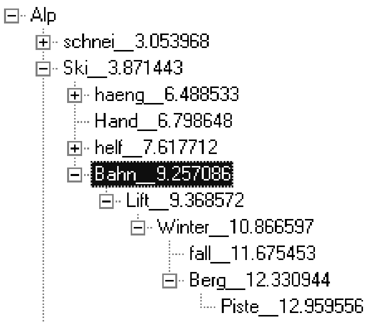

Figure 4: Fragment of DDS-tree of `Alpen`/*Alps* (root) as generated from *semantic space* data ($V = 345, H_i \geq 10$) of a German newspaper sample (Die Welt, 1964 Berlin edition).

$x_n \in V$ of word-types whose frequencies are denoted by $H_i = \sum_{t=1}^{T} h_{it}; 0 \leq h_{it} \leq H_i$ and a measure of similarity (or rather, dissimilarity) to specify the α-value distributions' differences

$$\delta(y_i, y_j) = \left(\sum_{n=1}^{N} (\alpha(x_i, x_n) - \alpha(x_j, x_n))^2 \right)^{\frac{1}{2}}; \qquad (4)$$
$$0 \leq \delta(y_i, y_j) \leq 2\sqrt{n}$$

The consecutive application of (*Eqn.* 2) on input texts and (*Eqn.* 1) on its output data allows to model the meanings of words as a two-level function of differences ($\tilde{\delta} \mid y_j$ *paradigmatic* selection) of usage regularities ($\tilde{\alpha} \mid x_i$ *syntagmatic* aggregation), schematized as semiotic morphisms in *Fig.* 3.

4 Dispositional Dependency Structures

Following a semiotic understanding of meaning more as a constitutional process rather than as a static entity of invariable constancy and representation, the present *semantic space* may be considered part of a word meaning/world knowledge representation system which separates the format of basic (stereotyped) meaning components (*meaning points*) from their latent (dependency) relational organization as meaning potential (*semantic dispositions*). Whereas here the former is represented as a static, topologically organized multi-dimensional memory structure, the latter can be characterized as a dynamic and flexible structuring process which reorganizes and thereby transforms the basic relatedness of the elements it operates on.

4.1 Tree Generation

This is achieved by a recursively defined procedure that produces a hierarchical ordering of the semantic space's meaning points which can be represented as a tree structure organized under a given aspect (root node) according to and in dependence of neighbors (descendant nodes) in cotextual relevancy to it. Taking up ideas from cognitive theories of semantic memory, *priming*, and *spreading activation* [3], the *DDS*-algorithm was devised to operate on the semantic space data and to generate *dispositional dependency structures* (DDS) in the format of n-ary trees. Given one meaning point's position, the algorithm will

1. take that meaning point's label as a start,
2. stack list labels of all its neighboring points by their decreasing distances,
3. initialize DDS-tree with starting point's label as primed head or root node. Then it will
4. take label on top of stack as new daughter node,

4.1 list all labels of new daughter's neighbors,
4.2 intersect it with nodes in tree,
4.3 determine from intersection the least distant one as current mother node,

5. link new daughter to identified mother node
6. and repeat 4. either

6.1 until 2. is empty
6.2 or other stop condition (given number of nodes, maximum distance, etc.) is reached

7. to end.

The tree structured graphs[5] may serve as a visualization of the dependencies that any labeled meaning point $z_i \in \langle S, \zeta \rangle$ chosen as root node will produce according to the adjacencies of other points in the *semantic space* (*Fig.* 4). Their semantic relatedness as represented by their topology—being determined by and reconstructed operationally as a function of the differences (*Eqn.* 1) of usage regularities (*Eqn.* 2) of word distributions in the texts analyzed—will thus allow for a directed, non-symmetric relation (*dependency*) being established between them, induced by the start area, i.e. the meaning point's position chosen as the tree's root node. Thus, it is this node's neighborhood which will control the topologically motivated dependencies between related meanings in a way that is highly sensitive to the *semantic context* of the meaning points' representations concerned. This type of algorithmically generated tree structure has been named *dispositional* because of the structured assembly of possible meaning relations and dependencies it offers as something like a potential for restricted choices to be made.

In order to illustrate the contextual sensitivity which distinguishes the DDS-algorithm from e.g. *minimal spanning trees* (MST) [7], the latter (*Fig.* 5) has been generated from the same data with the same starting node. Note, that the subtrees of `Bahn` (*track, course, trail*) found to be identical in both, the MST- and the DDS-tree, are positioned on extremely different levels (comparing 23 to 3)[6]. Although the DDS-algorithm which consumes all meaning points $z_n \in \langle S, \zeta \rangle$, can roughly be characterized as an encapsulated MST-procedure, this encapsulation apparently serves to catch an essential property of semiotic meaning constitution and representation tied to its contextuality. Where the MST is searching for shortest possible dis-

[5]The figures present subtrees of a semantic space as computed from a sample of texts from the German daily newspaper (Die Welt, 1964, Berlin edition). Nodes marked ⊞ hide subtrees whose expansions have been conflated for lack of space; the numerical values stated are direct ζ-distances to the root node.

[6]The numerical MST values given are direct ζ-distances between nodes (mother-daughter pairs).

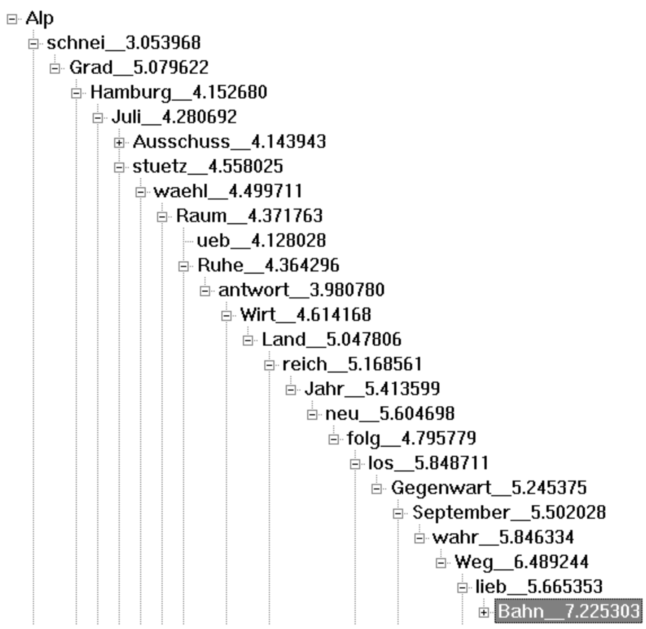

Figure 5: Fragment of MST-graph of `Alpen` (root) as generated from the same *semantic space* data.

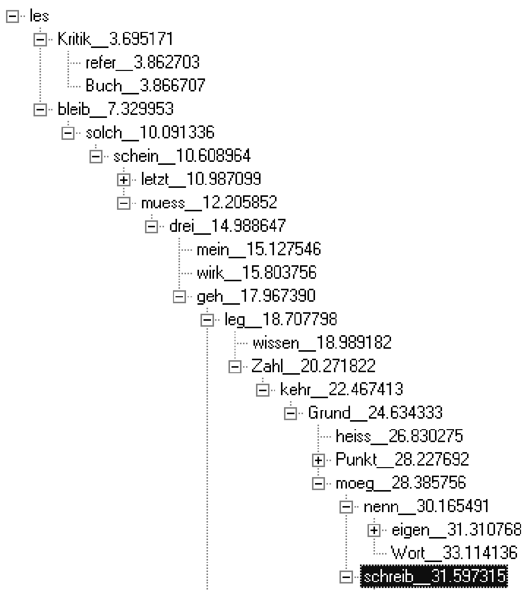

Figure 6: *Dependency path* of `lesen`/*to read* $\Longrightarrow$ `schreiben`/*to write* as traced in DDS-tree of `les`.

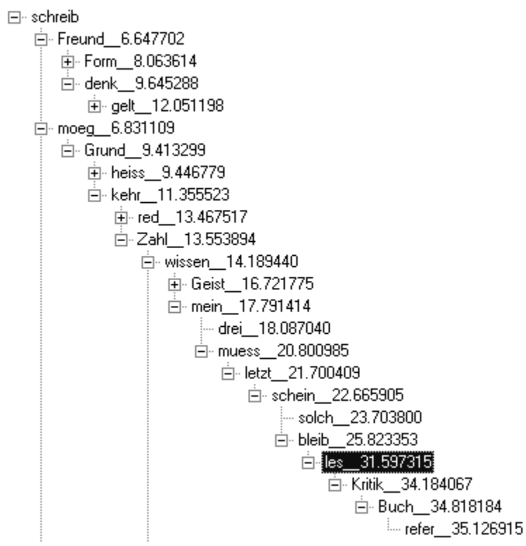

Figure 7: *Dependency path* of `schreiben`/*to write* $\Longrightarrow$ `lesen`/*to read* as traced in DDS-tree of `schreib`.

tance relations between points qualifying for tree node relatedness, the DDS is looking for highest *meaning similarities*, i.e. for shortest possible distance relations between points which are interpretable as *semiotically* derived representations. It is this holistic property of $\langle S, \zeta \rangle$ that allows the algorithm's search space to be *semantically* constrained on the starting point's or root node's topological environment (capsule), rendering it *aspect*-dependent and structurally *context sensitive*.

4.2 Some Properties

There are a number of consequences of which the following seem interesting enough to be illustrated and shortly commented on:

- ▷ The procedural (semiotic) approach replaces the storage of fixed and ready set relations of (semantic) networks in AI by source- or aspect-oriented induction of relations among meaning points by means of the DDS procedure;
- ▷ DDSs dependencies may be identified with an algorithmically induced *relevance* relation which is reflexive, non-symmetric, and (weakly) transitive as illustrated by the *dependency paths*' listings of node transitions `les/`*to read* $\Longrightarrow$ `schreib/`*to write* and its (partial) inverse `schreib/` $\Longrightarrow$ `les` (Figs. 6 and 7);
- ▷ the relevance relation gives rise to the notion of *criteriality* which allows estimates to what degree a mean-

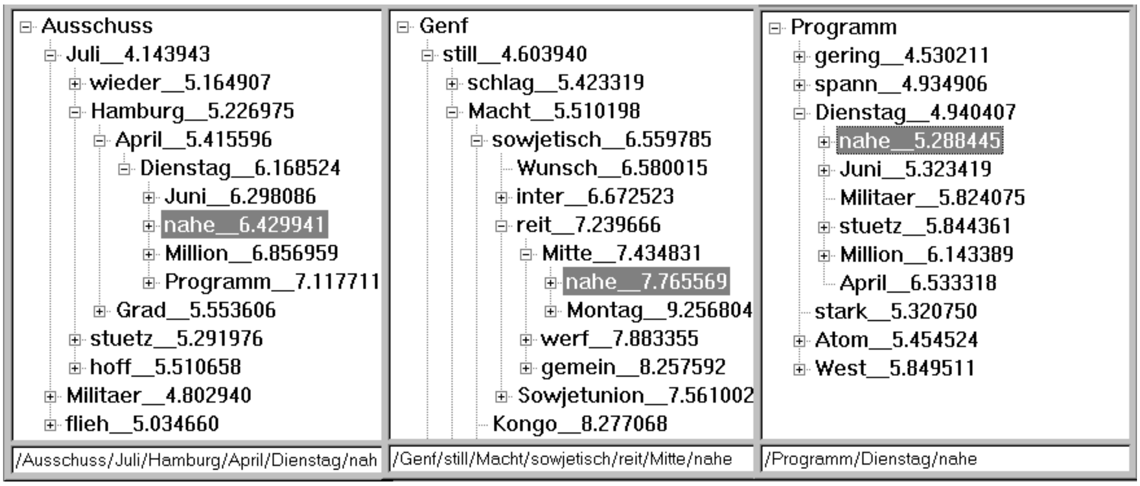

Figure 9: DDS-based *semantic inference* from `Ausschuss`/*committee*, `Genf`/*Geneva*, and `Programm`/*program* (premises) to `nahe`/*near* (conclusion) as computed from the semantic space data.

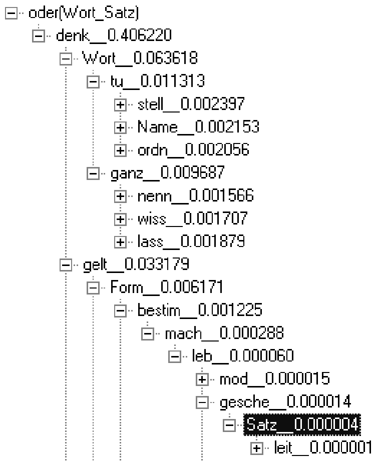

Figure 8: Fragment of DDS-tree of `Wort`/*word* $\vee$ `Satz`/*sentence* (root) as generated from OR-adjunction (max.) of these two meaning points in *semantic space*.

ing component (daughter node) contributes to the *meaning potential* a root node's DDS produces. It will render the DDS a weighted tree and may numerically be specified as a function of any node's level and ζ-distance by

$$Cr_i(d)_{\kappa+1} = Cr_i(m)_\kappa \cdot e^{-\frac{\zeta(d,i)}{\lambda+\zeta(d,m)}} \tag{5}$$

with i, m, d for *root*, *mother*, and *daughter* nodes respectively, and the counters κ for (left to right) nodes, and λ for (top down) levels in the tree;

▷ as the criteriality values are decreasing monotonously from 1.0 (root) they may be interpreted as membership values which reflect the relevance related *soft* structure of components (nodes) in the DDS as a *fuzzy meaning potential*. Fuzzy set theoretical extensions of logical operators (*and*, *or*, *non*, etc.) open up new possibilities to generate composite meaning points (`Wort`/*word* $\vee$ `Satz`/*sentence* in *Fig.* 8) without assuming a propositional structure, a n d to get these new composites'*meanings* represented as determined by their DDSs computable from the semantic space data;

▷ our experiments employing DDSs for *semantic inferencing* (SI) have turned out to be very promising. SI appears to be feasible without the need of having to state the premises in a predicative or propositional form prior to the concluding process. The DDS algorithm lends itself easily to the modeling of *analogical* reasoning processes by parallel processing of DDS trees.

As illustrated in *Fig.* 9, the semantic inference process will start from two (or more) root nodes as semantic *premises* (here the three: `Ausschu`/*committee*, `Genf`/*Geneva* and `Programm`/*program*), then it will run the two (or more) DDS processes concerned each of which—in selecting its daughter nodes—will tag the respective meaning points in the semantic space. Stop condition for this mutual processing—which proceeds (*least distance* or *highest criteriality*) breadth first through the respective DDSs—is defined by the first meaning point found to be tagged previously by one (or more) of the other processes active. This point (`nahe`/*near*) will be considered the (first) candidate inferred or concluded from the premises (with the option to extend the number of candidates under different stop conditions). The *dependencies* activated (bottom line of *Fig.* 9) are three paths: 1st *committee* → *July* → *Hamburg* → *April* → *Tuesday* → *near*, 2nd *Geneva* → *calm* → *power* → *soviet* → *ride* → *center* → *near*, and 3rd *program* → *Tuesday* → *near*) which translate to the premises' *inference paths* resulting in the concluded meaning (*near*) whose connotative embedding is provided by the subtrees shown according to its semantic relatedness mediated by the newspaper texts analyzed.

5 Conclusion

Devising representational structures which result from semiotic processing of natural language discourse as modeled by SCIP systems is to explore *syntagmatic* and *paradigmatic* constraints on different levels of item combinability in *pragmatically homogeneous* texts. Although tentative still, it is hoped to come up one day with a new understanding of how entities and structures are constituted that may indeed be called *semiotic*, i.e. do not only have an objective (material) extension in space-time, but can above that be understood as having interpretable meaning, too. In order to be able to interpret, (natural as well as artificial) semiotic cognitive information processing systems need structuredness. We are about to experience that the linguistically identified structures available so far do not serve the purposes too well when we have to deal with problems of a kind which we are unable to describe or represent, let alone analyze or even solve under these circumstances. Procedural models and their computational realizations might appear to be good candidates for some progress.

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