Computing dynamic meanings: Building integrated competence-performance theories for semantics

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Chapter 1

Introduction

– overview of the book, intended audience, getting started (installation instructions etc.)

1.1 Using `pyactr` – people familiar with Python

If you are familiar with Python, you can install `pyactr` (the Python package that enables ACT-R) and proceed to Chapter 2. `pyactr` is a Python 3 package and can be installed using `pip` (for Python 3): type the command below in your terminal.

```
$ pip3 install pyactr
```

Alternatively, you can download the package here: https://github.com/jakdot/pyactr and follow the instructions there to install the package.

If you are not familiar with Python, you should consider the steps below.

1.2 Using `pyactr` – beginners

`pyactr` is a package for Python 3. To get started, you should consider a web-based service for Python3 like `PythonAnywhere`. In this type of services, computation is hosted on separate servers and you don't have to install anything on your computer (of course, you'll need Internet access). If you find you like working with Python and `pyactr`, you can install them on your computer at a later point together with a good text editor for code – or install an integrated desktop environment (IDE) for Python – a common choice is `anaconda`, which comes with a variety of ways of working interactively with Python (IDE with Spyder as the editor, `ipython` notebooks etc.). But none of this is required to run `pyactr` and the code in this book.

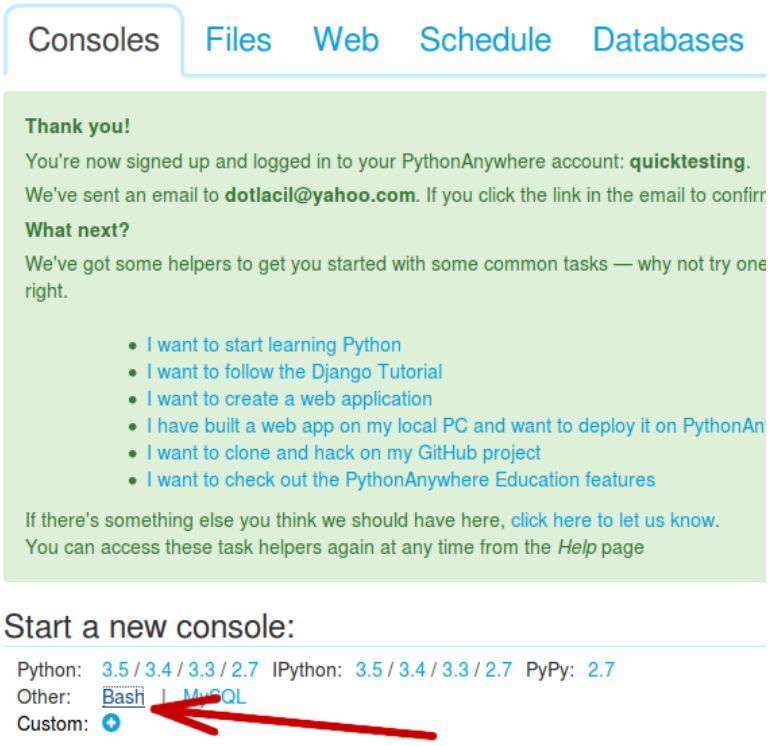
a. Go to www.pythonanywhere.com and sign up there.

b. You'll receive a confirmation e-mail. Confirm your account / e-mail address.

c. Log into your account on www.pythonanywhere.com.

d. You should see a window like the one below. Click on Bash (below "Start a new Console").

Figure 1: Opening Bash in PythonAnywhere.



e. In Bash, type:

```
$ pip3 install --user pyactr
```

This will install `pyactr` in your Python account (not on your computer). The output of this command should be similar to this:

```
Collecting pyactr
Downloading pyactr-0.1.9-py3-none-any.whl (50kB)
100%
Requirement already satisfied (use --upgrade to upgrade):
    pyparsing in /usr/local/lib/python3.5/dist-packages (from pyactr)
Requirement already satisfied (use --upgrade to upgrade):
    simpy in /usr/local/lib/python3.5/dist-packages (from pyactr)
Requirement already satisfied (use --upgrade to upgrade):
    numpy in /usr/local/lib/python3.5/dist-packages (from pyactr)
Installing collected packages: pyactr
Successfully installed pyactr
```

f. Go back to Consoles. Start Python by clicking on any version higher than 3.2.

g. A console should open. Type:

```
import pyactr
```

If no errors appear, you are set and can proceed to Chapter 2. You might get a warning about the lack of `tkinter` support and that the simulation GUI is set to false:

```
~/.local/lib/python3.5/site-packages/pyactr/simulation.py:10:
    UserWarning: Simulation cannot start a new window because tkinter
    is not installed. You will have no GUI for environment. If you want
    to change that, install tkinter. warnings.warn("Simulation cannot
    start a new window because tkinter is not installed. You will have
    no GUI for environment. If you want to change that, install tkinter.")
~/.local/lib/python3.5/site-packages/pyactr/simulation.py:11:
    UserWarning: Simulation GUI is set to False.
warnings.warn("Simulation GUI is set to False.")
```

Ignore it.

Throughout the book, we will introduce and discuss various ACT-R models coded in Python. You can either type them in line by line or even better, load them as files in your session on PythonAnywhere. Scripts are uploaded under the tab Files. You should be aware that the free account of PythonAnywhere allows you to run only two consoles, and there is a limit on the amount of CPU you might use per day. The limit should suffice for the tutorials but if you find this too constraining, you should consider installing Python (Python3) and `pyactr` on your computer and running scripts directly there.

1.3 The structure of the book

The book is structured as follows.

Chapter 2 introduces the ACT-R cognitive framework, the Python 3 implementation we will be using (`pyactr`) and ends with a basic ACT-R model for subject-verb agreement.

Chapter 3 introduces the basics of syntactic parsing in ACT-R. We build a top-down parser and learn more about how we can closely examine intermediate results of `pyactr` simulations to obtain detailed snapshots of the cognitive states our processing models predict.

Chapter 4 introduces a psycholinguistically realistic model of syntactic parsing (left-corner parsing), as well as vision and motor modules that enable our models of the human mind to interact with the environment in the same way human participants do in actual psycholinguistic experiments. This is an important contribution to the current psycholinguistic literature, which tends to focus exclusively on modeling only the declarative memory contribution to natural language processing rather than taking into account the full ACT-R cognitive architecture including the procedural memory module as well as the interface modules (motor and vision). This chapter and the subsequent ones are an even more important contribution to the landscape provided by the very rich experimental work in semantics / pragmatics produced over the last 10-15 years. Issues of processing always loom big in the background of this entire literature, but are rarely addressed head on with the systematicity

and high standards of formalization that questions in formal semantics and pragmatics are traditionally approached.

Chapter 5 introduces the basics of Bayesian modeling and Bayesian parameter estimation, and the main computational tools for Bayesian modeling in Python3. This is necessary to be able to estimate the subsymbolic parameters of ACT-R models for linguistic phenomena – and it is an important contribution relative to both the current work in the psycholinguistic ACT-R modeling literature and ACT-R modeling more generally. Parameters in ACT-R models are often tuned my manual trial and error, but the availability of the new `pyactr` library introduced in the present monograph as well as excellent novel libraries for Bayesian estimation like `pymc` should make this practice obsolete and replace it with the modeling and parameter-estimation workflow now standard in the statistical modeling and machine learning communities.

Chapter 6 introduces the 'subsymbolic' components needed to have a realistic model of human declarative memory, and shows how different Bayesian models can be fit to the classical forgetting data from Ebbinghaus (1913) and these models can be visually compared with respect to their data fit.

Chapter 7 brings together the Bayesian methods introduced in chapter 5 and the subsymbolic components of the ACT-R architecture introduced in chapter 6 to construct and compare two ACT-R models of lexical decision tasks. Once the better model is identified, we show how this can be integrated into an end-to-end model of lexical decision in `pyactr` that is able to realistically simulate human behavior in such tasks, from integrating visual input presented on a virtual screen to (subsymbolic) activation-modulated lexical retrieval from declarative memory and to providing the requisite motor response (key presses).

!!! TO BE UPDATED Subsequent chapters provide end-to-end models of self-paced reading and eye-tracking – focusing not only on the syntactic aspects of linguistic behavior in these tasks but crucially providing an explicit model of semantic interpretation. Specifically, we show how Discourse Representation Theory (DRT; Kamp 1981; Kamp and Reyle 1993)[1] can be integrated into the ACT-R cognitive architecture to provide the first fully formalized and computationally implemented psycholinguistic model of the human semantic parser / interpreter. We then show how this model enables us to provide an end-to-end account of (experimental data from) a self-paced reading task that involves the crucial interaction of cataphoric pronouns and presuppositions and the dynamic meanings of sentential connectives, specifically, conjunctions vs. conditionals.

[1] See also File Change Semantics (FCS; Heim 1982) and Dynamic Predicate Logic (DPL; Groenendijk and Stokhof 1991).

Chapter 2

The ACT-R cognitive architecture and its `pyactr` implementation

2.1 Introduction

Adaptive Control of Thought – Rational (ACT-R[1]) is a cognitive architecture: it is a theory of the structure of the human mind/brain that explains and predicts human cognition. The ACT-R theory has been implemented in several programming languages, including Java (jACT-R, Java ACT-R), Swift (PRIM), Python2 (ccm). The canonical implementation has been created and is maintained in Lisp.

In this book, we will use a novel Python3 implementation (`pyactr`). This implementation is very close to the official implementation in Lisp, so once you learn it you should be able to transfer your skills very quickly to code models in Lisp ACT-R if you wish to do that. At the same time, Python is currently much more widespread than Lisp and has a much larger and more diverse ecosystem of libraries, so coding parts that do not directly pertain to the ACT-R model are much better supported and much easier than in Lisp – for example, data manipulation/munging, statistical analysis, interactions with the operating system, displaying simulation results, incorporating them into tex / pdf documents etc.

Thus, we think `pyactr` is a better tool to learn ACT-R and cognitive modeling for linguists: the programming language is likely more familiar and commonly used, and data collection, piping, analysis and presentation as well as general software maintenance/enhancement tasks are much more likely to have good off-the-shelf solutions that require minimal customization. The tool will therefore stand less in the way of the task, so we can focus on doing cognitive modeling for linguistic phenomena, evaluating our models and communicating our results, rather than having to spend a significant amount of time on issues having to do with the computational tools we need to achieve our modeling goals.

In addition to the convenience and ease of use that comes with Python, reimplementing ACT-R in `pyactr` or, as we will sometimes do, implementing parts of ACT-R within Bayesian

[1] 'Control of thought' is used here in a descriptive way, similar to the sense of 'control' in the notion of 'control flow' in imperative programming languages: it determines the order in which programming statements (or cognitive actions) are executed / evaluated, and thus captures essential properties of an algorithm and its specific implementation in a program (or cognitive system). 'Control of thought' is definitely not used in a prescriptive way roughly equivalent to 'mind control' / indoctrination.

pymc3 models (pymc3 is a Python3 library for Bayesian modeling; see chapters 5-6) also serves to show that ACT-R is a mathematical theory of human cognition that stands on its own independently of its specific software implementations. While this is well-understood in the cognitive psychology community, it might not be self-evident to working linguists that ACT-R's empirical predictions are driven by general, formalized theoretical principles rather than tweaking arcane features of a software package.

This book and the cognitive models we build and discuss are not intended as a comprehensive introduction and/or reference manual for ACT-R. To become acquainted with ACT-R's theoretical foundations in their full glory as well as its plethora of applications in cognitive psychology, consider Anderson (1990); Anderson and Lebiere (1998); Anderson et al. (2004); Anderson (2007) among others as well as the ACT-R website http://act-r.psy.cmu.edu/.

The main goal of this book is to take a hands-on approach to introducing ACT-R by constructing models that aim to solve linguistic problems. We will interleave theoretical notes and pyactr code throughout the book. We will therefore often display python code and its associated output in numbered examples and/or numbered blocks so that we can refer to specific parts of the code and/or output and discuss them in more detail. For example, when we want to discuss the code, we will display it like so:

(1)
```
2 + 2 == 4                                                    1
3 + 2 == 6                                                    2
```

Note the numbers on the far right – we can use them to refer to specific lines of code, e.g.: the equality in (1), line 1 is true, while the equality in (1), line 2 is false. We will sometime also include in-line Python code, displayed like this: `2 + 2 == 4`.

Most of the time however, we will want to discuss both the code and its output and we will display them in the same way they would appear in the interactive Python interpreter, for example:

[py1]
```
>>> 2 + 2 == 4                                                1
True                                                          2
>>> 3 + 2 == 6                                                3
False                                                         4
```

Once again, all lines are numbered (both the Python code and its output) so that we can refer back to it.

Examples – whether formulas, linguistic examples, examples of code etc. – will be numbered as shown in (1) above. Blocks of python code meant to be run interactively, together with their associated output, will be numbered separately, as shown in [py1] above.

2.2 Why do we care about ACT-R, and cognitive architectures and modeling in general

Linguistics is part of the larger field of cognitive science. So the answer to the question "Why do we care about ACT-R and cognitive architectures / modeling in general?" is one that applies to cognitive sciences in general. Here is one recent formulation of what we

take to be the right answer, taken from chapter 1 of Lewandowsky and Farrell (2010). That chapter mounts an argument for *process* models as the proper scientific target to aim for in the cognitive sciences – roughly, models of human language performance – rather than *characterization* models – roughly, models of human language competence. Both process and characterization models are better than simply *descriptive* models,

> "whose sole purpose is to replace the intricacies of a full data set with a simpler representation in terms of the model's parameters. Although those models themselves have no psychological content, they may well have compelling psychological implications. [In contrast, both characterization and process models] seek to illuminate the workings of the mind, rather than data, but do so to a greatly varying extent. Models that characterize processes identify and measure cognitive stages, but they are neutral with respect to the exact mechanics of those stages. [Process] models, by contrast, describe all cognitive processes in great detail and leave nothing within their scope unspecified.
>
> Other distinctions between models are possible and have been proposed [...], and we make no claim that our classification is better than other accounts. Unlike other accounts, however, our three classes of models [descriptive, characterization and process models] map into three distinct tasks that confront cognitive scientists. Do we want to describe data? Do we want to identify and characterize broad stages of processing? Do we want to explain how exactly a set of postulated cognitive processes interact to produce the behavior of interest?" (Lewandowsky and Farrell, 2010, 25)

The advantages and disadvantages of process (performance) models relative to characterization (competence) models can be summarized as follows:

> "Like characterization models, [the power of process models] rests on hypothetical cognitive constructs, but [they provide] a detailed explanation of those constructs [...] One might wonder why not every model belongs to this class. After all, if one can specify a process, why not do that rather than just identify and characterize it? The answer is twofold.
>
> First, it is not always possible to specify a presumed process at the level of detail required for [a process] model [...] Second, there are cases in which a coarse characterization may be preferable to a detailed specification. For example, it is vastly more important for a weatherman to know whether it is raining or snowing, rather than being confronted with the exact details of the water molecules' Brownian motion.
>
> Likewise, in psychology [and linguistics!], modeling at this level has allowed theorists to identify common principles across seemingly disparate areas. That said, we believe that in most instances, cognitive scientists would ultimately prefer an explanatory process model over mere characterization." (Lewandowsky and Farrell, 2010, 19)

However, there is a more basic reason why generative linguists should consider process / performance models in addition to and at the same time as characterization / competence

models. The reason is that *a priori*, we cannot know whether the best analysis of a linguistic phenomenon is exclusively a matter of competence or performance or both, in much the same way that we do not know in advance whether certain phenomena are best analyzed in syntactic terms or semantic terms or both.[2] Such determinations can only be done *a posteriori*: a variety of accounts need to be devised first, instantiating various points on the competence-performance theoretical spectrum; once specified in sufficient detail, the accounts can be empirically and methodologically evaluated in systematic ways. Our goal in this book is to provide a framework for building process models, i.e., integrated competence-performance theories, for generative linguistics in general and formal semantics in particular.

Characterization / competence models have been the focus of linguistic theorizing over the 60 years in which the field of generative linguistics matured, and will rightly continue to be one of its main foci for the foreseeable future. However, we believe that the field of generative linguistics in general – and formal semantics in particular – is now mature enough to start considering process / performance models in a more systematic fashion.

Our main goal for this book is to enable semanticists to productively engage with performance questions related to the linguistic phenomena they investigate. We do this by making it possible and relatively easy for semanticists, and generative linguists in general, to build integrated competence/performance linguistic models of semantic phenomena that formalize explicit (quantitative) connections between theoretical constructs and experimental data. Our book should also be of interest to cognitive scientists other than linguists interested to see more ways in which contemporary generative linguistic theorizing can contribute back to the broader field of cognitive science.

2.3 Knowledge in ACT-R

There are two types of knowledge in ACT-R: declarative knowledge and procedural knowledge (see also Newell 1990).

The declarative knowledge represents our knowledge of facts. For example, if one knows what the capital of the Netherlands is, this would be represented in one's declarative knowledge.

Procedural knowledge is knowledge that we display in our behavior (cf. Newell 1973). It is often the case that our procedural knowledge is internalized, we are aware that we have it but we would be hard pressed to explicitly and precisely describe it. Driving, swimming, riding a bicycle are examples of procedural knowledge. Almost all people who can drive / swim / ride a bicycle do so in an automatic way. They are able to do it but they might completely fail to describe how exactly they do it when asked. This distinction is closely related to the distinction between explicit ('know that') and implicit ('know how') knowledge in analytical philosophy (Ryle 1949; Polanyi 1967; see also Davies 2001 and references therein for more recent discussions).

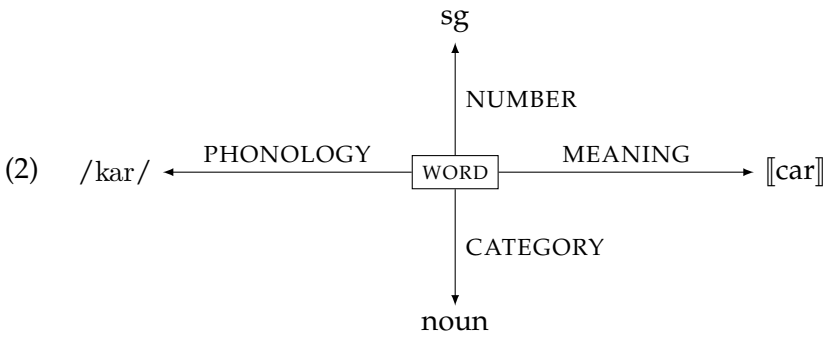
ACT-R represents these two types of knowledge in two very different ways. The declarative knowledge is instantiated in chunks. The procedural knowledge is instantiated in production rules, or productions for short.

[2] We selected syntax and semantics only as a convenient example, since issues at the syntax/semantics interface are by now a staple of generative linguistics. Any other linguistic subdisciplines and their interfaces, e.g., phonology or pragmatics, would serve equally well to make the same point.

2.3.1 Representing declarative knowledge: chunks

Chunks are lists of attribute-value pairs, familiar to linguists acquainted with feature-based phrase structure grammars (e.g., GPSG, HPSG or LFG – INSERT REFERENCES HERE). However, in ACT-R, we use the term *slot* instead of *attribute*. For example, we might think of one's knowledge of the word *carLexeme* as a chunk of type WORD with the value /kar/ for the slot *phonology*, the value ⟦car⟧ for the slot *meaning*, the value *noun* for the slot *category* and the value *sg* (singular) for the slot *number*. This is represented in (2) below:

(2)



The slot values are the primitive elements /kar/, ⟦carLexeme⟧, *noun* and *sg*, respectively. Chunks (complex, non-primitive elements) are boxed, whereas primitive elements are simple text. A simple arrow (⟶) signifies that the chunk at the start of the arrow has the value at the end of the arrow in the slot with the name that labels the arrow.

The graph representation in (2) will be useful when we introduce activations and more generally, ACT-R subsymbolic components (see Chapter 6). The same chunk can be represented as an attribute-value matrix (AVM), which is much more familiar to linguists. We will overwhelmingly use AVM representations like the one in (3) from now on.

(3)

$$\text{WORD}\begin{bmatrix}\text{PHONOLOGY:} & /\text{kar}/\\ \text{MEANING:} & [\![\text{car}]\!]\\ \text{CATEGORY:} & \text{noun}\\ \text{NUMBER:} & \text{sg}\end{bmatrix}$$

2.3.2 Representing procedural knowledge: productions

A production is an *if*-statement. It describes an action that takes place if the *if* 'part' (the antecedent clause) is satisfied; this is why we think of such productions / conditionals as ⟨precondition, action⟩ pairs. For example, agreement on a verb can be (abstractly) expressed as follows: *if* the subject number in the sentence currently under construction is *sg* (precondition), *then* check that the verb number in the sentence is *sg* (action). Of course, this is only half of the story – another production rule would state a similar ⟨precondition, action⟩ pair for *pl* number. Thus, the basic idea behind production rules is that the *if* 'part' specifies preconditions and if these preconditions are true, the action specified in the 'then' part of the rule is triggered.

Having two rules to specify subject-verb agreement – as we suggested in the previous paragraph – might seem like a cumbersome way of specifying agreement that misses an

important generalization: the two rules are really just one agreement rule with two distinct values for the number morphology. Could we then just state that the verb should have the same number specification as the subject? ACT-R allows us to state just that if we use variables.

A variable is assigned a value in the precondition part of a production and it has that same value in the action part, i.e., the scope of any variable assignment is the production rule in which that assignment happens. Given this scope specification for variable assignments, and employing the ACT-R convention that variable names are preceded by '=', we can reformulate our agreement rule as follows: *if* the subject number in the sentence currently under construction is =x, *then* check that the number specification on the (main) verb of the sentence is also =x.

2.4 The basics of `pyactr`: declaring chunks

We introduce the remainder of the ACT-R architecture by discussing its implementation in `pyactr`. In this section, we describe the details of declarative knowledge in ACT-R and the implementation of those details in `pyactr`. We will then turn to a discussion of modules and buffers, which are the building blocks of the mind in ACT-R (section §2.5). After this, we can finally turn to the second type of knowledge in ACT-R: procedural knowledge / productions (section §2.6).

To use `pyactr`, we have to import the relevant package:

```
[py2] >>> import pyactr as actr                                    1
```

We use the `as` keyword so that every time we use methods (functions), classes etc. from the `pyactr` package, we can access them by simply invoking `actr` instead of the longer `pyactr`.

Chunks / feature structures are typed (see Carpenter 1992 for an in-depth discussion of typed feature structures): before introducing a specific chunk, we need to specify a chunk type and all the slots / attributes of that chunk type. This is just good housekeeping: by first declaring a type and the attributes associated with that type, we are clear from the start about what kind of objects we take declarative memory to store.

Let's create a chunk type that will encode how our lexical knowledge is stored. We don't strive here for a linguistically realistic theory of lexical representations, we just want to get things off the ground and show the inner workings of ACT-R and `pyactr`:

```
[py3] >>> actr.chunktype("word", "phonology, meaning, category, number")   1
```

The function, a.k.a. method, `chunktype` creates a type `word` with four slots: `phonology`, `meaning`, `category`, `number`. The type name, provided as a character string `"word"`, is the first argument of the function. The list of slots, with the slots separated by commas, is the second argument. After declaring a type, we can create chunks of that type, e.g., a chunk that will encode our lexical knowledge about the noun *car*.

```
[py4] >>> carLexeme = actr.makechunk(nameofchunk="car",\                1
      ...                         typename="word",\                    2
```

```
... phonology="/kar/",\ 3
... meaning="[[car]]",\ 4
... category="noun",\ 5
... number="sg") 6
>>> print(carLexeme) 7
word(category= noun, meaning= [[car]], number= sg, phonology= /kar/) 8
```

The chunk is created using the method `makechunk`, which has two required arguments: `nameofchunk`, provided on line 1 in [py4], and `typename` (line 2). Other than these two slots (with their corresponding values), the chunk consists of whatever slot-value pairs we need it to contain – and they are specified as shown on lines 3-6 in [py4]. In general, we do not have to specify all the slots that a chunk of a particular type should have; the unspecified slots will be empty. If you want to inspect a chunk, you can print it – as shown on line 7 in [py4]. Note that the order of the slot-value pairs is different from the one we used when we declared the chunk: for example, we defined `phonology` first (line 3), but that slot appears last in the output on line 8. This is because chunks are unordered lists of slot-value pairs, and Python assumes an arbitrary (alphabetic) ordering when printing chunks.

Specifying chunk types is optional. In fact, the information contained in the chunk type is relevant for `pyactr`, but it has no theoretical significance in ACT-R – it is just 'syntactic sugar'. However, it is recommended to always declare a chunk type before instantiating a chunk of that type: declaring types clarifies what kind of AVMs are needed in our model and establishes a correspondence between the phenomena and generalizations we are trying to model and the computational model itself. For this reason, if we don't specify a chunk type before declaring a chunk of that type, `pyactr` will print a warning message. Among other things, this helps us debug our code – e.g., if we accidentally mistype and declare a chunk of type `"morphreme"` instead of the `"morpheme"` type we previously declared, we would get a warning message that a new chunk type has been created. We will not display warnings in the code output for the remainder of the book.[3]

It is also recommended that you only use attributes already defined in your chunk type declaration – or when you first used a chunk of a particular type. However, you can always add new attributes along the way if you need to: `pyactr` will assume that all the previously declared chunks of the same type had no value for those attributes. For example, imagine we realize half-way through our modeling session that it would be useful to specify what syntactic function a word has. We didn't have that slot in our `carLexeme` chunk. So let's create a new chunk `carLexeme2`, which is like `carLexeme` except it adds this extra piece of information in the slot `synfunction`. We will assume that the `synfunction` value of `carLexeme2` is `subject`, as shown on line 7 in [py5]:

```
[py5] >>> carLexeme2 = actr.makechunk(nameofchunk="car2",\ 1
... typename="word",\ 2
... phonology="/kar/",\ 3
... meaning="[[car]]",\ 4
... category="noun",\ 5
... number="sg",\ 6
... synfunction="subject") 7
```

[3] See the `pyactr` and Python3 documentation for more on warnings.

```
>>> print(carLexeme2)                                                    8
word(category= noun, meaning= [[car]], number= sg, phonology= /kar/,    9
   synfunction= subject)                                                10
```

The command goes through successfully, as shown by the fact that we can print carLexeme2), but a warning message is issued (not displayed above): `UserWarning: Chunk type word is extended with new attributes`.

Another, more intuitive way of specifying a chunk uses the method `chunkstring`. When declaring chunks with `chunkstring`, the chunk type is provided as the value of the `isa` attribute. The rest of the ⟨slot, value⟩ pairs are listed immediately after that, separated by commas. A ⟨slot, value⟩ pair is specified by separating the slot and value with a blank space.

[py6]
```
>>> carLexeme3 = actr.chunkstring(string="""                            1
...     isa word                                                         2
...     phonology '/kar/'                                                3
...     meaning '[[car]]'                                                4
...     category 'noun'                                                  5
...     number 'sg'                                                      6
...     synfunction 'subject'""")                                        7
>>> print(carLexeme3)                                                    8
word(category= noun, meaning= [[car]], number= sg, phonology= /kar/,    9
   synfunction= subject)                                                10
```

The method `chunkstring` provides the same functionality as `makechunk`. The argument `string` defines what the chunk consists of. The slot-value pairs are written as a plain string. Note that we use three quotation marks rather than one to provide the chunk string. These signal to Python that the string can appear on more than one line. The first slot-value pair ([py6], line 2) is special – it specifies the type of the chunk, and a special slot is used for this, `isa`. The resulting chunk is identical to the previous one: we print the chunk and the result listed on lines 9-10 of [py6] is the same as before.

Defining chunks as feature structures / AVMs induces a natural notion of identity and information-based ordering over the space of all chunks. A chunk is identical to another chunk if and only if (iff) they have the same attributes and the same values for those attributes. A chunk is a part of (less informative than) another chunk if the latter includes all the ⟨slot, value⟩ pairs of the former and possibly more. The `pyactr` library overloads standard comparison operators for these tasks, as shown below:

[py7]
```
>>> carLexeme2 == carLexeme3                                            1
True                                                                    2
>>> carLexeme == carLexeme2                                             3
False                                                                   4
>>> carLexeme <= carLexeme2                                             5
True                                                                    6
>>> carLexeme < carLexeme2                                              7
True                                                                    8
>>> carLexeme2 < carLexeme                                              9
False                                                                   10
```

Note that chunk types are irrelevant for deciding identity or part-of relations. This might be counter-intuitive, but it's an essential feature of ACT-R: chunk types are 'syntactic sugar', useful only for the human modeler. This means that if we define a new chunk type that happens to have the same slots as another chunk type, chunks of one type might be identical to or part of chunks of the other type:

[py8]
```
>>> actr.chunktype("syncat", "category")
>>> noun = actr.makechunk(nameofchunk="noun",
...                       typename="syncat",
...                       category="noun")
>>> noun < carLexeme
True
>>> noun < carLexeme2
True
```

This way of defining chunk identity is a direct expression of ACT-R's hypothesis that the human declarative memory is content-addressable memory: the only way we have to retrieve a chunk is by means of its slot-value content. Chunks are not indexed in any way and cannot be accessed via their index / memory address: the only way to access a chunk is by specifying a cue / pattern, which is a slot-value pair or a set of such pairs, and retrieving chunks that conform to that pattern, i.e., that are *subsumed* by it.[4]

2.5 Modules and buffers

Chunks do not live in a vacuum, they are always part of an ACT-R mental architecture. The ACT-R building blocks for the human mind are modules and buffers. Each module in ACT-R serves a different mental function. But these modules cannot be accessed or updated directly: input/output operations associated with a module are always mediated by a buffer – and each module comes equipped with one such buffer (think of it as the input/output interface for that mental module).

A buffer has a limited throughput capacity: at any given time, it can carry only one chunk. For example, the declarative memory module can only be accessed via the retrieval buffer. And while the memory module supports massively parallel processes – basically all chunks can be simultaneously checked against a pattern / cue, the module can only be accessed serially by placing one cue at a time in its associated retrieval buffer. This is a typical example of how the ACT-R architecture captures actual cognitive behavior by combining serial and parallel components in specific ways.

For ACT-R, the human mind is a system of modules and associated buffers within and across which chunks are stored and transacted. This flow of information is driven by productions: ACT-R is a production-system based cognitive architecture. Basically, productions

[4] A feature structure, a.k.a. chunk, C_1 subsumes another chunk C_2 iff all the information that is contained in C_1 is also contained in C_2. Basically, if C_1 is atomic / primitive, e.g., the number value *sg*, then C_1 subsumes C_2 iff C_2 is also atomic / primitive with the same atom. If C_1 is complex, i.e., it is a set of slot-value pairs, C_1 subsumes C_2 iff all the slots in the domain of C_1 are also in the domain of C_2, and for each of the slots in the domain of C_1, the value of that slot subsumes the value of the corresponding slot in C_2.

are stored in procedural memory while chunks are stored in declarative memory. The architecture is more complex than that, but in this chapter we will be concerned with only these two major components of the ACT-R architecture for the human mind: procedural memory and declarative memory.

As we already mentioned, procedural memory stores productions. Procedural memory is technically speaking a module, but it is the core / control module for human cognition so it does not have to be explicitly declared because is always assumed to be part of any mental architecture. The buffer associated with the procedural module is the goal buffer. This reflects the ACT-R view of human higher cognition as fundamentally goal-driven cognitive. Similarly, declarative memory is a module, and it stores chunks. The buffer associated with the declarative memory module is called the retrieval buffer.

Let's build a mind. The first thing we need to do is to create a container for the mind, which in `pyactr` terminology is a model:

[py9]
```
>>> agreement = actr.ACTRModel()
```

The mind we intend to build is simply supposed to check for number agreement between the main verb and subject of a sentence, hence the name of our ACT-R model in [py9] above. We can now start fleshing out the anatomy and physiology of this very simple agreeing mind. That is, we will add information about modules, buffers, chunks and productions.

As mentioned above, any ACT-R model has a procedural memory module, but for convenience it also comes equipped by default with a declarative memory module and the goal and retrieval buffers. When initialized, these buffers/modules are empty. We can check that for declarative memory, for example:

[py10]
```
>>> agreement.decmem
{}
```

`decmem` is an attribute of our `agreement` ACT-R model, and it stores the declarative memory module. The `retrieval` and `goal` attributes store the retrieval and the goal buffer, respectively.

[py11]
```
>>> agreement.goal
set()
>>> agreement.retrieval
set()
```

It is convenient to have a shorter alias for the declarative memory module, so we introduce a new variable `dm` and assign it the `decmem` module:

[py12]
```
>>> dm = agreement.decmem
```

We might want to add a chunk to our declarative memory, e.g., our `carLexeme2` chunk. We add chunks by invoking the `add` method associated with the declarative memory module; the argument of this function call is the chunk that should be added:

[py13]
```
>>> dm.add(carLexeme2)
>>> print(dm)
{word(category= noun, meaning= [[car]], number= sg, phonology= /kar/,
   synfunction= subject): array([ 0.])}
```

Note that when we inspect `dm`, we can see the chunk we just added. The chunk-encoding time is also recorded – this is the simulation time at which the chunk was added to declarative memory. We have not yet run the model / started the model simulation, so that time is 0 (line 4 of [py13]).

2.6 Writing productions in `pyactr`

Recall that productions are essentially conditionals (*if*-statements), with the preconditions that need to be satisfied listed in the antecedent of the conditional and the action that is triggered if the preconditions are satisfied listed in the consequent. Thus, productions have two parts: the preconditions that precede the double arrow (==>) and the actions that follow the arrow.

Let's add some productions to our model to simulate a basic form of verb agreement.[5] Our model of subject-verb agreement will be very elementary, but the point is learning how to assemble the basic architecture of the model / mind rather than building a realistic processing model of this linguistic phenomenon. We restrict ourselves to agreement in number for 3rd person present tense verbs. We make no attempt to model syntactic parsing, we will just assume that our declarative memory stores the subject of the clause and the current verb is already present in the goal buffer, where it is being actively assembled/specified.

What should our agreement model do? One production should state that if the goal buffer has a chunk of category 'verb' in it and the current task is to agree, then the subject should be retrieved. The second production should state that if the number specification on the subject in the retrieval buffer is =x, then the number of the verb in the goal buffer should also be =x (recall that the = sign before a string indicates that the string is the name of a variable). The third rule should say that if the verb is assigned a number, the task is done.

Let's start with the first production: noun retrieval. As shown in [py14], line 1 below, we give the production a descriptive name `"retrieve"` that will make the simulation output more readable. In general, productions are created by the method `productionstring` associated with our ACT-R model, and they have two arguments (there is actually a third argument; more on that later): `name`, the name of the production, and `string`, which provides the actual content of the production.

[py14]
```
>>> agreement.productionstring(name="retrieve", string="""
...     =g>
...     isa goal_lexeme
...     category 'verb'
...     task agree
...     ?retrieval>
...     buffer empty
```

[5] The full model is provided in the appendix to this chapter.

```
...     ==>                                                              8
...     =g>                                                              9
...     isa goal_lexeme                                                  10
...     task trigger_agreement                                           11
...     category 'verb'                                                  12
...     +retrieval>                                                      13
...     isa word                                                         14
...     category 'noun'                                                  15
...     synfunction 'subject'                                            16
...     """)                                                             17
{'=g': goal_lexeme(category= verb, task= agree), '?retrieval': {'buffer':  18
   'empty'}}                                                             19
==>                                                                      20
{'=g': goal_lexeme(category= verb, task= trigger_agreement), '+retrieval':  21
   word(category= noun, meaning= , number= , phonology= , synfunction=   22
   subject)}                                                             23
```

The preconditions (left hand side of the rule / antecedent of the conditional) and the actions (right hand side of the rule / consequent of the conditional) are separated by ==> – see line 8 of [py14] above. The rule has two preconditions. The first one starts on line 2: =g> indicates that this precondition will check that the chunk currently stored in the goal buffer (that's what g encodes) is (that's what = encodes) of a particular kind: the chunk has to be a goal_lexeme (line 3) of category 'verb' (line 4), and the current task for this lexeme should be agree (line 5). The second precondition starts on line 6: ?retrieval> indicates that this precondition will check whether the retrieval buffer is in a certain state (that's what ? encodes). The state is specified on line 7: the retrieval buffer needs to be empty (no chunk should be stored there).

In general, we can check for a variety of states that buffers could be in. For example: '?g> buffer full' checks whether the goal buffer is full (whether it carries a chunk); '?retrieval> state busy' checks if the retrieval buffer is working on retrieving a chunk; and '?retrieval> state error' checks if the last retrieval has failed (no chunk has been found).

If these two preconditions are met, the rule triggers two actions. The first action is stated starting on line 9 of [py14]: we modify the goal_lexeme chunk by changing the current task from agree to trigger_agreement. When such a feature-value update takes place, the other features of the updated chunk – here, the goal_lexeme chunk – remain the same.

The triggered agreement on the goal_lexeme chunk needs to identify a subject noun so that it can agree with that noun in number, which leads us to the second action. This action is stated starting on line 13: +retrieval> indicates that we access the retrieval buffer (recall that we just verified that this buffer is empty) and we add a new chunk to it (that's what + means). This chunk is our memory cue / query: we want to retrieve from declarative memory a chunk of type word that is a 'noun' and a 'subject'.[6]

Memory cues always consist of chunks, i.e., feature structures, and the retrieval process

[6]Strictly speaking, it is not necessary to ensure that the retrieval buffer is empty before placing a retrieval request. The model would have worked just as well if the retrieval buffer had been non-empty – the buffer would just be flushed/emptied first, and the memory cue would then be placed in it.

asks the declarative memory module to provide a larger chunk that the cue chunk is a part of (technically, a chunk in declarative memory that is subsumed by our cue chunk). In our specific case, the cue requests the retrieval of a chunk that has at least the following ⟨slot, value⟩ pairs: the chunk should be of type `word`, its category should be `'noun'` and its syntactic category should be `'subject'`.

We are now in a state in which a subject noun will be retrieved from declarative memory and placed in the retrieval buffer, and the goal lexeme is in an 'active' state of triggered agreement. The second production rule performs the agreement:

```
[py15] >>> agreement.productionstring(name="agree", string="""                    1
       ...     =g>                                                               2
       ...     isa goal_lexeme                                                   3
       ...     task trigger_agreement                                            4
       ...     category 'verb'                                                   5
       ...     =retrieval>                                                       6
       ...     isa word                                                          7
       ...     category 'noun'                                                   8
       ...     synfunction 'subject'                                             9
       ...     number =x                                                         10
       ...     ==>                                                               11
       ...     =g>                                                               12
       ...     isa goal_lexeme                                                   13
       ...     category 'verb'                                                   14
       ...     number =x                                                         15
       ...     task done                                                         16
       ...     """)                                                              17
       {'=g': goal_lexeme(category= verb, task= trigger_agreement), '=retrieval': 18
          word(category= noun, meaning= , number= =x, phonology= , synfunction=  19
          subject)}                                                              20
       ==>                                                                       21
       {'=g': goal_lexeme(category= verb, number= =x, task= done)}               22
```

The two preconditions of the rule in [py15] above ensure that we are in the correct state:

- lines 2-5: the chunk in the goal buffer is (=) a `goal_lexeme` of category `'verb'` that is in an active state of agreeing (the current `task` is `trigger_agreement`)
- lines 6-10: the chunk in the retrieval buffer is (=) a `word` of category `'noun'` that is a `'subject'` and that has a number specification `=x` (more precisely: take that number specification and assign it to the variable `=x`)

After checking that we are in the correct state, we trigger the agreeing action: lines 12-16 in [py15] tell us that the chunk that is currently in the goal buffer should be maintained there (that's what `=` on line 12 encodes) and its feature structure should be updated as follows: the type and category should stay the same (`goal_lexeme` and `'verb'`, respectively), but a new number specification should be added, namely `=x`, which is the same number specification as the one for the subject noun we have retrieved from declarative memory. Since this

completes the agreement operation, the `task` slot of the agreeing goal lexeme should also be updated and marked as `done`.

The third and final production rule just mops things up: we are done, so the goal buffer is flushed and our simulation can end. The action on line 6 in [py16], namely `~g>`, simply discards the chunk present in the goal buffer.

[py16]
```
>>> agreement.productionstring(name="done", string="""
...     =g>
...     isa goal_lexeme
...     task done
...     ==>
...     ~g>
...     """)
{'=g': goal_lexeme(category= , number= , task= done)}
==>
{'~g': None}
```

2.7 Running our first model

To start running the agreement model, we just have to add an appropriate chunk to the goal buffer. Recall that the ACT-R view of higher cognition is that it is goal-driven: if there is no goal, no productions will fire and the mind will not change state. We do this in [py17] below: we first declare our `goal_lexeme` type (line 1 in [py17]) and then add one such chunk to the goal buffer (lines 2-6; chunk are always added to buffers / modules using the method `add`). We check that the chunk has been added to the goal buffer by printing its contents (line 7); note that the number specification on line 8 is empty.

[py17]
```
>>> actr.chunktype("goal_lexeme", "task, category, number")
>>> agreement.goal.add(actr.chunkstring(string="""
...     isa goal_lexeme
...     task agree
...     category 'verb'
...     """))
>>> agreement.goal
{goal_lexeme(category= verb, number= , task= agree)}
```

We can now run the model by invoking the `simulation` method (with no arguments), as shown in [py18], line 1 below. This takes the model specification and initializes various parameters as dictated by the model (e.g., simulation start time). We can then execute one run of the simulation, as shown on line 2 in [py18].

[py18]
```
>>> agreement_sim = agreement.simulation()
>>> agreement_sim.run()
(0, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0, 'PROCEDURAL', 'RULE SELECTED: retrieve')
(0.05, 'PROCEDURAL', 'RULE FIRED: retrieve')
```

```
(0.05, 'g', 'MODIFIED')                                                    6
(0.05, 'retrieval', 'START RETRIEVAL')                                     7
(0.05, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                8
(0.05, 'PROCEDURAL', 'NO RULE FOUND')                                      9
(0.1, 'retrieval', 'CLEARED')                                              10
(0.1, 'retrieval', 'RETRIEVED: word(category= noun, meaning= [[car]],      11
   number= sg, phonology= /kar/, synfunction= subject)')                   12
(0.1, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                 13
(0.1, 'PROCEDURAL', 'RULE SELECTED: agree')                                14
(0.15, 'PROCEDURAL', 'RULE FIRED: agree')                                  15
(0.15, 'g', 'MODIFIED')                                                    16
(0.15, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                17
(0.15, 'PROCEDURAL', 'RULE SELECTED: done')                                18
(0.2, 'PROCEDURAL', 'RULE FIRED: done')                                    19
(0.2, 'g', 'CLEARED')                                                      20
(0.2, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                 21
(0.2, 'PROCEDURAL', 'NO RULE FOUND')                                       22
```

The output of the `run()` command is the temporal trace of our model simulation. Each line specifies three elements: (i) simulation time (in seconds); (ii) the module (name in upper-case letters) or buffer (name in lower-case letters) that is affected; and finally (iii) a description of what is happening to the module. Every cognitive step in the model takes by default 50 ms, i.e., 0.05 seconds – this is the ACT-R default time for an elementary cognitive operation.

The first line of our temporal trace (line 3 in [**py18**]) states that conflict resolution is taking place in the procedural memory module, i.e., the module where all the production rules reside. This happens at simulation time 0. The main function of 'conflict resolution' is to examine the current state of the mind (basically, the state of the buffers in our model) and to determine if any production rule can apply, i.e., if the current state of the mind satisfies the preconditions of any production rule. If the preconditions of multiple rules are satisfied, we have a conflict because only one production rule can fire at any given time. In that case, we need to select one rule ('resolve the conflict').

Note how ACT-R once again combines serial and parallel components to capture actual cognitive behavior. Checking if the current state of the mind satisfies the conditions of any rule is a massively parallel process: all rules are simultaneously and very quickly (instantaneously) checked. But rule firing is serial: at any given point in the cognitive process, only one rule can fire / apply. This is parallel to the interaction between the parallel computations in the declarative memory module (all chunks are simultaneously checked against a pattern / cue) and the serial way in which retrieval cues can be placed in the retrieval buffer (one at a time).

'Conflict resolution' is particularly simple in the present case. Given the state of the goal and retrieval buffers, only one rule can apply: our first production rule, which we named `retrieve` in [**py14**] above. Line 4 in [**py18**] shows that the `retrieve` rule is selected at time 0. The rule fires, and this takes the ACT-R default time of 50 ms, as shown on line 5. The state of our mind has changed as a consequence of this rule firing, and the subsequent lines in the output report on that new state: the goal buffer has been modified (line 6; the goal

lexeme has entered the active trigger_agreement state) and the retrieval buffer has started a memory retrieval procedure (line 7), which will take time to complete.

Now that the retrieve rule has fired, the procedural module enters a 'conflict resolution' state again and looks for production rules to apply (line 8). The current state of the mind (i.e., the buffer state) does not satisfy the preconditions of any rule, so none is fired (line 9).

However, a memory retrieval process has been started and is completed 50 ms later, i.e., at the next simulation time of 100 ms. Retrieval time is set to a default value of 50 ms here, but ACT-R specifies in great detail how memory behaves, and makes clear predictions about retrieval accuracy and retrieval latency. This is discussed in detail in chapter 6, but we want to keep our first model simple so we use the default 50 ms retrieval time here.

At the 100 ms point, the memory retrieval process has been completed and the retrieval buffer is cleared (line 10) so that the newly retrieved chunk can be placed there (lines 11-12).

The mind is now in a new state since the buffer contents have changed, so the procedural module reenters a 'conflict resolution' state of rule collection & rule selection (line 13). This time, the resolution process identifies one rule that can fire (line 14), namely the second production rule we discussed in [**py15**] above and which we named agree.

The agree rule takes 50 ms to fire (line 15 of [**py18**]), so we are now at 150 ms in simulation time. As a consequence of the agree rule, the chunk in the goal buffer has been modified (line 16): its number specification has been updated so that it is now the same number as the noun chunk in the retrieval buffer.

Agreement has been performed, so the third and final production rule is selected (lines 17-18). The rule takes 50 ms to fire (line 19), so at time 0.2 s, the goal buffer is cleared (line 20), and no further rule can apply (lines 21-22).

When the goal buffer is cleared, the information stored in it does not disappear. The ACT-R architecture specifies that the cleared information is automatically transferred to declarative memory. The intuition behind this is that our past accomplished goals, i.e., the results of our past successful cognitive processes, become our present (newly acquired) memory facts. This is also the case in pyactr. We can inspect the final state of the declarative memory module to see that it stores the cleared goal-buffer chunk:

[**py19**]
```
>>> dm
{goal_lexeme(category= verb, number= sg, task= done): array([ 0.2]),
   word(category= noun, meaning= [[car]], number= sg, phonology= /kar/,
   synfunction= subject): array([ 0.])}
```

Note that this newly added chunk is time-stamped with the simulation time at which the goal buffer was cleared (0.2 s).

And that's it. At its core, ACT-R provides a fairly simple framework for building process models that is accessible to generative linguists because it is production, a.k.a. rule, based and manipulates feature structures of a familiar kind.

To be sure, our first model and the introduction to ACT-R and pyactr in this chapter are overly simplistic in many ways. But the main point is that we can now start building explicit and more realistic computational models for linguistic processes and behaviors.

Our development of integrated competence-performance theories for linguistic phenomena is now at a stage similar to that point in a formal semantics intro course where the semantics for classical first order logic (FOL) has been introduced. FOL semantics is in many

ways an overly simplistic model for natural language semantics, but it provides the basic structure that more realistic theories of natural language interpretation (in the Montagovian tradition) can build on.

2.8 Appendix: The agreement model

File **ch2_agreement.py**:

```
"""
A basic model that simulates subject-verb agreement.
We abstract away from syntactic parsing, among other things.
"""

import pyactr as actr
import random

actr.chunktype("word", "phonology, meaning, category, number, synfunction")
actr.chunktype("goal_lexeme", "task, category, number")

carLexeme = actr.makechunk(
    nameofchunk="car",
    typename="word",
    phonology="/kar/",
    meaning="[[car]]",
    category="noun",
    number="sg",
    synfunction="subject")

agreement = actr.ACTRModel()

dm = agreement.decmem
dm.add(carLexeme)

agreement.goal.add(actr.chunkstring(string="""
    isa goal_lexeme
    task agree
    category 'verb'"""))

agreement.productionstring(name="retrieve", string="""
    =g>
    isa goal_lexeme
    category 'verb'
    task agree
    ?retrieval>
    buffer empty
    ==>
```

```
    =g>
    isa goal_lexeme
    task trigger_agreement
    category 'verb'
    +retrieval>
    isa word
    category 'noun'
    synfunction 'subject'
    """)

agreement.productionstring(name="agree", string="""
    =g>
    isa goal_lexeme
    task trigger_agreement
    category 'verb'
    =retrieval>
    isa word
    category 'noun'
    synfunction 'subject'
    number =x
    ==>
    =g>
    isa goal_lexeme
    category 'verb'
    number =x
    task done
    """)

agreement.productionstring(name="done", string="""
    =g>
    isa goal_lexeme
    task done
    ==>
    ~g>""")

if __name__ == "__main__":
    agreement_sim = agreement.simulation()
    agreement_sim.run()
    print("\nDeclarative memory at the end of the simulation:")
    print(dm)
```

Chapter 3

The basics of syntactic parsing in ACT-R

3.1 Top-down parsing

Now that the basic ACT-R cognitive architecture is in place and we're more familiar with its specific implementation in `pyactr`, let's build a basic model of syntactic parsing. Specifically, we will build a top-down parser, i.e., a parser that uses the grammar to make predictions about the sentential structure of the incoming word input.

There are three properties of the human parser / processor that we want our model to capture (Marslen-Wilson 1973, Frazier and Fodor 1978, Tanenhaus et al. 1995, Steedman 2001, Hale 2011 a.o.):

(i) the parser is incremental – syntactic parsing and semantic interpretation do not lag significantly behind the perception of individual words;

(ii) the parser is predictive – the processor forms explicit representations of words and phrases that have not yet been heard;

(iii) finally, the parser satisfies the competence hypothesis – understanding a sentence / discourse involves the recovery of the structural description of that sentence / discourse on the syntax side, and of the meaning representation on the semantic side.

A top-down parser is an imperfect model of the human parser / processor: it is predictive and it satisfies the competence hypothesis, but it is not incremental. As we will see, the predictions made about sentential syntactic structure are checked against the 'evidence' (the actual words in the sentence) only at the very end. However, top-down parsing is a good place to start. So, suppose we have a context-free grammar with the following rules:

(1)
	S	→	NP VP
	NP	→	ProperN
	VP	→	V NP
	ProperN	→	Mary
	ProperN	→	Bill
	V	→	likes

For simplicity, we assume we have only two proper names in our language and one transitive verb. Our goal is to build a top-down parser that is able to analyze the sentence *Mary likes Bill*. We assume the sentence is presented to the comprehender one word at a time in the manner of moving-window self-paced reading tasks (Just et al. 1982). In such tasks, the words are hidden (letters are replaced with dashes) and only one word is uncovered at a time with a spacebar press. The human reader decides when to press the spacebar to uncover the next word (which automatically hides the current word), hence the name of self-paced reading. So reading our sentence *Mary likes Bill* will happen in four successive stages

(2)
i. initial display: `---- ----- ----`
ii. after one spacebar press: `Mary ----- ----`
iii. after another spacebar press: `---- likes ----`
iv. after the third spacebar press: `---- ----- Bill`

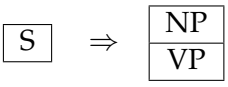
Self-paced reading tasks mimic an essential aspect of naturally-occurring language comprehension with auditory stimuli: the signal is strictly linearly and strictly incrementally presented one word at a time. Just as in naturally-occurring verbal interactions, and unlike normal reading situations, the linguistic signal cannot be 'rewound' to previous words (we cannot just look back and reread previous parts of the text) or 'fast-forwarded' to subsequent words (we cannot jump ahead to parts of the text that do not immediately follow the word currently being read).

With the empirical task fully characterized as a self-paced reading task, we can proceed to the characterization of our processing model. A top-down parser can be thought of as a push-down automaton, i.e., an automaton that has a basic form of memory represented as a stack. The stack stores parsing goals and subgoals in a strict, total order and these goals are accomplished one at a time by accessing the top of the stack. In our case, the parsing goals are simply syntactic categories that have to be parsed, i.e., that have to be identified in the incoming string.

For example, when we start the parsing process, we push the initial goal of parsing an S node onto the stack. The stack has now only one goal in it, namely 'parse an S', and the goal sits at the top of the stack.

(3) 

We pop goals off the stack one at a time: we can only look at the top of the stack and remove the current top goal when this goal is accomplished or broken down exhaustively into subgoals. For example, we will pop the 'parse an S' goal off the stack when we apply the first grammar rule in (1) above and replace this goal with two subgoals: first parse an NP (i.e., identify an NP in the incoming word input), then parse a VP. The resulting stack will now have two goals: the top one is 'parse an NP', and the one below it is 'parse a VP'.

(4) 

The parser works by modifying the contents of its stack based on two pieces of information: the top element on the stack and, possibly, the current word that has to be parsed (the leftmost word in the incoming string of words).

We can sum up top-down parsing as a parsing strategy that applies two algorithm schemata, *expand* and *scan*, in this order (see, for example, Hale 2014):

(5) Top-down parsing rules:
   a. *expand*: if the stack has a symbol X on top, and the grammar contains a rule $X \rightarrow AB$ or $X \rightarrow A$, pop X and push down onto the stack the symbols B and A (in that order), or the symbol A, respectively.
   b. *scan*: if the top of stack has a terminal symbol – a symbol like V or *ProperN* that rewrites to a lexical item; that is, a part of speech – and w, the leftmost word to be parsed, is of that part of speech, then pop the terminal symbol off the stack and remove w from the word string that is to be parsed.

Let us now code a top-down parser in pyactr that implements these two general parsing rules and uses the grammar in (1). Recall that the example sentence we will parse is *Mary likes Bill*.

3.2 Building a top-down parser in pyactr

Let us start with the first standard step, importing pyactr.

[py1]
```
>>> import pyactr as actr
```

We should now specify the types of chunks we need. We will have one type for parsing goals. The parsing goal will keep track of:

- the stack content: we only need two positions in the stack for our current purposes – the top and the bottom of the stack; this is a consequence of the fact that our grammar (1) generates at most binary branching trees;
- the current word being parsed (if any);
- the current task of the parser, that is, the current state our parsing model is in – basically, 'parsing' if the parse is still ongoing, and 'done' if the parsing is finished.

[py2]
```
>>> actr.chunktype("parsing_goal",\
...                "stack_top stack_bottom parsed_word task")
```

The second chunk type we need to declare is one that will enable us to represent the incoming sentence, i.e., the incoming word string, to be parsed. This might seem counter-intuitive: why should we represent the sentence to be parsed in a chunk? The sentence is external to the agent, it's what the agent reads or hears. However, at this point we have no way of represent the surrounding environment and the basic input/output interfaces between the mind and the environment. We therefore have to represent a sentence internally as a chunk. When we introduce the vision and motor modules in Chapter 4, we will be able to develop a more intuitive and elegant solution. The chunk type for sentences only needs to store three words since our target sentence is only that long.

[py3]
```
>>> actr.chunktype("sentence", "word1 word2 word3")
```

3.2.1 Modules, buffers, and the lexicon

Let us now initialize the model and set up more convenient ways of accessing the declarative memory module and the goal buffer:

```
[py4] >>> parser = actr.ACTRModel()                                    1
      >>> dm = parser.decmem                                          2
      >>> g = parser.goal                                             3
```

The goal buffer will store a `parsing_goal` chunk, which carries the information that drives the parsing process, and which is updated throughout that process. But we also need to store the word sequence that we need to parse, so we will create a second buffer that is similar to the goal buffer and that will store the sentence to be parsed.

Having two goal-like buffers is not uncommon in ACT-R. The first buffer is the actual goal buffer, which keeps track of the information driving the cognitive process. The other one is the *imaginal* buffer; this buffer is associated with the imaginal module and maintains an internal image of the information associated with the current cognitive process, thereby providing contextual information relevant for the current task. Thus, storing the sentence to be parsed in the imaginal buffer is an acceptable approximation of the cognitive behavior we're trying to model.

```
[py5] >>> imaginal = parser.set_goal(name="imaginal", delay=0.2)       1
```

In [py5], we create a new goal buffer, the `imaginal` buffer. The string `"imaginal"` sets the name under which the model will recognize and access the buffer (e.g., in production rules). The `delay` attribute of the imaginal buffer encodes the delay required to set a chunk in the buffer: it will take 0.2 seconds (200 ms) to set a chunk in the `imaginal` buffer. This is the standard value for this buffer, in contrast to the `goal` buffer which sets a chunk immediately. Finally, [py5] assigns this new buffer to a variable `imaginal` so that we can access it more easily in the Python interpreter.

The goal and imaginal buffers, and more generally the state of the buffers at any given point in a cognitive process provides the internal state, or the context, of the cognitive process at that point. For example, items in memory that share values with items in the goal or imaginal buffers are contextually 'primed', i.e., they are more salient than other items and are easier to retrieve because they are relevant in context. Thus, the cognitive context in the sense of 'the current state of the buffers' has a function similar to variable assignments in first-order logic. Assignments in first-order logic provide the current context of interpretation relative to which incoming expressions are interpreted, and the state of the buffers in an ACT-R model of the mind similarly provide the context for the next step in the cognitive process. The counterpart of the model in first-order logic is the content of the modules, particularly the facts stored in declarative memory and the rules stored in procedural memory.

We can now add chunks to the `goal` and `imaginal` buffers:

```
[py6] >>> g.add(actr.chunkstring(string="""                            1
      ...     isa parsing_goal                                        2
      ...     task parsing                                            3
      ...     stack_top 'S'                                           4
```

```
... """))
>>> g
{parsing_goal(parsed_word= , stack_bottom= , stack_top= S, task= parsing)}
>>> imaginal.add(actr.chunkstring(string="""
...     isa sentence
...     word1 'Mary'
...     word2 'likes'
...     word3 'Bill'
... """))
>>> imaginal
{sentence(word1= Mary, word2= likes, word3= Bill)}
```

The `goal` buffer switches to an active `parsing` state / `task`, and the current parsing goal, i.e., the top of the stack, is set to parsing a sentence (`'S'`). In the `imaginal` buffer, we set the `sentence` to be parsed to *Mary likes Bill*.

We are now ready to start answering the main question of the chapter: how do we code the top-down parser itself? We will assume that the grammar and associated parsing rules are part of the `procedural` module, i.e., they are encoded by production rules. This contrasts with lexical information, which is commonly encoded in declarative memory (see Lewis and Vasishth 2005 for more discussion and arguments for this division of labor).

We specify our lexicon first. For simplicity, our lexical representations will encode only the phonological form (replaced with the standard English spelling) and the part of speech / syntactic category of our lexical items:

[py7]
```
>>> actr.chunktype("word", "form, cat")
>>> dm.add(actr.chunkstring(string="""
...     isa word
...     form 'Mary'
...     cat 'ProperN'
... """))
>>> dm.add(actr.chunkstring(string="""
...     isa word
...     form 'Bill'
...     cat 'ProperN'
... """))
>>> dm.add(actr.chunkstring(string="""
...     isa word
...     form 'likes'
...     cat 'V'
... """))
>>> dm
{word(cat= ProperN, form= Bill): array([ 0.]), word(cat= ProperN, form=
   Mary): array([ 0.]), word(cat= V, form= likes): array([ 0.])}
```

3.2.2 Production rules

We now turn to the production rules that encode both our context-free grammar rules in (1) and the top-down parsing strategy represented in the `expand` and `scan` rules in (5).

The first rule is an expanding rule, encoding the first phrase structure rule of our grammar: we expand S into NP and VP, in that order.

```
[py8] >>> parser.productionstring(name="expand: S ==> NP VP", string="""
...       =g>
...       isa parsing_goal
...       task parsing
...       stack_top 'S'
...       ==>
...       =g>
...       isa parsing_goal
...       stack_top 'NP'
...       stack_bottom 'VP'
...  """)
      {'=g': parsing_goal(parsed_word= , stack_bottom= , stack_top= S, task=
         parsing)}
      ==>
      {'=g': parsing_goal(parsed_word= , stack_bottom= VP, stack_top= NP, task=
         )}
```

Note how the rule pops the `'S'` goal off the stack and replaces it with two subgoals `'NP'` and `'VP'`, in that order. We do not modify the current `task`, which should remain in an active `parsing` state, so we omit it from the specification of the action: the chunk in the consequent / right-hand side of the production rule only specifies the slots whose values should be updated, namely `stack_top` and `stack_bottom`.

The second rule is once again an expanding rule: NP is expanded into ProperN.

```
[py9] >>> parser.productionstring(name="expand: NP ==> ProperN", string="""
...       =g>
...       isa parsing_goal
...       task parsing
...       stack_top 'NP'
...       ==>
...       =g>
...       isa parsing_goal
...       stack_top 'ProperN'
...  """)
      {'=g': parsing_goal(parsed_word= , stack_bottom= , stack_top= NP, task=
         parsing)}
      ==>
      {'=g': parsing_goal(parsed_word= , stack_bottom= , stack_top= ProperN,
         task= )}
```

Note that the rule only updates the top of the stack; the bottom of the stack is left unmodified, so it is omitted throughout the rule.

The third production rule expands VP into V and NP:

```
[py10] >>> parser.productionstring(name="expand: VP ==> V NP", string="""
       ...     =g>
       ...     isa parsing_goal
       ...     task parsing
       ...     stack_top 'VP'
       ...     ==>
       ...     =g>
       ...     isa parsing_goal
       ...     stack_top 'V'
       ...     stack_bottom 'NP'
       ... """)
       {'=g': parsing_goal(parsed_word= , stack_bottom= , stack_top= VP, task=
          parsing)}
       ==>
       {'=g': parsing_goal(parsed_word= , stack_bottom= NP, stack_top= V, task= )}
```

This rule is almost identical to the first rule: we only changed the syntactic category symbols. Crucially, note that the rule is triggered only when the 'parse a VP' goal is at the *top* of the stack. Thus, to trigger this third rule, something must happen after the successive application of the first and second rules `"expand: S ==> NP VP"` and `"expand: NP ==> ProperN"` that will promote the VP goal from the bottom of the stack to the top of the stack.

Goals at the bottom of the stack can be promoted to the top when the top goal is popped off the stack and is not replaced by another goal. This is what happens in a *scan* step: in our case, a `scan` rule needs to pop the `'ProperN'` goal off the top of the stack and at the same time scans / parses the first word `'Mary'` of our target sentence.

That is, once we have a terminal (`ProperN`, `V`) at the top of our stack, we have to check that the terminal matches the category of the word to be parsed. If so, the word is scanned / parsed. We achieve this by means of two rules. First, we place a retrieval request for a lexical item stored in declarative memory whose form is the current word to be parsed. If a lexical item is successfully retrieved and the syntactic category of that lexical item is the same as the terminal at the top of our stack, the current word is scanned and the top symbol / goal on our stack is popped.

The two retrieval rules for our two terminal symbols (ProperN, V) are provided below. In both cases, we place a retrieval request based on the form of the first word in the sentence to be parsed (`=w1`) and we change the state of the parsing goal to `retrieving` (rather than `parsing`):

```
[py11] >>> parser.productionstring(name="retrieve: ProperN", string="""
       ...     =g>
       ...     isa parsing_goal
       ...     task parsing
       ...     stack_top 'ProperN'
```

```
...     =imaginal>
...     isa sentence
...     word1 =w1
...     ==>
...     =g>
...     isa parsing_goal
...     task retrieving
...     +retrieval>
...     isa word
...     form =w1
... """)
{'=imaginal': sentence(word1= =w1, word2= , word3= ), '=g':
   parsing_goal(parsed_word= , stack_bottom= , stack_top= ProperN, task=
   parsing)}
==>
{'=g': parsing_goal(parsed_word= , stack_bottom= , stack_top= , task=
   retrieving), '+retrieval': word(cat= , form= =w1)}
```

[py12]
```
>>> parser.productionstring(name="retrieve: V", string="""
...     =g>
...     isa parsing_goal
...     task parsing
...     stack_top 'V'
...     =imaginal>
...     isa sentence
...     word1 =w1
...     ==>
...     =g>
...     isa parsing_goal
...     task retrieving
...     +retrieval>
...     isa word
...     form =w1
... """)
{'=imaginal': sentence(word1= =w1, word2= , word3= ), '=g':
   parsing_goal(parsed_word= , stack_bottom= , stack_top= V, task=
   parsing)}
==>
{'=g': parsing_goal(parsed_word= , stack_bottom= , stack_top= , task=
   retrieving), '+retrieval': word(cat= , form= =w1)}
```

If the retrieved lexical item matches the top of our stack in syntactic category, we parse the word, pop the top symbol off the stack, and scan the next word in our sentence (that is, we promote `word2` in our sentence to `word1`, and `word3` to `word2`):

[py13]
```
>>> parser.productionstring(name="scan: word", string="""
...     =g>
```

```
...     isa parsing_goal                                                    3
...     task retrieving                                                     4
...     stack_top =y                                                        5
...     stack_bottom =x                                                     6
...     =retrieval>                                                         7
...     isa word                                                            8
...     form =w1                                                            9
...     cat =y                                                              10
...     =imaginal>                                                          11
...     isa sentence                                                        12
...     word1 =w1                                                           13
...     word2 =w2                                                           14
...     word3 =w3                                                           15
...     ==>                                                                 16
...     =g>                                                                 17
...     isa parsing_goal                                                    18
...     task printing                                                       19
...     stack_top =x                                                        20
...     stack_bottom empty                                                  21
...     parsed_word =w1                                                     22
...     =imaginal>                                                          23
...     isa sentence                                                        24
...     word1 =w2                                                           25
...     word2 =w3                                                           26
...     word3 empty                                                         27
...     ~retrieval>                                                         28
... """)                                                                    29
{'=imaginal': sentence(word1= =w1, word2= =w2, word3= =w3), '=g':           30
   parsing_goal(parsed_word= , stack_bottom= =x, stack_top= =y, task=       31
   retrieving), '=retrieval': word(cat= =y, form= =w1)}                     32
==>                                                                         33
{'~retrieval': None, '=imaginal': sentence(word1= =w2, word2= =w3, word3=   34
   empty), '=g': parsing_goal(parsed_word= =w1, stack_bottom= empty,        35
   stack_top= =x, task= printing)}                                          36
```

Note how on lines 20-21 of [py13], the top of the stack is popped, so the symbol on the bottom of the stack is promoted to the top of the stack. Similarly, the imaginal buffer is updated on lines 23-27: the word `=w1` that we just parsed is deleted from the sentence; the new sentence / word string that we still need to parse contains only words `=w2` and `=w3`, which are promoted to the `word1` and `word2` positions. We also clear the retrieval buffer (`~retrieval>` on line 28).

Finally, as a convenience, the parsed word `=w1` is stored in the `parsed_word` slot of the parsing goal chunk (line 22 in [py13]) and we enter a new `printing` state (line 19 in [py13]) that will enable us to print a message reporting which word was just parsed. This printing action, performed by the rule in [py14] below, is helpful to us as modelers but it is not a necessary part of our processing model.

```
[py14] >>> parser.productionstring(name="print parsed word", string="""
...     =g>
...     isa parsing_goal
...     task printing
...     =imaginal>
...     isa sentence
...     word1 ~empty
...     ==>
...     !g>
...     show parsed_word
...     =g>
...     isa parsing_goal
...     task parsing
...     parsed_word None
... """)
{'=imaginal': sentence(word1= ~empty, word2= , word3= ), '=g':
   parsing_goal(parsed_word= , stack_bottom= , stack_top= , task=
   printing)}
==>
{'=g': parsing_goal(parsed_word= None, stack_bottom= , stack_top= , task=
   parsing), '!g': ([['show', 'parsed_word'], {})], {})}
```

The production rule in [py14] says that if the current parsing goal is in a `printing` state (line 4 in [py14]) and the slot `word1` in the imaginal buffer is not empty (the squiggle ~ on line 7 is negation), that is, we still have words to parse, then we should print the `parsed_word` in the `goal` buffer (lines 9-10). Line 9 !g> indicates that our python interpreter should execute an action that involves the goal buffer; the action is specified on line 10: call the method `show` on the value of the `parsed_word` slot. When we're done printing, we delete the contents of the `parsed_word` slot and re-enter an active state of `parsing` (lines 11-14).

The last production we have to consider is the 'wrap-up' production we trigger at the end of the parsing process, provided in [py15] below. The parsing process ends when the `word1` slot in the imaginal buffer chunk has the value `empty` (line 7) and the task is `printing` (line 4). We therefore print the final word of the sentence which was just parsed (lines 9-10) and declare the parsing process done by clearing the `imaginal` and `goal` buffers (lines 11-12).

```
[py15] >>> parser.productionstring(name="done", string="""
...     =g>
...     isa parsing_goal
...     task printing
...     =imaginal>
...     isa sentence
...     word1 empty
...     ==>
...     !g>
...     show parsed_word
...     ~imaginal>
```

```
...      ~g>                                                                    12
... """)                                                                        13
{'=imaginal': sentence(word1= empty, word2= , word3= ), '=g':                   14
   parsing_goal(parsed_word= , stack_bottom= , stack_top= , task=               15
   printing)}                                                                   16
==>                                                                             17
{'~g': None, '~imaginal': None, '!g': ([(['show', 'parsed_word'], {})],         18
   {})}                                                                         19
```

3.3 Running the model

We run the model as before: we first instantiate a simulation of the model and then run it.

[py16]
```
>>> parser_sim = parser.simulation()                                            1
>>> parser_sim.run()                                                            2
(0, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                        3
(0, 'PROCEDURAL', 'RULE SELECTED: expand: S ==> NP VP')                         4
(0.05, 'PROCEDURAL', 'RULE FIRED: expand: S ==> NP VP')                         5
(0.05, 'g', 'MODIFIED')                                                         6
(0.05, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                     7
(0.05, 'PROCEDURAL', 'RULE SELECTED: expand: NP ==> ProperN')                   8
(0.1, 'PROCEDURAL', 'RULE FIRED: expand: NP ==> ProperN')                       9
(0.1, 'g', 'MODIFIED')                                                          10
(0.1, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                      11
(0.1, 'PROCEDURAL', 'RULE SELECTED: retrieve: ProperN')                         12
(0.15, 'PROCEDURAL', 'RULE FIRED: retrieve: ProperN')                           13
(0.15, 'g', 'MODIFIED')                                                         14
(0.15, 'retrieval', 'START RETRIEVAL')                                          15
(0.15, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                     16
(0.15, 'PROCEDURAL', 'NO RULE FOUND')                                           17
(0.2, 'retrieval', 'CLEARED')                                                   18
(0.2, 'retrieval', 'RETRIEVED: word(cat= ProperN, form= Mary)')                 19
(0.2, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                      20
(0.2, 'PROCEDURAL', 'RULE SELECTED: scan: word')                                21
(0.25, 'PROCEDURAL', 'RULE FIRED: scan: word')                                  22
(0.25, 'imaginal', 'MODIFIED')                                                  23
(0.25, 'g', 'MODIFIED')                                                         24
(0.25, 'retrieval', 'CLEARED')                                                  25
(0.25, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                     26
(0.25, 'PROCEDURAL', 'RULE SELECTED: print parsed word')                        27
(0.3, 'PROCEDURAL', 'RULE FIRED: print parsed word')                            28
parsed_word Mary                                                                29
(0.3, 'g', 'EXECUTED')                                                          30
(0.3, 'g', 'MODIFIED')                                                          31
(0.3, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                      32
(0.3, 'PROCEDURAL', 'RULE SELECTED: expand: VP ==> V NP')                       33
```

```
(0.35, 'PROCEDURAL', 'RULE FIRED: expand: VP ==> V NP')
(0.35, 'g', 'MODIFIED')
(0.35, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.35, 'PROCEDURAL', 'RULE SELECTED: retrieve: V')
(0.4, 'PROCEDURAL', 'RULE FIRED: retrieve: V')
(0.4, 'g', 'MODIFIED')
(0.4, 'retrieval', 'START RETRIEVAL')
(0.4, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.4, 'PROCEDURAL', 'NO RULE FOUND')
(0.45, 'retrieval', 'CLEARED')
(0.45, 'retrieval', 'RETRIEVED: word(cat= V, form= likes)')
(0.45, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.45, 'PROCEDURAL', 'RULE SELECTED: scan: word')
(0.5, 'PROCEDURAL', 'RULE FIRED: scan: word')
(0.5, 'imaginal', 'MODIFIED')
(0.5, 'g', 'MODIFIED')
(0.5, 'retrieval', 'CLEARED')
(0.5, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.5, 'PROCEDURAL', 'RULE SELECTED: print parsed word')
(0.55, 'PROCEDURAL', 'RULE FIRED: print parsed word')
parsed_word likes
(0.55, 'g', 'EXECUTED')
(0.55, 'g', 'MODIFIED')
(0.55, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.55, 'PROCEDURAL', 'RULE SELECTED: expand: NP ==> ProperN')
(0.6, 'PROCEDURAL', 'RULE FIRED: expand: NP ==> ProperN')
(0.6, 'g', 'MODIFIED')
(0.6, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.6, 'PROCEDURAL', 'RULE SELECTED: retrieve: ProperN')
(0.65, 'PROCEDURAL', 'RULE FIRED: retrieve: ProperN')
(0.65, 'g', 'MODIFIED')
(0.65, 'retrieval', 'START RETRIEVAL')
(0.65, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.65, 'PROCEDURAL', 'NO RULE FOUND')
(0.7, 'retrieval', 'CLEARED')
(0.7, 'retrieval', 'RETRIEVED: word(cat= ProperN, form= Bill)')
(0.7, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.7, 'PROCEDURAL', 'RULE SELECTED: scan: word')
(0.75, 'PROCEDURAL', 'RULE FIRED: scan: word')
(0.75, 'imaginal', 'MODIFIED')
(0.75, 'g', 'MODIFIED')
(0.75, 'retrieval', 'CLEARED')
(0.75, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.75, 'PROCEDURAL', 'RULE SELECTED: done')
(0.8, 'PROCEDURAL', 'RULE FIRED: done')
parsed_word Bill
```

```
(0.8, 'g', 'EXECUTED')
(0.8, 'g', 'CLEARED')
(0.8, 'imaginal', 'CLEARED')
(0.8, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.8, 'PROCEDURAL', 'NO RULE FOUND')
```

The parser runs as expected: we successfully parse our three-word sentence, and the time course of the parsing is as follows. The first word *Mary* is parsed by the time 300 ms of simulation time have elapsed (line 29 in [py16]); in fact, the first word is parsed at the 250 ms mark when the `scan: word` rule is fired for the first time (lines 22-25). The second word *likes* is parsed after 550 ms of total simulation time (line 54); in fact, just as for the previous word, the word *likes* is parsed at the 500 ms mark when the `scan: word` rule is fired for the second time (lines 47-50). The final word *Bill* is parsed after 800 ms of simulation time have passed (line 79), but just as before, the actual parsing happens at the 750 ms mark when the `scan: word` rule is fired for the third and final time (lines 72-75).

Let us examine the content of the declarative memory module at the end of the simulation. It should contain the lexical items we added at the very beginning of the simulation, as well as the chunks stored in the goal and imaginal buffers right before we cleared them at the end of the parsing process (recall that clearing the buffers always moves their contents to declarative memory).

[py17]
```
>>> dm
{word(cat= ProperN, form= Bill): array([ 0.  ,  0.75]), sentence(word1=
   empty, word2= empty, word3= empty): array([ 0.8]),
   parsing_goal(parsed_word= Bill, stack_bottom= empty, stack_top= empty,
   task= printing): array([ 0.8]), word(cat= ProperN, form= Mary): array([
   0.  ,  0.25]), word(cat= V, form= likes): array([ 0. ,  0.5])}
```

As expected, we see in [py17] that the goal chunk stored in declarative memory has an empty stack, and the imaginal chunk has an empty sentence (no words). Furthermore, both these chunks have been stored / activated in memory at the 800 ms mark, i.e., at the end of the simulation. We also see the three lexical items *Mary*, *likes* and *Bill*, each of which has two activation time stamps: one at 0 ms when they were added to declarative memory before running the simulation, and one at 250, 500 and 750 ms respectively, when they were parsed during the simulation and the retrieval buffer was cleared by the three firings of the `scan: word` rule. We will see in Chapter 6 where we discuss the inner workings of declarative memory in detail that this schedule of activations for items in memory is a crucial component of determining the relative salience of the item in memory, and therefore how easy they are to retrieve.

3.4 Failures to parse and taking snapshots of the mind when it fails

We can run the parser on ungrammatical sentences to see if and how exactly it fails. Let's try to parse the word sequence *Bill Mary likes*. The parser should fail while parsing the second word *Mary* because the noun does not match its expectation to see a verb. We add the relevant chunks to the goal and imaginal buffers and start a new simulation.

[py18]
```
>>> g.add(actr.chunkstring(string="""
...     isa parsing_goal
...     task parsing
...     stack_top 'S'
... """))
>>> imaginal.add(actr.chunkstring(string="""
...     isa sentence
...     word1 'Bill'
...     word2 'Mary'
...     word3 'likes'
... """))
>>> parser_sim2 = parser.simulation()
>>> parser_sim2.run()
(0, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0, 'PROCEDURAL', 'RULE SELECTED: expand: S ==> NP VP')
(0.05, 'PROCEDURAL', 'RULE FIRED: expand: S ==> NP VP')
(0.05, 'g', 'MODIFIED')
(0.05, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.05, 'PROCEDURAL', 'RULE SELECTED: expand: NP ==> ProperN')
(0.1, 'PROCEDURAL', 'RULE FIRED: expand: NP ==> ProperN')
(0.1, 'g', 'MODIFIED')
(0.1, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.1, 'PROCEDURAL', 'RULE SELECTED: retrieve: ProperN')
(0.15, 'PROCEDURAL', 'RULE FIRED: retrieve: ProperN')
(0.15, 'g', 'MODIFIED')
(0.15, 'retrieval', 'START RETRIEVAL')
(0.15, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.15, 'PROCEDURAL', 'NO RULE FOUND')
(0.2, 'retrieval', 'CLEARED')
(0.2, 'retrieval', 'RETRIEVED: word(cat= ProperN, form= Bill)')
(0.2, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.2, 'PROCEDURAL', 'RULE SELECTED: scan: word')
(0.25, 'PROCEDURAL', 'RULE FIRED: scan: word')
(0.25, 'imaginal', 'MODIFIED')
(0.25, 'g', 'MODIFIED')
(0.25, 'retrieval', 'CLEARED')
(0.25, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.25, 'PROCEDURAL', 'RULE SELECTED: print parsed word')
(0.3, 'PROCEDURAL', 'RULE FIRED: print parsed word')
parsed_word Bill
(0.3, 'g', 'EXECUTED')
(0.3, 'g', 'MODIFIED')
(0.3, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.3, 'PROCEDURAL', 'RULE SELECTED: expand: VP ==> V NP')
(0.35, 'PROCEDURAL', 'RULE FIRED: expand: VP ==> V NP')
(0.35, 'g', 'MODIFIED')
```

```
(0.35, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                  47
(0.35, 'PROCEDURAL', 'RULE SELECTED: retrieve: V')                           48
(0.4, 'PROCEDURAL', 'RULE FIRED: retrieve: V')                               49
(0.4, 'g', 'MODIFIED')                                                       50
(0.4, 'retrieval', 'START RETRIEVAL')                                        51
(0.4, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                   52
(0.4, 'PROCEDURAL', 'NO RULE FOUND')                                         53
(0.45, 'retrieval', 'CLEARED')                                               54
(0.45, 'retrieval', 'RETRIEVED: word(cat= ProperN, form= Mary)')             55
(0.45, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                  56
(0.45, 'PROCEDURAL', 'NO RULE FOUND')                                        57
```

Just as before, our goal is to parse a sentence `'S'` ([py18], line 4), namely *Bill Mary likes* (lines 8-10). The parser correctly parses the first word *Bill* and prints it (line 40). But the parsing process stops after 450 ms because the word *Mary* retrieved from declarative memory is of category ProperN (line 55) while the top of the parsing goal stack stores the category V, which is what the parser was expecting to retrieve (lines 48-49).

To facilitate the inspection of simulations and models, `pyactr` provides a way to advance simulations one step at a time rather than letting them run from beginning to end. This makes it easy to check the internal state of the buffers, as well as diagnose / debug our models – e.g., if the model gets stuck in an infinite loop. Let's run the simulation in [py18] again and go through it step by step.

[py19]
```
>>> g.add(actr.chunkstring(string="""                                        1
...     isa parsing_goal                                                     2
...     task parsing                                                         3
...     stack_top 'S'                                                        4
... """))                                                                    5
>>> imaginal.add(actr.chunkstring(string="""                                 6
...     isa sentence                                                         7
...     word1 'Bill'                                                         8
...     word2 'Mary'                                                         9
...     word3 'likes'                                                        10
... """))                                                                    11
>>> parser_sim3 = parser.simulation()                                        12
>>> parser_sim3.step()                                                       13
(0, 'PROCEDURAL', 'CONFLICT RESOLUTION')                                     14
```

Very little happens in the first step: the parser simply enters a 'conflict resolution' state in which it identifies the rules that can be fired given the initial cognitive state (that is, the initial state of the buffers). Let's go through some more steps. To do that, we use the method `steps` with a parameter that provides the exact number of steps the simulation should advance through. In [py20], we advance 10 steps, as reflected in the 10 lines of simulation output.

[py20]
```
>>> parser_sim3.steps(10)                                                    1
(0, 'PROCEDURAL', 'RULE SELECTED: expand: S ==> NP VP')                      2
(0.05, 'PROCEDURAL', 'RULE FIRED: expand: S ==> NP VP')                      3
```

```
(0.05, 'g', 'MODIFIED')
(0.05, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.05, 'PROCEDURAL', 'RULE SELECTED: expand: NP ==> ProperN')
(0.1, 'PROCEDURAL', 'RULE FIRED: expand: NP ==> ProperN')
(0.1, 'g', 'MODIFIED')
(0.1, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.1, 'PROCEDURAL', 'RULE SELECTED: retrieve: ProperN')
(0.15, 'PROCEDURAL', 'RULE FIRED: retrieve: ProperN')
```

Let's now advance our simulation to the point where the rule `"scan: word"` has just fired. To be able to do that, we have to be able to check the current event, i.e., the most recent step taken in the simulation, and stop when this event is a `"scan: word"`-rule firing. The current event is an attribute of the simulation; for example, the current event in our simulation is a ProperN retrieval:

[py21]
```
>>> parser_sim3.current_event
Event(time=0.15, proc='PROCEDURAL', action='RULE FIRED: retrieve: ProperN')
```

As shown in [py21], the event has three attributes: `time` – the simulation time at which the event occurred (150 ms in our case), `proc` – the module that is affected (procedural memory in our case), and `action` – the cognitive action that has taken place.

Let us now advance to the first firing of the `"scan: word"` rule. We do this by running a `while` loop in the Python interpreter: the command on line 2 of [py22], i.e., advance one step through the simulation, should be taken while the condition on line 1 is satisfied. That condition says that the `action` attribute of the current event should *not* be a `"scan: word"` firing. Note that `!=` is non-identity in Python; `!` is customarily used for negation in programming languages, and it is distinct from ACT-R negation `~`.

[py22]
```
>>> while parser_sim3.current_event.action != 'RULE FIRED: scan: word':
...     parser_sim3.step()
...
(0.15, 'g', 'MODIFIED')
(0.15, 'retrieval', 'START RETRIEVAL')
(0.15, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.15, 'PROCEDURAL', 'NO RULE FOUND')
(0.2, 'retrieval', 'CLEARED')
(0.2, 'retrieval', 'RETRIEVED: word(cat= ProperN, form= Bill)')
(0.2, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.2, 'PROCEDURAL', 'RULE SELECTED: scan: word')
(0.25, 'PROCEDURAL', 'RULE FIRED: scan: word')
```

We can now inspect our buffers. As expected, the top of our parsing goal stack is a ProperN terminal, the first word *Bill* has been removed from the sentence stored in the imaginal buffer, and the lexical representation for *Bill* is accessible in the retrieval buffer:

[py23]
```
>>> g
{parsing_goal(parsed_word= None, stack_bottom= VP, stack_top= ProperN,
```

```
   task= retrieving)}
>>> imaginal
{sentence(word1= Mary, word2= likes, word3= empty)}
>>> parser.retrieval
{word(cat= ProperN, form= Bill)}
```

Let us now advance to the point where the parsing process failed. We will step through the simulation until the `action` attribute of the current event starts with the string `'RETRIEVED'`. That will be the point where the second word in our string, namely *Mary* has been retrieved:

[py24]
```
>>> while not parser_sim3.current_event.action.startswith('RETRIEVED'):
...     parser_sim3.step()
...
(0.25, 'imaginal', 'MODIFIED')
(0.25, 'g', 'MODIFIED')
(0.25, 'retrieval', 'CLEARED')
(0.25, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.25, 'PROCEDURAL', 'RULE SELECTED: print parsed word')
(0.3, 'PROCEDURAL', 'RULE FIRED: print parsed word')
parsed_word Bill
(0.3, 'g', 'EXECUTED')
(0.3, 'g', 'MODIFIED')
(0.3, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.3, 'PROCEDURAL', 'RULE SELECTED: expand: VP ==> V NP')
(0.35, 'PROCEDURAL', 'RULE FIRED: expand: VP ==> V NP')
(0.35, 'g', 'MODIFIED')
(0.35, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.35, 'PROCEDURAL', 'RULE SELECTED: retrieve: V')
(0.4, 'PROCEDURAL', 'RULE FIRED: retrieve: V')
(0.4, 'g', 'MODIFIED')
(0.4, 'retrieval', 'START RETRIEVAL')
(0.4, 'PROCEDURAL', 'CONFLICT RESOLUTION')
(0.4, 'PROCEDURAL', 'NO RULE FOUND')
(0.45, 'retrieval', 'CLEARED')
(0.45, 'retrieval', 'RETRIEVED: word(cat= ProperN, form= Mary)')
```

We can once again inspect the current cognitive state of the model / mind, i.e., the buffer contents:

[py25]
```
>>> parser.retrieval
{word(cat= ProperN, form= Mary)}
>>> g
{parsing_goal(parsed_word= None, stack_bottom= NP, stack_top= V, task=
   retrieving)}
>>> imaginal
{sentence(word1= Mary, word2= likes, word3= empty)}
```

And the cause of the parsing failure is apparent: the retrieval buffer stores a ProperN while the top of the parsing goal stack, i.e., our current parsing expectation / prediction, is a V. The parser therefore halts before the second word in our sentence can be scanned, as shown by the unchanged chunk in the imaginal buffer.

3.5 Top-down parsing as an imperfect psycholinguistic model

It is however not enough that our parser correctly parses grammatical sentences and fails for ungrammatical ones. Our top-down ACT-R parser is not simply an implementation of an arbitrary parsing algorithm that is satisfactory as long as it works correctly (much better implementations exist, with substantial empirical coverage). This parser is meant to be a limited but realistic model of a certain kind of human cognitive behavior, namely syntactic parsing in comprehension-like tasks (self-paced reading). Is our parser even remotely adequate as a psycholinguistic model?

One of the empirical adequacy desiderata for our parser is that the temporal trace of parsing a sentence should correspond to the temporal trace of an average human participant completing the same task. For example, we see that our parser takes 800 ms to parse the sentence *Mary likes Bill*. This is roughly correct, but there are various other properties of our parser that are more worrying. For one, the parser requires this much time while abstracting away from what human participants have to do during an actual self-paced reading task: internalizing visual information, projecting sentence meaning, executing motor actions (pressing keys) etc., so ultimately 800 ms might be too much given the very narrow amount of work our parser actually does.

Another issue is that retrieving lexical information always takes 50 ms in our current models and simulations, but this is hardly realistic. We know that lexical retrieval is dependent on various factors, particularly word frequency (but also priming etc.). These factors are completely completely ignored here.

Finally, top-down parsers work well for right-branching structures like the sentence *Mary likes Bill*, but they have significant difficulties with left branching structures. For such structures, the parser would have to store as many symbols on the stack as there are levels of embedding, and since every expansion of a rule takes 50 ms, we expect left branching structures with n levels of embedding to take $50 * n$ ms. This is at odds with actual human performance (see Resnik 1992, for example). The main reason for this is that our parser generates predictions about syntactic structure exclusively based on the grammar and completely ignores the actual evidence (the sentence to be parsed) until it reaches a terminal on the leftmost branch.

In fact, purely top-down / recursive descent parsers consult the evidence / word string only after they predict all the way to lexical items. That is, such pure top-down parsers would place memory retrieval requests based on the terminal at the top of the parsing goal stack. For example, if a ProperN is at the top of the stack, they would retrieve an arbitrary ProperN from declarative memory and only after that check whether the form of the retrieved ProperN matches the leftmost word to be parsed. If not, a new retrieval request would be placed for a new ProperN in hopes that the form of that new chunk would match the word to be parsed. In the worst case, such a purely top-down parser would retrieve all chunks of category ProperN one at at a time from declarative memory and finally identify the one whose form matches the current word to be parsed. The temporal trace of such a parser

would be very far from the temporal trace of an average human participant completing the same task: if the lexicon contains 20 chunks of ProperN category, and a retrieval takes around 50 ms, it would take a full second to parse the first word in the sentence *Mary likes Bill*. And this ignores the time needed to verify that 19 of the retrieved chunks are mismatches, and then the time needed to backtrack / restart the retrieval process.

Thus, a more plausible human parser would consult the evidence, i.e., the word string to be parsed, earlier and more often in the parsing process. Our top-down parsing strategy needs to be complemented by a bottom-up parsing strategy. In principle, we could switch from a purely top-down parser to a purely bottom-up parser that is completely driven by the evidence. Such a parser would be incremental, but it would not be predictive in the same way that the human parser seems to be. We will therefore not explore purely bottom-up (shift-reduce) parsers and instead move directly to left-corner parsers

Left-corner parsers combine top-down and bottom-up features: they can be thought of as predictive top-down parsers with incremental bottom-up filtering. The next chapter introduces left-corner parsers and models them in ACT-R / `pyactr`.

Exercise: extending the grammar and the top-down parser

Consider extending our grammar and the top-down parser with intransitive verbs like *sleeps*, as well as sentential-complement taking verbs like *believe*. That is, add the following phrase-structure and lexical-insertion rules to the grammar:

(6)
	VP	→	V
	VP	→	V CP
	CP	→	C S
	V	→	sleeps
	V	→	believes
	C	→	that

Add the new lexical items to declarative memory and add new production rules to procedural memory to encode the new phrase-structure rules. Once your model is in place, parse the sentence *Mary believes that Bill sleeps*.

You can probably already see that the new parser might run into problems. For example, the parser might get stuck when parsing the target sentence *Mary believes that Bill sleeps* if it decides to expand the first (matrix-clause) VP into V and NP, i.e., if it incorrectly expects a transitive verb instead of a sentential-complement taking verb, or into just V, i.e., if it incorrectly expects an intransitive verb. As we already discussed, this is a typical issue with top-down parsing: categories and structures are hypothesized / predicted before seeing any evidence for them. The extended top-down parser has several ways to expand VPs and it fails to parse the input if it uses a VP expansion rule that happens to be incompatible with the sentence to be parsed.

3.6 Appendix: The top-down parser

File **ch3_topdown_parser.py**:

```
"""
A simple top-down parser.
"""

import pyactr as actr

actr.chunktype("parsing_goal", "stack_top stack_bottom parsed_word task")
actr.chunktype("sentence", "word1 word2 word3")
actr.chunktype("word", "form, cat")

parser = actr.ACTRModel()
dm = parser.decmem
g = parser.goal
imaginal = parser.set_goal(name="imaginal", delay=0.2)

dm.add(actr.chunkstring(string="""
    isa word
    form 'Mary'
    cat 'ProperN'
"""))
dm.add(actr.chunkstring(string="""
    isa word
    form 'Bill'
    cat 'ProperN'
"""))
dm.add(actr.chunkstring(string="""
    isa word
    form 'likes'
    cat 'V'
"""))

g.add(actr.chunkstring(string="""
    isa parsing_goal
    task parsing
    stack_top 'S'
"""))
imaginal.add(actr.chunkstring(string="""
    isa sentence
    word1 'Mary'
    word2 'likes'
    word3 'Bill'
"""))

parser.productionstring(name="expand: S ==> NP VP", string="""
    =g>
    isa parsing_goal
```

```
    task parsing
    stack_top 'S'
    ==>
    =g>
    isa parsing_goal
    stack_top 'NP'
    stack_bottom 'VP'
""")

parser.productionstring(name="expand: NP ==> ProperN", string="""
    =g>
    isa parsing_goal
    task parsing
    stack_top 'NP'
    ==>
    =g>
    isa parsing_goal
    stack_top 'ProperN'
""")

parser.productionstring(name="expand: VP ==> V NP", string="""
    =g>
    isa parsing_goal
    task parsing
    stack_top 'VP'
    ==>
    =g>
    isa parsing_goal
    stack_top 'V'
    stack_bottom 'NP'
""")

parser.productionstring(name="retrieve: ProperN", string="""
    =g>
    isa parsing_goal
    task parsing
    stack_top 'ProperN'
    =imaginal>
    isa sentence
    word1 =w1
    ==>
    =g>
    isa parsing_goal
    task retrieving
    +retrieval>
    isa word
```

```
    form =w1                                                                    93
""")                                                                            94
                                                                                95
parser.productionstring(name="retrieve: V", string="""                          96
    =g>                                                                         97
    isa parsing_goal                                                            98
    task parsing                                                                99
    stack_top 'V'                                                               100
    =imaginal>                                                                  101
    isa sentence                                                                102
    word1 =w1                                                                   103
    ==>                                                                         104
    =g>                                                                         105
    isa parsing_goal                                                            106
    task retrieving                                                             107
    +retrieval>                                                                 108
    isa word                                                                    109
    form =w1                                                                    110
""")                                                                            111
                                                                                112
parser.productionstring(name="scan: word", string="""                           113
    =g>                                                                         114
    isa parsing_goal                                                            115
    task retrieving                                                             116
    stack_top =y                                                                117
    stack_bottom =x                                                             118
    =retrieval>                                                                 119
    isa word                                                                    120
    form =w1                                                                    121
    cat =y                                                                      122
    =imaginal>                                                                  123
    isa sentence                                                                124
    word1 =w1                                                                   125
    word2 =w2                                                                   126
    word3 =w3                                                                   127
    ==>                                                                         128
    =g>                                                                         129
    isa parsing_goal                                                            130
    task printing                                                               131
    stack_top =x                                                                132
    stack_bottom empty                                                          133
    parsed_word =w1                                                             134
    =imaginal>                                                                  135
    isa sentence                                                                136
    word1 =w2                                                                   137
    word2 =w3                                                                   138
```

```
    word3 empty
    ~retrieval>
""")

parser.productionstring(name="print parsed word", string="""
    =g>
    isa parsing_goal
    task printing
    =imaginal>
    isa sentence
    word1 ~empty
    ==>
    !g>
    show parsed_word
    =g>
    isa parsing_goal
    task parsing
    parsed_word None
""")

parser.productionstring(name="done", string="""
    =g>
    isa parsing_goal
    task printing
    =imaginal>
    isa sentence
    word1 empty
    ==>
    =g>
    isa parsing_goal
    task done
    !g>
    show parsed_word
    ~imaginal>
    ~g>
""")


if __name__ == "__main__":
    parser_sim = parser.simulation()
    parser_sim.run()
    print("\nDeclarative memory at the end of the simulation:")
    print(dm)
```