A Summary of Traditional Approaches to Natural Language Processing

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Chapter 1

Introduction

> *HAL:* Hey, Dave, what are you doing?
> Bowman works swiftly.
> *HAL:* Hey, Dave. I've got ten years of service experience and an irreplaceable amount of time and effort has gone into making me what I am.
>
> Stanley Kubrick and Arthur C. Clarke
> 2001: A Space Odyssey

This chapter aims to give a rough introduction to the field of computational linguistics. Is it really possible to create an artificial agent, capable of such advanced language-capabilities as speaking English? What would it take to build a computer like HAL? These are the questions we will be addressing in the subsequent sections.

1.1 Overview

Let's first consider an example. Suppose we confront HAL with the following sentence:

(1.1) Joe taught Steve to play the guitar.

First of all it is important to understand the different representations the information from example 1.1 goes through, beginning with a sound-wave and ending in a semantic representation of the concepts behind the utterance.

Sound is what figure 1.1 shows. It is an oscillogram[1] of the utterance from example 1.1. It is a graphical representation of the input a sound-device gets when recording voice with a microphone.

[1] In our case: graph of pressure fluctuation versus time.

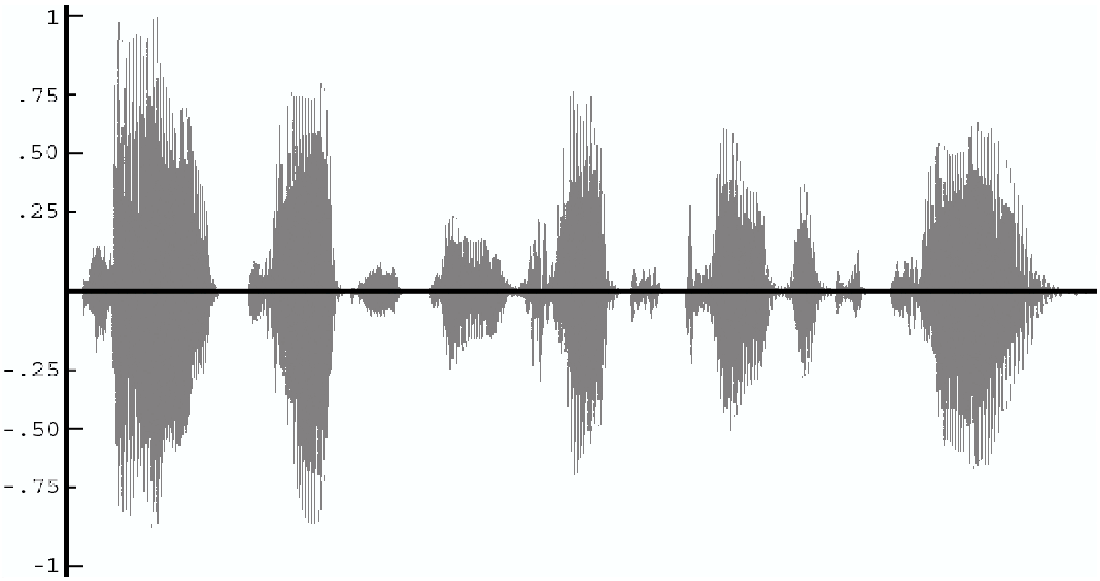


Figure 1.1: An oscillogram of the utterance *Joe taught steve to play the guitar*

Speech recognition is what HAL would have to be doing to convert this representation of a sound-wave into a "written" representation, or, putting it more accurately, a string of morphemes, which could be called the "nuclear" unit of speech and language, that can be matched against a dictionary in order to obtain a written representation. Today powerful speech-recognition-systems, which perform exactly that task, are available commercially at a broad range, handling many different languages, specialized vocabularies and difficult recording-situations. This is why we will not deal with speech-related issues in this paper, but rather start with a string-representation of written language.

An ASCII-coded string is therefore the first representation our system would be confronted with.

Morphological analysis is what the next step is sometimes referred to. Now that a string of words making up a sentence is available, each word being a string of characters, we can go about analyzing the words. In this step the system would have to find out that "taught" is a past-tense form of the verb "teach", etc.

An intermediate representation could be used to pass data from the morphological analysis to the syntactic one. Usually this isn't neccessary because, in practice, morphological and syntactic analysis are often handled in a highly integrated way.

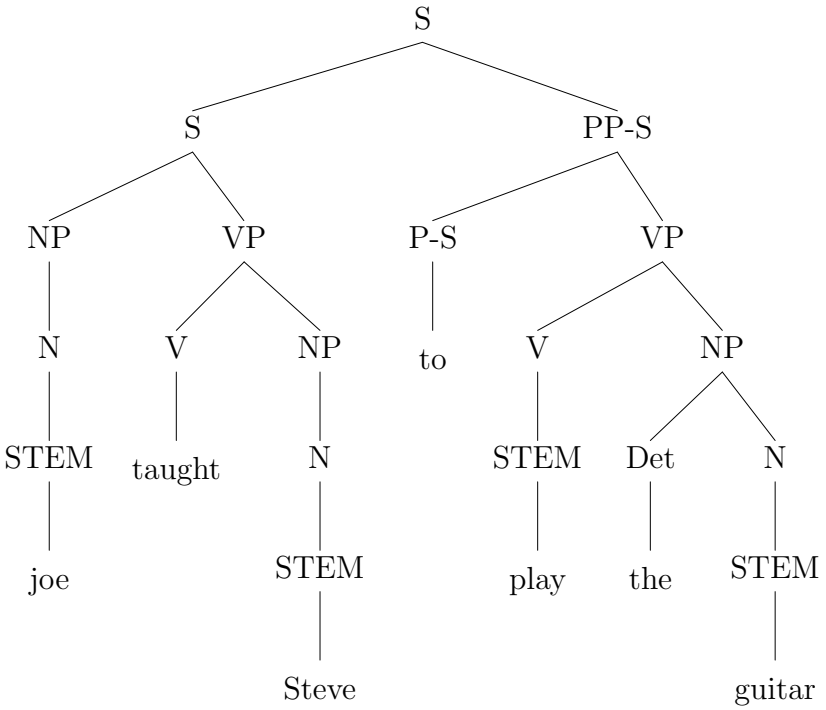


Figure 1.2: A syntax tree based on the ERG

Syntactic analysis is the process of putting the words into a more structured form, taking into account the grammar of the language.

A syntax-tree could be a way to represent output from the syntactic analysis. Such a tree could make statements like, "This sentence consists of a subject in nominative singular S, a predicate P and two accusative-objects O_1 and O_2, S being *Joe*, P being *taught*, O_1 being *Steve*, and O_2 consisting of the function word *to*, the verb V, the function word *the*, and a noun N, V being *play* and N being *guitar*".

It is important to keep in mind that this is only one possibility. The output of a syntactic analysis could instead make statements like, "This sentence is an active-voice sentence, the agent being *Joe*, the experiencer being *Steve*, the action being *teach*, etc.".

What exactly such an output looks like is highly dependent on the grammatical framework of choice. Figure 1.2 shows an output based on a syntactic analysis carried out using the ERG (English Resource Grammar: as distributed by Stanford's LinGO-initiative).

Semantic analysis is a more accurate term of what is commonly seen as the "understanding"-part of NLU (Natural Language Understanding). Whether a

computer will ever be able to truly "understand" a meaningful sentence is subject to broad discussions in the field of AI-research and philosophy. For now, let's just settle with the rather pragmatic approach to semantics Winograd (1971, p281) used.

> A semantic theory must describe the relationship between the words and syntactic structures of natural language and the postulated formalism of concepts and operations on concepts.

Semantic representation If we chose, for example, First Order Predicate-Calculus (FOPC, for short) as a semantic representation, the output of the semantic analysis could be something like

$$\forall g \exists e, p Isa(e, Teaching) \wedge Teacher(e, Joe) \wedge Student(e, Steve) \wedge Subject(e, p) \wedge Isa(p, PlayInstrument) \wedge Instrument(p, g) \wedge Isa(g, Guitar)$$

This notation could be read like "for every g there exists an e and a p, such that e is the event of teaching, the teacher participating in e being Joe, the student participating in e being $Steve$ the subject being taught in e being p, p being the event of playing an instrument, the instrument in p being g, and g being any $Guitar$".

Again FOPC is only one way of representing semantic data and the actual semantic representation is dependent on the semantic model of choice. Some semantic models don't even require a semantic representation at all.

1.2 Ambiguity

One of the most difficult tasks in discovering the meaning of a sentence is to choose between the meanings it could possibly have. Usually in a given situation a sentence can only be assigned one meaning that is plausible, but how is an artificial agent to decide upon the "plausibility" of an interpretation of a sentence?

Consider the following sentence from Schank (1971)

> We saw the Grand Canyon flying to Chicago.

There are many interpretations that could be assigned to this sentence. Here are some of them:

- While we were flapping our wings, flying to Chicago, we saw the Grand Canyon.
- We saw the Grand Canyon, which was travelling in an airplane to Chicago.
- When travelling to Chicago in an airplane, we saw the Grand Canyon.

That there are multiple interpretations for this single sentence is due to ambiguities on almost every level of language processing: sense-ambiguity, for example. The word *fly* can be used in the sense of *travel by airplane* as in *We flew to Chicago*, or in the sense of flying as in *Birds fly*.

Another example for ambiguity is structural ambiguity. In order to understand the above sentence, HAL will have to decide where the gerundive phrase *flying to Chicago* should be attached. It can either be part of a gerundive sentence, whose subject is *the Grand Canyon*, or it can be an adjunct modifying the phrase headed by *saw*, leaving either *We* as the ones who perform the action of flying, or *the Grand Canyon*, that does the flying.

This task of choosing the right interpretation is called "disambiguation", and many of the problems researchers in the field of NLP are concerned with are instances of disambiguation-problems.

1.3 Knowledge

Disambiguation often requires the machine to have knowledge about the "world" it operates in. A machine operating in a so called "real-world-environment", like HAL, would therefore need substantial knowledge of the real world. HAL has to be aware of facts such as, that people have no wings, and can only fly by plane, or that the Grand Canyon cannot fly, neither by plane, nor by flapping its wings.

Giving HAL such knowledge is probably one of the most difficult tasks AI-research has to face. John McCarthy, one of the big names in AI, has done remarkable research in that area. The reader is referred to his book McCarthy (1990) and especially to some of his papers McCarthy (1958), McCarthy & Hayes (1969), McCarthy (1977, 1989) and the paper about his 1971 lecture, for which he was awarded the Turing Award McCarthy (1987).

Chapter 2

Morphology

> The major problem [in time travel] is quite simply one of grammar, and the main work to consult in this matter is Dr Dan Streetmentioner's *Time Traveller's Handbook of 1001 Tense Formations*. It will tell you for instance how to describe something that was about to happen to you in the past before you avoided it by time-jumping forward two days in order to avoid it. The event will be described differently according to whether you are talking about it from the standpoint of your own natural time, from a time in the further future, or a time in the further past and is further complicated by the possibility of conducting conversations whilst you are actually travelling from one time to another with the intention of becoming your own mother or father.
>
> Most readers get as far as the Future Semi-Conditionally Modified Subinverted Plagal Past Subjunctive Intentional before giving up: [...]
>
> Douglas Adams
> The Restaurant at the End of the Universe

2.1 Overview

(2.1) After playing for hours the guitarists recharged their tuner's batteries.

Example 2.1 aims to introduce the reader to the most important scenarios in morphological processing.

A computer-program attempting to understand this sentence would have to know each word in the sentence, but how is a computer supposed to understand the word, or rather, the substring *recharged* from the above string? It certainly

wouldn't find it in any dictionary (in the sense of a string-array listing word-forms). It would be nonsensical to build up a dictionary containing all thinkable forms of a free morpheme like *charge*, since it would have to list

- (a) charge
- (more) charges
- (to) charge
- (He) charges
- (It is) charging
- (Yesterday I) charged
- (to) recharge
- (He) recharges
- (It is) recharging
- (Yesterday I) recharged
- (it is) charged
- (it is) uncharged
- (it is) unchargeable
- ...

Such a dictionary wouldn't only use up masses of memory, it would also be completely unmaintainable.

It would be desirable to have a dictionary list only-so called "root forms", like *charge*, and equip the system with rules like

1. It can be used as a verb
2. It can be used as a noun
3. It can be used as an adjective
4. The past-tense form of the verb can be derived by attaching the suffix *-ed*
5. The third-person-singular form of the verb can be derived by attaching the suffix *-es*
6. The progressive form of the verb can be derived by attaching the suffix *-ing*

7. The prefix *re-* can be attached to the verb
8. The plural form of the noun can be derived by attaching the suffix *-es*.
9. The prefix *un-* can be attached to the adjective
10. The suffix *-able* can be attached to the adjective

Rule 4 applies to almost every verb in the dictionary. (We will use the term "in the dictionary" to actually describe the concept of "either listed in the dictionary or derivable from a form in the dictionary".) Therefore the possibility of storing such rules centrally eliminates a considerable amount of redundancy from the system.

This doesn't only save physical storage-capacity, it also leaves the system of morphological rules and their applications as an independent module, which has many advantages. One of them is giving the system the ability to apply known rules to new words. If a human listener is confronted with new words he has never heard before, say *a great gardel* and *a big red tarivar* he can assume that *I gardelized my tarivar* could possibly mean "I turned my tarivar into a gardel", regardless of what the words are supposed to mean.

2.2 A Linguistic Perspective to Morphology

So far we have seen the need for a dictionary listing root-forms and morphological rules, and a system capable of applying the rules to words in the dictionary. In this section we will have a closer look at some examples of morphological rules in order to give the reader a rough idea of English morphology and the difficulties it confronts a non-human understander with. A more detailled description can be found in Weisler & Milekic (2000, pp79ff).

2.2.1 Derivational Morphology

Rules of derivational morphology are simply rules "deriving" more complex word-forms from simpler ones, often altering their meaning or syntactic category.

One of the most prominent rules of derivational morphology is probably the appending of the suffix *-ly* to derive an adverb from an adjective. This rule can be applied to almost any adjective, with three consequences:

- the substring *ly* is appended to the word-form
- the word-form is now an adverb, rather than an adjective
- the meaning of the word changes to "in an X manner"

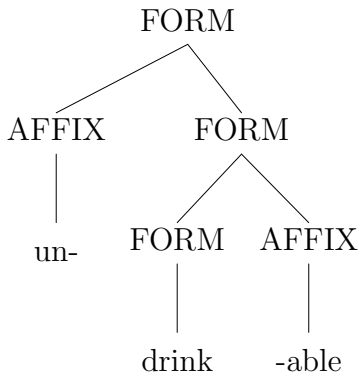


Figure 2.1: A tree showing the derivation of *undrinkable*

Another rule of derivational morphology uses the suffix *-er*, to derive *painter* from *(to) paint*. It alters the meaning to "someone who Xs".

In the case of *-ist*, it gets obvious, that not every rule can be applied to every word form. A *guitarist* is someone who plays the guitar, a *violinist* is someone who plays the violin, but no one has ever heard of a **drumist*.

Considering the suffix *-able*, turning a verb into an adjective, leaving the meaning as "it is possible to X it.", and the prefix *un-*, altering the meaning of an adjective to "not X" makes clear that it is also possible to subsequently apply rules to forms that are already morphologically derived from a root form. The form *undrinkable* can only be derived by first deriving *drinkable* from *drink*. The *un-*-rule can then be applied to the new form *drinkable* to produce *undrinkable*. Figure 2.1 shows a tree-representation of this concept.

Some more complications can be seen when, for example, considering the *de-* prefix, altering the meaning of a verb to "to reverse the action of Xing". Words like *deflate* suggest that not all root-forms actually exist, given a derived form that exists. **flate* is obviously not an English word, although the *de-* prefix seems to exactly behave like a morphological rule. That the morpheme **flate* might actually exist is further suggested by the evidence that forms like *inflate* and *inflation* can be derived from it.

The word *deodorize* seems to be of similar nature, but this time the unbound morpheme *odor* does exist as a root form, while the derivation **odorize* does not exist as a word-form. Yet it is still possible to do further derivations, like applying the *de-*-rule, leaving the form as *deodorize*, which is again an existent word-form.

delete and *depress* are similar cases. While *delete* does not seem to have anything to do with a morphological derivation, but only happens to start with *de* "by chance", the form *press* does exist, yet the application of the *de-*-rule doesn't derive that meaning of *depress*.

2.2.2 Inflectional Morphology

While the manifestation of derivational morphology is usually limited to a change in its written form (usually an affix), a change of syntactic category and a change in meaning, inflectional morphology serves a rather different purpose. Rules of inflectional morphology produce an extremely regular semantic effect by modulating certain grammatical aspects of meaning, such as person, number, tense, case, etc. They are usually more regular than rules of derivational morphology and they never change syntactic category.

Nominative Sg.	filia (daughter)
Nominative Pl.	filiae (daughters)
Genetive Sg.	filiae (daughter's)
Genetive Pl.	filiarum (daughters')
Dative Sg.	filiae (I told my daughter something)
Dative Pl.	filiis (I told my daughters something)
Accusative Sg.	filiam (I love my daughter)
Accusative Pl.	filias (I love my daughters)
Vocative Sg.	filia ('Daughter, I love you!')
Vocative Pl.	filiae ('Daughters, I love you both!')
Ablative Sg.	filia (N/A)
Ablative Pl.	filiis (N/A)

Table 2.1: Inflectional table of the latin word "filia"

Generally nouns inflect for case and number, but case is usually neglected because it doesn't alter the appearence of a word-form in English. Table 2.1 is an inflectional table of the latin word *filia, -ae*. In Latin the word form depends on its case, that means it depends on how and where the form is used in a sentence. Therefore *daughter* as in *I love my daughter* is a different word-form as in *I've told my daughter a thousand times not to do that.*

While case is widely irrelevant for English morphology, number isn't. The plural form of *dog*, *dogs* can be derived by applying a rule of inflectional morphology, in this case the suffix *-s*. Again exceptions like *foot/feet*, *goose/geese* or *fish/fish* complicate things. Plural-nouns are another exception. These are nouns that are understood to only make sense in a plural form like *jeans*, and mass-nouns, that are understood to describe an uncountable amount of something, and are only valid in their singular forms, like *money*.

The inflectional system of verbs is a lot more complex, because verbs inflect for person, number, tense and in many languages for features like whether it is used in a conjunctive construction. The German language for example has an indicative and two different conjunctive forms of a verb and six tenses, leaving each word form with $3 * 2 * 6 * 3 = 108$ possible inflections. Fortunately they are highly redundant.

A typical example of verbal inflection is the rule appending *-ed* to a verb, in order to derive a past-tense word-form. Again exceptions are present like *teach/taught*, *catch/caught* or *take/took* and numerous other irregular forms.

2.3 A Naive Approach to Model Morphological Knowledge

The reader should by now have a picture of what morphology is all about and what kind of data is needed to do morphological analysis, but how is it modeled? How do we get a computer to recognize a word like *undrinkable*, given a dictionary-entry *drink*, a rule for *-able* and a rule for *un-*? How do we store such data physically?

Let's start with some morphological data for a parser in a simple problem-domain, say animals.

What we need is a dictionary listing root-forms:

- bird
- cat
- dog
- fish
- frog

In order to inflect the words for number we need rule R_1

1. Rule R_1 can be applied to any form in the dictionary but 'fish'
2. When applied, R_1
   (a) appends the string s to the root-form
   (b) changes the number to PLURAL.

And in order to handle the word *fish* we need another rule R_2

1. Rule R_2 can be applied only to the form *fish*.
2. When applied, R_2
   (a) changes the number to PLURAL.

Then we want to model some derivational morphology, let's call it "babytalk", producing forms like *doggie*, *fishie* or *froggie*.

1. Rule R_3 can be applied to the forms *bird* and *fish*
2. When applied, R_3
   (a) appends the string *-ie* to the root-form
   (b) sets the "babytalk-mark" to TRUE.

1. Rule R_4 can be applied to the forms *dog* and *frog*
2. When applied, R_4
   (a) appends the string *-gie* to the root-form
   (b) sets the "babytalk-mark" to TRUE.

1. Rule R_5 can be applied to the form *cat*
2. When applied, R_5
   (a) changes the form to *kittie*
   (b) sets the "babytalk-mark" to TRUE.

A model like this might already be directly implementable using a rule-based inference-system like PROLOG, but in order to achieve better performance, let's "precompute" some values, and put our morphological model in a procedural terminology, defining the functions as shown in table 2.2.

P_1	NUM=PLURAL
P_2	NUM=PLURAL
P_3	BABYTALK=TRUE
P_4	BABYTALK=TRUE
P_5	BABYTALK=TRUE

Table 2.2: Function-definitions of the procedures P_1 through P_5

In table 2.2 we simply turned the rules into procedures. Instead of rule R_1 which requires the grammatical numerus (NUM) to be PLURAL, we now have a procedure P_1, which carries out this action, namely assign a global-flag (which we'll call NUM) the value PLURAL.

Given these function-definitions we can show the return-values of the possible function-calls to be:

bird

cat

dog

$$fish$$
$$frog$$
$$birdie \leftarrow P_3(bird)$$
$$fishie \leftarrow P_3(fish)$$
$$doggie \leftarrow P_4(dog)$$
$$froggie \leftarrow P_4(frog)$$
$$kittie \leftarrow P_5(cat)$$
$$birds \leftarrow P_1(bird)$$
$$dogs \leftarrow P_1(dog)$$
$$frogs \leftarrow P_1(frog)$$
$$cats \leftarrow P_1(cat)$$
$$fish \leftarrow P_2(fish)$$
$$birdies \leftarrow P_1(birdie) \leftarrow P_1(P_3(bird))$$
$$fishies \leftarrow P_1(fishie) \leftarrow P_1(P_3(fish))$$
$$doggies \leftarrow P_1(doggie) \leftarrow P_1(P_4(dog))$$
$$froggies \leftarrow P_1(froggie) \leftarrow P_1(P_4(frog))$$
$$kitties \leftarrow P_1(kittie) \leftarrow P_1(P_5(cat))$$

While *bird* is itself a word-form, P_3 derives $birdie \leftarrow P_3(bird)$, and P_1 derives $birds \leftarrow R_1(bird)$. The new form *birdie* can again be used as an argument to P_1, this time deriving $birdies \leftarrow P_1(birdie)$, or, putting it differently, $birdies \leftarrow P_1(P_3(bird))$

If we group the above list by procedures, listing only arguments and return-values, we get table 2.3.

P_1	$NUM = PLURAL$	$birds \leftarrow bird$ $cats \leftarrow cat$ $dogs \leftarrow dog$ $frogs \leftarrow frog$ $birdies \leftarrow birdie$ $fishies \leftarrow fishie$ $doggies \leftarrow doggie$ $froggies \leftarrow froggie$ $kitties \leftarrow kittie$
P_2	$NUM = PLURAL$	$fish \leftarrow fish$
P_3	$BABYTALK = TRUE$	$birdie \leftarrow bird$ $fishie \leftarrow fish$
P_4	$BABYTALK = TRUE$	$doggie \leftarrow dog$ $froggie \leftarrow frog$
P_5	$BABYTALK = TRUE$	$kittie \leftarrow cat$

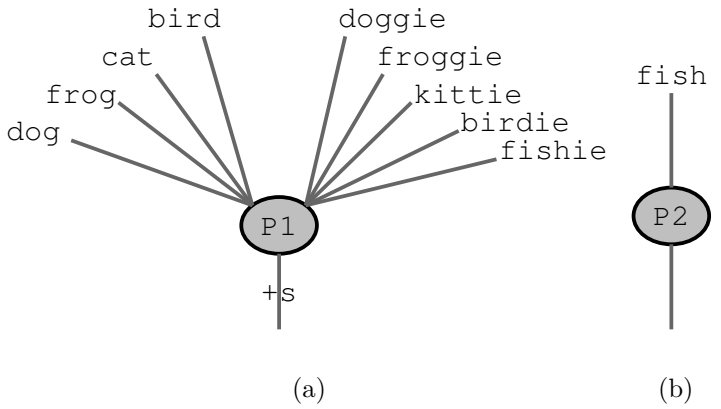


Figure 2.2: The subsystem handling plural-inflection

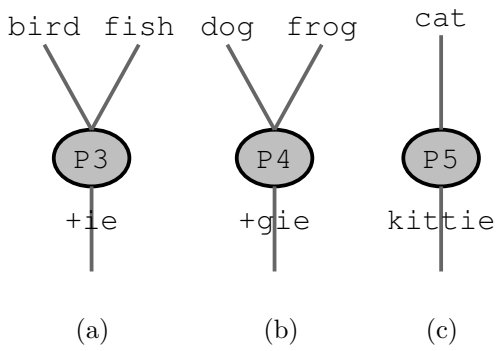


Figure 2.3: The subsystem handling babytalk-derivation

The graphical representations from figures 2.2 and 2.3 show the same data from table 2.3, namely functions and their input and output-values.

Figures 2.2 through 2.8 make use of the convention that unlabelled arcs pass whatever they received as an input to the called function. This value can also be referenced explicitly with the symbol "+", so the appending of an affix can be effectively depicted.

Figure 2.2 shows the functions needed for inflectional, figure 2.3 the ones needed for derivational morphology.

The next question we ask ourselves, or rather the model, is: Where does the data come from? Where does it go to? If we compose figures 2.2 and 2.3 into figure 2.4, we get a model capable of answering that. Note that so far we have never added any data to the model, we have simply rearranged it. In figure 2.4 it is still possible to make out each "subdiagram" as shown in figure 2.2 or 2.3.

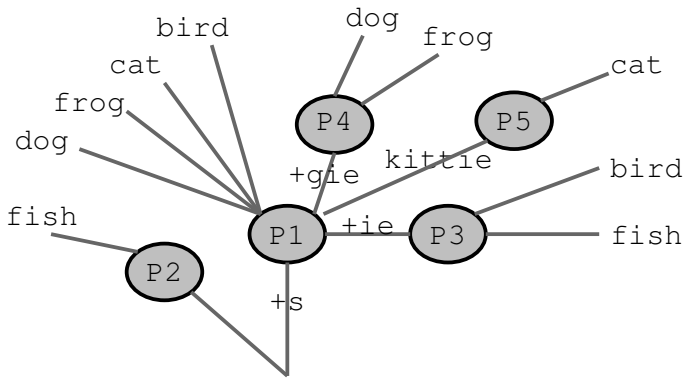


Figure 2.4: A more detailled version of figures 2.2 and 2.3

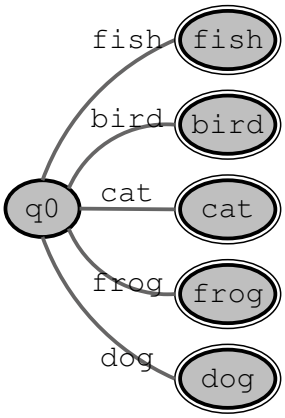


Figure 2.5: A model for basic input

Next we need a final shift in perspectives:

We propose the function q_0 that "produces" all of the input to our system, and some functions $fish$, $bird$, cat, ... each of which gets as input the atomic values. 'fish', 'cat', 'frog', ... This is shown in figure 2.5. The new functions are depicted using a double circle because they do not neccessarily have to do any output. They could simply "swallow" their input.

Next we have to account for plural inflection. This can be done by simply copying the plural-inflection-related parts of the diagrams from figure 2.2 into figure 2.5. The outcome is shown in figure 2.6. Again arcs depict function calls and they are labeled corresponding to the data they pass. We insert the new procedure q_1, which "is interested" in all plural-forms.

Since we also want to cope with babytalk-derivation we do the same for the procedures P_3, P_4 and P_5, in other words copy figure 2.3 into figure 2.5, to get figure 2.7, proposing a function q_2 getting the babytalk forms.

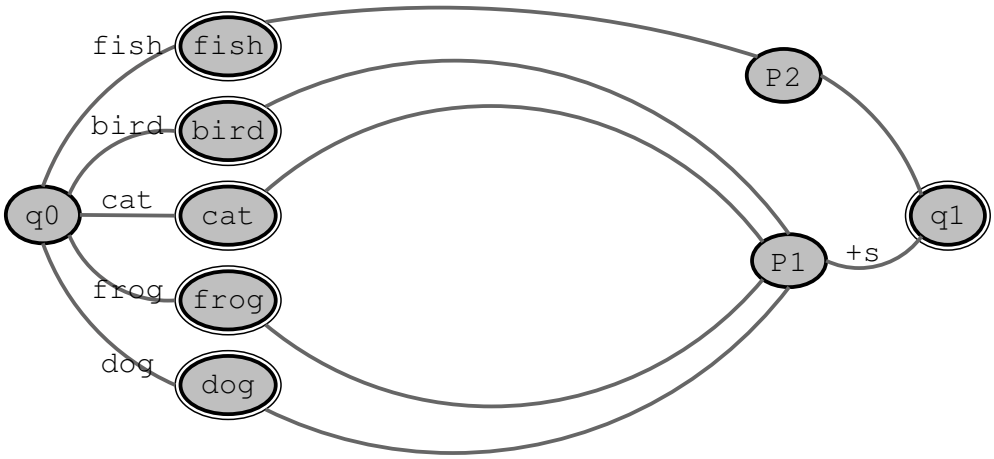


Figure 2.6: A model for basic and plural-inflected input

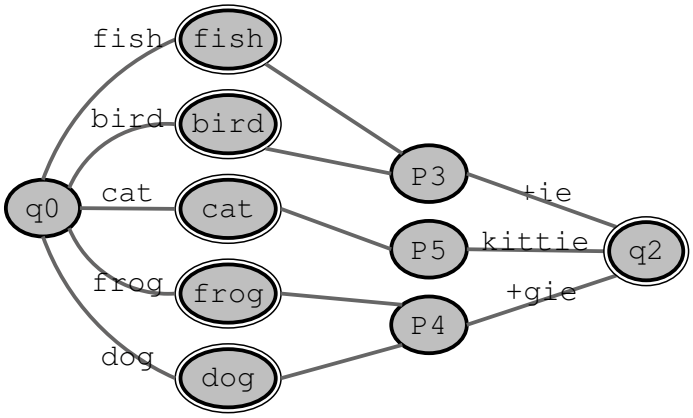


Figure 2.7: A model for basic input and derived babytalk-forms

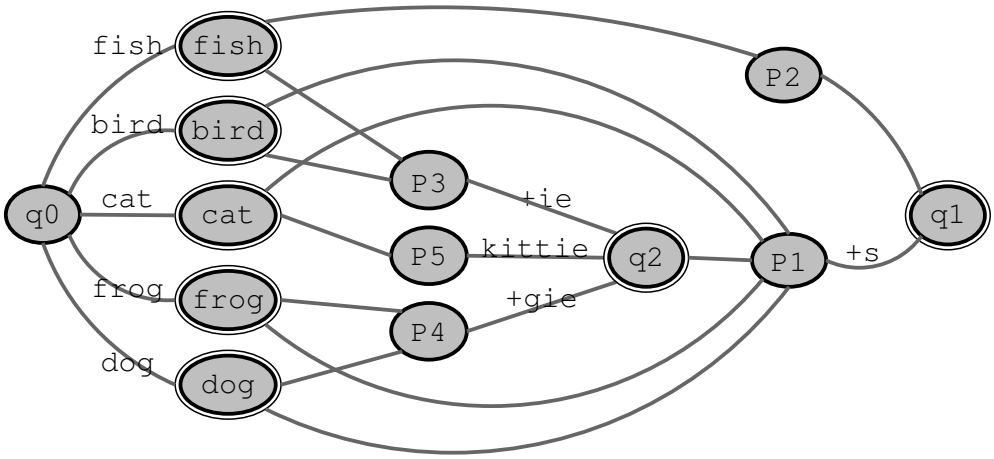


Figure 2.8: A model for the whole system

Figures 2.6 and 2.7 can be easily integrated into figure 2.8, to give a system handling both plural-inflection and babytalk-derivation.

Still we haven't added any information to the model, that couldn't be found in our initial rule-based system described by R_1 through R_5. We have step by step transformed our rule-based approach to a procedural one, and finally into an automaton, as described in the next section.

2.4 Finite State Automata

Although it's syntactically not quite correct, conceptually figure 2.8 can already be interpreted as what is called a "Finite State Automaton", FSA for short.

This section will give the reader a rough introduction to FSAs. More detailled information on FSAs and their applications in Speech and Language Processing can be found in Jurafsky & Martin (2000). Readers already familiar with FSAs might want to skip it.

The first approach to FSAs might come to our minds, when trying to build an effective model for accessing a simple list of words. Think of how one usually looks up a word in the dictionary, say we are trying to look up *dictionary* in our dictionary.

1. For all items in the dictionary:
2. Find an item that begins with *d*.
3. If there is no item that begins with *d*, *dictionary* can't be in the dictionary.
4. For all items that begin with *d*

(a) Find an item that begins with *di*.

(b) If there is no item that begins with *di*, *dictionary* can't be in the dictionary.

(c) For all items that begin with *di*:

   i. Find an item that begins with *dic*

   ii. ...

   iii. If there is no item that is *dictionary*, *dictionary* can't be in the dictionary.

   iv. If there is an item that is *dictionary*, *dictionary* is in the dictionary.

The recursive nature already gets obvious here.

Now think of a dictionary containing some root-forms and for each one a unique root-form-ID, that identifies the root-form in further processing, as shown in table 2.3.

xabcde	1001
xabfgh	1002
nnki	1003
aabcde	1004
aabfgh	1005
xarki	1006

Table 2.3: A sample dictionary

Figure 2.9 shows a tree-representation of the same table, that fits the above algorithm much better. Now what makes this tree-representation of the above recursive-algorithm and FSA? The interpretation does. One starts at node q_0. Nodes depict the model's idea of "states", so we say, "The automaton IS in state q_0". If the word to be looked up begins with x, one simply follows the arc to q_6, or putting it in a more professional terminology; "The automaton takes the transition to q_6" because arcs depict possible transitions. If the next character is an a, the automaton takes the transition from state q_6 to q_5, etc.

Note that this tree representation is already an "FST", not just an FSA. FST is short for "Finite State Transducer", and it is similar to the idea of an FSA. The only difference is that the transducer has the ability, not just to match a given input-stream, but also to recode it to an output-stream. In our example this can be seen for example at the transition between states q_5 and q_{26}. This transition is the first one, where it is completely determined, that if the input should match an entry in the transducer the output is going to be *1006*, the *xarki*-entry's root-form-ID. The new syntax is this: When a transition is labelled *i:o*, then the transition is taken as soon as the input-signal i is read from the input-stream, and whenever that transition is taken the signal o is sent to the

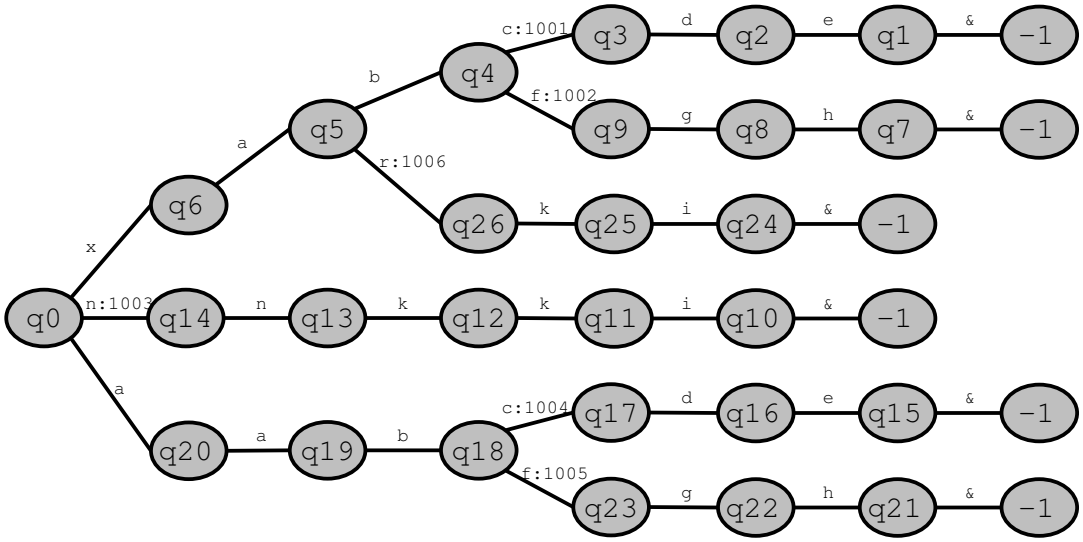


Figure 2.9: A dictionary as a tree

output-stream.

Note that this paper doesn't follow the normal convention in that respect. Usually an FST is understood to recode an input-stream to a similar but slightly modified output-stream, which is why the convention that a transition labelled i, means $i{:}i$ is widely used. Since the FSTs we are handling aren't slightly recoding an input-signal, but rather mapping two sets of values to each other it is more practical to follow the convention that i actually means $i{:}\epsilon$, which leads us to a new syntactic element of FSTs and FSAs: The ϵ-signal.

ϵ matching an input-stream means "don't read any signals from the input-stream, simply follow the transition", ϵ feeding an output-stream means "don't do any output". Its meaning is roughly related to the concept of the "empty string", which might be more accessible to readers from a technical background.

In figure 2.9 it is apparent that the subtrees headed by q_3 and q_{17} are completely redundant, as well as the ones headed by q_9 and q_{23}, and the ones headed by q_{26} and q_{12}. q_1, q_7, q_{24}, q_{10}, q_{15} and q_{21} are also completely equal. These redundant nodes or subtrees can now be removed by showing them only once in the diagram, and referencing them in all "situations" needed. The outcome of such a proceeding is shown in figure 2.10.

Figure 2.10 shows us the power of the FST. What we have created is a compact data-structure, highly optimized towards performant lookup. A system checking whether *xabcde* is in the FST would simply traverse it. As soon as it gets to a final state (q_{10} in our example), the string is matched. By the time it's matched, the output will already be ready in the output-stream, and the time used to do the traversal is quite short: It can be expressed as shown in Equation 2.1.

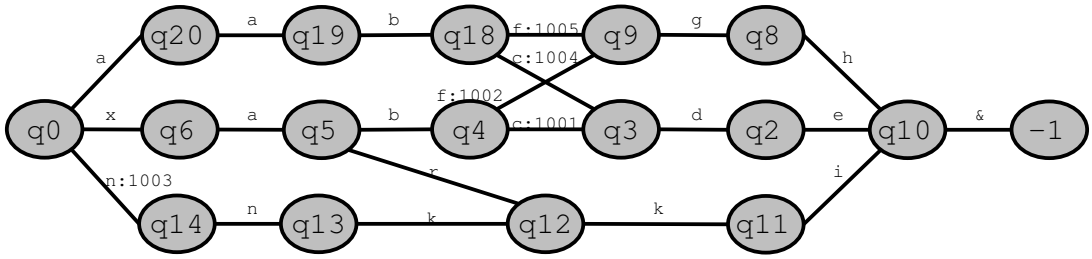


Figure 2.10: The same dictionary as FST

$$\overline{T}(L) \simeq L * \frac{num(states)}{num(transitions)} + O + F \tag{2.1}$$

The average time taken to match a string that is in the FST is directly proportional to the product of its length L, and the branching factor B, because the time taken to match a whole string is directly proportional to the time it takes to process a single state and to the number of states that are to be processed. The average time taken to process a single state is directly proportional to the branching factor B, that is the average count of transitions leaving a single node, therefore B is the count of states in the FST divided by the count of transitions. Of course the actual branching-factor along that arc is dependent on the string itself. The number of states to be processed is usually (in the simplified framework presented here) the number of characters in the string. The variable O is symbolic for a constant summand, accounting for the time it takes to do the output. F accounts for the constant amount of time it takes the framework to enter and leave the FST.

The reader interested in a more detailed and technically sophisticated description of FST-processing is referred to the sourcecode-documentation of LISA's FST-toolkit, presented in the second part.

2.5 Finite State Morphological Parsing

In the previous section we saw how to model a simple dictionary using an FST. It has already been mentioned that figure 2.8 can already be viewed as an automaton. Although it is syntactically not quite correct, conceptually it can be interpreted just like an automaton, given that the unlabelled arcs are ϵ-transitions.

Say we wanted to do morphological analysis of the string *birdies*: The automaton would start in state q_0, then read the substring *bird*, then take the ϵ-transitions to P_3, then read the substring *ie*, take the transition to q_2, then take the ϵ-transition to P_1, read the last substring *s*, and get to the final state q_1. If we give procedures *bird*, P_1 and P_3 the ability to set the global flags ROOT-

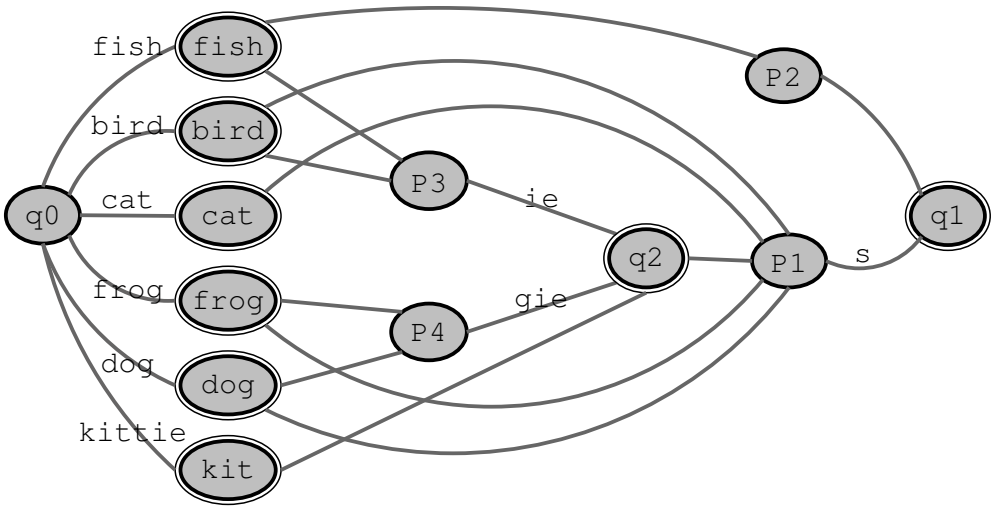


Figure 2.11: A syntactically correct FSA derived from figure 2.8

FORM=BIRD, NUM=PLURAL and BABYTALK=TRUE (as defined in table 2.2) a complete morphological analysis will be available.

The concept of ambiguity enters the scene as soon as we have a more detailled look at the word *fish*. After reading the substring *fish* and doing a transition to the state $fish$, the system has no way to determine whether to take that state as a final state, leaving ROOTFORM=FISH, NUM=SINGULAR and BABYTALK=FALSE (given that the default-value of NUM is SINGULAR, and the default-value of BABYTALK is FALSE), or to do the ϵ-transitions to P_2 and q_1 leaving NUM=PLURAL. This is completely intuitive. Not even a human reader has the ability of telling whether the word-form *fish* is singular or plural, when confronted only with the string *fish*. We have to give our system the ability to let the ambiguity arise at this stage of processing, leaving the disambiguation for the syntactic or semantic analysis. This will not be handled in greater detail here, we will only give two key concepts of handling nondeterministic FSAs: The problem could be handled by parallel processing for example by forking the interpreter-process traversing the FSA, leaving one process for each possibility. One might also use backtracking for example by maintaining a stack of return-states to try after processing of one possibility is finished.

The big syntactic flaw of figure 2.8 is that it completely fails to match *kittie*, when interpreted as an FSA, since the substring 'cat' would have to be matched to get to state *cat*. This syntactic error comes from composing the procedure's I/O-diagrams into figure 2.8, but there's nothing simpler than correcting that, as figure 2.11 shows. All that's needed is a new state, let's call it *kit*, that is reached after reading 'kittie', setting both ROOT=CAT and BABYTALK=TRUE.

But still figure 2.11 isn't a very elegant way to do finite state morphological

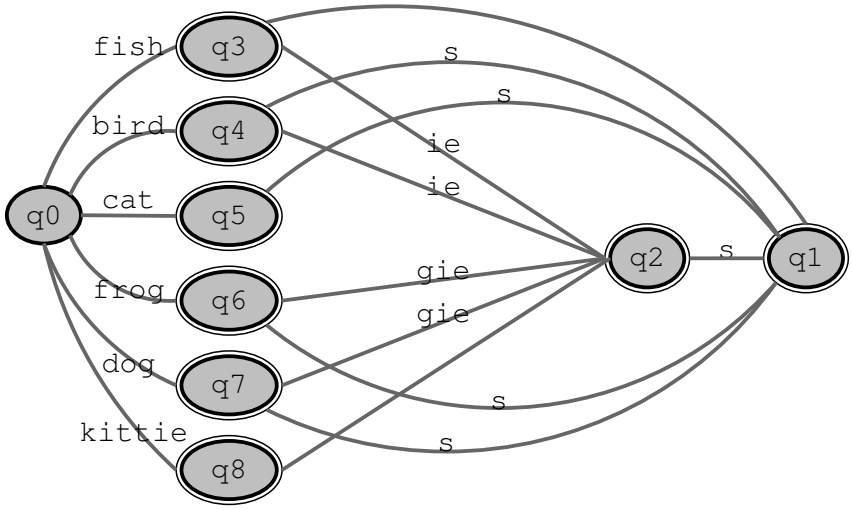


Figure 2.12: Getting rid of the indeterminisms from figure 2.11

parsing. One of the main problems with figure 2.11 is the great degree of indeterminisms that arise from the ϵ-transitions that were carried over from the conceptual I/O-diagrams.

In order to get rid of these indeterminisms we need to finally get rid of our artificial procedures P_1 and P_5, transferring the program-logic into the transitions rather than the states. The idea is depicted in figures 2.12 and 2.13.

The FSA in figure 2.12 has only two kinds of indeterminisms involved. The first one arises from the ambiguity of the interpretation of the word-form *fish*, the other one is deciding whether to stay in a final state if one is reached or trying to do a transition. We can get rid of that kind of indeterminism by proposing a signal that terminates each word. We can then propose a new state q_F, and instead of making all of the other states final ones, we equip them with a transition to this final state q_F that is taken if, and only if, the end-of-word-signal is read.

Of course it is possible to augment an FST representing a dictionary and an FST representing the morphological system around it into a single one. The dictionary-FST would in our example replace states q_3 through q_8, and the transitions leading to them. Such an FST would match single input characters instead of substrings, and it would be possible to directly compile such an FST, to achieve optimal performance.

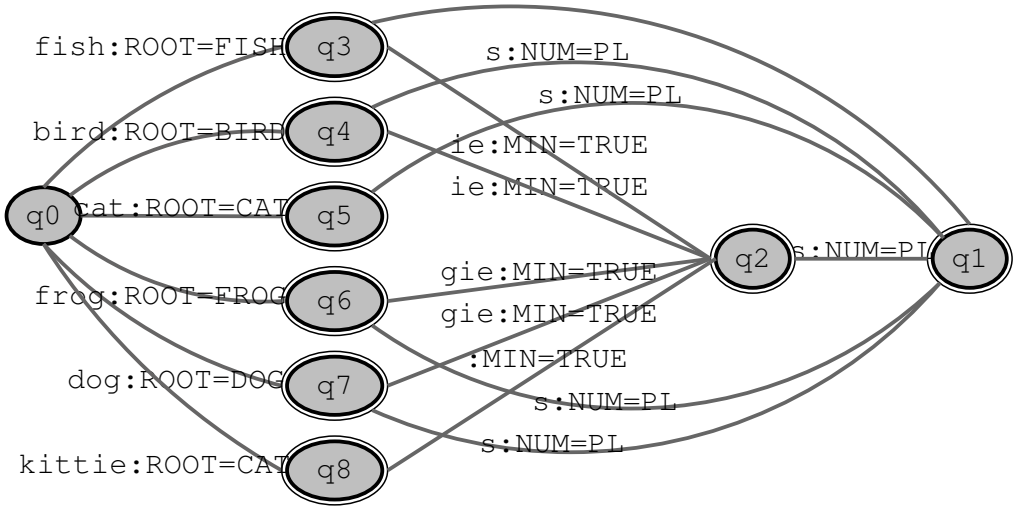


Figure 2.13: A more accurate version of figure 2.12

Chapter 3

Syntax

3.1 Overview

In order to gain a deeper understanding of syntax, it is important to understand the role of syntax in the overall process of "understanding" a meaningful sentence, which turns out to be a rather difficult task. This is also the reason why so many syntactic theories have been developed, and why some of them hardly seem to have anything in common.

Instead of going into a detailed discussion about this, we will only give an overview of the traditional approaches to "sentence-structure".

The word sentence-structure already points us in the right direction of the linguistic approach to syntax. The purpose of syntax is to put a string of symbols in relation to each other. Linguistics is the study of language, and therefore the role of syntax in linguistics is to put words in relation to each other, which is widely related to the idea known as "grammar".

Weisler & Milekic (2000, p124) define this term as follows:

> A *grammar* - a theory of linguistic knowledge - must characterize what we know about the physical signals on one end of the lingusitic equation, and what we know about meaning on the other. [...]

This already confronts us with semantics, which we want to leave for the next chapter. That's why we actually talk about the syntactic aspects of grammar only, whenever we use the term "grammar" in this chapter.

The "Context-Free Grammar", CFG for short, is the kind of grammar we will be concerned with most of the time. The CFG dates back to Chomsky (1956), independently discovered by Backus (1959).

It is based on the idea of "constituency", which states that a group of words may behave as a single unit or phrase, called a "constituent".

(3.1) The big ugly dog bit the boy.

In example 3.1 the phrase *big ugly dog* might be a constituent. Grammatically it behaves just like a single word, which is suggested by the fact that we could freely exchange it.

(3.2) The goldfish bit the boy.

In example 3.2 *big ugly dog* has been replaced by *goldfish*, and it's still grammatical. It doesn't make sense perhaps, but it is grammatical.

The idea of "replacement" is quite central to the formalism of the CFG.

What we have just observed could be expressed as a CFG as:

$$\begin{aligned} S &\leftarrow \text{The } ANIMAL \text{ bit the boy} \\ ANIMAL &\leftarrow \text{big ugly dog} \\ ANIMAL &\leftarrow \text{goldfish} \end{aligned}$$

A CFG is defined as $G = (V_N, V_T, P, S)$. V_N is a set of so-called non-terminal symbols. In our example we have two non-terminal symbols, namely S and $ANIMAL$. V_T is the set of terminal symbols. These are usually words, or whatever data-structure we get from the morphological analyzer. P is a set of reduction-rules like the ones given above, and S is the start-symbol, that is the symbol we ultimately want to describe the whole sentence with.

The first rule in the above example makes use of a symbolic expression, $ANIMAL$. The other rules give information about what exactly an $ANIMAL$ is. One states that the symbol could be rewritten as *big ugly dog* and the other one lets the interpreter rewrite it as *goldfish*.

Therefore the interpretation of the above grammar would generate examples 3.1 and 3.2.

3.2 A Linguistic Perspective to Sentence-Structure

Now that we know what syntax is all about, and how we can talk about syntax using the notion of grammar, especially the formalism of the CFG, we can go deeper into English sentence structure, introducing the reader to the problems and requirements English sentence-structure confronts a symbolic theory of syntax with.

3.2.1 Parts of Speech

Noun, verb, pronoun, preposition, adverb, conjunction, participle and article: This pretty much summarizes the concept behind the term "Parts of Speech", POS for short.

The above collection of parts of speech goes back to ancient Greece, yet seems surprisingly accurate. This is due to the fact that it became the basis for most

subsequent POS-descriptions, which are considerably larger today. The Penn Treebank Marcus et al. (1993) enlists 45 parts of speech.

The central role of the parts of speech in each grammar is due to the significant amount of information the POS gives us about the word, and its surrounding.

It is important to understand that the parts of speech are defined through functions or classes of functions in the grammar. Traditional definitions of parts of speech tend to use a semantic approach rather than a functional/grammatical one: "A noun is the name of a person, place or thing". Although these definitions head us in the right direction they are too imprecise for our formal theory. Fortunately there are other techniques for grammatical categorization.

A noun, like *dog*, for example, can appear after determiners like *the*; *dog* is a noun because *the dog* is grammatical; *identify* is not a noun, because **the identify* is ungrammatical. How do we know that *the* is a determiner? Because it can appear before a noun like *dog*; *the* is a determiner because *the dog* is grammatical; *easily* is not a determiner because **easily dog* is ungrammatical.

Note that the definitions are circular, yet the circularity isn't in any way problematic for the system.

Let's consider an example: We know about the following facts:

a. *the dog* is grammatical

b. *easily identify* is grammatical

c. **easily dog* is ungrammarical

d. **the identify* is ungrammatical

e. Verbs can appear after adverbs.

f. Nouns can appear after determiners.

Given these facts, our task is now to find the parts of speech of the words *the*, *easily*, *dog* and *identify*.

Let's assume that *the* was a determiner. From facts *a* and *f* we can now conclude that *dog* is a noun. From facts *d* and *f* we can conclude that *identify* is not a noun and considering *e* and *f* (words appearing second in a clause must be either a verb or a noun) we know that it is a verb. Given that *identify* is a verb, we can now conclude that *easily* is an adverb, from *b* and *e*.

Let's assume that *the* was an adverb. From facts *a* and *e* we could now conclude that *dog* is a verb. From *d* and *e* we can conclude that *identify* is not a verb and, just as we did before, considering *e* and *f*, we know that *identify* is a noun. Given that, we can conclude that *easily* is a determiner, from *b* and *f*.

Circularity made it possible to conclude that *dog* is a verb, and *identify* is a noun, which is, according to what we learned in school, simply wrong, but why

is that completely irrelevant to our computational model of syntax? Let's try to formalize what we've just observed in the CFG-formalism.

The first possiblity (the "correct" one), would be something like

$$\begin{aligned} N &\rightarrow \textit{dog} \\ V &\rightarrow \textit{identify} \\ \textit{Det} &\rightarrow \textit{the} \\ \textit{Adv} &\rightarrow \textit{easily} \\ S &\rightarrow \textit{Det}\ N \\ S &\rightarrow \textit{Adv}\ V \end{aligned}$$

The second possibility (the "incorrect" one), would then be

$$\begin{aligned} V &\rightarrow \textit{dog} \\ N &\rightarrow \textit{identify} \\ \textit{Adv} &\rightarrow \textit{the} \\ \textit{Det} &\rightarrow \textit{easily} \\ S &\rightarrow \textit{Adv}\ V \\ S &\rightarrow \textit{Det}\ N \end{aligned}$$

What is the difference between these two CFGs? We simply exchanged the names of the parts of speech. Now we call nouns verbs, and we call adverbs determiners, and vice versa, but the names of the parts of speech are as abstract as can be. Recall that parts of speech are defined in terms of functions or classes of functions in the grammar, and these functions would stay exactly the same. The grammar would match exactly the same strings and put them exactly into the same relations regardless of what symbol we assign to what POS.

One might also use morphological criteria, for assigning words to their POS. If, for example,*determine* has a past-tense form like *determined* it must be a verb. *dog* is not a verb, since a form like **dogged* does not exist.

Note that the same circularity we just showed arises when defining POS in terms of functions in their grammar (at the interface between grammar and word), arises when defining POS in terms of morphology (at the interface between word and morpheme), since a morphological analyzer would have to know about the part of speech, to decide whether rules like that appending the affix *-ed* are appliable in the first place.

3.2.2 A Simple Grammar

Proposing Some Rules to Get Started

We have introduced the concept of a CFG, we have established some equivalence-classes that anchor our analysis, why not start and write a grammar for English.

(3.3) Steve played the guitar brilliantly.

(3.4) Old Bebe played.

(3.5) The guitarist on the left is the best.

Now let's transform these example-sentences into a syntactically correct CFG.

$$\begin{aligned} S \rightarrow &\text{ Steve played the guitar brilliantly} \\ S \rightarrow &\text{ Old Bebe played} \\ S \rightarrow &\text{ The guitarist on the left is the best} \end{aligned}$$

We have just created a CFG successfully matching all of our example sentences, producing all grammatical and no ungrammatical forms. A perfect grammar, yet completely pointless. Didn't we want to put the words into some kind of relationship?

$$\begin{aligned} S &\rightarrow N\ V\ Det\ N\ Adv \\ S &\rightarrow Adj\ N\ V \\ S &\rightarrow Det\ N\ P\ Det\ N\ V\ Det\ N \end{aligned} \tag{4}$$

We have built a grammar that is a lot more general, by simply introducing non-terminals for each part of speech, and replacing every word by its POS-symbol. Rule 4 from the above grammar doesn't only take care of *Steve played the guitar brilliantly*, it also matches *Matt screwed the solo completely* or *Brad ruined the guitar entirely*, suggesting some kind of syntactic and semantic isomorphy between these sentences (up to the point where one would have to "fill in" the words for the parts of speech).

The Noun-Phrase

But still we haven't made use of the notion of constituency yet, so we simply introduce the first class of constituents, which we call "noun-phrase". *Steve*, *the guitar*, *I*, *old Bebe*, *the guitarist on the left* are all examples of noun-phrases.

$$
\begin{aligned}
S &\rightarrow NP\ V\ NP\ Adv && (7)\\
S &\rightarrow NP\ V\\
S &\rightarrow NP\ V\ NP\\
NP &\rightarrow N && (10)\\
NP &\rightarrow Det\ NP && (11)\\
NP &\rightarrow Adj\ NP && (12)\\
NP &\rightarrow NP\ P\ NP && (13)
\end{aligned}
$$

This introduces the first non-terminal symbol that is not the start symbol, NP (except, of course, for our POS-symbols).

Rule 10 says that any noun can be interpreted as a noun-phrase. That rule would take care of *Steve*, or *guitar*.

Rule 11 states that any determiner followed by a noun-phrase makes up a noun-phrase. This would match for example *the guitar*, *the guitarist*, *the left*, etc.

Rule 12 states that any adjective followed by a noun-phrase makes up a noun-phrase, such as *big red guitar*, etc.

And finally Rule 13 makes it possible to view any two noun-phrases as a single noun-phrase, when they are concatenated by a preposition, such as *guitarist on the left*.

Our grammar is a lot more general now. Rule 7, matches all sentences rule 4 matched, because we got rule 7 by replacing N and $Det\ N$ by NP, and since $NP \leftarrow Det\ N$ and $NP \leftarrow N$ it must match everything it matched before, but now it allows to freely exchange noun-phrases, for example instead of *Steve played the guitar brilliantly*, *The guitarist on the left played the guitar brilliantly*.

Note that our grammar "overgenerates" the noun-phrase a bit. For example if $NP \leftarrow Adj\ NP$ and $NP \leftarrow Det\ NP$, then **big black the guitar* would be a valid noun-phrase. Therefore we introduce a new symbol called N', and redefine rules 10 to 13 that describe the NP by the following ones:

$$
\begin{aligned}
NP &\rightarrow N'\\
NP &\rightarrow Det\ N'\\
N' &\rightarrow N'\ P\ NP\\
N' &\rightarrow Adj\ N'\\
N' &\rightarrow N
\end{aligned}
$$

The Verb-Phrase

A closer look at the rules that define the sentence S in our grammar makes another redundancy obvious. It's the pattern $V\ NP$, that we'll call the Verb-Phrase, or VP.

Constituents like *played the guitar brilliantly*, *played*, *is the best* are all VPs.

$$\begin{aligned} S &\rightarrow NP\ VP \\ NP &\rightarrow N' \\ NP &\rightarrow Det\ N' \\ N' &\rightarrow N'\ P\ NP \\ N' &\rightarrow Adj\ N' \\ N' &\rightarrow N \\ VP &\rightarrow V \\ VP &\rightarrow V\ NP \\ VP &\rightarrow VP\ Adv \end{aligned} \tag{22}$$

Again our initial approach overgenerates the VP a little. Recursive application of rule 22 would allow us to stack up adverbs at the end of a VP, as in *[[[[[[played] the guitar] brilliantly] incredibly] suddenly], therefore, just as we did with the NP, we redefine the VP using a new non-terminal V'.

$$\begin{aligned} VP &\rightarrow V' \\ VP &\rightarrow V'\ Adv \\ V' &\rightarrow V\ NP \\ V' &\rightarrow V \end{aligned}$$

3.2.3 Representations for Sentence Structure

When talking about syntactic structures it is convenient to use a representation for the structural aspects of a string of words.

If we have a constituent like *the boy* we might want to express that *the boy* is an NP consisting of a Det and an N, the Det being *the*, the N being *boy*. We might represent that like $[_{NP}\ [_{Det}$ the$][_{N}$ boy$]]$, using brackets, or using the graphical representation, referred to as "syntax tree" that we'll be introducing in the rest of this section.

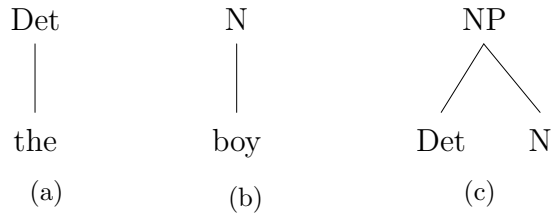


Figure 3.1: Some grammar rules in tree-notation

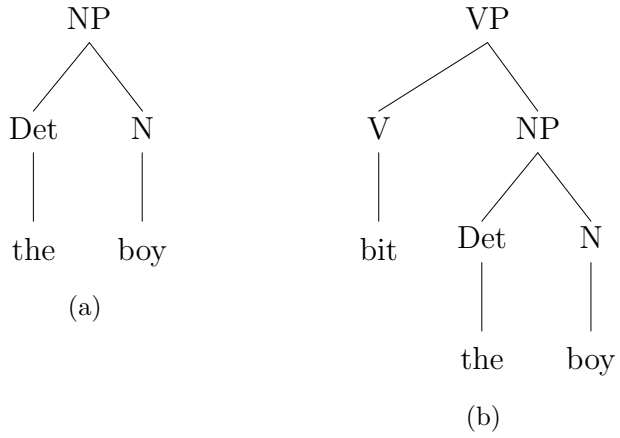


Figure 3.2: Syntax trees

A node in a syntax tree represents a nonterminal symbol, a leaf represents a terminal. A set of symbols connected to the same parent-symbol could be viewed as an alternative representation of a grammar rule. Here the parent node can be seen as the left-hand side of a CFG-rule, and the child nodes are the right-hand side symbols in a left-to-right order.

Figure 3.1 gives some examples. Figure 3.1(a) shows the (rather boring) rule $Det \rightarrow the$, and figure 3.1(b) the rule $N \rightarrow boy$. Rule $NP \rightarrow Det\ N$ can be represented as in figure 3.1(c).

To turn this graphical representation of grammar rules into a tree representing sentence structure we simply make use of recursion in the CFG-formalism, by integrating the subtrees of the used rules. We can for example integrate the rules depicted in figure 3.1 as shown in figure 3.2(a) in order to express something like "The whole thing is an NP. The Det is resolved using the $Det \rightarrow the$-rule, the N is resolved using the $N \rightarrow boy$-rule.".

We can use that approach to further extend our syntax tree to represent the VP *bit the boy*, as shown in figure 3.2(b).

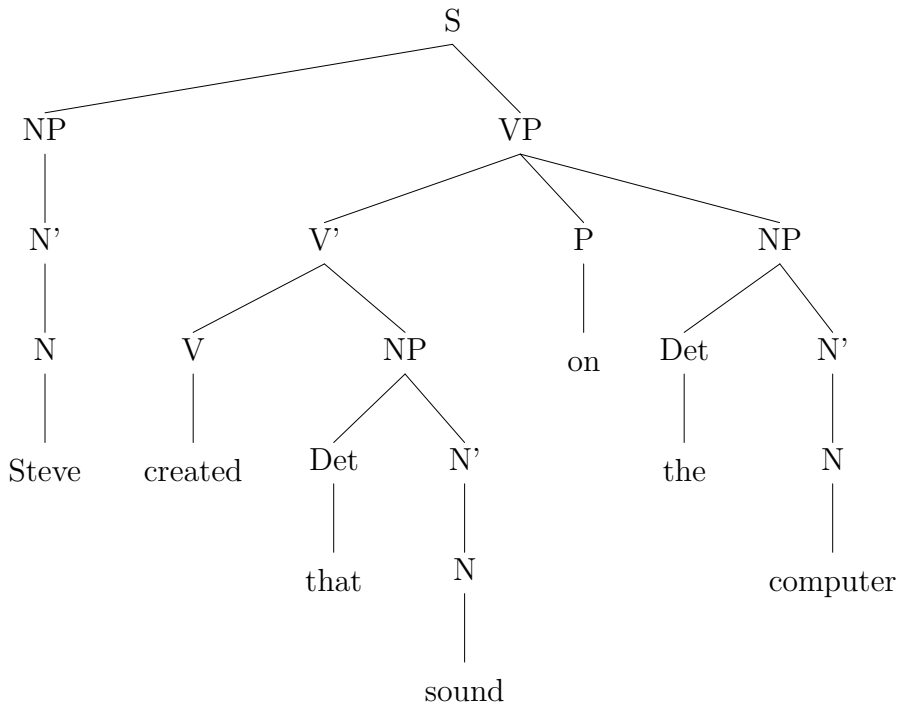


Figure 3.3: A syntax tree for example 3.6

3.2.4 Ambiguity

In the previous sections we have developed a grammar that is far from exhaustive, yet generates a basic portion of the English language.

(3.6) Steve created that sound on the computer.

Considering example 3.6, we find another grammatical phenomenon our grammar doesn't handle. Figure 3.3 shows a syntax tree as a native speaker would draw it. Here *created that sound* is one constituent and *on* is used to further specify it, in our case, to give information about the instrument he used, introducing the NP *the computer*. That constituent could be freely exchanged to give *on his guitar* or *on the piano*.

So far our grammar doesn't allow that, which is why we redefine the VP a little:

$$\begin{aligned} VP &\rightarrow V' \\ VP &\rightarrow V'\ Adv \\ VP &\rightarrow V'\ P\ NP \end{aligned} \tag{27}$$

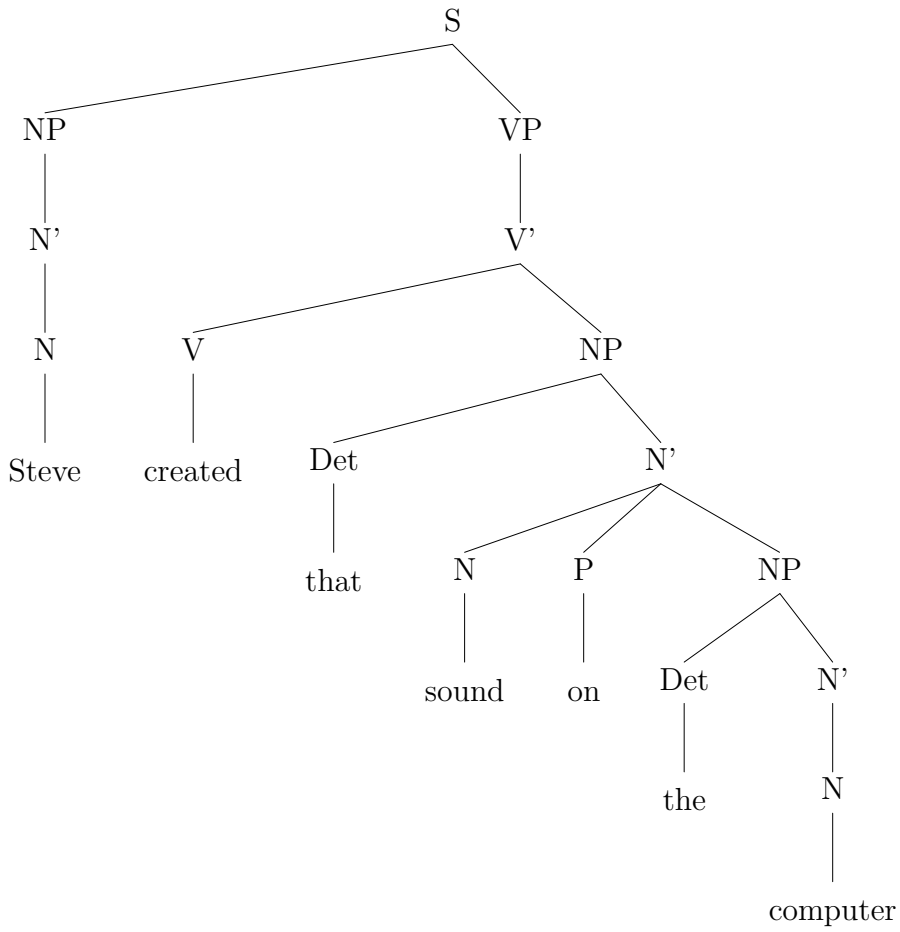


Figure 3.4: Another syntax tree for example 3.6

Rule 27 is new. It allows the grammar to use the subtree of figure 3.3 that handles our new constituent.

After redefining our grammar in such a way our grammar is said to be "ambiguous". This is due to the fact that several parse trees for example 3.6 are derivable from it.

Figure 3.4 gives another, equally possible, parse-tree that can be applied to our example. In this case *that sound on the computer* is one constituent, so *on the computer* doesn't modify *created*, but rather *that sound*, giving information about which sound we are talking about. The phrase *the computer* could in this case be exchanged by other places, where sound can be found, as in *that sound on his new CD* or *that sound on the tape*.

$$
\begin{aligned}
S &\rightarrow NP\ VP \\
NP &\rightarrow N' \\
NP &\rightarrow Det\ N' \\
N' &\rightarrow N'\ P\ NP \\
N' &\rightarrow Adj\ N' \\
N' &\rightarrow N \\
VP &\rightarrow V' \\
VP &\rightarrow V'\ Adv \\
VP &\rightarrow V'\ P\ NP \\
V' &\rightarrow V\ NP \\
V' &\rightarrow V
\end{aligned}
$$

Figure 3.5: Our complete sample-grammar

3.2.5 Specifiers

Although this grammar has the ability to relate the words in accordance with their parts of speech quite well, it completely fails to handle other kinds of features such as number, person, tense, transitivity, etc. It, for example, accepts constituents like **two dog*, **a dogs*, **the dogs die yesterday*, **the dog walk into the room*, etc.

What we need is a way to constrain the application of rules based on features of the terminal-symbols that get abstracted by the non-terminals. The model needs the ability to transitively pass that information and to augment rules with constraints controlling their appliability.

In order to prevent overgeneration of, for example, the NP **a dogs*, we would have to view the form *dogs* as an instance of the class of word-forms for *dog*, distinguished from the singular form *dog* by its number, the form *dog* having the feature NUM=SINGULAR, the form *dogs* having the feature NUM=PLURAL. Then we could augment our grammar with constraints doing simple operations like equality checks. We would, therefore, rewrite a rule like $NP \rightarrow Det\ N$ to something like

$$NP \rightarrow Det\ N$$

Apply this rule only if the Det's NUM*-feature is equal to the N's* NUM*-feature*
the resulting NP would have the same value for NUM *as the Det and the N*

Such a rule would only match noun-phrases if the Det and the N agree in number, and it would produce an NP that also has a NUM-feature that can be

used in further processing. For example, a rule like

$$S \rightarrow NP\ VP$$

Apply this rule only if the NP's NUM*-feature is equal to the VP's* NUM*-feature*

would only match *the dog enters the room*, and *the dogs enter the room*, and not **the dogs enters the room* or **the dog enter the room*, given that the NP *the dog* has the feature NUM=SINGULAR, and the VP *enters the room* has the feature NUM=SINGULAR, while *the dogs* has the feature NUM=PLURAL and *enter the room* NUM=PLURAL, which is exactly what we wanted to achieve.

3.3 Parsing

Thanks to the CFG, it is possible for linguists to provide computer scientists with a detailed description of language and its underlying syntactic structures, in a form adequate for symbolic computation. It serves as a basis for computer-understanding of natural language structure, but makes no statements on what to do with it. It still needs to be interpreted. A computer-program could apply the knowledge it gained from interpreting the CFG to a given input-sentence, and come up with a representation accounting for sentence structure. In this section we will be concerned with this kind of interpretation of a CFG.

It is, of course, possible to directly view a CFG-description of a language as a rule-based program. All one would have to do is rewrite the CFG-rules to a form that is syntactically acceptable for a logic programming language such as PROLOG, and provide some underlying logic to the idea of the CFG to get a program capable of interpreting a CFG. A system like PROLOG would usually use search-trees and unification-based algorithms to handle this, but there are strategies specific to CFGs that are a lot more efficient. We will discuss some of these parsing strategies and their underlying ideas in this section.

3.3.1 Excursion: Backtracking through State-spaces

One of the most basic and most generally appliable algorithms in artificial intelligence is that of backtracking. Backtracking is a search-strategy based on the formalism of the state-space, and it is so generally appliable, because most of the problems that arise in artificial intelligence can easily be formalized in the state-space-paradigm.

A state-space is formalized as (S, F, G) representing a set of possible starting-states S, a set of operations appliable to the states F and a set of desired states, or goals G.

We can make things clearer by considering the example of the *three coins problem* Jackson (1985) uses to illustrate the state-space formalism. Figure 3.6 depicts the start-state: three coins, arranged in such a way, that the first one

Figure 3.6: A tree showing the derivation of *undrinkable*

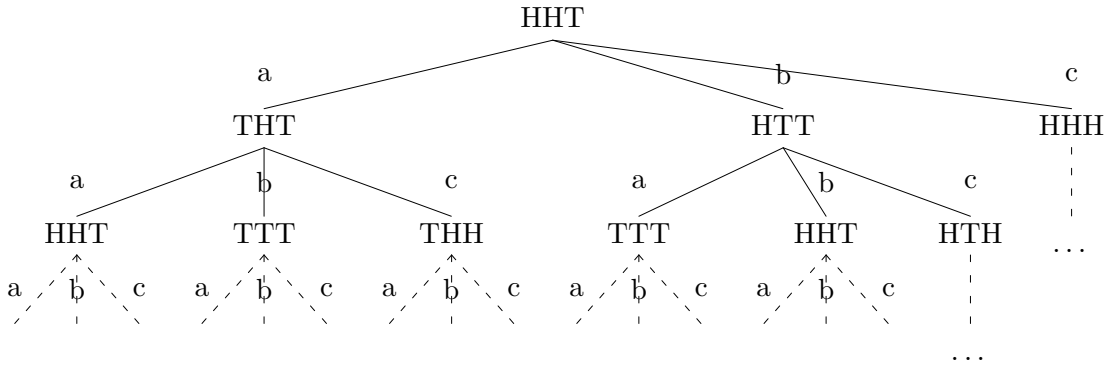


Figure 3.7: A search-tree through the state-space of the *three coins problem*

shows the head, the second one shows the head and the third one shows the tail. We could simplify things by using a special representation for these configurations of coins. The start-state could, for example, be represented as HHT (indicating head-head-tail).

There are three possible actions we can apply to this state:

a. Flip the first coin

b. Flip the second coin

c. Flip the third coin

The problem is this: What do we have to do to make all the coins show the same side? This gives us the desired state, the goal, which is either TTT, or HHH.

Figure 3.7 depicts the state-space graphically. It shows some of the possible states, for example, the start-state in the top node. Each of the arcs connecting this node with its child-nodes represents one action. Each action leads to a new state, a child-node, which can itself be the base for subsequent applications of actions. Note that state-spaces don't neccessarily have to take the form of a tree, but we will consider only this class of state-spaces.

Therefore figure 3.7 is also a graphical representation of the search-tree itself. There can be three procedures involved in finding a solution. One takes care of generating the state-space, one checks the state-space for a solution. A procedure

doing both is called a "search procedure". Usually a computer has to be somewhat selective in generating a state-space, because state-spaces can get very large. This is where a third procedure comes in. It evaluates actions, giving information about their likelihood of containing a solution. A search-procedure making use of such an evaluator, to selectively generate only the most promising parts of a state-space is said to be a "heuristic search".

This is mentioned only for the sake of completeness. We won't make use of any heuristics here, but simply look at the most prominent search-procedure, which is known as backtracking.

Backtracking is simply the depth-first-traversion of a search-tree. Putting it strongly simplified, we can think of backtracking as doing the following:

- Generate the state S_1 the first action (a_1) leads to.
- Is it impossible to create S_1? Then we know that a_1 doesn't lead to a solution.
- Is the S_1 the desired state? Then we know that a_1 leads to a solution.
- Is S_1 not the desired state? Use this algorithm recursively to find out whether S_1 is the top of a subtree that does contain the solution, which would imply that a_1 leads to a solution.
- Does a_1 lead to a solution? Then we can terminate.
- Otherwise: Generate the state S_2 the second action (a_2) leads to.
- Is it impossible to create S_2? ...

Keep in mind that backtracking is one of the simplest, but most prominent, and most widely used search-strategies, but a great variety of other search-strategies have evolved from artificial-intelligence-research. Some are, for example, based on a breadth-first-traversion of a search-tree. It is possible to traverse the tree from the top down or from the bottom up, which is widely known as goal-directed respectively data-directed search. It is even possible to traverse the tree in both directions at the same time. Traversal can be done in parallel, for example by forking a process, or pseudo-parallely, by maintaining a stack, representing a TODO-List containing "states still to be examined", and so on.

Note that the three-coins-problem would turn out to be rather problematic, when solved using backtracking, since it contains "left recursion". It would start by applying a to HHT, generating THT. Since THT is not the desired state it would recursively apply itself to THT, which means that it, again, starts by applying a to this newly created state, leading to HHT. It would then recursively apply itself to HHT, again applying action a, and would therefore never terminate.

3.3.2 Basic Parsing Strategies

We have already pointed out the parallelity between the runtime-structure of a system of logical inference and a parser. Just like a rule-based program, a grammar is a system containing rules and facts (terminal-symbols), and the interpreter is supposed to process a query (start symbol), by systematically applying rules to each other, until a rule matching the query is deduced from the system. (Which is, again, closely related to state-spaces. Just think of the application of a rule as being an action, and the resulting rule with terminals/facts filled in as a state.)

Thinking of parsing, as solving the problem of assigning the correct parse-tree to a given input, there are two ways of formalizing this problem. One could either think of parsing as the problem of expanding a given top-node (usually S) in such a way that it matches the input (then the inital state would be the top-node S, and the goal would be a state, where the terminals match the input), or one could think of parsing as the problem of relating a given input in such a way that it can be shown to be an S (then the initial state would be the input, and the goal would be any state with the top-node S). These two ways of formalizing the problem of parsing give rise to the basic parsing-strategies, known as "top-down" and "bottom-up".

A "top-down"-parser would work its way from the top of the syntax-tree, down, until it discovers a terminal-symbol, either backtracking if the symbol doesn't match, or continuing if it does match the given input-symbol.

The "bottom-up"-strategy would, in contrast, start by examining the input-symbol, and work its way up the syntax-tree, until it finds the start-symbol.

While a top-down parser doesn't waste time in examining structures that will never lead to the start-symbol, the bottom-up-parser doesn't look at structures that will never match the input, which is why the size of the grammar and the length of the input are important considerations in deciding which strategy is best.

3.3.3 Parsing by Problem-Solving

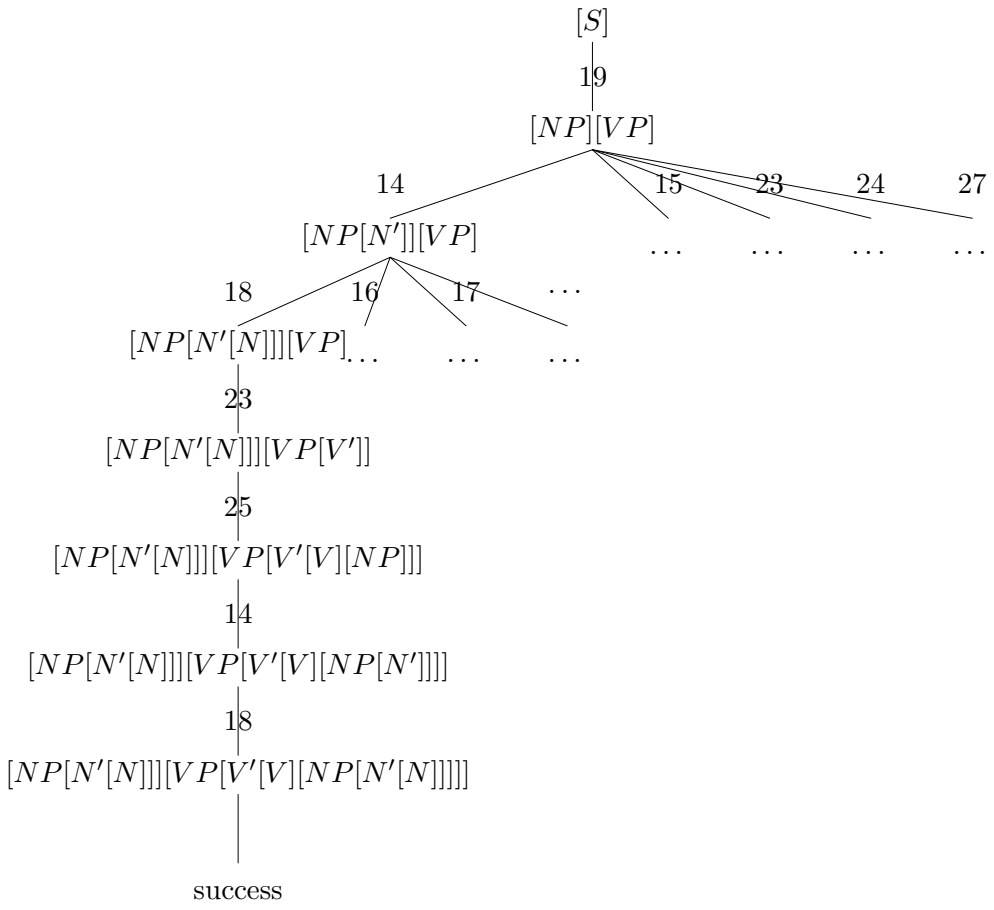
(3.7) Steve plays chess.

A problem-solver can directly be used as a parser. What we have is a state space (S, F, G). States are partial parse-trees. We could represent the initial state by something like $[S]$, when we do a top-down parse. Each of the rules in the grammar is then an action.

We will consider example 3.7, using the grammar given in figure 3.5.

Figure 3.8 shows a state-space (which is, again, also a search-tree). The first nodes are depicted in full detail, the others are left out, due to limitations in space, but the principle should get clear anyway.

Each of the rules in the sample-grammar is an action. There is one action, appliable to the state $[S]$, which is the rule $S \rightarrow NP\ VP$, because it is the only



$$
\begin{aligned}
S &\rightarrow NP\ VP \\
NP &\rightarrow N' \\
NP &\rightarrow Det\ N' \\
N' &\rightarrow N'\ P\ NP \\
N' &\rightarrow Adj\ N' \\
N' &\rightarrow N \\
VP &\rightarrow V' \\
VP &\rightarrow V'\ Adv \\
VP &\rightarrow V'\ P\ NP \\
V' &\rightarrow V\ NP \\
V' &\rightarrow V
\end{aligned}
$$

Figure 3.8: A search-tree through the state-space of a parsing-problem

one expanding the symbol we are looking for. By applying this action, we deduce the new state $[NP][VP]$. Now we can apply all the actions expanding either NP or VP, namely rules 14, 15, 23, 24 and 27. In the figure only the path to the goal is shown, but our parser usually has no way of telling which one is "right". It might as well try, for example, rule 15 first. Applying rule 14, which is $NP \rightarrow N'$ to the state $[NP][VP]$ creates the state $[NP[N']][VP]$. This time all rules expanding either N' or VP are appliable, and so fort. We can go on like this till we discover a state consisting only of terminals. If these terminals match the input, the state is a goal-state, if not, we use backtracking to try out another path through the state-space that might lead to the goal-state.

The backtracking-approach, in general, suffers from vast ineffectivity in parsing because it runs in exponential-time, spending most of it examining fruitless subtrees and reexamining the same fruitless subtrees over and over. Although it is possible to improve these algorithms somewhat by adding "bottom-up-filtering" to a top-down parser respectively "top-down-filtering" to a "bottom-up-parser" or heuristic methods, the major disadvantage of ineffectivity, when using exponential-time problem-solvers like backtracking, remains the same.

3.3.4 The Earley Algorithm

A great way to improve efficiency of exponential-time algorithms comes from a framework called "dynamic programming", and is sometimes referred to as "memoization".

If we apply this technique to the basic idea of a top-down parser with bottom-up filtering, we get an algorithm similar to that of Earley (1970), which we'll describe in greater detail in this section.

The Earley-Algorithm avoids reexecuting computations done in the course of parsing an input, by "remembering" subproblems and their solutions in the so-called "chart". That's why approaches similar to Earley's are often referred to as "chart-parsers".

The chart can be seen as the algorithm's "agenda". While executing it, it appends new items to this "agenda", therefore dynamically manipulating its runtime-structure. When finished, the chart contains all subproblems and their solutions, and the solution to the whole problem. Figure 3.9 shows such a chart.

This data-structure contains a set of states. A state represents a rule applied for a particular set of symbols at a specific point in the progress of proving it to be appliable to these input symbols. This can be achieved by simply inserting a symbolic "•" at some position in the rule, indicating that everything to the left of the • has already been read, and everything to the right still has to be read, and remembering two positions in the input, one giving information about where the state begins, and one giving information about where the • from this rule, can be found.

chart[0]

[0]	$\lambda \rightarrow \bullet S$	[0, 0, 0]
[1]	$S \rightarrow \bullet NP\ VP$	[0, 0, 0]
[2]	$NP \rightarrow \bullet N'$	[0, 0, 0]
[3]	$NP \rightarrow \bullet Det\ N'$	[0, 0, 0]
[4]	$N' \rightarrow \bullet N'\ P\ NP$	[0, 0, 0]
[5]	$N' \rightarrow \bullet Adj\ N'$	[0, 0, 0]
[6]	$N' \rightarrow \bullet N$	[0, 0, 0]

chart[1]

[0]	$N \rightarrow steve\bullet$	[0, 1, 1]
[1]	$N' \rightarrow N\bullet$	[0, 1, 1]
[2]	$NP \rightarrow N'\bullet$	[0, 1, 1]
[3]	$N' \rightarrow N'\bullet\ P\ NP$	[0, 1, 1]
[4]	$S \rightarrow NP \bullet VP$	[0, 1, 1]
[5]	$VP \rightarrow \bullet V'$	[1, 1, 0]
[6]	$VP \rightarrow \bullet V'\ Adv$	[1, 1, 0]
[7]	$VP \rightarrow \bullet V'\ P\ NP$	[1, 1, 0]
[8]	$V' \rightarrow \bullet V$	[1, 1, 0]
[9]	$V' \rightarrow \bullet V\ NP$	[1, 1, 0]

chart[2]

[0]	$V \rightarrow created\bullet$	[1, 2, 1]
[1]	$V' \rightarrow V\bullet$	[1, 2, 1]
[2]	$V' \rightarrow V \bullet NP$	[1, 2, 1]
[3]	$VP \rightarrow V'\bullet$	[1, 2, 1]
[4]	$VP \rightarrow V'\bullet\ Adv$	[1, 2, 1]
[5]	$VP \rightarrow V'\bullet\ P\ NP$	[1, 2, 1]
[6]	$NP \rightarrow \bullet N'$	[2, 2, 0]
[7]	$NP \rightarrow \bullet Det\ N'$	[2, 2, 0]
[8]	$S \rightarrow NP\ VP\bullet$	[0, 2, 2]
[9]	$N' \rightarrow \bullet N'\ P\ NP$	[2, 2, 0]
[10]	$N' \rightarrow \bullet Adj\ N'$	[2, 2, 0]
[11]	$N' \rightarrow \bullet N$	[2, 2, 0]
[12]	$\lambda \rightarrow S\bullet$	[0, 2, 1]

chart[3]

[0]	$Det \rightarrow that\bullet$	[2, 3, 1]
[1]	$NP \rightarrow Det\ N'\bullet$	[2, 3, 1]
[2]	$N' \rightarrow \bullet N'\ P\ NP$	[3, 3, 0]
[3]	$N' \rightarrow \bullet Adj\ N'$	[3, 3, 0]
[4]	$N' \rightarrow \bullet N$	[3, 3, 0]

chart[4]

[0]	$N \rightarrow sound\bullet$	[3, 4, 1]
[1]	$N' \rightarrow N\bullet$	[3, 4, 1]
[2]	$NP \rightarrow Det\ N'\bullet$	[2, 4, 2]
[3]	$N' \rightarrow N'\bullet\ P\ NP$	[3, 4, 1]
[4]	$V' \rightarrow V\ NP\bullet$	[1, 4, 2]
[5]	$VP \rightarrow V'\bullet$	[1, 4, 1]
[6]	$VP \rightarrow V'\bullet\ Adv$	[1, 4, 1]
[7]	$VP \rightarrow V'\bullet\ P\ NP$	[1, 4, 1]
[8]	$S \rightarrow NP\ VP\bullet$	[0, 4, 2]
[9]	$\lambda \rightarrow S\bullet$	[0, 4, 1]

chart[5]

[0]	$P \rightarrow on\bullet$	[4, 5, 1]
[1]	$N' \rightarrow N'\ P\bullet\ NP$	[3, 5, 2]
[2]	$VP \rightarrow V'\ P\bullet\ NP$	[1, 5, 2]
[3]	$NP \rightarrow \bullet N'$	[5, 5, 0]
[4]	$NP \rightarrow \bullet Det\ N'$	[5, 5, 0]
[5]	$N' \rightarrow \bullet N'\ P\ NP$	[5, 5, 0]
[6]	$N' \rightarrow \bullet Adj\ N'$	[5, 5, 0]
[7]	$N' \rightarrow \bullet N$	[5, 5, 0]

chart[6]

[0]	$Det \rightarrow the\bullet$	[5, 6, 1]
[1]	$NP \rightarrow Det\bullet\ N'$	[5, 6, 1]
[2]	$N' \rightarrow \bullet N'\ P\ NP$	[6, 6, 0]
[3]	$N' \rightarrow \bullet Adj\ N'$	[6, 6, 0]
[4]	$N' \rightarrow \bullet N$	[6, 6, 0]

chart[7]

[0]	$N \rightarrow computer\bullet$	[6, 7, 1]
[1]	$N' \rightarrow N\bullet$	[6, 7, 1]
[2]	$NP \rightarrow Det\ N'\bullet$	[5, 7, 2]
[3]	$N' \rightarrow N'\bullet\ P\ NP$	[6, 7, 1]
[4]	$N' \rightarrow N'\ P\ NP\bullet$	[3, 7, 3]
[5]	$VP \rightarrow V'\ P\ NP\bullet$	[1, 7, 3]
[6]	$NP \rightarrow Det\ N'\bullet$	[2, 7, 2]
[7]	$N' \rightarrow N'\bullet\ P\ NP$	[3, 7, 1]
[8]	$S \rightarrow NP\ VP\bullet$	[0, 7, 2]
[9]	$V' \rightarrow V\ NP\bullet$	[1, 7, 2]
[10]	$\lambda \rightarrow S\bullet$	[0, 7, 1]
[11]	$VP \rightarrow V'\bullet$	[1, 7, 1]
[12]	$VP \rightarrow V'\bullet\ Adv$	[1, 7, 1]
[13]	$VP \rightarrow V'\bullet\ P\ NP$	[1, 7, 1]

Figure 3.9: A chart for a run of our Earley parser against example 3.6

Let's have a look at some examples. Figure 3.9 was created by an Earley-Parser using our sample-grammar, and parsing example 3.6, that is repeated here as example 3.8, with a numbered set of bullets added.

(3.8) $\bullet_0$ Steve $\bullet_1$ created $\bullet_2$ that $\bullet_3$ sound $\bullet_4$ on $\bullet_5$ the $\bullet_6$ computer $\bullet_7$

Let's have a closer look at the state from figure 3.9, with the number [1] in *chart*[5], repeated here.

$$N' \rightarrow N'\ P \bullet NP[3,5]$$

In this state the parser tries to prove the rule $N' \rightarrow N'\ P\ NP$ to be appliable to the input, beginning at $\bullet_3$. The $\bullet$ can be found in the input-stream as $\bullet_5$, and given that it's right of $N'\ P$, and left of NP, it means that an N' and the P have already been recognized, and the NP still has to be read.

For each state in the chart, the Earley-Algorithm applies one of three operations known as PREDICTOR, SCANNER and COMPLETER, each of which add new states to the current or next chart. A state that is already in the chart is never added a second time, even if the operation would normally do so. This is how data- and runtime-structure effectively avoid redundancy.

The Predictor is applied to each rule that still has non-terminals immediately to the right of the $\bullet$, that is, to each state that still has to prove a new non-terminal to appear next. In order to do so the PREDICTOR adds new states to the chart, "expanding" the non-terminal-symbol in question by the rules replacing this particular symbol, therefore running in a "top-down"-manner.

Let's again consider an example. The initial state of the parser is the "artificial" state

$$\lambda \rightarrow \bullet S[0,0]$$

the chart is initialized with. When the algorithm comes across this state it finds the non-terminal S to the right of the dot. There is one rule expanding S, namely $S \rightarrow NP\ VP$, therefore the PREDICTOR would add the new state $S \rightarrow \bullet NP\ VP[0,0]$ to the chart. Next the PREDICTOR comes across this newly created state, finding the non-terminal NP to the right of the $\bullet$. There are two rules that expand the NP, namely $NP \rightarrow N'$ and $NP \rightarrow Det\ N'$, therefore the PREDICTOR creates two new states, $NP \rightarrow \bullet N'[0,0]$ and $NP \rightarrow \bullet Det\ N'[0,0]$, and so on.

The Scanner is, as the name suggests, used to advance a state by scanning the input. Let's look at the operation of the SCANNER, by considering the state

$$N' \rightarrow N' \bullet P\ NP[3,4]$$

that can be found in the figure 3.9 in *chart*[4] at position [3]. In this state the $\bullet$ is to the left of the P, therefore the parser has to prove a symbol of category P to appear next in the input. Now it's the SCANNER's job to look at the input, and verify whether the next input-symbol is a P or not. In the input, the signal to the right of $\bullet_4$ is "on", so the SCANNER adds the new rule $P \rightarrow on \bullet [4, 5]$ to the next chart. When the parser proceeds to the next word, the COMPLETER takes care of proceeding the $\bullet$ in state $N' \rightarrow N' \bullet P\ NP[3, 4]$ to give $N' \rightarrow N'\ P \bullet NP[3, 5]$.

The Completer is called for a state which is "complete". A state is considered complete, when the $\bullet$ is at the far right of the rule. In the last paragraph we added the state $P \rightarrow on \bullet [4, 5]$. Therefore, any state "looking" for a P in the input at $\bullet_4$, can be advanced, which means the $\bullet$ can be moved from the left of a P to the right.

The COMPLETER, coming across $P \rightarrow on \bullet [4, 5]$ in *chart*[5] would, therefore, look through all the states in *chart*[4]. When it finds, for example, $N' \rightarrow N' \bullet P\ NP[3, 4]$ in *chart*[4], it advances the $\bullet$, and adds the new state $N' \rightarrow N'\ P \bullet NP[3, 5]$ to *chart*[5].

An Example-Run

Because a fundamental understanding of the Earley-algorithm is vital to this project, we will not introduce any new concepts in this section, but dedicate it to revise what we've heard about the Earley-algorithm so far, by following an Earley-parser all the way through a parse.

(3.9) Steve plays chess.

The chart in figure 3.10 represents a run of an Earley-parser, parsing example 3.9 with a simplified version of our grammar.

The first state ($\lambda \rightarrow \bullet S[0, 0]$) is added as an initialization-value for the chart, and is handled just like any other state. Since it has a non-terminal to the right of the $\bullet$, the PREDICTOR is called to handle that state. The PREDICTOR finds the symbol S to the right of the $\bullet$, and looks up all the rules in the grammar that have the form $S \rightarrow \ldots$ and adds them to the current chart (which is *chart*[0]). In this case, there is only one rule of that form in the grammar, which is $S \rightarrow NP\ VP$. Therefore the state $S \rightarrow \bullet NP\ VP[0, 0]$ is added to the chart. Whenever a grammar-rule is newly added to the chart by the PREDICTOR its $\bullet$ is on the far left (since we haven't read any symbols for this rule so far), which is why its rule-position must match its global position. The global position itself is always carried over from the original state the PREDICTOR was called for (which is $\lambda \rightarrow \bullet S[0, 0]$ in our case), to ensure that when "working off" the new state, the parser looks for the symbols at the same position in the input where the original state would have expected them.

chart[0]

[0]	$\lambda \rightarrow \bullet S$	[0, 0, 0]
[1]	$S \rightarrow \bullet NP\ VP$	[0, 0, 0]
[2]	$NP \rightarrow \bullet Det\ N$	[0, 0, 0]
[3]	$NP \rightarrow \bullet N$	[0, 0, 0]

chart[1]

[0]	$N \rightarrow steve\bullet$	[0, 1, 1]
[1]	$NP \rightarrow N\bullet$	[0, 1, 1]
[2]	$S \rightarrow NP \bullet VP$	[0, 1, 1]
[3]	$VP \rightarrow \bullet VNP$	[1, 1, 0]

chart[2]

[0]	$V \rightarrow plays\bullet$	[1, 2, 1]
[1]	$VP \rightarrow V \bullet NP$	[1, 2, 1]
[2]	$NP \rightarrow \bullet Det\ N$	[2, 2, 0]
[3]	$NP \rightarrow \bullet N$	[2, 2, 0]

chart[3]

[0]	$N \rightarrow chess\bullet$	[2, 3, 1]
[1]	$NP \rightarrow N\bullet$	[2, 3, 1]
[2]	$VP \rightarrow V\ NP\bullet$	[1, 3, 2]
[3]	$S \rightarrow NP\ VP\bullet$	[0, 3, 2]
[4]	$\lambda \rightarrow S\bullet$	[0, 3, 1]

Figure 3.10: A chart for a run of our Earley parser on example 3.9

Working off the agenda, our parser now finds the state $S \rightarrow \bullet NP\ VP[0,0]$ we just added and interprets it in exactly the same way by calling the PREDICTOR, since the symbol to the right of the $\bullet$ is NP, which is a non-terminal. The PREDICTOR looks up all the rules in the grammar that have the form $NP \rightarrow \ldots$. In our grammar there are two such rules: $NP \rightarrow Det\ N$ and $NP \rightarrow N$, which is why the two states $NP \rightarrow \bullet Det\ N[0,0]$ and $NP \rightarrow \bullet N[0,0]$ are added.

Now the parser finds the state $NP \rightarrow \bullet Det\ N[0,0]$ that was just added. This time the symbol to the right of the bullet is Det, which is a terminal. That's why we call the SCANNER now, instead of the PREDICTOR. Instead of looking up a rule in the grammar, the SCANNER looks up the word in the input. In our case it would look for a Det appearing in the input to the right of $\bullet_0$ (or, to put it simply, the first word). The first word is *Steve*, and *Steve* can under no circumstances be a Det. That's why the SCANNER doesn't add any states.

The next state the parser considers is $NP \rightarrow \bullet N[0,0]$. Again, the SCANNER is called, but this time the input (*Steve*) does match the terminal to the right of the $\bullet$ (N), which is why the state $N \rightarrow steve \bullet [0,1]$ gets added to the *next* chart (which is $chart[1]$). The rule-position is still 0, because we, or merely the rule in the state, are still talking about the first word in the input. The rule $N \rightarrow steve$ has been proven to be appliable for the first word in the input. The $\bullet$ is now to the right of *steve*, since we have already read *steve*. Of course, this increases the global position, since the $\bullet$ from the state $N \rightarrow steve \bullet [0,1]$ now corresponds to $\bullet_1$ from the input, and not to $\bullet_0$.

Since there is no further rule in the current chart ($chart[0]$), the parser can now move on to the next chart ($chart[1]$). The first state it finds there is the state $N \rightarrow steve \bullet [0,1]$, that was just added by the SCANNER. This state is said to be *complete*, since there is no further symbol to the right of the $\bullet$, which is why the COMPLETER is called to handle this state. The COMPLETER now does the job of looking through the old states to see if any of the states were looking for the symbol we just found in the input, so it looks through the states in $chart[0]$. The symbol we just found in the input is the lefthand-side of the state we were called for ($N \rightarrow steve \bullet [0,1]$) which is N, so it is interested in all the states of the form $? \rightarrow \ldots \bullet N \ldots$ in that chart the rule-position of the complete state points to. (In our case the rule-position is 0, so it looks in $chart[0]$.) There is only one such state in $chart[0]$, which is $NP \rightarrow \bullet N[0,0]$. This state is now "advanced", which is simply the process of moving the $\bullet$ from the lefthand-side of the symbol over to the righthand-side, therefore our COMPLETER would use the state $NP \rightarrow \bullet N[0,0]$ from $chart[0]$, and advance it by adding the state $NP \rightarrow N \bullet [0,1]$ to $chart[1]$ according to the state it was called for ($N \rightarrow steve \bullet [0,1]$).

Again, the parser can move on in the agenda. This time it finds the state $NP \rightarrow N \bullet [0,1]$ we just added. This is, again, a complete state (there is no further symbol to the right of the $\bullet$), which is why the COMPLETER is called to handle this state, which goes through the same procedure of searching $chart[0]$ for states looking for an NP to be advanced. There is one such state, which is

$S \rightarrow \bullet NP\ VP[0,0]$, so the COMPLETER adds the state $S \rightarrow NP \bullet VP[0,1]$.

Now our parser is confronted with the state $S \rightarrow NP \bullet VP[0,1]$, which has a non-terminal (VP) to the right of the $\bullet$, so the PREDICTOR is called, to add states from the grammar, that have the form $VP \rightarrow \ldots$. In the grammar there is one such rule, namely $VP \rightarrow V\ NP$, so the rule $VP \rightarrow \bullet V\ NP[1,1]$ is added (recall that the bullet for predicted states is always at the far left, and the rule-position as well as the global position are initialized to the original state's global position).

When handling state $VP \rightarrow \bullet V\ NP[1,1]$, the parser calls the SCANNER to scan for a V, appearing in the input at $\bullet_1$. The SCANNER is, in this case, successful in doing so, since the second word is *plays*. Therefore it adds a new complete state, regarding that V, so the COMPLETER takes care of advancing $VP \rightarrow \bullet V\ NP[1,1]$ to give $VP \rightarrow V \bullet NP[1,2]$.

This state is then handled by the PREDICTOR which adds the states $NP \rightarrow \bullet Det\ N[2,2]$ and $NP \rightarrow \bullet N[2,2]$, both of which are handled by the SCANNER, which fails for the first one, and succeeds for the second one, because the word it finds at $\bullet_2$, *chess* is a N, and can't be a *Det*. That's how state $N \rightarrow chess \bullet [2,3]$ enters $chart[3]$. It's used by the COMPLETER to advance state $NP \rightarrow \bullet N[2,2]$, which is why it adds state $NP \rightarrow N \bullet [2,3]$. This state itself is complete and therefore, once again, the COMPLETER is called, this time to advance state $VP \rightarrow V \bullet NP[1,2]$ to give $VP \rightarrow V\ NP \bullet [1,3]$, again a complete state, used by the COMPLETER to advance state $S \rightarrow NP \bullet VP[0,1]$ to give $S \rightarrow NP\ VP \bullet [0,3]$.

This can then be used to complete the initial state $\lambda \rightarrow \bullet S[0,0]$ to give $\lambda \rightarrow S \bullet [0,3]$, which is the end of our odyssee through the chart shown in figure 3.10.

Building the Parse-Forest

Actually, the algorithm we just showed is not a parser, but rather, a recognizer. It is a way of telling whether a given input is grammatical, but there's no way to retrieve a parse-tree from the chart, shown in figure 3.9. When the algorithm terminates, it can search the last chart for a state like $\lambda \rightarrow S\bullet$. If there is no such state, the input does not match, if there is one, it does match the input.

In figure 3.11 we showed how a chart of an Earley-parser could look, in contrast to the chart of an Earley-recognizer. We have added a column containing the pointers that make up the so-called parse-forest. Recalling that natural-language grammars are ambiguous, we need a representation dealing with a whole set of possible parse-trees, rather than a single one. Such a set of parse-trees is sometimes referred to as a parse-forest.

Let's start our examination of these pointers with the state $\lambda \rightarrow S\bullet$, that represents the successfully parsed input. The pointer we added, (7, 8), points to the state numbered [8] in $chart[7]$, which is $S \rightarrow NP\ VP\bullet$. This could be read as, "This S was successfully parsed because $S \rightarrow NP\ VP\bullet$". This state, again,

chart[0]

[0]	$\lambda \rightarrow \bullet S$	[0, 0, 0]	[]
[1]	$S \rightarrow \bullet NP\ VP$	[0, 0, 0]	[]
[2]	$NP \rightarrow \bullet N'$	[0, 0, 0]	[]
[3]	$NP \rightarrow \bullet Det\ N'$	[0, 0, 0]	[]
[4]	$N' \rightarrow \bullet N'\ P\ NP$	[0, 0, 0]	[]
[5]	$N' \rightarrow \bullet Adj\ N'$	[0, 0, 0]	[]
[6]	$N' \rightarrow \bullet N$	[0, 0, 0]	[]

chart[1]

[0]	$N \rightarrow steve\bullet$	[0, 1, 1]	[]
[1]	$N' \rightarrow N\bullet$	[0, 1, 1]	[[(1, 0)]]
[2]	$NP \rightarrow N'\bullet$	[0, 1, 1]	[[(1, 1)]]
[3]	$N' \rightarrow N' \bullet P\ NP$	[0, 1, 1]	[[(1, 1)]]
[4]	$S \rightarrow NP \bullet VP$	[0, 1, 1]	[[(1, 2)]]
[5]	$VP \rightarrow \bullet V'$	[1, 1, 0]	[]
[6]	$VP \rightarrow \bullet V'\ Adv$	[1, 1, 0]	[]
[7]	$VP \rightarrow \bullet V'\ P\ NP$	[1, 1, 0]	[]
[8]	$V' \rightarrow \bullet V$	[1, 1, 0]	[]
[9]	$V' \rightarrow \bullet V\ NP$	[1, 1, 0]	[]

chart[2]

[0]	$V \rightarrow created\bullet$	[1, 2, 1]	[]
[1]	$V' \rightarrow V\bullet$	[1, 2, 1]	[[(2, 0)]]
[2]	$V' \rightarrow V \bullet NP$	[1, 2, 1]	[[(2, 0)]]
[3]	$VP \rightarrow V'\bullet$	[1, 2, 1]	[[(2, 1)]]
[4]	$VP \rightarrow V' \bullet Adv$	[1, 2, 1]	[[(2, 1)]]
[5]	$VP \rightarrow V' \bullet P\ NP$	[1, 2, 1]	[[(2, 1)]]
[6]	$NP \rightarrow \bullet N'$	[2, 2, 0]	[]
[7]	$NP \rightarrow \bullet Det\ N'$	[2, 2, 0]	[]
[8]	$S \rightarrow NP\ VP\bullet$	[0, 2, 2]	[[(1, 2)], [(2, 3)]]
[9]	$N' \rightarrow \bullet N'\ P\ NP$	[2, 2, 0]	[]
[10]	$N' \rightarrow \bullet Adj\ N'$	[2, 2, 0]	[]
[11]	$N' \rightarrow \bullet N$	[2, 2, 0]	[]
[12]	$\lambda \rightarrow S\bullet$	[0, 2, 1]	[[(2, 8)]]

chart[3]

[0]	$Det \rightarrow that\bullet$	[2, 3, 1]	[]
[1]	$NP \rightarrow Det\ N'\bullet$	[2, 3, 1]	[[(3, 0)]]
[2]	$N' \rightarrow \bullet N'\ P\ NP$	[3, 3, 0]	[]
[3]	$N' \rightarrow \bullet Adj\ N'$	[3, 3, 0]	[]
[4]	$N' \rightarrow \bullet N$	[3, 3, 0]	[]

chart[4]

[0]	$N \rightarrow sound\bullet$	[3, 4, 1]	[]
[1]	$N' \rightarrow N\bullet$	[3, 4, 1]	[[(4, 0)]]
[2]	$NP \rightarrow Det\ N'\bullet$	[2, 4, 2]	[[(3, 0)], [(4, 1)]]
[3]	$N' \rightarrow N' \bullet P\ NP$	[3, 4, 1]	[[(4, 1)]]
[4]	$V' \rightarrow V\ NP\bullet$	[1, 4, 2]	[[(2, 0)], [(4, 2)]]
[5]	$VP \rightarrow V'\bullet$	[1, 4, 1]	[[(4, 4)]]
[6]	$VP \rightarrow V' \bullet Adv$	[1, 4, 1]	[[(4, 4)]]
[7]	$VP \rightarrow V' \bullet P\ NP$	[1, 4, 1]	[[(4, 4)]]
[8]	$S \rightarrow NP\ VP\bullet$	[0, 4, 2]	[[(1, 2)], [(4, 5)]]
[9]	$\lambda \rightarrow S\bullet$	[0, 4, 1]	[[(4, 8)]]

chart[5]

[0]	$P \rightarrow on\bullet$	[4, 5, 1]	[]
[1]	$N' \rightarrow N'\ P \bullet NP$	[3, 5, 2]	[[(4, 1)], [(5, 0)]]
[2]	$VP \rightarrow V'\ P \bullet NP$	[1, 5, 2]	[[(4, 4)], [(5, 0)]]
[3]	$NP \rightarrow \bullet N'$	[5, 5, 0]	[]
[4]	$NP \rightarrow \bullet Det\ N'$	[5, 5, 0]	[]
[5]	$N' \rightarrow \bullet N'\ P\ NP$	[5, 5, 0]	[]
[6]	$N' \rightarrow \bullet Adj\ N'$	[5, 5, 0]	[]
[7]	$N' \rightarrow \bullet N$	[5, 5, 0]	[]

chart[6]

[0]	$Det \rightarrow the\bullet$	[5, 6, 1]	[]
[1]	$NP \rightarrow Det \bullet N'$	[5, 6, 1]	[[(6, 0)]]
[2]	$N' \rightarrow \bullet N'\ P\ NP$	[6, 6, 0]	[]
[3]	$N' \rightarrow \bullet Adj\ N'$	[6, 6, 0]	[]
[4]	$N' \rightarrow \bullet N$	[6, 6, 0]	[]

chart[7]

[0]	$N \rightarrow computer\bullet$	[6, 7, 1]	[]
[1]	$N' \rightarrow N\bullet$	[6, 7, 1]	[[(7, 0)]]
[2]	$NP \rightarrow Det\ N'\bullet$	[5, 7, 2]	[[(6, 0)], [(7, 1)]]
[3]	$N' \rightarrow N' \bullet P\ NP$	[6, 7, 1]	[[(7, 1)]]
[4]	$N' \rightarrow N'\ P\ NP\bullet$	[3, 7, 3]	[[(4, 1)], [(5, 0)], [(7, 2)]]
[5]	$VP \rightarrow V'\ P\ NP\bullet$	[1, 7, 3]	[[(4, 4)], [(5, 0)], [(7, 2)]]
[6]	$NP \rightarrow Det\ N'\bullet$	[2, 7, 2]	[[(3, 0)], [(7, 4)]]
[7]	$N' \rightarrow N' \bullet P\ NP$	[3, 7, 1]	[[(7, 4)]]
[8]	$S \rightarrow NP\ VP\bullet$	[0, 7, 2]	[[(1, 2)], [(7, 5), (7, 11)]]
[9]	$V' \rightarrow V\ NP\bullet$	[1, 7, 2]	[[(2, 0)], [(7, 6)]]
[10]	$\lambda \rightarrow S\bullet$	[0, 7, 1]	[[(7, 8)]]
[11]	$VP \rightarrow V'\bullet$	[1, 7, 1]	[[(7, 9)]]
[12]	$VP \rightarrow V' \bullet Adv$	[1, 7, 1]	[[(7, 9)]]
[13]	$VP \rightarrow V' \bullet P\ NP$	[1, 7, 1]	[[(7, 9)]]

Figure 3.11: A chart for a run of our Earley parser against example 3.6, this time with the parse-forest

is augmented with the pointer

$$[[(1,2)],[(7,5),(7,11)]]$$

which demonstrates the full complexity of this data-structure. The array of arrays has to be read in the same order as the rule. Therefore $[(1,2)]$ is related to the NP, and $[(7,5),(7,11)]$ is related to the VP, meaning the NP is the one expanded in state [2] in *chart*[1], and the VP could either be the one from state [5] or [11] in *chart*[7].

This parse-forest can be easily built by augmenting the COMPLETER a bit. Every time the COMPLETER advances a rule by "applying" a complete state, it adds a pointer to the "applying" state (the incomplete one, the one that needs to be advanced), pointing to the "applied" one (the complete state), corresponding to the position of the • in the rule. This would leave the chart with pointers that can easily be traversed using standard tree-handling algorithms.

A more detailled description of an actual implementaion of an Earley-parser is presented in the second part of this paper.

3.4 Feature Structures

In the previous section we already mentioned specifiers from a linguistic point of view. Feature structures are a computational model linguistic specifiers are traditionally implemented with.

We mentioned that terminal-symbols, in our case morphological items, have a set of specifiers associated with them, and that it should be possible that these specifiers constrain the appliability of certain rules.

In the first chapter we showed how a word-form like "doggies" goes through the morphological analyzer, that sets some "global flags", as we called them, like, ROOTFORM=DOG, NUM=PLURAL, BABYTALK=TRUE. Such a morphological item could be returned by the morphological analyzer using a feature-structure that, when denoted as an attribute-value matrix, AVM for short, looks like

$$\mathit{doggies}\begin{bmatrix}\text{CATEG} & N\\ \text{ROOTFORM} & dog\\ \text{NUM} & plural\\ \text{BABYTALK} & true\end{bmatrix}$$

This is simply a way of encoding a set of feature-value pairs. The value of each feature can either be atomic or another feature structure. Let's consider an example that is a little bit more complex.

$$\mathit{swims}\begin{bmatrix}\text{CATEG} & V\\ \text{ROOTFORM} & swim\\ \text{TRANS} & intrans\\ \text{AGREEMENT} & \begin{bmatrix}\text{NUMBER} & SG\\ \text{PERSON} & 3\end{bmatrix}\end{bmatrix}$$

This example shows the feature AGREEMENT that takes another feature structure as its value. This hierachical organization of feature structures doesn't only allow to logically group subsets of related features together, and easily access them, it also makes it possible to build more complex data-structures like lists or trees, to encode not only lexical items, but all data-structures that arise in NLP, including rules and complete parse-forests.

Although practical systems are often built in a way, that the only data-structure they need to deal with is the feature-structure, encoding rules and even complete parse-forests as feature structures, we will describe the basic idea using the simplified approach given in Jurafsky & Martin (2000), to avoid going into too much detail. The interested reader is referred to Copestake (2002) for a description of implementing so-called "typed feature structure grammars". This book also puts a strong emphasis on how they are used in the LKB-system (the system for grammar-engineering distributed by Stanford's LinGO-initiative).

In our simplified approach we will augment a "normal" CFG with a feature structure, that constrains its use. The rule $NP \rightarrow Det\ N$ serves as a good example. Say we wanted to augment this rule, so it accepts *this dog*, and it rejects **these dog*.

Let's first consider the feature structures for these words.

$$_{dog}\begin{bmatrix}\text{CATEG} & N\\ \text{ROOTFORM} & dog\\ \text{NUM} & SG\end{bmatrix} \qquad _{these}\begin{bmatrix}\text{CATEG} & Det\\ \text{ROOTFORM} & this\\ \text{NUM} & PL\end{bmatrix} \qquad _{this}\begin{bmatrix}\text{CATEG} & Det\\ \text{ROOTFORM} & this\\ \text{NUM} & SG\end{bmatrix}$$

We could use a rule like:

$$NP \rightarrow Det\ N \begin{bmatrix}\text{NUM} & SG & \\ \text{DET} & [\text{NUM} & SG]\\ \text{N} & [\text{NUM} & SG]\end{bmatrix}$$

Such a rule reads "Replace a Det and an N by an NP, if, and only if, the Det has the feature NUM=SG and the N has the feature NUM=SG. The resulting NP should then also get the feature NUM=SG.

Feature-structures can use so-called "reentrant" structures. The above feature-structure could be rewritten as follows, using reentrancy.

$$\begin{bmatrix}\text{NUM} & \boxed{1} & \\ \text{DET} & [\text{NUM} & \boxed{1}]\\ \text{N} & [\text{NUM} & \boxed{1}\ SG]\end{bmatrix}$$

In this case the features "refer" to each other's value, which wouldn't change anything in this example, since all the NUM-features would still be bound to SG. The advantage of such a notation comes in, when considering feature-structures like the following one, that don't give a feature an actual value, yet still require it to be equal.

$$\begin{bmatrix} \text{NUM} & \boxed{1} \\ \text{DET} & \left[\text{NUM} \ \boxed{1}\right] \\ \text{N} & \left[\text{NUM} \ \boxed{1}\right] \end{bmatrix}$$

This would enable us to use one augmented rule, to handle both singular and plural NPs, rather than using two distinct rules, the only difference being NUM's value.

Therefore our complete rule, accepting NPs like *this dog*, and rejecting **these dog* would look like:

$$NP \rightarrow Det\ N \begin{bmatrix} \text{NUM} & \boxed{1} \\ \text{DET} & \left[\text{NUM} \ \boxed{1}\right] \\ \text{N} & \left[\text{NUM} \ \boxed{1}\right] \end{bmatrix}$$

3.4.1 Unification

In this section we will introduce one of the mightiest operators in computer-science, called "unification" and how it is applied to feature structures, in order to equip them with a limited degree of "intelligent" behavior. The unification-operator is simple, yet so powerful, that it suffices to give programming-languages (like PROLOG) the ability to read and write simple and complex data-structures, to perform logical and therefore numerical operations and to control its program's runtime-flow (usually in combination with a search-strategy like backtracking).

This section will only give the basic ideas of unification by showing a few examples. The reader is again referred to Jurafsky & Martin (2000) and Copestake (2002) for a detailled description of unification and its applications to language-processing, and to Sterling & Shapiro (1994) which gives the details on how unification is used in logic programming languages.

Let's start by considering the most basic example of the unification operator (written $\sqcup$ in the following).

$$\left[\text{NUMBER} \ \ SG\right] \sqcup \left[\text{NUMBER} \ \ SG\right] = \left[\text{NUMBER} \ \ SG\right]$$

$$\left[\text{NUMBER} \ \ SG\right] \sqcup \left[\text{NUMBER} \ \ PL\right] \ \textit{Fails!}$$

This illustrates how unification can be used for simple equality checks. Unification succeeds, if two completely specified feature-structures are actually equal, returning that feature structure, and failing otherwise.

$$\left[\text{NUMBER} \ \ SG\right] \sqcup \left[\text{NUMBER} \ \ []\right] = \left[\text{NUMBER} \ \ SG\right]$$

$$\left[\text{NUMBER} \ \ SG\right] \sqcup \left[\text{PERSON} \ \ 3\right] = \begin{bmatrix} \text{NUMBER} & SG \\ \text{PERSON} & 3 \end{bmatrix}$$

In these cases the feature-structures are "compatible". Values that are left unspecified can be matched against any value. This is how unification "merges" compatible feature-structures.

$$\begin{bmatrix} \textsc{num} & \boxed{1} \\ \textsc{Det} & [\textsc{num}\ \boxed{1}] \\ \textsc{N} & [\textsc{num}\ \boxed{1}] \end{bmatrix} \sqcup \left[\textsc{Det}\ \begin{bmatrix} \textsc{rootform} & \textit{this} \\ \textsc{num} & \textit{PL} \end{bmatrix}\right] = \begin{bmatrix} \textsc{num} & \boxed{1} \\ \textsc{Det} & \begin{bmatrix} \textsc{rootform} & \textit{this} \\ \textsc{num} & \boxed{1}\ \textit{PL} \end{bmatrix} \\ \textsc{N} & [\textsc{num}\ \boxed{1}] \end{bmatrix}$$

This shows how unification works for reentrant data-structures. While reentrancy from the first argument is preserved, the data from the second argument can be successfully "merged in". This has the consequence, that the value for the *Det*'s NUM-feature gets bound to *PL*, and so do the other NUM-feature's values, that are required to be equal to it.

From a linguistic point of view this behavior comes very handy. Consider a morphological analyzer confronted with the word-form *fish*. The morphological analyzer has no way of telling whether it is singular or plural. However a human understander would have no problem telling that *fish* in *this fish* is singular, and *fish* in *these fish* is plural.

This can be easily implemented using unification. A morphological analyzer would return a feature-structure that doesn't specify the NUM-feature for *fish*. When unifying that item in the course of parsing the NP *these fish*, unification would automatically bind the *fish*'s NUM-feature to *PL*.

$$\begin{bmatrix} \textsc{num} & \boxed{1} \\ \textsc{Det} & \begin{bmatrix} \textsc{rootform} & \textit{this} \\ \textsc{num} & \boxed{1}\ \textit{PL} \end{bmatrix} \\ \textsc{N} & [\textsc{num}\ \boxed{1}] \end{bmatrix} \sqcup \left[\textsc{N}\ \left[\textsc{rootform}\ \textit{fish}\right]\right] = \begin{bmatrix} \textsc{num} & \boxed{1} \\ \textsc{Det} & \begin{bmatrix} \textsc{rootform} & \textit{this} \\ \textsc{num} & \boxed{1}\ \textit{PL} \end{bmatrix} \\ \textsc{N} & \begin{bmatrix} \textsc{rootform} & \textit{fish} \\ \textsc{num} & \boxed{1} \end{bmatrix} \end{bmatrix}$$

3.4.2 Parsing with Feature Structures

In this chapter we will refine our Earley-Parser with two goals in mind: blocking constituents violating unification-constraints, and providing a richer representation for constituents using our framework based on feature-structures.

This can be done with two slight modifications to the Earley-Parser presented earlier. The first one concerns the representation of a state in the chart. A state like $N' \rightarrow N'\ P \bullet NP[3,5]$ would now be represented like

$$N' \rightarrow N'\ P \bullet NP[3,5] \begin{bmatrix} \textsc{N'} & \left[\textsc{N}\ \begin{bmatrix} \textsc{rootform} & \textit{sound} \\ \textsc{num} & \textit{SG} \end{bmatrix}\right] \\ \textsc{P} & [\textsc{rootform}\ \textit{on}] \\ \textsc{NP} & [] \end{bmatrix}$$

This new representation simply adds a new field to the state, carrying the feature-structure. A machine might represent it as a directed acyclic graph, DAG for short, which is basically the data-structure behind our feature-structures.

The second change affects the algorithm itself, the COMPLETER to be precise. Recall that the COMPLETER is that part of the Earley-algorithm that takes care of advancing every state that "is looking for" a symbol that has just been completed. In our revised Earley-COMPLETER, we can now try to unify the feature-structure of the state that is to be advanced with the feature-structure of the state that is already complete. The result of this unification is stored as the new feature-structure associated with this state. If the unification fails, the state is not advanced at all, therefore blocking a constituent violating a unification-constraint from "taking part" in the parse.

Although we will not give a full Earley-chart for a parse (which is left as an exercise for a reader with a really long sheet of paper), we will try to give an example.

(3.10) Thick strings are better than thin ones.

(3.11) Thick strings is better than thin ones.

In the course of parsing example 3.10 the COMPLETER will come across a state

$$N' \rightarrow Adj\ N' \bullet [0,2] \begin{bmatrix} \text{ADJ} & \begin{bmatrix} \text{ROOTFORM} & \textit{thick} \\ \text{NUM} & \boxed{1} \end{bmatrix} \\ \text{N'} & \begin{bmatrix} \text{N} & \begin{bmatrix} \text{ROOTFORM} & \textit{string} \\ \text{NUM} & \boxed{1}\ \textit{PL} \end{bmatrix} \end{bmatrix} \end{bmatrix}$$

This state represents the complete constituent *Thick strings* as an N'. The COMPLETER can now use this state to complete the state

$$NP \rightarrow \bullet N'[0,0] \begin{bmatrix} \text{NUM} & \boxed{1} \\ \text{N'} & [\text{NUM}\ \boxed{1}] \end{bmatrix}$$

This can be done by unifying the complete state with the $fs4.n'$-part of the one that is to be completed, to give

$$NP \rightarrow N' \bullet [0,2] \begin{bmatrix} \text{NUM} & \boxed{1} \\ \text{N'} & \begin{bmatrix} \text{ADJ} & \begin{bmatrix} \text{ROOTFORM} & \textit{thick} \\ \text{NUM} & \boxed{1} \end{bmatrix} \\ \text{N'} & \begin{bmatrix} \text{N} & \begin{bmatrix} \text{ROOTFORM} & \textit{string} \\ \text{NUM} & \boxed{1}\ \textit{PL} \end{bmatrix} \end{bmatrix} \end{bmatrix} \end{bmatrix}$$

What we have parsed so far is the NP *thick strings*, and we have found out that it is plural. Now we can advance the S rule using our completed NP.

$$S \rightarrow NP \bullet VP[0,2] \left[\begin{array}{ll} \text{NP} & \left[\begin{array}{ll} \text{NUM} & \boxed{1} \\ \text{N'} & \left[\begin{array}{ll} \textsc{Adj} & \left[\begin{array}{ll} \text{ROOTFORM} & \textit{thick} \\ \text{NUM} & \boxed{1} \end{array}\right] \\ \text{N'} & \left[\text{N} \left[\begin{array}{ll} \text{ROOTFORM} & \textit{string} \\ \text{NUM} & \boxed{1}\ PL \end{array}\right]\right] \end{array}\right] \end{array}\right] \\ \text{VP} & \left[\text{NUM}\ \boxed{1}\right] \end{array}\right]$$

After a while the parser will also have the VP, that is in question accessible. The VP from example 3.10 would give a state like

$$VP \rightarrow V' \bullet [2,7] \left[\begin{array}{ll} \text{V'} & \left[\begin{array}{ll} \text{NUM} & \boxed{1} \\ \text{V} & \left[\begin{array}{ll} \text{ROOTFORM} & \textit{be} \\ \text{NUM} & \boxed{1}\ PL \end{array}\right] \\ \ldots & \end{array}\right] \end{array}\right]$$

while the VP from example 3.11 would look like

$$VP \rightarrow V' \bullet [2,7] \left[\begin{array}{ll} \text{V'} & \left[\begin{array}{ll} \text{NUM} & \boxed{1} \\ \text{V} & \left[\begin{array}{ll} \text{ROOTFORM} & \textit{be} \\ \text{NUM} & \boxed{1}\ SG \end{array}\right] \\ \ldots & \end{array}\right] \end{array}\right]$$

(the only difference being NUM's value). When the completer tries to advance the S-rule by unifying this VP with the state for the S, unification succeeds in example 3.10, to give

$$S \rightarrow NP\ VP \bullet [0,7] \left[\begin{array}{ll} \text{NP} & \left[\begin{array}{ll} \text{NUM} & \boxed{1} \\ \text{N'} & \left[\begin{array}{ll} \textsc{Adj} & \left[\begin{array}{ll} \text{ROOTFORM} & \textit{thick} \\ \text{NUM} & \boxed{1} \end{array}\right] \\ \text{N'} & \left[\text{N} \left[\begin{array}{ll} \text{ROOTFORM} & \textit{string} \\ \text{NUM} & \boxed{1}\ PL \end{array}\right]\right] \end{array}\right] \end{array}\right] \\ \text{VP} & \left[\begin{array}{ll} \text{V'} & \left[\begin{array}{ll} \text{NUM} & \boxed{1} \\ \text{V} & \left[\begin{array}{ll} \text{ROOTFORM} & \textit{be} \\ \text{NUM} & \boxed{1} \end{array}\right] \\ \ldots & \end{array}\right] \end{array}\right] \end{array}\right]$$

In example 3.11 such a unification would fail, and therefore the S-state would not be completed by applying this state.

Chapter 4

Semantics

McCarthy (1989) makes a statement about his notion of "common-sense knowledge", that fits perfectly into our idea of semantics.

> Common-sense knowledge includes the basic facts about events (including actions) and their effects, facts about knowledge and how it is obtained, facts about beliefs and desires.

We already pointed out that FOPC and other equivalent first-order logic languages are commonly used to describe these facts about events, actions and so on, which is why, in this section, we will mainly be concerned with the problem of providing an interface between what syntactic analysis left us with (let's say a parse forest, to keep it simple), and an FOPC-representation of the underlying meaning. Such a representation would enable a computer-system to draw conclusions from it, which shall suffice as evidence that the computer understood the sentence, in our rather pragmatic approach to the "myths and magics" of the true nature of intelligence and understanding.

4.1 Overview

(4.1) Steve plays the guitar.

In order to give the reader a rough overview of semantic analysis, in this section we will consider example 4.1 and try to develop an adequate meaning representation by composing simpler meaning representations of the constituents, based on the syntax-tree given in figure 4.1.

Let's first try to capture the meaning of the word *guitar* in this sentence, which turns out to be rather trivial: The term *guitar* can be used "for every g such that g is a guitar".

$$\forall g IsA(g, Guitar)$$

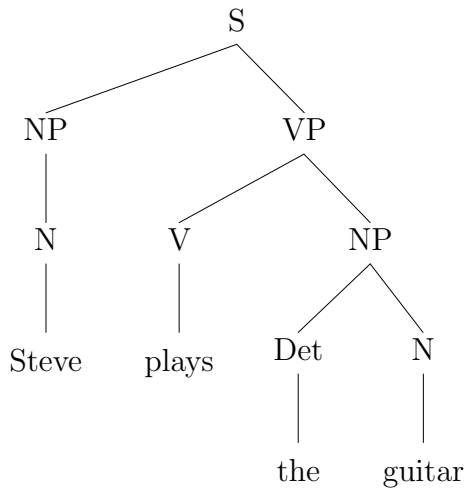


Figure 4.1: A parse-tree for example 4.1

Neglecting the meaning of the determiner *the*, we can move on to the verb heading the VP containing this phrase, namely *plays*.

In example 4.1, we can say that *play* means that someone (p) is capable of playing something (i), which could be captured by

$$\exists p \forall i Plays(p, i)$$

The NP *the guitar* can be viewed as a parameter that is passed as an i to this fact.

$$\exists p \forall i Plays(p, i) \wedge IsA(i, Guitar)$$

If we move up another level to the S headed by the NP *Steve* with a semantic representation

$$\exists p HasName(p, Steve)$$

we can do the same thing again, to get

$$\exists p \forall i Plays(p, i) \wedge IsA(i, Guitar) \wedge HasName(p, Steve)$$

What our system just did was successfully understand that *Steve plays the guitar*, describes a relation $Plays$ that holds between a p and every i such that another relation IsA holds between i and some constant $Guitar$ and yet another relation $HasName$ between p and some constant $Steve$.

Note that terms like $Guitar$ and $Steve$ are simple constants bearing no meaning as such. They have to be defined in the semantic framework. If, for example, there is a rule $IsA(Evo, Guitar)$, we can deduce that $Steve$ is capable of playing Evo, which could be the name of Steve's favourite guitar.

4.1.1 Ambiguity

Note that a computer trying to do what we just did would, of course, be confronted with ambiguity. The word *play* can have several meanings, some of which are given in M1-M5.

$$\exists p \forall i IsCapableOfPlayingInstrument(p, i)$$

as in *Steve plays the guitar*, or

$$\exists p, g IsCapableOfPlayingGame(p, g)$$

as in *Steve plays chess*, or

$$\exists p, t UsuallyPlaysWithToy(p, t)$$

as in *Steve plays with dolls*,
or

$$\exists p, m PlaysInABandTogetherWith(p, m)$$

as in *Steve plays with Joe* etc.

Differences can only be observed in predicate names and quantifiers, which is another piece of evidence that we've successfully singled out semantic problems, since disambiguation can only be done on a semantic basis (it requires knowledge of the problem-domain, and logical inference to disambiguate, for example, that if *the guitar* is an instrument and not a game, the meaning of *play* is M1, rather than M2).

Syntactic ambiguities, such as deciding in the sentence *We bought the dog* whether *bought* is transitive or ditransitive as in *We bought the dog a nice toy* would never "make it that far" in our analysis, since a rule like $VP \rightarrow VNPNP, cns1$ and another one like $VP \rightarrow VNP, cns2$ would already have distinguished between the two lexemes, and we can freely provide them with different semantic representations, given

$$_{cns1}\left[\text{V}\left[\text{TRANS}\ \ ditrans\right]\right]$$

$$_{cns2}\left[\text{V}\left[\text{TRANS}\ \ trans\right]\right]$$

The problem we are facing when we have to choose the "correct" meaning from M1-M5, is often referred to as "sense-ambiguity".

4.1.2 Knowledge

One might easily be misled into thinking that ambiguity in the above example was created quite artificially by introducing so many predicates for *play*, and that the problem could easily be circumvented by proposing only a single predicate $Plays$ as in the previous section.

The point that is crucial to the understanding of FOPC and its use as a "meaning representation" is that, by themselves, predicates and symbols do not carry meaning. They rather introduce it indirectly by establishing equivalence classes between equal (or rather unifiable) symbols.

Ambiguity arises as soon as semantic knowledge, that is modelled neither in a unique "dictionary definition" of the lexeme or grammar rule, nor in the specification of the problem domain (the machine's knowledge of the world it operates in), is neccessary to successfully create a unique meaning representation. In a way it could be viewed as the consequences of incompleteness in modelling the neccessary knowledge.

Say we wanted our system to tell whether somebody is intelligent, and whether somebody is musically talented, and we equip our system with a few facts about its problem-domain:

$$
\begin{gathered}
IsDifficult(Chess) \\
IsDifficult(Mastermind) \\
\forall x, gIntelligent(x) \Leftarrow IsCapableOfPlayingGame(x, g) \wedge IsDifficult(g) \\
IsDifficult(Violin) \\
IsDifficult(Clarinet) \\
\forall x, iTalented(x) \Leftarrow IsCapableOfPlayingInstrument(x, i) \wedge IsDifficult(i)
\end{gathered}
$$

Given this scenario it would, of course, be possible to use a single predicate like $Plays$, but this would require us to rewrite these rules as:

$$
\begin{gathered}
IsDifficult(Chess) \\
IsDifficult(Mastermind) \\
IsA(Chess, Game) \\
IsA(Mastermind, Game) \\
\forall x, gIntelligent(x) \Leftarrow Plays(x, g) \wedge IsA(x, Game) \wedge IsDifficult(g) \\
IsDifficult(Violin) \\
IsDifficult(Clarinet) \\
IsA(Violin, Instrument) \\
IsA(Clarinet, Instrument) \\
\forall x, iTalented(x) \Leftarrow Plays(x, i) \wedge IsA(i, Instrument) \wedge IsDifficult(i)
\end{gathered}
$$

By doing so we actually disambiguated the input by providing the system with information about what is an instrument and what is a game. This new information, that is additionally (to the model of the problem domain) required for disambiguation could be formalized as follows:

$$IsA(Chess, Game)$$
$$IsA(Mastermind, Game)$$
$$IsA(Violin, Instrument)$$
$$IsA(Clarinet, Instrument)$$
$$\forall x, oIsCapableOfPlayingGame(x, o) \Leftarrow Plays(x, o) \wedge IsA(o, Game)$$
$$\forall x, oIsCapableOfPlayingInstrument(x, o) \Leftarrow Plays(x, o) \wedge IsA(x, Instrument)$$

A human understander takes this knowledge required for semantic disambiguation of natural language from a knowledge-repository known as "common sense". Making it accessible to machines is a rather difficult task and one of the most central problems for symbolic artificial intelligence. Maybe efforts like CYC Lenat (1995) will make "common sense" possible for machines one day, but this is certainly not within the scope of this paper.

4.2 A Linguistic Perspective to Meaning

In the above section it got obvious that meaning is a rather difficult concept to formalize. What is meaning? Is it possible to capture meaning in a formal system? Does a single word have meaning? Is it possible to tell how many meanings a single word has? Does a sentence have meaning? Can the meaning of a sentence be composed by combining "smaller meanings" of the words and grammatical rules that make up the sentence?

These are questions we are facing here, and the answer to most of them might be "no", possibly uttered by an "old-school"-philosopher, followed by a big "but" uttered by someone following the more recent tradition of analytic philosophy: No, but if we make the right presumptions, accept little weaknesses and apply a certain degree of pragmatism, we can have considerable success when measured in terms of practical application of our theory.

We might easily agree that language is, at its core, a symbolic system, and any symbolic system can be viewed as a language. This is why the process of "understanding" language is sometimes viewed as the process of "translating" from one language, such as English, into another language, such as FOPC.

Note that this step might be seen as illegal, because such a view would put the semantic level into the interface between one language and another. Let's consider the example of a human trying to translate an English sentence into the German language. The translator would have to "understand" the English sentence - something we tried to deal with using the notion of capturing the

meaning of a sentence in a "semantic representation". This "understanding" would then be used by a human translator to form a German sentence. Now, if we wanted a computer to translate an English sentence into FOPC, and it would first have to capture the meaning in a "semantic representation", what would this representation be? Certainly not FOPC.

In a way, we completely skip the idea of meaning. What we want to develop here could be viewed as a model of translating from one language into another without having to really understand. Such a model is backed by presumptions which have turned out to be fruitful in their application rather than the metaphysical truth behind the concept of meaning.

4.2.1 Sense

A tool that's very useful for translating from one language into another is a dictionary - a dataset associating a set of words in one language with a set of words in the other language making statements about their interchangability. If I didn't know the German word for *guitar* and I looked it up in a dictionary it would give me *Gitarre*, suggesting that *guitar* is a linguistic symbol used by the English language to refer to the same sense as *Gitarre* in German.

Note that sense is, in our theory, a purely virtual level. This can be seen, when we consider ambiguity. The example we just gave was very simple: *guitar* refers to exactly one sense, the same and the only sense that *Gitarre* refers to. Let's consider an example that involves ambiguity. If we looked up *bass* in a dictionary it would give us two German words: *Bass* and *Barsch*. The first one is a musical instrument, the second one is a kind of fish. A good dictionary helps in doing this kind of disambiguation by giving a glossary describing the terms.

Note the parallelity between this concept, and the exemplaric formalization of an English sentence in FOPC we just did. The glossary is exactly the same "information that is additionally (to the model of the problem domain) required for disambiguation", we were using in the previous section.

What does this mean for the concept of sense? Our dictionary, disambiguating its entries by giving glossaries, is now using a semantic level to anchor the process of associating English and German words. And again we run into the same limitation we were just talking about. What semantic level can be used by a computer translating English into FOPC?

We can get around that problem by sticking with our view of understanding by translating and viewing the semantic level in between as a black-box. There is no problem in modelling a data-structure that is aware of one sense described by the tuple [*bass*,*Barsch*] and one sense by [*bass*,*Bass*]. We can view "true meaning" as attached to this data-structure like *[bass,Bass] is a musical instrument* and *[bass,Barsch] is a kind of fish*, yet when modelling language for use by an automaton we simply leave out this attachment.

Putting it simply: A traditional English-German-dictionary makes statements

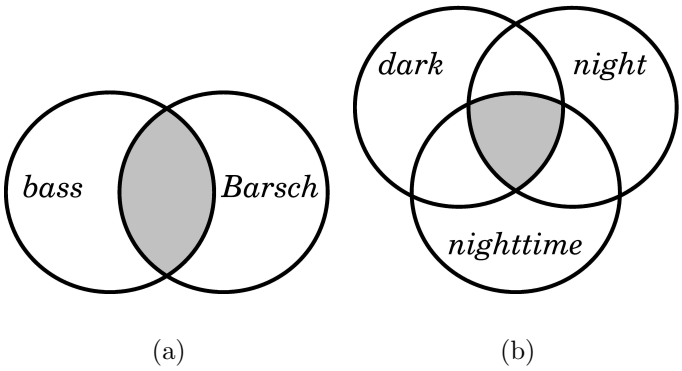


Figure 4.2: A black-box-view of sense

like "You can use the word *Bass* for *bass* if you are talking about a musical instrument" and "You can use the word *Barsch* for *bass* if you are talking about fish". In our analytic dictionary we cannot make these statements, because we can't model the "if ..."-part of that statement, but we can make statements like "There exists a sense that is the intersection of the meanings of *Bass* and *bass*" and "There exists *another* sense that is the intersection of the meanings of *Barsch* and *bass*". If we do that we establish a so called *differential theory* of semantics.

We developed this idea by following an example of translating from English to German, which is why we came up with English/German-tuples like [*bass*,*Barsch*] to account for our black-box-notion of sense, but it is important to note that this is not the only way one could go about this. The only thing that really matters is to capture meaning by some sort of unambiguous data-structure mapping to linguistic symbols.

The creators of WordNet[1], who emphasized the importance of synonymy in capturing meaning did something similar. In WordNet so-called *synsets* are used to account for sense. These synsets aren't tuples as in our example, but rather sets of English words that can be used interchangably in some sense. For example (*night*,*nighttime*,*dark*) is one synset. The words could be used interchangably in a sentence like *She walked home alone in the night*, but not in others like *She wants to go out Saturday night*.

The parallelity between our approach, and that of WordNet can also be depicted graphically as in figure 4.2. Figure 4.2(a) shows how sense is created in our example as an intersection of the meanings of an English and a German word, and figure 4.2(b) accounts for WordNet's idea of synsets. Figure 4.3 shows how different words contribute to two distinct senses of the same word, *dark*. One sense is created by the synset (*night*,*nighttime*,*dark*) and one by (*black*,*sinister*,*dark*).

[1]see Miller et al. (1993), Miller (1993), Fellbaum et al. (1993), Fellbaum (n.d.) and Beckwith et al. (n.d.) for details on WordNet

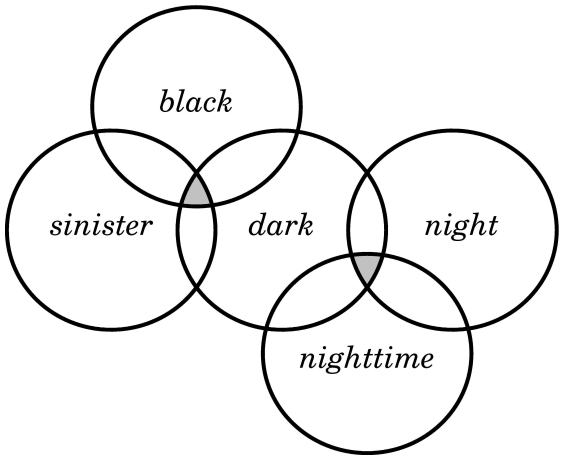


Figure 4.3: Two senses of *dark*

The examples chosen here shouldn't mislead the reader into thinking that a synset always consists of three words. There can, of course, be more or less than three words contributing to a synset, the example was chosen for the sake of readability of the diagram.

4.2.2 Reference

Although sense is a very important theoretic aspect in describing meaning it is still somewhat abstract. If Steve's son asked him what a guitar was, he probably wouldn't come up with something like "The concept behind what could be described by the English word *guitar* and the German word *Gitarre*", he would merely grab *Evo*, his favourite guitar, and say, "This is a guitar", making use of the concept of reference, which could be viewed as the ultimate goal of language. The symbols used in language are ultimately used to refer to concrete or abstract entities we have in mind.

While Steve might think of *Evo*, a white electric guitar with steel-strings, when he hears the word *guitar*, Jack might think of his favourite guitar, *Liz*, a wooden acoustic guitar with nylon-strings.

This suggests a kind of referential ambiguity that arises when mapping from a sense to its referent, analogously to sense-ambiguity that arises when mapping from a word to its sense.

Not only is it possible that one sense might be associated with different referents, it is also possible that distinct senses resolve to the same referent. For example, *the capital of Norway* and *Oslo* refer to the same place, somewhere in Scandinavia. Does this mean that *the capital of Norway* and *Oslo* have the same sense - are synonyms? Certainly not, because if the Norwegian government decides to declare Nuuk the new capital, *Oslo* would still be Oslo.

4.2.3 Lexical Semantics

Now that we know how a word is related to its sense, which is again related to its referent, we can have a more detailled look at how words and their senses relate to each other, a study widely known as lexical semantics. This field has seen a lot of research in the recent past. WordNet was definitely one of the more ambitioned projects, with its attempt to actually build a dictionary organizing words and their senses and providing valuable information about how they relate to each other. These are sometimes referred to as *lexical databases*. In this section we will have a closer look at those relations WordNet attempts to cover.

Synonymy

The most important relation in WordNet is synonymy, because it is the synonymy-relation that enables WordNet to capture meaning. It is usually viewed to hold between two expressions, if the substitution of one for the other never changes the truth-value of the sentence the substitution is made in. This is where the concept of meaning comes in. If two expressions are substitutable, then they could be said to *mean* the same. Miller et al. (1993) point out a problem with this definition of synonymy, and offer a solution.

> By that definition, true synonyms are rare, if they exist at all. A weakened version of this definition would make synonymy relative to a context: two expressions are synonyms in a linguistic context C if the substitution of one for the other in C does not alter the truth value.

This is why, in WordNet, words are considered synonyms, if there is a linguistic context where the words are synonymous.

The use of substitutability to define synonymy has two important consequences: First, two words can only be synonymous if they belong to the same POS. A verb and a noun, for example, are never substitutable. Secondly synonymy is symmetric: if x is synonymous to y, then y is synonymous to x.

Lexical Relations

Lexical relations are relations that hold between word-forms, and not neccessarily between their senses. We will give a brief overview of the most commonly used lexical relations.

Polysemy/Homonymy Although polysemy is a relation that appears in WordNet only implicitly, it is of central importance, for example, for sense-disambiguation. Two words are polysemous if their word-forms are the same, but their senses

aren't. In a way polysemy is closely related to synonymy. Both arise from ambiguity in the mapping between word-form and word-sense. While when we're mapping from a sense to its word-forms we are dealing with synonymy, we are dealing with polysemy when we're mapping from a word-form to its sense. Homonymy is very similar to polysemy. Homonymy is usually viewed to hold between word-forms whose senses are completely unrelated, while two words can be polysemous also when their senses are somehow related, as long as they aren't equal. This was mentioned only for preventing confusion, because homonymy and polysemy are widely used in that way. For our differential theory of sense, this is somewhat awkward, because here sense can never be related yet unequal, which is why we will use the terms *polysemy* and *homonymy* interchangably in the rest of this paper.

Antonymy is, although speakers of English have little difficulty recognizing it, rather difficult to formalize. It could be thought of as the opposite of polysemy. Sometimes the antonym of x is *not-x*, but not always. Miller et al. (1993) use the example of *rich* and *poor*. These words are antonymous, but if someone is not rich, it doesn't neccessarily mean that he is poor. It is interesting to mention, that antonymy, besides synonymy, is the only relation that is maintained in WordNet for all parts of speech.

Semantic Relations

Semantic relations are relations that hold between senses, in contrast to the lexical relations we mentioned in the previous section, which hold between word-forms.

Hyponymy and Hypernymy are also called subordination and superordination. They are used to organize the lexical database hierachically (for example, to set up an inheritance system, a concept we will deal with in greater detail later). For example *guitar* is a hyponym of *stringed instrument* which is again a hyponym of *instrument*. Generally one can say, that x is a hyponym of y if a native speaker accepts sentences like *x is a kind of y*. Hyponymy is transitive, therefore if x is a hyponym of y and y is a hyponym of z, then x is a hyponym of z. Unlike synonymy, hyponymy is asymmetrical. If x is a hyponym of y, y is not a hyponym of x, but rather a hypernym. WordNet maintains hyponymy and hypernymy for nouns and verbs.

Meronymy and Holonymy can also be used to organize a database hierachically, with some reservations. For example *neck* is a meronym of *guitar*. Generally one can say that x is a meronym of y if a native speaker accepts sentences like *an x is a part of a y*. This relation is also transitive and asymmetrical. Again if x is a meronym of y and y is a meronym of z, then x is a meronym of z and

	F_1	F_2	F_3	...	F_n
M_1	$E_{1,1}$	$E_{1,2}$			
M_2		$E_{2,2}$			
M_3			$E_{3,3}$		
...				...	
M_m					$E_{m,n}$

Figure 4.4: A Lexical Matrix

if x is a meronym of y, then y is a holonym of x. Sometimes additional classification of meronymy is done. WordNet uses three kinds of meronymy/holonymy: member-, substance- and part-meronymy, which are maintained only for nouns (which doesn't come as a surprise, but was mentioned for completeness).

Entailment is used in WordNet to organize verbs. For example *snore* entails *sleep*. The term *entailment* is defined in logic (where it is also known as *strict implication*) as follows: A proposition P entails a proposition Q if it is under no circumstances possible to make P true and Q false. In lexical semantics a verb p entails a verb q if the statement *Someone p* logically entails the statement *Someone q*. Lexical entailment is a unilateral relation: If q entails p, then p cannot entail q. See Fellbaum (n.d.) for the details on entailment in WordNet.

The lexical matrix

Figure 4.4 shows a matrix, that could be thought of as a datastructure for mapping words to their senses, and senses to their words. This table, taken from Miller et al. (1993), could be thought of as another way of depicting the same concept as figure 4.2(b), namely formalizing sense in a differential approach to meaning. We could view $F_1..F_n$ as symbols representing all possible word-forms, and $M_1..M_n$ as representing all possible meanings. An entry like $E_{1,1}$ would be read *The word-form F_1 can be used to express the meaning M_1*.

This simple data-structure deals elegantly with the two most important relations of lexical semantics: synonymy and polysemy. If we wanted to look up the meaning of a word-form F_2, we would simply have to look at column F_2 to find two appropriate meanings: M_1 and M_2, which confronts us with polysemy. If we wanted to look up a word-form for a meaning we have in mind, say M_1, we would have a look at the row M_1, discovering two possible word-forms, namely F_1 and F_2, which confronts us with synonymy.

The lexical matrix also helps to visualize the layer in between word-form and word-meaning, namely the data-cells denoted $E_{j,i}$. In our simple approach this would be a truth-value, saying "this association is valid" or "this association is invalid", but in a more sophisticated approach to lexical semantics it might be

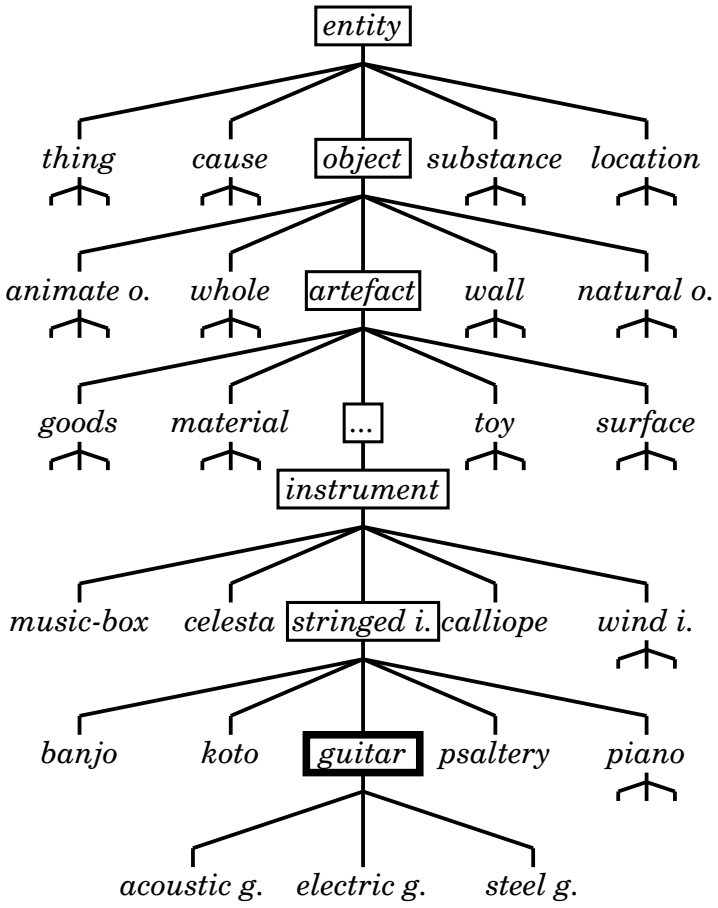


Figure 4.5: A sample of WordNet's hyponymy-structure

desireable to use a numeric value, for example saying "this association is true at a probability of 0.67", or signals helping with disambiguation, etc.

The Lexical Inheritance System

A lexical inheritance system is used, for example, in WordNet to organize nouns and equip them with a limited degree of semantic information. How do conventional dictionaries get semantic information across? If we looked up the word *guitar* in a dictionary, it would give us a glossary like *a stringed instrument that is small, light, made of wood, and has six strings usually plucked by hand or a pick*. Now what is a *stringed instrument*? If we looked that word up in the dictionary, we would get something like *a musical instrument producing sound through vibrating strings*. What does that tell us about guitars? Obviously, that a guitar is *a musical instrument producing sound through vibrating strings, that is small, light, made of wood, and has six strings usually plucked by hand or a*

pick.

What we just did was, we resolved the lexical inheritance system of our dictionary. We could go on like this for quite a while, looking up *guitar*, then *stringed instrument*, then *instrument* until we end up at a word, that stands for itself, like *entity*.

That we already mentioned the sequence *guitar-stringed instrument-instrument* in this paper is not a coincidence: We mentioned it as an example for hyponymy, which is the basic building-block organizing the nouns in our dictionary into a hierachical system as depicted in figure 4.5. In WordNet the top of this tree-structure is the synset for the word *entity* which is the most abstract "thing" a noun can be. Then WordNet tells us about different kinds of "entities", including objects, places, agents etc. When we go a step down this hierachy towards, say, *object* the concept of inheritance allows us to view an object as an entity. This implies that an *object* has all attributes, parts and functions, that an *entity* has. If we go down another step in this hierachy, say to the synset for *artifact* we are again allowed to view an artifact as an object. Therefore *artifact* inherits all attributes, parts and functions from *object*, and implicitly also from *entity*, because *object*, as we just mentioned, inherits all attributes, parts and functions from *entity*. If we keep on doing this, going down the hierachy, until we arrive at *guitar* we know that a guitar is something "which is perceived or known or inferred to have its own physical existence", although this can not be found in the definition of a *guitar*, because this fact was inherited all the way down from *entity* to *guitar*. The application of this concept of inheritance to our hierachical system, created by the hyponymy-relations, is what makes this hierachy an inheritance system. The details on lexical inheritance and its use in WordNet can be found in Miller (1993).

4.3 A Formal Perspective to Meaning

Now that we know how to capture the meaning of a single word we can go on to develop a formal approach to meaning and its representation in FOPC.

4.3.1 Representing Lexemes

(4.2) Steve plays the guitar.

When developing a meaning representation for example 4.1, repeated here as example 4.2, in section 4.1 we started out by representing the meaning of the word *play* as the following FOPC-expression:

$$\exists p \forall i Plays(p, i)$$

Mapping words to this kind of expression is the dictionary's job, since both words and expressions like the above one could, in their language, somehow be viewed as the nuclear meaning-carrying unit.

First of all, it is important to recognize the need for the consistent use of predicates and predicate-structures in dictionary definitions. FOPC doesn't as such provide data-structures for handling knowledge or common-sense, it's just a formalism for describing relations among symbolic expressions. The way a problem-domain is actually modelled in FOPC places some restrictions on what dictionary-definitions of words might look like. These restrictions could be thought of as an interface between the "natural-language-part" (dictionary, grammar, etc.) and the "processing-part" (the formalization of the problem domain) of our natural-language-processor.

Let's return to the example from section 4.1.2: We had a problem domain for a system telling whether someone is intelligent and whether someone is talented, that looked like:

$$IsDifficult(Chess)$$
$$IsDifficult(Mastermind)$$
$$\forall x, gIntelligent(x) \Leftarrow IsCapableOfPlayingGame(x, g) \wedge IsDifficult(g)$$
$$IsDifficult(Violin)$$
$$IsDifficult(Clarinet)$$
$$\forall x, iTalented(x) \Leftarrow IsCapableOfPlayingInstrument(x, i) \wedge IsDifficult(i)$$

Given this problem domain it would not make sense for the dictionary to map the word *play* to $\exists p \forall i Plays(p, i)$, because given $Plays(Steve, Violin)$ our program cannot deduce $Talented(Steve)$. This is how the definition of the problem-domain implicitly creates an interface that the dictionary has to implement if the whole system is to be operational. This interface would make statements like "For expressing meaning the dictionary can use the predicates $IsDifficult$, $IsCapableOfPlayingGame$ and $IsCapableOfPlayingInstrument$".

This interface is rather problematic since it gives rise to ambiguity and knowledge-problems. How should the dictionary know the difference between $IsCapableOfPlayingGame$ and $IsCapableOfPlayingInstrument$ when deciding how to translate the word *plays*? It is clearly not the dictionary's job to find out (at least in our approach), because it would require further knowlege about the problem domain to do so, and therefore we have to redefine the problem domain, just as we did in section 4.1.2, so that the interface reads "For expressing meaning the dictionary can use the predicates $IsDifficult$ and $Plays$ as well as $IsA(X, Game)$ and $IsA(X, Instrument)$". This eliminated ambiguity, because every symbolic expression in the English language, e.g. *plays* has exactly one corresponding symbolic expression in the FOPC-modelled problem-domain, $\exists p \forall i Plays(p, i)$ for instance.

4.3.2 Knowledge-Representation in Natural Language Processing

To maintain a certain degree of generality in their problem-domains linguists usually use models from artificial intelligence which were originally targeted towards accounting for true "common-sense" or "knowledge" or whatever term you prefer for McCarthy's level-4-use of logic (McCarthy 1989, p9), but never really reached that goal, yet turned out to be very useful for modelling natural language, which is a symbolic system that operates exactly at that level.

In such a formalism you wouldn't find a predicate like $Plays(p, i)$ to account for the meaning of the verb *play*, but rather a notion of events that can sometimes seem somewhat artificial. Such a formalism would also make use of some very important predicates like IsA or AM to represent certain aspects of modelling nouns, referents and their properties.

Before we will have a look at these conventions in this section, recall that according to McCarthy (1989), common-sense knowledge includes facts about

- events (including actions) and their effects
- knowledge and how it is obtained
- beliefs and desires
- objects and their properties

Verbs: Events and Actions

Therefore to formalize a verb like *play* we would introduce an event to account for the action of *playing*. The action of playing involves two so-called "semantic roles", that of the agent, and that of the experiencer. The agent is that object, which causes the action to happen, the player, in our example. The experiencer is that object which experiences the action, in our case, that "which gets played", the "playee" so-to-speak. (Although words like playee are somewhat awkward, they are commonly used to emphasize the semantic-role-concept, showing the analogy of the playee in a playing-event, the employee in an employing-event, the trustee in a trusting-event and so on.)

Given that, we can define the verb *play* by the playing-event it describes as:

$$\exists p, s, g IsA(p, Playing) \wedge Player(p, s) \wedge Playee(p, g)$$

Therefore the word *play* indicates that "there exists a p, such that p is the event of playing something, the player taking part in p is s and the playee taking part in p is g".

Nouns: Objects ...

The meaning of nouns is widely covered by the IsA-relation we've been using all the time. We can simply describe nouns by atomic symbols. A guitar would then be $Guitar$, as bass a $Bass$ and so on. The Isa-relation associates noun-senses like $Guitar$ and possible referents like Evo. (Evo is, as we've mentioned earlier, Steve's favourite guitar.) Making assertions like $Isa(Evo, Guitar)$.

Distinguishing sense and reference is sometimes a pitfall: *Steve plays the guitar* in its *Steve is capable to play the guitar*-sense cannot be formalized as

$$\exists p IsA(p, Playing) \wedge Player(p, Steve) \wedge Playee(p, Guitar)$$

Given that we use the IsA relation to account for reference (and the $HasName$ relation to account for names) the above statement would not imply

$$\exists p IsA(p, Playing) \wedge Player(p, Steve) \wedge Playee(p, Evo)$$

Once we decide we want to use the IsA-relation, we have to capture a noun like *guitar* by $\forall x Isa(x, Guitar)$ or $\exists x Isa(x, Guitar)$ whenever we are actually talking about the class of all guitars or a specific guitar.

We would therefore have to formalize *Steve plays the guitar* as

$$\exists p \forall s, g IsA(p, Playing) \wedge Player(p, s)$$
$$\wedge HasName(s, Steve) \wedge Playee(p, g) \wedge IsA(g, Guitar)$$

Because given that $Isa(Evo, Guitar)$ and $HasName(Steve, Steve)$ this does entail

$$\exists p IsA(p, Playing) \wedge Player(p, Steve)$$
$$\wedge HasName(Steve, Steve) \wedge Playee(p, Evo) \wedge Isa(Evo, Guitar)$$

which is exactly what we wanted to achieve.

Relations like $HasName(Steve, Steve)$ might seem awkward, but this is due to this example. Weisler & Milekic (2000) show why naming can be dealt with on a separate "linguistic level".

Adjectives: ... and their Properties

In a framework called "intersective semantics" the noun-phrase *a great guitar* would be formalized in the following way:

$$\exists x Isa(x, Guitar) \wedge Isa(x, Great)$$

The meaning of *a great guitar* is, in this framework, viewed as the intersection of the set containing all guitars and the set containing all great things.

Jurafsky & Martin (2000) use three examples for showing why this approach is a bit peculiar.

(4.3) small elephant

(4.4) former friend

(4.5) fake gun

that would be formalized as

$$\exists x Isa(x, Elephant) \wedge Isa(x, Small)$$
$$\exists x Isa(x, Friend) \wedge Isa(x, Former)$$
$$\exists x Isa(x, Gun) \wedge Isa(x, Fake)$$

This would state that a small elephant is a member of the set of small things, that a former friend is a member of the set of friends, which is simply false, and a member of the set of former things, which is somewhat unreasonable, similarly to a fake gun, which is, in this model, considered a gun.

Unfortunately there is no easy way out of this problem, as long as we stick with the principle of compositionality, but we might at least distinguish the IsA relation from the AM-relation, just like Jurafsky & Martin (2000) did, and leave further processing to the problem-domain, defining *a great guitar* as

$$\exists x Isa(x, Guitar) \wedge AM(x, Great)$$

4.3.3 Lambda-Expressions

Before we can move on to account for the semantic representation of grammar-rules we first have to provide a means to represent meanings that are "not yet finished". The dictionary definition of a single word or a phrase of a sentence cannot usually stand for itself, it is rather a partial meaning, a subgoal on our way to the complete meaning-representation of a sentence. This gives rise to the need for an intermediate meaning-representation that accounts for these partial meanings.

The approach is simple: a partial meaning can be viewed as a template, like a form that has to be filled out before it carries any relevant meaning. Representing this can be easily achieved, using the FOPC-formalism, if we make one fundamental extension: the Lambda-symbol, which acts similarly to a quantifier, and states "this is a form-variable that has to be specified in detail in later processing".

(4.6) I play no instrument

(4.7) Nobody plays the piano

Turning back to our example of $\exists p \forall i Plays(p, i)$, one might criticize the use of the quantifiers $\exists$ and $\forall$. Does the word *play* really imply that there exists some p, such that p plays i, and that p can really play every i? Examples 4.6 and 4.7

provide enough evidence, that another formalism is needed to account for the "missing parts" in meaning: The lambda-expression.

Using a lambda-expression we could formalize the maining of *play* as

$$\lambda p, iPlays(p, i)$$

which roughly reads "there is a p and an i, that still have to be specified in detail, but we already know that there is a relation $Plays$ that holds between them".

Let's consider an example that's a bit more interesting. In section 4.1 we represented the VP *plays the guitar* as

$$\exists p \forall i Plays(p, i) \wedge Isa(i, Guitar)$$

Of course this VP doesn't yet "know" who will be the agent, therefore we would have to use the following lambda-expression

$$sampleVP = \lambda p \forall i Plays(p, i) \wedge Isa(i, Guitar)$$

This time we also gave the lambda-expression a name, because we want to introduce the following notation, which creates an expression where the variable marked by λ in $sampleVP$ gets replaced by the expression $Steve$:

$$sampleVP(Steve)$$

This would be the same as writing

$$\forall i Plays(Steve, i) \wedge Isa(i, Guitar)$$

This can also be done with complex-terms, like

$$sampleVP(\exists e HasName(e, Steve))$$

In general complex-terms take the form

$$< \ quantifier \ variable \ body \ >$$

Our example would, in the first place, resolve to something like

$$\forall i Plays(\ < \ \exists e HasName(e, Steve) \ > \ , i) \wedge Isa(i, Guitar)$$

which isn't really syntactically correct FOPC, but it is possible to convert it back to syntactically correct FOPC by rewriting the predicate, that uses the complex-term

$$P(\ < \ quantifier \ variable \ body \ > \ )$$

as

$$quantifier \ variable \ body \ connective \ P(variable)$$

The connective depends on the quantifier. Variables that are quantified with $\exists$ are connected with $\wedge$, variables that are quantified with $\forall$ are connected with $\Rightarrow$.

Therefore our sample-expression would be rewritten as

$$\forall i \exists e HasName(e, Steve) \wedge Plays(e, i) \wedge Isa(i, Guitar)$$

Such a proceeding is called *lambda-reduction*.

4.3.4 Representing Grammar-Rules

We might easily agree that the way a sentence is put together, the syntax, the grammar-rules putting together the words in order to make up a meaningful sentence, do themselves carry meaning.

A question that is a bit more tricky is what a grammar carrying out semantic analysis should look like. We will use a quite simplistic approach called *syntax-driven semantic analysis*, based on the presumption that semantic analysis can be carried out in exactly the same structure as syntactic analysis.

To be more specific, this means, that if it is, on a syntactic level, possible to deduce the syntax of a VP like

$$[_{VP}\ [_{V}\ plays\ ][_{NP}\ [_{Det}\ the\ ][_{N}\ guitar\ ]]]$$

from its parts, namely the V

$$[_{V}\ plays\ ]$$

the NP

$$[_{NP}\ [_{Det}\ the\ ][_{N}\ guitar\ ]]$$

and the rule putting them together

$$VP \rightarrow V\ NP$$

then it is also possible, on a semantic level, to deduce the semantics of the corresponding VP

$$\lambda s \exists p, gIsA(p, Playing) \wedge Player(p, s)$$
$$\wedge Playee(p, g) \wedge IsA(g, Guitar)$$

from the same parts, namely the V

$$V = \lambda g, s \exists p IsA(p, Playing) \wedge Player(p, s) \wedge Playee(p, g)$$

the NP

$$NP = \exists g IsA(g, Guitar)$$

and the rule putting them together, which is

$$V(NP)$$

Figure 4.6 depicts the same idea graphically in greater detail. Figure 4.3.4 is basically a syntax tree of example 4.1, this time in its *There is a guitar that is currently played by Steve*-sense. The presumption of syntax-driven semantic analysis allows us to use this syntax-tree not only as the structure building up the whole syntax from its parts but also for building up the whole semantics

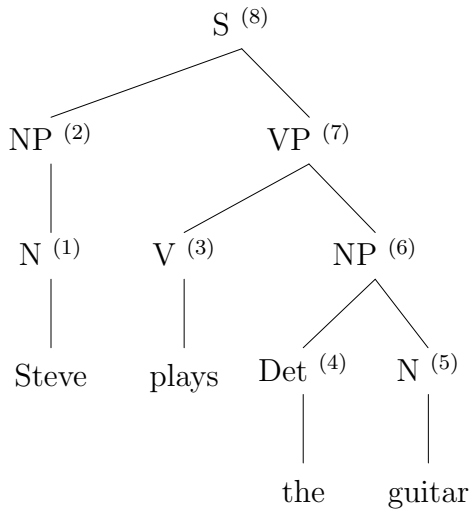


Figure 4.6: Compositional structure

	syntax	semantics
(1)	$[_N$ Steve]	$\exists s HasName(s, Steve)$
(2)	$[_{NP}[_N$ Steve]]	$\exists s HasName(s, Steve)$
(3)	$[_V$ plays]	$\lambda g, s \exists p IsA(p, Playing) \wedge Player(p, s) \wedge Playee(p, g)$
(4)	$[_{Det}$ the]	nil
(5)	$[_N$ guitar]	$\exists g IsA(g, Guitar)$
(6)	$[_{NP}[_{Det}$ the$][_N$ guitar]]	$\exists g IsA(g, Guitar)$
(7)	$[_{VP}[_V$ plays$][_{NP}[_{Det}$ the] $[_N$ guitar]]]	$\lambda s \exists p, g IsA(p, Playing) \wedge Player(p, s)$ $\wedge Playee(p, g) \wedge Isa(g, Guitar)$
(8)	$[_S\ [_N$ Steve$][_{VP}[_V$ plays] $[_{NP}[_{Det}$ the$][_N$ guitar]]]]	$\exists s, p, g IsA(p, Playing) \wedge Player(p, s)$ $\wedge HasName(s, Steve) \wedge Playee(p, g) \wedge Isa(g, Guitar)$

Figure 4.7: Tree-nodes and their syntactic and semantic content

	syntactic rule	semantic attachment
(2)	$NP \rightarrow N$	N
(6)	$NP \rightarrow Det\ N$	N
(7)	$VP \rightarrow V\ NP$	$V(NP)$
(8)	$S \rightarrow NP\ VP$	$VP(NP)$

Figure 4.8: grammatical production of the analysis-tree

from its parts. Figure 4.7 shows what these nodes would in detail look like on a semantic and on a syntactic level. Figure 4.8 shows the grammatical rules that made the derivation of nodes (2),(6),(7) and (8) possible, again on a semantic and on a syntactic level. (The derivation of the other nodes isn't particularly interesting, since they are based on simple dictionary look-ups.)

The semantic rules are, of course, lambda-reductions. The reader is invited to use the process of lambda-reduction, introduced in the previous section, to see that it is in fact possible to derive the meaning-representation of the whole sentence, given in node (8) in figure 4.7 from the "semantic grammar" given in figure 4.8, and the "semantic dictionary", given in nodes (1), (3), (4) and (5) of figure 4.7, and that this derivation really has the same structure as the syntax-tree given in figure 4.3.4.

As we've just shown, the principle of syntax-driven-semantic analysis allows us to guide the semantic derivation along the lines of the parsing-tree. This allows us to handle semantics by simply adding a new field to the sample-grammar we've been using all the time, just as we did, when we augmented the CFG-rules with constraints based on feature-structures.

The S-rule, we've been using so far would have looked like:

$$S \rightarrow NP\ VP \qquad \begin{bmatrix} \text{NUM } \boxed{1} & \\ \text{NP} & [\text{NUM } \boxed{1}] \\ \text{VP} & [\text{NUM } \boxed{1}] \end{bmatrix}$$

Remember that it consists of a CFG-rule saying that an NP and V can be replaced by an S, if it is possible to unify both the feature-structure $S.NP$ with the NP's feature structure and the feature-structure $S.VP$ with the VP's feature-structure, and the feature-structure in this case enforcing number-agreement.

In order to handle semantic processing we would now add another data-structure to our grammar rule, leaving the S-rule as something like:

$$S \rightarrow NP\ VP \qquad \begin{bmatrix} \text{NUM } \boxed{1} & \\ \text{NP} & [\text{NUM } \boxed{1}] \\ \text{VP} & [\text{NUM } \boxed{1}] \end{bmatrix} \qquad VP(NP)$$

Of course the implementation of such complex grammars isn't usually done in this datastructure, containing a CFG-rule, a FS-constraint and a semantic attachment, but rather, in an integrated way. The ERG, for example, is based solely on feature-structures, because semantic attachments, as well as CFG-rules, can all be integrated into one powerful feature structure. This formalism was chosen simply for the sake of readability.

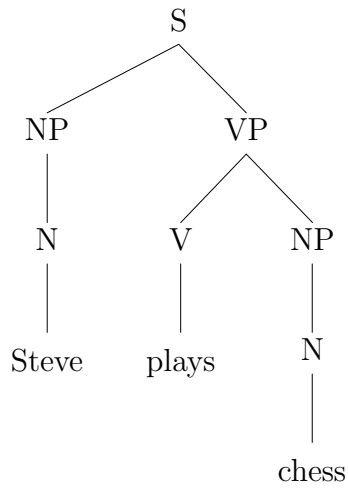


Figure 4.9: A parse-tree for example 4.8

4.4 Augmenting a Parser with a Semantic Analyzer

Now we know what a semantic dictionary could look like, how a grammar can be augmented with semantic attachments, and how these partial meanings coming from the dictionary and the grammar can be combined based on the presumptions of syntax-driven semantic analysis using lambda-reductions.

What we want to do in this section is try to get our parser to do this combination-task. Given that we've made the semantic dictionary and the semantic grammar available to our parser, we want it to be able to come up with a complete meaning-representation of a natural-language sentence it parses.

(4.8) Steve plays chess.

We will, therefore, turn to example 4.8 (repeated from example 3.9). Its syntax-tree is given in figure 4.9. This time we'll follow an Earley-parser on its way through the chart, and show how it does semantic analysis.

Figure 4.10 shows the chart created by a simple Earley-parser, when parsing example 4.8 using the simplified grammar from the "syntactic production"-column of figure 4.8.

Very similarly to what we did to the Earley-parser, when we extended it to handle feature structures in section 3.4.2 we have to make two changes to the parser: The first one concerns the representation of states. Additionally to the normal fields of the state, and the associated feature structure we need a field carrying the current semantic content of that state. Therefore a state like

$$NP \rightarrow N \bullet [2, 3]$$

chart[0]

[0]	$\lambda \rightarrow \bullet S$	[0, 0, 0]	[]
[1]	$S \rightarrow \bullet NP\ VP$	[0, 0, 0]	[]
[2]	$NP \rightarrow \bullet Det\ N$	[0, 0, 0]	[]
[3]	$NP \rightarrow \bullet N$	[0, 0, 0]	[]

chart[1]

[0]	$N \rightarrow steve\bullet$	[0, 1, 1]	[]
[1]	$NP \rightarrow N\bullet$	[0, 1, 1]	[[(1, 0)]]
[2]	$S \rightarrow NP \bullet VP$	[0, 1, 1]	[[(1, 1)]]
[3]	$VP \rightarrow V \bullet NP$	[1, 1, 0]	[]

chart[2]

[0]	$V \rightarrow plays\bullet$	[1, 2, 1]	[]
[1]	$VP \rightarrow V \bullet NP$	[1, 2, 1]	[[(2, 0)]]
[2]	$NP \rightarrow \bullet Det\ N$	[2, 2, 0]	[]
[3]	$NP \rightarrow \bullet N$	[2, 2, 0]	[]

chart[3]

[0]	$N \rightarrow chess\bullet$	[2, 3, 1]	[]
[1]	$NP \rightarrow N\bullet$	[2, 3, 1]	[[(3, 0)]]
[2]	$VP \rightarrow V\ NP\bullet$	[1, 3, 2]	[[(2, 0)], [(3, 1)]]
[3]	$S \rightarrow NP\ VP\bullet$	[0, 3, 2]	[[(1, 1)], [(3, 2)]]
[4]	$\lambda \rightarrow S\bullet$	[0, 3, 1]	[[(3, 3)]]

Figure 4.10: A chart for a run of our Earley parser on example 4.8 (Same as figure with backpointers added)

which can be found in entry [1] of $chart[3]$ would now be

$$NP \rightarrow N \bullet [2,3], \exists gIsA(g, Chess)$$

Feature-structures and backpointers for are left out for readability.

The second change concerns the COMPLETER. Recall that the COMPLETER is that part of the Earley-algorithm that takes care of advancing every state that "is looking for" a symbol that has just been completed, and that a state is considered complete if its $\bullet$ is at the far right of the rule in the state, for example as a result of the SCANNER having successfully read an input-token that matches the POS we are looking for. The COMPLETER would, therefore, be the part of the program responsibe for carrying out the lambda-reduction indicated in the grammar-rule of the state that was just completed, carrying over the result of this lambda reduction to the state "looking for" the constituent that was just completed and, by the lambda-reduction, semantically analyzed.

In our example, the first time the COMPLETER is called is for the complete state [0] in $chart[1]$

$$N \rightarrow steve \bullet [0,1], \exists sHasName(s, Steve)$$

(the value of the semantic attachment was provided by the SCANNER, which simply did a dictionary-lookup in the semantic dictionary, after having recognized the word *steve*).

The completer then finds a state that can be advanced because of this newly completed N-constituent: state [3] in $chart[0]$, which is

$$NP \rightarrow \bullet N[0,0], nil$$

Because advancing the $\bullet$ over the N in this state would create a complete state, the completer can now carry out semantic analysis. Note that it is usually necessary to wait for all constituents used by the current state to be completely parsed and analyzed, before analysis of the current state can be done. In this case, we have all constituents used by the $NP \rightarrow N$-state, namely the N available, so we can do the lambda-reduction which isn't particularly exciting, given that the semantic attachment to the $NP \rightarrow N$-rule is simply N, (as can be seen in figure 4.8), ordering the parser to simply carry over the meaning from the N. Therefore the COMPLETER creates state [1] from $chart[1]$

$$NP \rightarrow N \bullet [0,1], \exists sHasName(s, Steve)$$

And because this state the COMPLETER just created is itself complete, the COMPLETER would now be called for that state. Looking for states in need of an NP, the COMPLETER would now find state [1] from $chart[0]$

$$S \rightarrow \bullet NP\ VP[0,0], nil$$

The • in this state can now be advanced over the NP. In this case the COMPLETER doesn't carry out any semantic action, because the new state wouldn't be complete, therefore creating state [2] in *chart*[1] as

$$S \rightarrow NP \bullet VP[0,1], nil$$

The PREDICTOR, finding the non-terminal-symbol VP in this state to the left of the •, would now take care of adding state [3] to *chart*[1], and we can move on to the next chart.

The SCANNER would now find the token *plays* in the input, and, after looking the word up in the semantic dictionary create state [0] in *chart*[2] as

$$V \rightarrow plays \bullet [1,2], \lambda g, s \exists p IsA(p, Playing) \wedge Player(p, s) \wedge Playee(p, g)$$

This state is complete, and therefore it's now the COMPLETER's turn again, adding state [1] to *chart*[2] without doing semantic analysis, because, as we've just mentioned, this would require all constituents to be completed. In our case it is the NP that we lack information about. The PREDICTOR would then create states [2] and [3] in *chart*[2], and we could again go on to the next chart.

In *chart*[3] the SCANNER would find the token *chess* in the input and therefore create state [0] in *chart*[3] as

$$N \rightarrow chess \bullet [2,3], \exists g IsA(g, Chess)$$

Using this state the COMPLETER can now complete state [3] in *chart*[2]. In this case the resulting state would again be a complete one, therefore semantic analysis is carried out in this case, doing the lambda-reduction from the $NP \rightarrow N$-rule which is simply N, therefore carrying over the semantic attachment from the N to the new state for the NP which is added as state [1] to *chart*[3] as

$$NP \rightarrow N \bullet [2,3], \exists g IsA(g, Chess)$$

This state is exactly what state [3] in *chart*[1] "has been looking for". The COMPLETER when called for the state we just created, would, therefore, try to advance state [3] in *chart*[1], using state [1] in *chart*[3]. Because advancing the • in $VP \rightarrow V \bullet NP$ over the NP would create a completed state, the COMPLETER has to do semantic analysis, which is in this case a bit more interesting, because the semantic attachment to the $VP \rightarrow V\ NP$-rule is $V(NP)$. The NP is what we just completed, and the V can be found by the lambda-reducer using the backpointers. The new semantic attachment must be the result of the lambda-reduction $V(NP)$, which, fully written, looks like

$$\lambda g, s \exists p\ IsA(p, Playing) \wedge Player(p, s)$$
$$\wedge Playee(p, g)\ (\ <\ \exists g IsA(g, Chess)\ >\ )$$

A technique called *currying* allows us to handle lambda-expressions like this one, where there are two variables marked with lambda, but only one is to be reduced. It simply states, that in such a case the lambda-variable at the left end of the quantification-block is reduced, and the result is itself a lambda-expression, containing the lambda-variables that were not reduced. In our case we would reduce g, and leave s a lambda-variable. This lambda-reduction would therefore evaluate to

$$\lambda s \exists g, p \; IsA(p, Playing) \wedge Player(p, s) \\ \wedge Playee(p, g) \wedge IsA(g, Chess)$$

Now the completer can add the new state [2] to $chart[3]$

$$VP \rightarrow V \; NP\bullet[1, 3], \lambda s \exists g, p \, IsA(p, Playing) \wedge Player(p, s) \wedge Playee(p, g) \wedge IsA(g, Chess)$$

This state can now be used by the COMPLETER to complete state [2] in $chart[1]$. This time the state we want to complete comes from the rule $S \rightarrow NP \; VP$ which has the semantic attachment $VP(NP)$. In our case that resolves to $sem9(sem3)$ which is

$$\lambda s \exists g, p \; IsA(p, Playing) \wedge Player(p, s) \\ \wedge Playee(p, g) \wedge IsA(g, Chess) \; (\; < \; \exists s HasName(s, Steve) \; > \;)$$

that evaluates to

$$\exists s, g, p \; IsA(p, Playing) \wedge Player(p, s) \wedge HasName(s, Steve) \\ \wedge Playee(p, g) \wedge IsA(g, Chess)$$

QED.

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