gefördert vom
Bundesministerium
für Forschung
und Technologie

Verbmobil
Verbundvorhaben

Knowledge-Based Disambiguation for Machine Translation

J. Joachim Quantz
Birte Schmitz

Technische Universität Berlin

Vm
Report 44
December 1994

December 1994

J. Joachim Quantz
Birte Schmitz

Technische Universität Berlin
Fachbereich Informatik (13)
Projektgruppe KIT-VM11
Sekr. FR 5-12
Franklinstraße 28/29
D-10587 Berlin

Tel.: (030) 314 - 27778
e-mail: kitvm11@cs.tu-berlin.de

Gehört zum Antragsabschnitt: 11.1 Interpretationshypothesen Deutsch

This report has also been published in *Mind and Machines* **4**, 39–57, 1994.
This work was funded by the German Federal Ministry for Research and Technology (BMFT) in the framework of the Verbmobil Project under Grant 01 IV 101 Q 8. The responsibility for the contents of this study lies with the authors.

Abstract

The resolution of ambiguities is one of the central problems for Machine Translation. In this paper we propose a knowledge-based approach to disambiguation which uses Description Logics (DL) as representation formalism. We present the process of anaphora resolution implemented in the Machine Translation system FAST and show how the DL system BACK is used to support disambiguation.

The disambiguation strategy uses factors representing syntactic, semantic, and conceptual constraints with different weights to choose the most adequate antecedent candidate. We show how these factors can be declaratively represented as defaults in BACK. Disambiguation is then achieved by determining the interpretation that yields a qualitatively minimal number of exceptions to the defaults, and can thus be formalized as exception minimization.

1 Introduction

Ambiguity is a notorious problem for Natural Language Processing (NLP). In general, an NL expression is called ambiguous if it has more than one formal representation or interpretation. Ambiguity is thus a relative notion, which depends on the representation formalism used to represent the interpretations of NL expressions. In the context of Machine Translation (MT) ambiguities in the source language (SL) have to be resolved if the interpretations of an expression yield varying expressions in the target language (TL).

Within the MT project KIT-FAST, which started in 1985, a particular problem of disambiguation, namely the interpretation of anaphoric relations, was investigated in detail. The FAST system includes three levels of representation (see Figure 1). The first level represents surface syntactic structures based on GPSG [Gazdar et al. 85]. The second level is called Functor-Argument Structure (FAS). It can best be described as an abstract syntax with additional semantic features and is used for the transfer process. The third level uses the knowledge representation system KIT-BACK and contains information on discourse referents and conceptual knowledge.

The disambiguation strategy chosen in the FAST project is to use syntactic, semantic, and conceptual information to determine the antecedent from a set of antecedent candidates. To do so, factors with different weights are used to encode the different constraints relevant for disambiguation. We have shown elsewhere

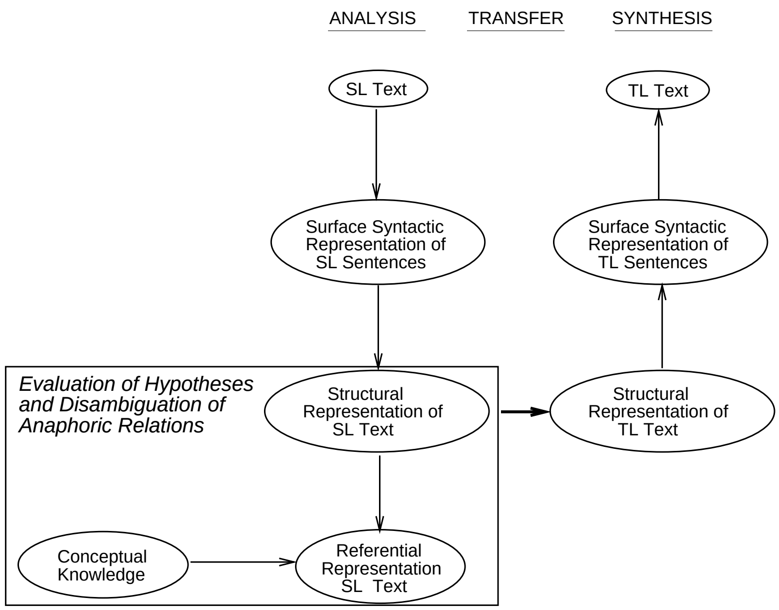

Figure 1: The architecture of the MT system KIT-FAST.

that this strategy is also appropriate for handling lexical and structural ambiguities [Schmitz, Quantz 93]. There are two main characteristics of our approach to disambiguation:

1. In general, the information needed for disambiguation is of rather heterogeneous nature and comprises, for example, syntactic, semantic, conceptual, and encyclopedic information.

2. In most cases, disambiguation has to rely on partial, i.e. uncertain information. Therefore the factors used to determine the preferred interpretation cannot be modeled as strict constraints but are rather preference rules in the sense of [Jackendoff 83] or defaults with different degree of relevance.

In Section 3 we show in detail, how anaphora resolution is obtained in the FAST system by evaluating a set of factors modeling different kinds of information. Since one of these factors takes into account information on discourse referents and conceptual knowledge represented in the BACK system, we use the next section to give a brief introduction into knowledge representation with BACK.

At the end of Section 3 we sketch how this knowledge-based approach to disambiguation can be extended by modeling also the syntactic and semantic factors in BACK. In doing so we take into account the above characteristics in a declarative and formally well-founded way and obtain interpretation by exception minimization (see [Quantz 93] for details).

2 Knowledge Representation with BACK

The knowldege representation system KIT-BACK has been developed in three ESPRIT projects, starting in 1985. It belongs to a family of systems which use a Description Logic (DL) as representation language.

DL can be seen as a formal elaboration of the ideas underlying *Semantic Networks*, e.g., [Quillian 68], and *Frames*, e.g., [Minsky 75]. Both representation languages share the idea of a hierarchically organized knowledge structure in which information is inherited from general concepts or frames to more specific ones. They also provide means for an internal structuring of concepts or frames which leads to horizontal connections: frames contain slots whose fillers are known to be instances of other frames; concepts contain properties that are modeled by links leading to other concepts.

In the second half of the 1970's representation languages from the area of semantic networks, frames, or scripts were seriously attacked in a number of papers for their apparent lack of formal rigor, for example in [Woods 75] and [Hayes 77]. The key issue was the relationship between knowledge representation and formal logic. Brachman endorsed the logic-oriented view on knowledge representation in his early papers on semantic networks. In [Brachman 79] he examined in detail, what the constructs used in semantic networks were supposed to represent. As a result he presented a collection of so-called *epistemological primitives*, which were supposed to be application-independent and became the basic language constructs of KL-ONE.

An overview over the basic features of the KL-ONE formalism circulated in the beginning of the 1980's and was finally published in [Brachman, Schmolze 85]. In the following years, several DL systems, such as BACK [Hoppe et al. 93], CLASSIC [Brachman et al. 91], or LOOM [MacGregor 91] were developed incorporating different dialects, which are nevertheless similar with respect to the underlying representation philosophy. In addition to these practice-oriented implementations, thorough theoretical investigations yielded numerous results concerning decidability, tractability, and proof theory (cf., for example, [Donini et al. 91] and [Royer, Quantz 92]). Unfortunately, there is some terminological confusion concerning the appropriate name for this paradigm of knowledge representation—besides description logics the names KL-ONE alike systems, hybrid representation systems, term subsumption systems, concept logics, and terminological logics can be found in the literature.

The basic difference between DL on the one hand and Semantic Networks or Frames on the other, concerns the attitude towards theoretical foundations and towards the question of what is constitutive for a representation *formalism*. According to DL philosophy, a representation formalism should have a formal syntax, a formal semantics, a proof theory, and efficient inference algorithms.

In DL one typically distinguishes between *terms* and *objects* as basic language entities from which two kinds of formulae can be formed: *subsumptions* and *descriptions*. There are two special kinds of subsumptions which are used in a DL modeling, namely *definitions* and *rules* (a sample modeling is given below). A definition has the form $\mathrm{t}_n := \mathrm{t}$ and expresses that the name t_n is used as an abbreviation for the term t. There is also the possibility of introducing primitive terms by giving only necessary but not sufficient conditions ($\mathrm{t}_n :< \mathrm{t}$). All DLs provide two types of terms, namely *concepts* (unary predicates) and *roles* (binary predicates), but they differ with respect to the term-forming operators they contain. Common term-forming operators are conjunction, disjunction, or negation, as well as composition and inversion for roles [Quantz 90], and quantified restrictions for concepts [Quantz 92b]. In a description, an object is described as being an instance of a concept (o :: c), or as being related to another object by a role (o_1 :: r:o_2). Rules have the form $\mathrm{c}_1 => \mathrm{c}_2$ and stipulate that each instance of the concept c_1 is also an instance of the concept c_2. Some DLs also support the modeling of defaults $\mathrm{c}_1 \leadsto \mathrm{c}_2$.

The following list contains the syntax of the DL constructs used in this paper. Note that we use the concrete syntax of BACK V5 [Hoppe et al. 93] rather than the abstract syntax used in theoretical papers. Note also that t_n stands for term-names, n for natural numbers, and γ for formulae.

$$\begin{array}{rcl}
\mathrm{t} & \rightarrow & \mathrm{c, r, t}_n \\
\mathrm{c} & \rightarrow & \textbf{anything}, \textbf{nothing}, \mathrm{c}_1 \ \&\ \mathrm{c}_2 \ , \textbf{not}(\mathrm{c}) \ , \mathrm{r{:}o} \ , \textbf{all}(\mathrm{r,c}) \ , \mathrm{r}_1 = \mathrm{r}_2 \\
 & & \textbf{atleast}(n,\mathrm{r}) \ , \textbf{atmost}(n,\mathrm{r}) \ , \textbf{the}(\mathrm{r,c}) \ , \textbf{some}(\mathrm{r,c}) \ , \textbf{exactly}(n,\mathrm{r}) \\
\mathrm{r} & \rightarrow & \textbf{domain}(\mathrm{c}) \ , \textbf{range}(\mathrm{c}) \ , \mathrm{r}_1 \ \&\ \mathrm{r}_2 \ , \textbf{inv}(\mathrm{r}) \ , \mathrm{r}_1.\mathrm{r}_2 \\
\gamma & \rightarrow & \mathrm{t}_n := \mathrm{t} \ , \mathrm{t}_1 :< \mathrm{t}_2 \ , \mathrm{c}_1 => \mathrm{c}_2 \ , \mathrm{o} :: \mathrm{c} \ , \mathrm{c}_1 \leadsto \mathrm{c}_2
\end{array}$$

For this language a modeltheoretic semantics can be given where a model $\mathcal{M}$ of a set of DL formulae Γ is a pair $\langle D, \mathcal{I} \rangle$. $\mathcal{I}$ maps concepts into subsets of D, roles into subsets of $D \times D$, and object-names injectively into D, in accordance with the following equations (we use $r(d)$ to denote $\{e : \langle d, e \rangle \in r\}$):

$$
\begin{aligned}
[\![\textbf{anything}]\!]^{\mathcal{I}} &= D \\
[\![\textbf{nothing}]\!]^{\mathcal{I}} &= \emptyset \\
[\![\mathrm{t}_1\&\mathrm{t}_2]\!]^{\mathcal{I}} &= [\![t_1]\!]^{\mathcal{I}} \cap [\![t_2]\!]^{\mathcal{I}} \\
[\![\textbf{not}(\mathrm{c})]\!]^{\mathcal{I}} &= D \setminus [\![c]\!]^{\mathcal{I}} \\
[\![\mathrm{r} : \mathrm{o}]\!]^{\mathcal{I}} &= \{d \in D : [\![o]\!]^{\mathcal{I}} \in [\![r]\!]^{\mathcal{I}}(d)\} \\
[\![\textbf{all}(\mathrm{r}, \mathrm{c})]\!]^{\mathcal{I}} &= \{d \in D : [\![r]\!]^{\mathcal{I}}(d) \subseteq [\![c]\!]^{\mathcal{I}}\} \\
[\![\mathrm{r}_1 = \mathrm{r}_2]\!]^{\mathcal{I}} &= \{d \in D : [\![r_1]\!]^{\mathcal{I}}(d) = [\![r_2]\!]^{\mathcal{I}}(d)\} \\
[\![\textbf{atleast}(n, \mathrm{r})]\!]^{\mathcal{I}} &= \{d \in D : |[\![r]\!]^{\mathcal{I}}(d)| \geq n\} \\
[\![\textbf{atmost}(n, \mathrm{r})]\!]^{\mathcal{I}} &= \{d \in D : |[\![r]\!]^{\mathcal{I}}(d)| \leq n\} \\
[\![\textbf{domain}(\mathrm{c})]\!]^{\mathcal{I}} &= [\![c]\!]^{\mathcal{I}} \times D \\
[\![\textbf{range}(\mathrm{c})]\!]^{\mathcal{I}} &= D \times [\![c]\!]^{\mathcal{I}} \\
[\![\textbf{inv}(\mathrm{r})]\!]^{\mathcal{I}} &= \{\langle d, e \rangle \in D \times D : \langle e, d \rangle \in [\![r]\!]^{\mathcal{I}}\} \\
[\![\mathrm{r}_1.\mathrm{r}_2]\!]^{\mathcal{I}} &= [\![r_1]\!]^{\mathcal{I}} \circ [\![r_2]\!]^{\mathcal{I}}
\end{aligned}
$$

Note that some DLs support special roles called *features*: roles are interpreted as general relations, whereas features are functional roles, i.e. each object can have at most one filler for a feature.

The concept-forming operators **exactly**, **the** and **some** can then be defined as macros:

$$
\begin{aligned}
\textbf{exactly}(n, \mathrm{r}) &\stackrel{\text{def}}{=} \textbf{atleast}(n,\mathrm{r})\&\textbf{atmost}(n,\mathrm{r}) \\
\textbf{the}(\mathrm{r}, \mathrm{c}) &\stackrel{\text{def}}{=} \textbf{exactly}(1,\mathrm{r})\&\textbf{all}(\mathrm{r},\mathrm{c}) \\
\textbf{some}(\mathrm{r}, \mathrm{c}) &\stackrel{\text{def}}{=} \textbf{atleast}(1, \mathrm{r}\ \&\ \textbf{range}(\mathrm{c}))
\end{aligned}
$$

Satisfaction of formulae is defined as follows (a semantics for defaults is given in [Quantz, Royer 92]):

$$
\begin{aligned}
\mathcal{M} \models \mathrm{t}_1 :< \mathrm{t}_2 \quad &\text{iff} \quad [\![t_1]\!]^{\mathcal{I}} \subseteq [\![t_2]\!]^{\mathcal{I}} \\
\mathcal{M} \models \mathrm{t}_n := \mathrm{t} \quad &\text{iff} \quad [\![t_n]\!]^{\mathcal{I}} = [\![t]\!]^{\mathcal{I}} \\
\mathcal{M} \models \mathrm{c}_1 => \mathrm{c}_2 \quad &\text{iff} \quad [\![c_1]\!]^{\mathcal{I}} \subseteq [\![c_2]\!]^{\mathcal{I}} \\
\mathcal{M} \models \mathrm{o} :: \mathrm{c} \quad &\text{iff} \quad [\![o]\!]^{\mathcal{I}} \in [\![c]\!]^{\mathcal{I}}
\end{aligned}
$$

A structure $\mathcal{M}$ is a model of a formula γ iff $\mathcal{M} \models \gamma$; it is a model of a set of formulae Γ iff it is a model of every formula in Γ. A formula γ is entailed by a set

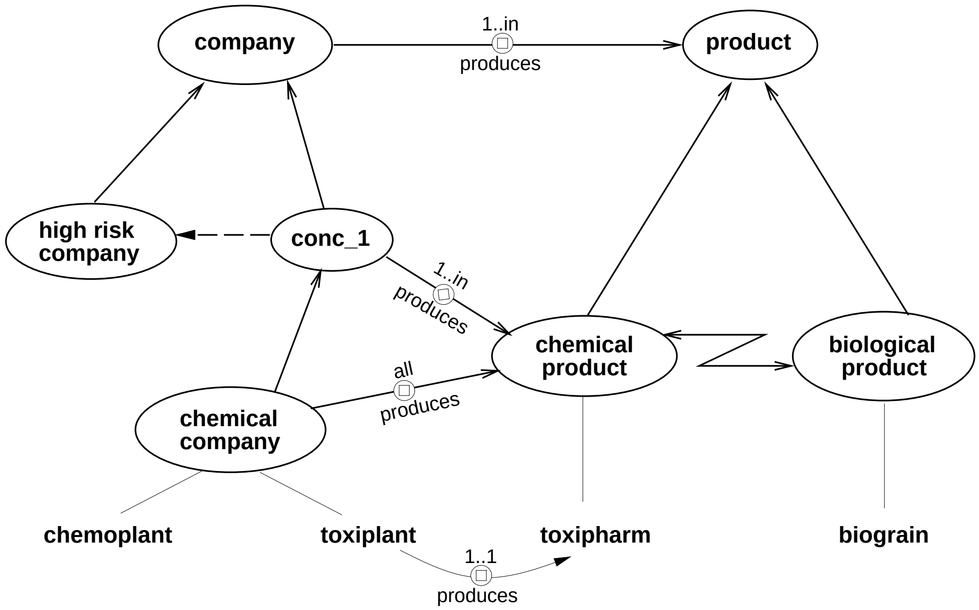

Figure 2: The network representation of the sample domain model. 'conc_1' abbreviates
the concept **some**(produces,chemical product). The plain arrows indicate subsumption, the dashed arrow stands for a rule, the jagged one denotes disjointness. Note that some of the arrows are only implicitly given by the modeling.

of formulae Γ (written $\Gamma \models \gamma$) iff every structure which is a model of Γ is also a model of γ.

To see the connection between this theoretical characterization of DL and practical applications of DL systems, let us briefly consider a sample *domain modeling*. A domain modeling contains information about a particular domain and comprises a terminology, a set of rules, and a set of descriptions. In the terminology the technical terms used in the domain are defined, the rules model additional constraints holding in the domain, and the descriptions contain information about individual objects. In the highly simplified domain modeling below, whose network representation is shown in Figure 2 one role and six concepts are defined, five of which are primitive (only necessary, but no sufficient conditions are given). Furthermore, the modeling contains one rule and four object descriptions.

product	:<	**anything**
chemical product	:<	product
biological product	:<	product & **not**(chemical product)
produces	:<	**range**(**anything**)
company	:<	**some**(produces,product)
high risk company	:<	company
chemical company	:=	company & **all**(produces,chemical product)
some(produces,chemical product)	=>	high risk company
toxipharm	::	chemical product
biograin	::	biological product
chemoplant	::	chemical company
toxiplant	::	**atmost**(1,produces) & produces:toxipharm

In DL, such a modeling is regarded as a set of formulae Γ. Given the formal semantics of a DL, such a set of formulae will entail other formulae, i.e., there is an entailment relation $\Gamma \models \gamma$. Now the service provided by DL systems is basically to answer queries as to whether some formula γ is entailed by a modeling Γ. The following types of queries can be answered by a DL system like BACK:

- $\Gamma \models \mathrm{t}_1 :< \mathrm{t}_2$
  Is a term t_1 more specific than a term t_2, i.e., is t_1 *subsumed* by t_2? In the sample modeling, the concept 'chemical company' is subsumed by 'high risk company', i.e., every chemical company is a high risk company.

- $\Gamma \models \mathrm{t}_1$ & t_2 :< **nothing**
  Are two terms t_1 and t_2 incompatible or disjoint? In the sample modeling, the concepts 'chemical product' and 'biological product' are disjoint, i.e., no object can be both a chemical and a biological product.

- $\Gamma \models \mathrm{o} :: \mathrm{c}$
  Is an object o an instance of concept c (object classification)? In the sample modeling, 'toxiplant' is recognized as a 'chemical company'.

- $\Gamma \models \mathrm{o}_1 :: \mathrm{r}{:}\mathrm{o}_2$
  Are two objects o_1,o_2 related by a role r, i.e., is o_2 a role-filler for r at o_1? In the sample modeling, 'toxipharm' is a role-filler for the role 'produces' at 'toxiplant'.

- $\Gamma \models X :: c$
  Which objects are instances of a concept c (retrieval)? In the sample modeling, 'chemoplant' and 'toxiplant' are retrieved as instances of the concept 'high risk company'.

- $\Gamma \cup \{o :: c\} \models \perp$
  Is a description o :: c inconsistent with the modeling (consistency check)? With respect to the sample modeling, 'biograin' cannot be produced by 'chemoplant', i.e. the description 'chemoplant :: produces:biograin' is rejected as inconsistent by the system.

In the following section we show how a domain modeling containing information about semantic roles and selectional restrictions is used in the FAST project. We also indicate how BACK can be used to model syntactic information. In principle, it is possible to model arbitrary information such as syntactic, semantic, conceptual, or encyclopedic information with DL.

3 Disambiguation in MT

In this section we present some of the results obtained in the MT project FAST. In its last phase (1990-1992) the project took initial steps towards dealing with inter-sentential phenomena by addressing the problem of how to interprete anaphoric relations in texts. The scope of investigation was confined to *anaphoric* pronouns – defined as relating to an element in the text – in contrast to *deictic* pronouns whose referents are determined by the situational context. It was further confined to personal and possessive pronouns referring to objects, neglecting pronouns referring to events. An anaphor can relate to its antecedent in different ways like part-whole, identity of sense, or identity of reference [Quantz 92a]. In the work described here only referential identity was taken into account, i.e. only identity anaphora were treated.

The interpretation of anaphoric personal and possessive pronouns is obviously relevant for machine translation.

(1) a. Fortgeschrittene Systeme erkennen die Information in der Form, in der <u>sie</u>$_1$ generiert wird. <u>Sie</u>$_2$ integrieren <u>sie</u>$_3$ in das gespeicherte Wissen.

b. Advanced systems perceive information in the form in which <u>it</u> is generated. <u>They</u> integrate <u>it</u> into the stored knowledge.

The German personal pronoun ‘sie’ is ambiguous between feminine singular and feminine, masculine, or neuter plural. The translation of the pronoun depends on the translation of the antecedent with respect to number and gender. The antecedent of ‘sie’$_1$ in example (1) is ‘Information’, the adequate translation is ‘it’, since the English ‘information’ is neuter singular. The antecedent of ‘sie$_2$’ is ‘Systeme’, in English ‘systems’, which is plural, thus the translation of ‘sie$_2$’ should be ‘they’. ‘sie$_3$’ is coreferential with ‘sie$_1$’. (A detailed description of the disambiguation process is given below.)

The disambiguation of ‘sie$_3$’ demonstrates that both structural information and information concerning the contents of the utterance play a role in solving the ambiguity. The antecedent candidates for ‘sie$_3$’ are ‘Systeme’, ‘Information’, ‘Form’, ‘sie$_1$’, the relative pronoun ‘der’, ‘sie$_2$’ and ‘Wissen’. On account of the binding principle ‘sie$_2$’ is excluded as the antecedent of ‘sie$_3$’. For a detailed description of our formulation of the binding principle cf. [Preuß et al. 92]. In this case it suffices to know that our version of the binding principle works on information expressed in terms of the Functor-Argument-Structure (FAS, see below). It states that all neighboring arguments in an FAS tree are excluded as antecedents. Since ‘sie$_2$’ and ‘sie$_3$’ are neighboring arguments, ‘sie$_2$’ is excluded. This is clearly structural information. Due to referential information we can eliminate ‘Systeme’ from the list of candidates; since ‘sie$_2$’ and ‘Systeme’ are coreferential, ‘Systeme’ is also out of the question as an antecedent for ‘sie$_3$’.

We therefore define both *anaphor* and *antecedent* as complex items consisting of the discourse referent they relate to and the structural position they occur in.

It seems crucial to us that on the one hand structural information and on the other hand information concerning the contents of the text contributes to the interpretation of anaphoric pronouns. This is reflected in the architecture of the FAST system. The structural aspects of the text and its referential aspects are represented seperately. In our view anaphoric relations suggest two perspectives on the information conveyed by a text: on the one hand, there is information in its sequential structure, on the other, there are predications about the referents. Therefore, in the FAST system there exist both a structural and a referential text representation.

The *structural text representation* contains information about:

- functor-argument relations (of e.g. nouns, verbs and adjectives),
- semantic roles of arguments like ‘agent’, ‘affected’, ‘attribuand’, ‘associated’, ‘location’, ‘aim’ [Steiner et al. 88],

- the thematic structure of a sentence in the spirit of the Prague School [Sgall et al. 73],
- semantic features that express local or temporal conceptualization as known from cognitive grammar [Zelinsky-Wibbelt 88],
- and anaphoric relations represented by coindexation.

This information is represented by the Functor-Argument-Structure (FAS). It can be regarded as an abstract syntax with additional semantic features that represents the functional structure of sentences. It abstracts from redundant information that is needed in the surface syntax in order to formulate well-formedness conditions like e.g. agreement features within verbal or nominal phrases. For details of the FAS cf. [Hauenschild, Umbach 88] and [Busemann, Hauenschild 89]. Figure 3 shows a sample FAS representation (only the features that are relevant for anaphora resolution are represented in the figure).

In the current version of the model the structural text representation consists of a list of FAS structures of sentences. Information about textual coherence is conveyed by coindexation of coreferential phrases. A next step could be to integrate more information about the structure of the text by not only collecting several subsequent sentences into a larger information unit, but also representing the relations holding between these units (cf. [Grosz, Sidner 86]).

The *referential text representation* contains parts of the contents of the text, at present the discourse referents and the semantic relations holding between them. Coreferential expressions are represented by a single discourse referent. The descriptions are made on the basis of partial information about the semantic contents of the lexemes. This information is modeled in terms of DL concepts. Up to now it comprises the semantic type of a lexeme, its semantic roles, and information about the semantic types of its role-fillers (selectional restrictions). A sample representation of the DL concepts modeled in BACK is given below. Figure 4 shows the descriptions for the sentence represented in Figure 3.

As mentioned above, our twofold text representation enables us to distinguish two aspects of anaphoric expressions (for a similar proposal see [LuperFoy, Rich 90]):

1. their position in the linguistic structure and what other linguistic expression they relate to. The structural aspect of the anaphoric relation is expressed via coindexation in the structural text representation.

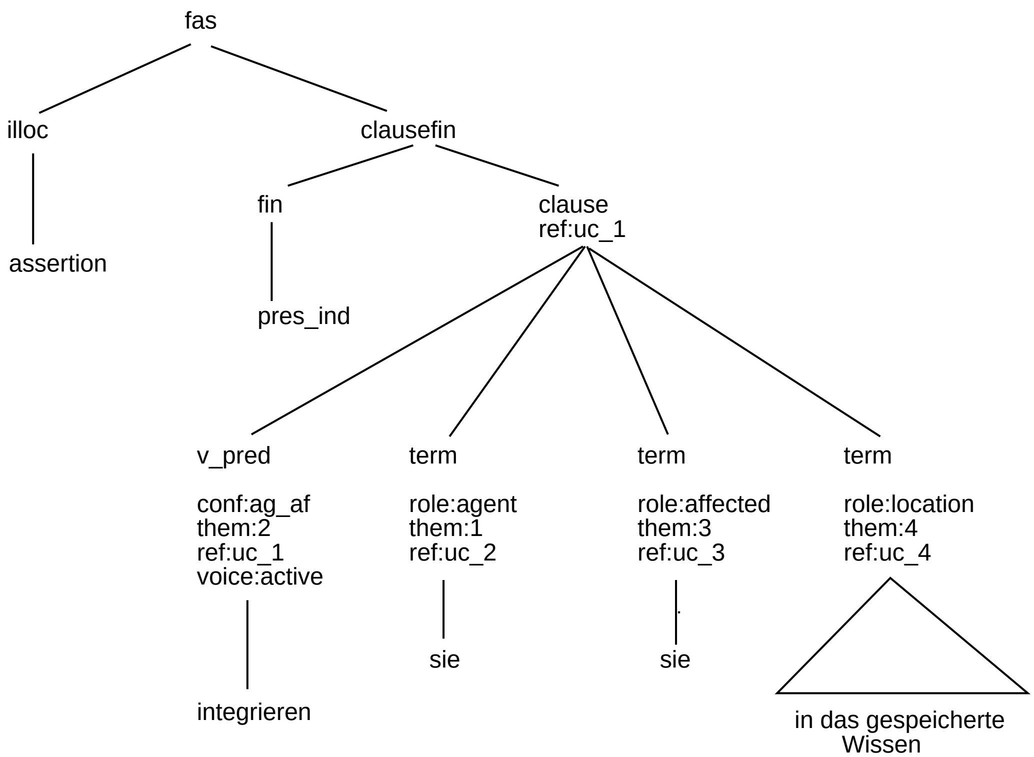

Figure 3: Structural (FAS) representation for 'Sie integrieren sie in das gespeicherte Wissen.' (English: 'They integrate it into the stored knowledge.') 'fas' is the root node of a FAS structure; 'illoc' (illocution) expresses whether the sentence is an assertion, an order, or a question; 'clausefin' represents a finite clause; 'fin' contains information about tense and mood; 'v_pred' represents a verbal functor (the leftmost daughter always denotes the functor); the feature 'them' represents the thematic structure of a sentence; the feature 'ref' expresses the link to objects in the referential text representation (see Figure 4).

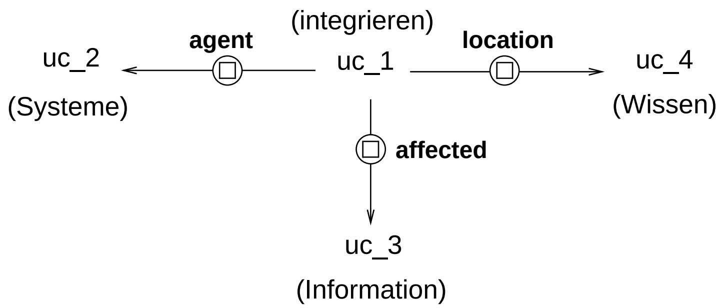

Figure 4: Simplified referential representation for ‘Sie integrieren sie in das gespeicherte Wissen.’ The objects uc_2 and uc_3 were introduced by the preceding sentence ‘Fortgeschrittene Systeme erkennen die Information in der Form, in der sie generiert wird.’ The arrows denote roles, e.g. ‘Systeme’ is the agent of ‘integrieren’.

2. the kind of relation between discourse referents that is introduced by the anaphoric expression (like identity of sense, identity of reference, part-whole-relation, cf. [Quantz 92a]). This aspect is expressed in the referential representation of the text.

Factors for anaphora resolution

Most linguistic approaches to the interpretation of anaphoric expressions, like Chomsky's binding principles or Reinhart's c-command [Reinhart 83], propose a treatment on the basis of purely syntactic information. The problem is that these approaches cannot explain all cases of anaphoric binding. To cope with the problematic cases, the description of the binding mechanism was recently more and more elaborated, taking into account “discourse based” information like point of view [Pollard, Sag 93] or the notion of internal perspective [Engdahl 91].

Besides the linguistic approaches to anaphora there are AI approaches which are based upon semantic information, background knowledge [Hobbs 78] and the notion of focus [Bosch 88].

In 1983 Hauenschild and Pause bridged the gap between the linguistic and AI approaches by proposing a framework for anaphora resolution based on syntactic, semantic and conceptual information (cf. [Hauenschild, Pause 83]). The FAST approach to anaphora resolution started from this framework. We formalized and integrated the following factors into a disambiguation system:

Agreement: An antecedent candidate that does not agree with the anaphor with respect to person, number and gender is regarded as very poor.

Binding: A candidate that does not fulfill the binding principle as described in [Preuß et al. 92] is regarded as very poor.

Proximity: Structurally close antecedent candidates are preferred.

Subject preference: The subject is preferred.

Topic preference: The topic is preferred.

Negative preference for free adjuncts: Free adjuncts are regarded as very poor.

Identity of roles: Candidates that fill the same semantic role as the anaphor are preferred.

Conceptual consistency: The antecedent has to be compatible with the selectional restrictions that derive from the predications on the anaphor.

These factors are implemented as preference rules with different weights that express the influence each factor has in the process of anaphora resolution. Based on these factors we implemented a scoring device that determines the intended antecedent by adding up the different positive or negative scores of the factors for each candidate. We demonstrate with example (1) how anaphora resolution works.

(1) a. Fortgeschrittene Systeme erkennen die Information in der Form, in der $\underline{\text{sie}}_1$ generiert wird. $\underline{\text{Sie}}_2$ integrieren $\underline{\text{sie}}_3$ in das gespeicherte Wissen.

b. Advanced systems perceive information in the form in which $\underline{\text{it}}$ is generated. $\underline{\text{They}}$ integrate $\underline{\text{it}}$ into the stored knowledge.

The tables in Figures 5 to 7 show how each antecedent candidate is scored by each factor. The different scores of the factors are the result of empirical investigations. Some of the factors, i.e. agreement, binding and discourse, give such a high negative score that they might be compared to strict constraints. The main difference is that in situations where all candidates gain high negative scores on account of one of these factors, there still might be one candidate which reached a better score

factors	*antecedent candidates*			
	system	information	form	relpron
agreement	-1000	0	0	0
binding	0	0	0	0
proximity	80	80	0	0
subject	60	0	0	0
topic	20	0	0	0
role identity	0	80	0	0
free adjunct	0	0	-70	-70
discourse	0	0	0	0
sum	-840	160	-70	-70

Figure 5: Disambiguation of ‘sie_1’.

compared to the other candidates. In Figure 5 ‘information’ is the best antecedent since it does not gain a high negative score due to one of the constraint-like factors, and furthermore it gains positive scores on account of the proximity factor and the role identity factor (both the personal pronoun and the antecedent fill the affected role).

In the disambiguation process of ‘sie_2’ (Figure 6) most factors are in favor of ‘system’ as antecedent. In this example the discourse factor gives a high negative score to all candidates except ‘system’. The discourse factor implies a test on conceptual consistency. Although even inconsistent propositions can lead to a more or less coherent text, we start from the working hypothesis that the texts we want to translate are consistent, i.e. we suppose our texts not to contain any contradictions. This can be exploited in the process of anaphora resolution, since the predications on the anaphor should be compatible with the predications made on the intended antecent. To test this consistency, a sophisticated representation of the semantics of both lexemes and whole phrases enriched by rules concerning encyclopedic facts would be necessary.

As a starting point we decided to model selectional restrictions by using the term language of the BACK system. The personal pronoun ‘sie_2’ fills the agent role of the verb ‘integrieren’.The semantics of ‘integrieren’ states that the agent role has to be filled by a *potential-agent-object*. The anaphora resolution process has to look up which of the candidates do not meet this condition. Thus all candidates except ‘system’ are ruled out.

factors	*antecedent candidates*						
	system	information	form	sie_1	relpron	sie_3	wissen
agreement	0	-1000	-1000	-1000	-1000	0	-1000
binding	0	0	0	0	0	-1000	0
proximity	40	40	40	20	20	0	0
subject	60	0	0	60	0	0	0
topic	20	0	0	0	0	0	0
role identity	80	0	0	0	0	0	0
free adjunct	0	0	-70	0	-70	0	-70
discourse	0	-1000	-1000	-1000	-1000	-1000	-1000
sum	200	-1960	-2030	-1920	-2050	-2000	-2070

Figure 6: Disambiguation of 'sie_2'.

The information needed to perform tasks like these is represented by means of the BACK system. In this case the disambiguation relies on the following information:

event	:<	**anything**
agent-affected-event	:<	event & **exactly**(1,affected) & **the**(agent,potential-agent-object)
integrieren	:<	agent-affected-event
systeme	:<	potential-agent-object

The value restriction '**the**(agent,potential-agent-object)' expresses that the filler of the 'agent' role has to be a 'potential-agent-object'.

Though the anaphora resolution implemented in the FAST system performs quite successfully, there is one major shortcoming: the factors used in the resolution process are not represented declaratively, but are rather contained in the scoring device. This is in contrast to the general philosophy of using declarative formalisms such as GPSG, FAS, and BACK to represent the information of the different levels. In the remainder of this section we will show a declarative reformulation of the above factors in terms of DL. We think that such a declarative representation is highly desirable. See [Kay et al. 91] for some of the benefits of declarativity.

factors	*antecedent candidates*						
	system	information	form	sie_1	relpron	sie_2	wissen
agreement	0	0	0	0	0	0	-1000
binding	-1000	0	0	0	0	-1000	0
proximity	40	40	40	20	20	0	0
subject	60	0	0	60	0	60	0
topic	20	0	0	0	0	20	0
role identity	0	80	0	80	0	0	0
free adjunct	0	0	-70	0	-70	0	-70
discourse	0	0	0	0	0	0	0
sum	-880	120	- 30	160	-50	-920	-1070

Figure 7: Disambiguation of ‘sie_3’.

DL Based Disambiguation

The factors used for anaphora resolution can be modeled declaratively as follows (to keep the presentation simple we omit the factors for binding and proximity):

$$\begin{aligned}
\delta_1 : \text{anaphor} &\rightsquigarrow \text{num} = \text{ant.num\&gen} = \text{ant.gen} \\
\delta_2 : \text{anaphor} &\rightsquigarrow \textbf{the}(\text{ant}, \text{subject}) \\
\delta_3 : \text{anaphor} &\rightsquigarrow \textbf{the}(\text{ant}, \text{topic}) \\
\delta_4 : \text{anaphor} &\rightsquigarrow \text{sem-role} = \text{ant.sem-role} \\
\delta_5 : \text{anaphor} &\rightsquigarrow \textbf{the}(\text{ant}, \text{non-adjunct})
\end{aligned}$$

Let us briefly explain this modeling. We assume a concept ‘anaphor’, which is used to describe anaphoric phrases. Note that we do only consider pronominal identity anaphora here. In order to handle other types of anaphora, such as substitution anaphora, contiguity anaphora, or bound anaphora [Quantz 92a], a finer grained modeling is necessary.

We further assume that anaphoric phrases have a feature ‘ant’, whose filler is the antecedent phrase. The default δ_1 thus models agreement: usually an anaphor agrees with its antecedent wrt number and gender. The defaults δ_2 and δ_3 capture the fact that subjects and topics are preferred antecedent candidates of an anaphor. Similarly, δ_5 expresses a negative preference for adjuncts, which is modeled here as a preference for non-adjuncts. Finally, δ_4 says that usually anaphor and antecedent fill the same semantic role.

To illustrate how such a DL modeling can be used for anaphora resolution, we will briefly address two further issues. First, we show how the concepts and roles used in the above modeling (e.g. 'subject' or 'sem-role') are modeled themselves. Then we explain how disambiguation can be achieved by minimizing exceptions to defaults.

The concepts and roles used in the above modeling describe linguistic signs, i.e. phrases or words, their syntactic properties, and the relations between them. In other words, the domain we are modeling is the domain of linguistic signs and the terminology we have to represent is the linguistic terminology. In the following we will use the basic terminology from *Head-Driven Phrase Structure Grammar* (HPSG) [Pollard, Sag 87], since this formalism is declarative to a large degree and relies on a typed feature logic which is very similar to the general format of DL [Carpenter 92].

According to HPSG a phrase is a linguistic sign which is composed of other linguistic signs, i.e. its constituents. Since the constituent structure is usually represented in a phrase structure tree, in which the constituents are the daughters of the overall phrase, the role used to describe the constituent relation is called 'dtrs'. In HPSG one distinguishes different kinds of daughters, such as head-daughters, complement-daughters and adjunct-daughters. The most important way of constructing a phrase consists in the combination of a head-daughter with its arguments or complements. For example, each verb has a specific valency, i.e., it takes a certain number of complements, which have to be of a certain type. Consider a simplified lexical entry for the German verb 'integrieren':

integrieren	:<	v & **the**(arg1,np & cas:nom) &
		the(arg2,np & cas:acc) &
		the(agent,potential-agent) &
		agent = arg1 & affected = arg2

This lexical entry stipulates that the phrase being the first argument of 'integrieren' must be an NP with nominative case, whereas the second argument is an NP with accusative case. Furthermore, the phrase filling the 'agent' role must be a potential agent. Finally, the syntactic arguments are mapped to the semantic roles: the first argument is the agent, the second argument the affected.

In Figure 8 we have shown the DL representation of a phrase structure tree for the sentence 'sie integrieren sie' ('they integrate it'). We have four signs, one being the overall sentence 'uc_4', the other three being the words occurring in the sentence. The arrows between these signs are the roles existing between them—the dashed arrows signify that these roles can be computed by the system.

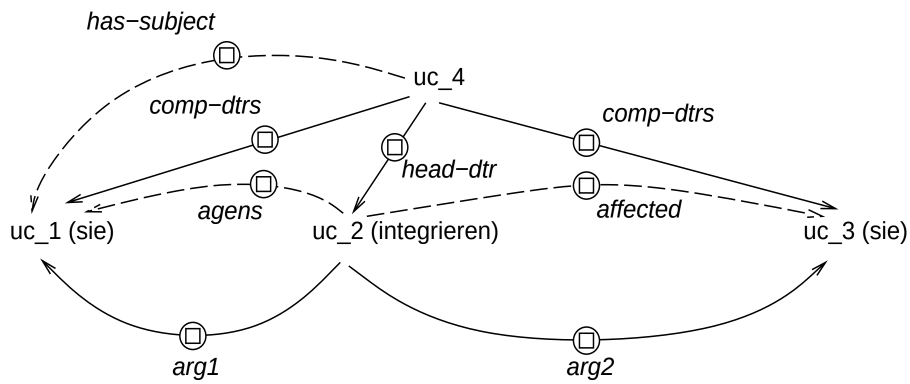

Figure 8: DL representation of ‘sie integieren sie’.

To see how the filler for the role ‘has-subject’ can be computed consider the following modeling:

has-subject	:=	**domain**(s) & head-dtr.arg1
has-topic	:=	dtrs & **domain**(s) & **range**(top:+)
subject	:=	**atleast**(1,**inv**(has-subject))
topic	:=	**atleast**(1,**inv**(has-topic))
non-adjunct	:=	**atmost**(0,**inv**(adjunct-dtr))
atleast(1,**inv**(agent))	=>	sem-role:ag
atleast(1,**inv**(affected))	=>	sem-role:af

The role ‘has-subject’ is defined as relating a sign which is a sentence with the filler at the role ‘arg1’ at its head daughter. The role ‘has-topic’ is defined as relating a sign which is a sentence with those of its daughters that have the value ‘+’ for the feature ‘top’.

Given these roles we say that a sign is a subject iff it occurs at some other sign as the filler for the role ‘has-subject’ (an analogous definition is given for ‘topic’). Non-Adjuncts are those signs which do not occur as fillers of the role ‘adjunct-dtr’. Finally, if a sign occurs as an agent (affected) at some other sign, its value for the feature ‘sem-role’ is ‘ag’ (‘af’).

For the signs ‘uc_1’ and ‘uc_3’ in Figure 8 we therefore obtain the following descriptions:

uc_1	::	subject & topic & non-adjunct & sem-role:ag
uc_3	::	non-adjunct & sem-role:af

Part of this information follows immediately from the above modeling and the information about the phrase structure shown in Figure 8. To compute that 'uc_1' is a 'topic' and that 'uc_1' and 'uc_3' are 'non-adjuncts' some additional constraints not shown in the modeling are taken into account. We are currently implementing a DL-based parser for an HPSG fragment of German, which uses the modeling sketched above.

Note finally that the information about 'uc_1' and 'uc_3' can immediately be used to evaluate the defaults representing the factors needed for anaphora resolution. As can be seen from our sample sentences, in most cases each antecedent candidates violates some of the defaults, and the preferred antecedent can be determined by comparing the sets of violated defaults. The basic idea is to choose the intepretation which yields a qualitatively minimal number of exceptions (see [Quantz 93] for details).

4 Conclusion

We have presented the basic ideas of Description Logics (DL) and shown how the DL system BACK is used in the process of anaphora resolution in the Machine Translation system FAST. So far this disambiguation process uses factors which are not explicitly represented but rather are contained in the procedures of the scoring device. To obtain a declarative representation of these factors, we proposed to view them as preference rules and to model them as defaults in BACK. In doing so we represented syntactic, semantic, and encyclopedic knowledge as DL formulae.

We regard the logical framework presented here as a formal foundation for developing NL systems. The major benefit of a homogeneous treatment of different levels of information in a single representation formalism is that interdependencies between the levels can be modeled in a straightforward manner. We regard this as a necessary prerequisite for studying the interplay of the factors guiding disambiguation, which is so far only poorly understood. Once we know more about the contextual factors guiding disambiguation and their interplay, we might decide to replace the uniform representation system by several components which efficiently perform the inferences most needed on each level.

Acknowledgements

This paper contains many results obtained in the KIT projects BACK and FAST and we would therefore like to thank all member of these projects. Furthermore, we thank Bob Carpenter, Christa Hauenschild, Bob Kasper, Susanne Preuß, and Carla Umbach for discussing our ideas and/or providing valuable information.

References

[Bosch 88] P. Bosch, “Representing and Accessing Focussed Referents”, in *Language and Cognitive Processes*, **3**, 3, 207–231, 1988

[Brachman 79] R.J. Brachman, “On the Epistemological Status of Semantic Networks”, in N.V. Findler (Ed.), *Associative Networks: Representation and Use of Knowledge by Computers*, New York: Academic Press, 3–50

[Brachman, Schmolze 85] R.J. Brachman, J.G. Schmolze, “An Overview of the KL-ONE Knowledge Representation System” *Cognitive Science* **9**, 171–216, 1985

[Brachman et al. 91] R. Brachman, D.L. McGuiness, P.F. Patel-Schneider, L. Alperin Resnick, A. Borgida, “Living with CLASSIC”, in J. Sowa (Ed.), *Principles of Semantic Networks: Explorations in the Representation of Knowledge*, 401–456

[Busemann, Hauenschild 89] S. Busemann, C. Hauenschild, “From FAS Representation to GPSG Structures”, in: S.Busemann, C.Hauenschild, C.Umbach (eds), *Views of the Syntax/Semantics Interface*, KIT-Report 74, Technische Universität Berlin

[Carpenter 92] B. Carpenter, *The Logic of Typed Feature Structures*, Cambridge: Cambridge University Press, 1992

[Donini et al. 91] F.M. Donini, M. Lenzerini, D. Nardi, W. Nutt, “The Complexity of Concept Languages”, *KR’91*, 151–162

[Engdahl 91] E. Engdahl, “Argument Roles and Anaphora” in R.H. Cooper, K. Mukai, J. Perry (eds), *Situation Theory and its Applications I*, Stanford: CSLI Lecture Notes 22, 379–393

[Gazdar et al. 85] G. Gazdar, E. Klein, G. Pullum, I. Sag, *Generalized Phrase Structure Grammar* , Oxford: Basil Blackwell, 1985

[Grosz, Sidner 86] B. Grosz, C. Sidner, “Attention, Intentions, And the Structure of Discourse” in *Computaional Linguistics*, **12**, 3, 175–204,

[Hauenschild, Pause 83] C. Hauenschild, P.E. Pause “Faktoren-Analyse zur Modellierung des Textverstehens” in *Linguistische Berichte* 88, 101–121, 1983

[Hauenschild, Umbach 88] C. Hauenschild, C. Umbach, “Funktor-Argument-Struktur. Die satzsemantische Repräsentations- und Transferebene im Projekt KIT-FAST”, in J.Schütz (ed), *Workshop Semantik und Transfer*, EUROTRA-D

Working Papers 6, Saarbrücken, 16–35, 1988

[Hayes 77] P.J. Hayes, "In Defense of Logic", *IJCAI'77*, 559–565

[Hobbs 78] J.H. Hobbs "Resolving Pronoun References", in *Lingua*, **44**, 311–338, 1978

[Hoppe et al. 93] T. Hoppe, C. Kindermann, J.J. Quantz, A. Schmiedel, M. Fischer, BACK V5 *Tutorial & Manual*, KIT Report 100, Technische Universität Berlin, 1993

[Jackendoff 83] R. Jackendoff, *Semantics and Cognition* MIT Press, Cambridge, 1983

[Kay et al. 91] M. Kay, J.M. Gawron, P. Norvig, 'Verbmobil: A Translation System for Face-to-Face Dialog'

[LuperFoy, Rich 90] S. LuperFoy, E. Rich, *A Computational Model for the Resolution of Context Dependent References* in: MCC Technical Report, Austin, 1990

[MacGregor 91] R. MacGregor, "Using a Description Classifier to Enhance Deductive Inference", in *Proceedings Seventh IEEE Conference on AI Applications*, Miami, Florida, February, 1991, 141–147

[Minsky 75] M. Minsky, "A Framework for Representing Knowledge", in P.H. Winston (Ed.), *The Psychology of Computer Vision*, New York: McGraw-Hill, 211–277

[Pollard, Sag 87] C. Pollard, I.A. Sag, *An Information Based Syntax and Semantics*, Vol. I Fundamentals, Stanford: CSLI Lecture Notes 13, 1987

[Pollard, Sag 93] C. Pollard, I.A. Sag, *Head-Driven Phrase Structure Grammar* University of Chicago Press, 1993

[Preuß et al. 92] S. Preuß, B. Schmitz, C. Hauenschild, C. Umbach, *Anaphora Resolution in Machine Translation*, KIT Report 104, Technische Universität Berlin, 1992

[Quantz 90] J.J. Quantz, *Modeling and Reasoning with Defined Roles* KIT Report 84, Technische Universität Berlin, 1990

[Quantz 92a] J.J. Quantz, *Semantische Repräsentation anaphorischer Bezüge in terminologischen Logiken*, KIT Report 96, Technische Universität Berlin, 1992

[Quantz 92b] J.J. Quantz, "How to Fit Generalized Quantifiers into Terminological Logics", *ECAI-92*, 543–547

[Quantz 93] J.J. Quantz, *Interpretation as Exception Minimization*, to appear in *IJCAI'93*

[Quantz, Royer 92] J.J. Quantz, V. Royer, "A Preference Semantics for Defaults in Terminological Logics", in B. Nebel, C. Rich, W. Swartout (eds), *Princi-*

ples of Knowledge Representation and Reasoning: Proceedings of the Third International Conference (KR'92), San Mateo: Morgan Kaufmann, 294–305

[Quillian 68] M.R. Quillian, "Semantic Memory", in M. Minsky (Ed.), *Semantic Information Processing*, Cambridge (Mass): MIT Press, 216–270

[Reinhart 83] T. Reinhart, "Coreference and Bound Anaphora: A Restatement of The Anaphora Questions", *Linguistics and Philosophy* **6**, 47–88

[Royer, Quantz 92] V. Royer, J.J. Quantz, "Deriving Inference Rules for Terminological Logics", in D. Pearce, G. Wagner (eds), *Logics in AI, Proceedings of JELIA'92*, Berlin: Springer, 84–105

[Schmitz, Quantz 93] B. Schmitz, J.J. Quantz, "Defaults in Machine Translation", KIT Report 106, Technische Universität Berlin, 1993

[Sgall et al. 73] P. Sgall, E. Hajičová, E. Benešová, *Topic, Focus and Generative Semantics*, Kronberg: Scriptor, 1973

[Steiner et al. 88] Erich Steiner, Paul Schmidt und Cornelia Zelinsky-Wibbelt, *From Syntax to Semantics: Insights from Machine Translation*, London: Pinter, 1988

[Woods 75] W.A. Woods, "What's in A Link: Foundations for Semantic Networks" in D.G. Bobrow, A.M. Collins (eds), *Representation and Understanding: Studies in Cognitive Science*, New York: Academic Press, 35–82

[Zelinsky-Wibbelt 88] C. Zelinsky-Wibbelt, "From Cognitive Grammar to the Generation of Semantic Interpretation in Machine Translation" in [Steiner et al. 88], 105–132