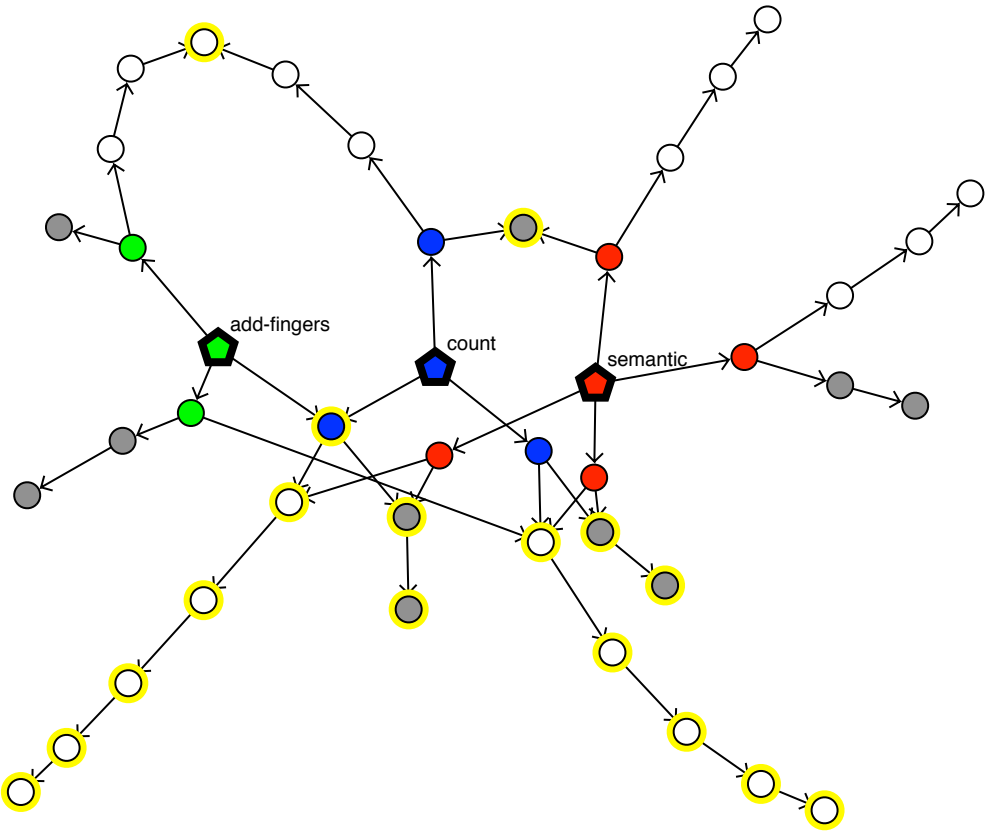
# PRIMS TUTORIAL

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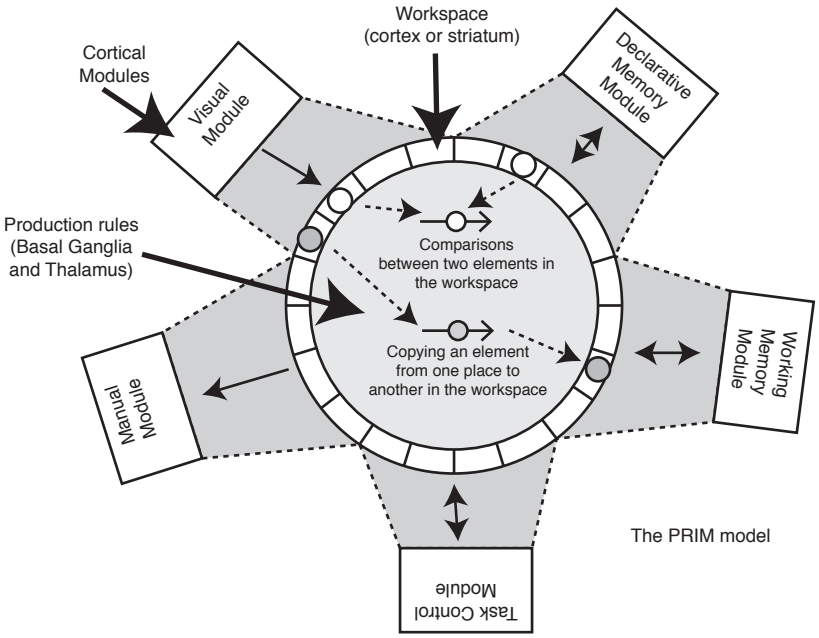
# UNIT 1

## *Introduction to PRIMs*

The PRIMs cognitive architecture has evolved from the ACT-R cognitive architecture (Anderson, 2007). Although familiarity with ACT-R is useful, no prior ACT-R knowledge is necessary for this tutorial. We will start the tutorial with some concepts that have been adapted from ACT-R before starting with the structure of a PRIMs model.

## Main concepts

Like many other current cognitive architectures, PRIMs is modular. It assumes the cognitive system has specific modules for vision, motor control, goal focus, declarative memory, working memory, etc. Modules can operate in parallel, but can only do one thing at a time. Communication between these modules is carried out through buffers. Each buffer has a number of slots through which it can exchange information with other buffer, where each slot can hold a single piece of information. All the buffers together comprise the (global) workspace of the system.



The PRIM model

The core PRIMs theory focusses on how information is exchanged within this workspace. The process of information exchange is carried out by production rules that do simple comparisons and copy operations between slots in the workspace. However, the control of this process is determined by declarative knowledge. Declarative memory contains both knowledge of facts (3 +4 = 7, an elephant is a mammal, my birthday is 6 May, etc.) as well as knowledge on how to do things (how to solve a multi-column addition, how to count a number of marbles, how to ride a bicycle), in other words procedural knowledge that many other architectures (including ACT-R) assume resides in a specific procedural memory.

Given the importance of declarative memory, we discuss it in a bit more detail.

## Declarative Memory

The elements in declarative memory are called *chunks*. A chunk is a unit of information that consists of a name and a set of attribute-value pairs. A typical chunk that might represent the fact that 3 + 4 = 7 may look like:

```
FACT347
       SLOT1 ADDITION-FACT
       SLOT2 THREE
       SLOT3 FOUR
       SLOT4 SEVEN
```

In this example the name of the chunk is `FACT347`. The name is in this case fairly meaningless, but sometimes we want to give chunks a meaningful name so that it is easier for us to read a model. The chunk has four attributes. Contrary to most cognitive architectures, attributes do not have names, but just numbers. The order of the attributes matters, because in this particular case `SLOT2` and `SLOT3` contain the numbers that are added, while `SLOT4` holds the answer. This fact is not represented anywhere explicitly, but is implicit in the knowledge that knows how to do calculations with numbers (as we will see later on). The values connected to the attributes refer to other chunks, `ADDITION-FACT`, `THREE`, `FOUR` and `SEVEN`. Most of the time chunks refer to other chunks, although a value may also be a number.

Each chunk has an activation value. The activation value is comprised of two main components. The first is *base-level activation* that represents how frequent and recent the chunk has been used, and therefore represents the history of a chunk. Chunks that have been used more frequently and recently receive a higher activation, so base-level activation represents the natural decay and repetition effects of memory. The second component is spreading activation from the current context. Chunks can have a strength of association with each other. Chunks that are already in the workspace and that are associated with chunks in declarative memory spread activation to those chunks. For example, if `THREE` and `FOUR` are already in the workspace, then `FACT347` will receive extra activation because `THREE` and `FOUR` each have a positive association with `FACT347`.

Activation has three purposes. The first is *selection*. If two chunks both match the retrieval request, the chunk with the highest activation will be chosen. On each cycle, some noise will be added/subtracted from the activation, so selection is a stochastic process.

The second is *forgetting*. If the activation of a chunk drop below a certain retrieval threshold, the chunk cannot be retrieved from memory.

The third is that activation determines the time that is necessary to retrieve the chunk. A higher activation translates into a short retrieval time.

The details of how activations are calculated can be found at the end of this unit.

## The structure of a PRIMs model

A PRIMs model consists of several components. It contains the name of the task with some parameters, the specification of a set of skills to perform the task, each of which consists of a set of operators, possibly additional facts necessary to carry out the task, and a script that simulates the environment or experiment.

The example we will use consists of two models: count and semantic. We will see that there can be quite a bit of transfer between the two tasks, even though they are not very similar at first glance.

Let us look at the file `count.prims`. It starts by specifying what task we are going to carry out:

```
define task count {
  initial-skills: (count)
  default-activation: 1.0
  ol: t
  rt: -2.0
  lf: 0.2
  default-operator-self-assoc: 0.0
  egs: 0.05
}
```

In PRIMs, a task can be implemented by several skills, but the count task is only implemented by one, also named count. The `initial-skills: (count)` line specifies this.

The remaining lines in the task definition are model parameters, some of which are straight from ACT-R (`ol:` optimized learning, `rt:` retrieval threshold, `lf:` latency factor, `egs:` utility noise), but others are specific to PRIMs. The model's parameters are not particularly critical for the operation of this model, so we will not discuss them yet.

The next part of the model defines operators to carry out the task. Operators are organized within skills. We have only one skill, the count skill, so we define it as:

```
define skills count {
… Operator definitions …
}
```

The result of this organization is that all the operators within a skill definition will be associated with that skill, that is, whenever a skill is in one of the goal buffer slots, the associated operators receive spreading activation and are therefore more likely to be retrieved.

We then see definitions of the three operators that are needed to count. The first is:

```
operator start-count {
 V1 <> nil  // There has to be a visual input with the starting number
 WM1 = nil  // Imaginal should be empty
==>
 V1 -> WM1 // Copy the start number to working memory
 count-fact -> RT1 // Start retrieving the next number
 V1 -> RT2
 say -> AC1 // Say the current number
 V1 -> AC2
 }
```

As the name implies, this operator initiates counting. Each operator consists of one or more condition PRIMs, and one or more action PRIMs, each on a separate line. PRIMs always refer to two specific slots in two buffers (or one slot in one buffer and nil). In between is either a comparison (= or <>), or a copy operation (–>). An arrow ==> separates the conditions and actions, and anything after `//` is ignored. Note that comparison between two slots, even an <> comparison, will only succeed if both slots contain a value. In other words, `V2<>WM1` will only match if both `V2` and `WM1` have a value, and these values are different.

`nil` is used to denote that a slot is empty, and can therefore be used to check whether a slot is empty or not empty, and can also be used to clear a slot (e.g., `nil -> WM1`).

The letters indicate the buffer, and the number the slot number within that buffer. In this example, we will use the following buffers:

- `V`: Visual, or input buffer. This buffer contains the visual input. In this particular model, `V1` has the starting number for counting, and `V2` the ending number.
- `WM`: Working memory or imaginal buffer. This buffer is used to store intermediate results. Here we only use one slot to represent the current count.
- `RT`: Retrieval. Used to retrieve items from declarative memory. In this model it is used to retrieve count-facts from memory.
- `AC`: Action. Used specify actions the model takes. This model will use it to "say" numbers.
- `G`: Goal. Goal slots hold skills that are used to activate operators that are relevant for the current task. Because of our initial-skills declaration, `count` will be put into `G1`.

- C: Constant. This is not actually a buffer, and it also doesn't show up in the operator definition. However, each time a PRIM in an operator has a constant in it, that is, a specification that is not a buffer/slotnumber combination (and not nil), that constant is put in one of the slots of the operator chunk. In our example, count-fact and say are both constants that will be put into C1 and C2, respectively. Although it appears in the syntax as if we can also use constants in PRIMs, "under the hood" they are replaced by buffer slots as well.

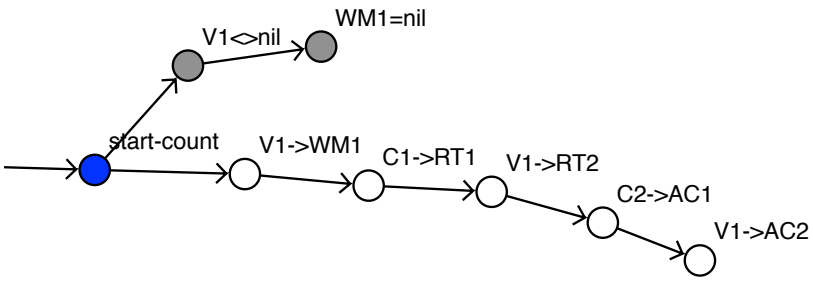
If an operator is selected, its conditions are checked first. In this case, a check is made whether V1 is not empty, denoted by V1 <> nil. The second check (WM1 = nil) is to check whether WM1 is empty, indicating we haven't started counting yet.

If these conditions are satisfied, the operator will start carrying out its actions. Typically, actions involve updating WM slots and specifying actions that are carried out by the modules. In this example, we first store the input into working memory in order to maintain a counter: V1 -> WM1. We then specify a retrieval request, which consists of two PRIMs: count-fact -> RT1 specifies slot1 of the retrieval, and V1 -> RT2 slot2 of the retrieval. In other words, we want a count-fact about the starting number. Furthermore, we want to say that number, which is specified by say -> AC1 and V1 -> AC2.

Although an operator does not really look like declarative chunk, it is in fact represented in declarative memory. The PRIMs parser takes care of the translation process to a chunk definition that looks like:

```
start-count
  isa  operator
  slot1  count-fact
  slot2  say
  condition  V1<>nil;WM1=nil
  action  V1->WM1;C1->RT1;V1->RT2;C2->AC1;V1->AC2
```

The chunks in the condition and action slots represent the first in a list of PRIMs. V1->WM1;C1->RT1;V1->RT2;C2->AC1;V1->AC2 is a PRIM that carries out V1->WM1 and points to C1->RT1;V1->RT2;C2->AC1;V1->AC2, which in turn carries out C1->RT1, and points to V1->RT2;C2->AC1;V1->AC2, etcetera. The following figure visualizes the structure of the operator, in which each node is a chunk:




The second and third operator are as follows:

```
operator iterate {
  RT2 = WM1
  V2 <> WM1
 ==>
  RT3 -> WM1
  count-fact -> RT1
  RT3 -> RT2
  say -> AC1
  RT3 ->AC2
}

operator final {
  V2 = WM1
 ==>
  say -> AC1
  stop -> AC2
  nil -> G1
}
```

They do the rest of the counting: the iterate operator iterates as long as the final number has not been reached (`V2 <> WM1`), and the third operator terminates the count.

The next definition in the file defines facts that will be put into declarative memory. A fact definition consists of lists of values enclosed in parentheses. Each of these lists is translated into a chunk

```
define facts {
(cf1 count-fact  one  two)
(cf2 count-fact  two  three)
(cf3  count-fact  three  four)
(cf4  count-fact  four  five)
(cf5  count-fact  five  six)
…
}
```

The first item in the list will become the name of the new chunk, while the remaining items will be put into slots. For example, `(cf1 count-fact one two)` will be translated into the following chunk:

```
cf1
  isa  fact
  slot1  count-fact
  slot2  one
  slot3  two
```

Although we have specified in the model that it should "say" things, we haven't really specified what it means to say something. In this case we do not really care, but we do want the action to take a certain amount of time. The following declaration takes care of this:

```
define action say {
  latency: 0.3
  noise: 0.1
  distribution: uniform
  output: Saying
}
```

It specifies that the latency to say something is 0.3 ± 0.1 seconds, with a uniform distribution of the noise. The action will show up in the trace as "Saying".

The final part is a script that runs the task.

```
define script {
    digits = ["one","two","three","four","five","six","seven",
        "eight","nine","ten"]
    start = random(3)
    end = start + 1 + random(3)
    print("Counting from",digits[start],"to",digits[end])
    screen(digits[start],digits[end])
    run-until-action("say","stop")
    issue-reward()
    trial-end()
}
```

We will discuss in more detail how to build scripts, but the syntax is similar to C-style languages, so should speak for itself (to some extent). The script here first defines an array of the numbers one through ten, then picks a random start number and end number. The screen function puts the selected numbers in the V-buffer (so `digits[start]` ends up in `V1` and `digits[end]` in `V2`). It then tells the model to run until it the action "say stop" is carried out. It then issues a reward to the model, and ends the trial.

### The Zero Slot

Up to now we have done all the operations on slots in the buffers. But what if we want to refer to the chunk as a whole? For example, if you have just retrieved `cf1`, you can access `count-fact`, `one` and `two` in `RT1`, `RT2`, and `RT3`. But how to access `cf1` itself? For this we have the "zero" slot, `RT0`. It is important realize the it is not really a slot, but refers to the chunk as a whole. As a consequence, putting `nil` in the zero slot, for example with `nil -> WM0`, clears the whole buffer. In the case of `nil -> WM0`, the chunk is entered into declarative memory, which is a way to create new chunks.

## The PRIMs execution cycle

Operators only move around information within the workspace. It is therefore up to the different modules to carry out actions that result from this. The execution cycle is therefore as follows:

1. Retrieve the operator with the highest activation
2. Check the conditions of that operator. If a condition is not satisfied, retrieve the operator with the next highest activation and try again.
3. Carry out the actions of the operator (i.e., move information between slots in the workspace).
4. Based on the new state of the workspace, let all the modules perform their function in parallel. This can be: retrieval from memory, consolidation of the item working memory, and/or carry out an action. The result of this may change the content of the buffers in the workspace again: a declarative retrieval can be placed in the retrieval buffer, and some actions may result in a change in input.

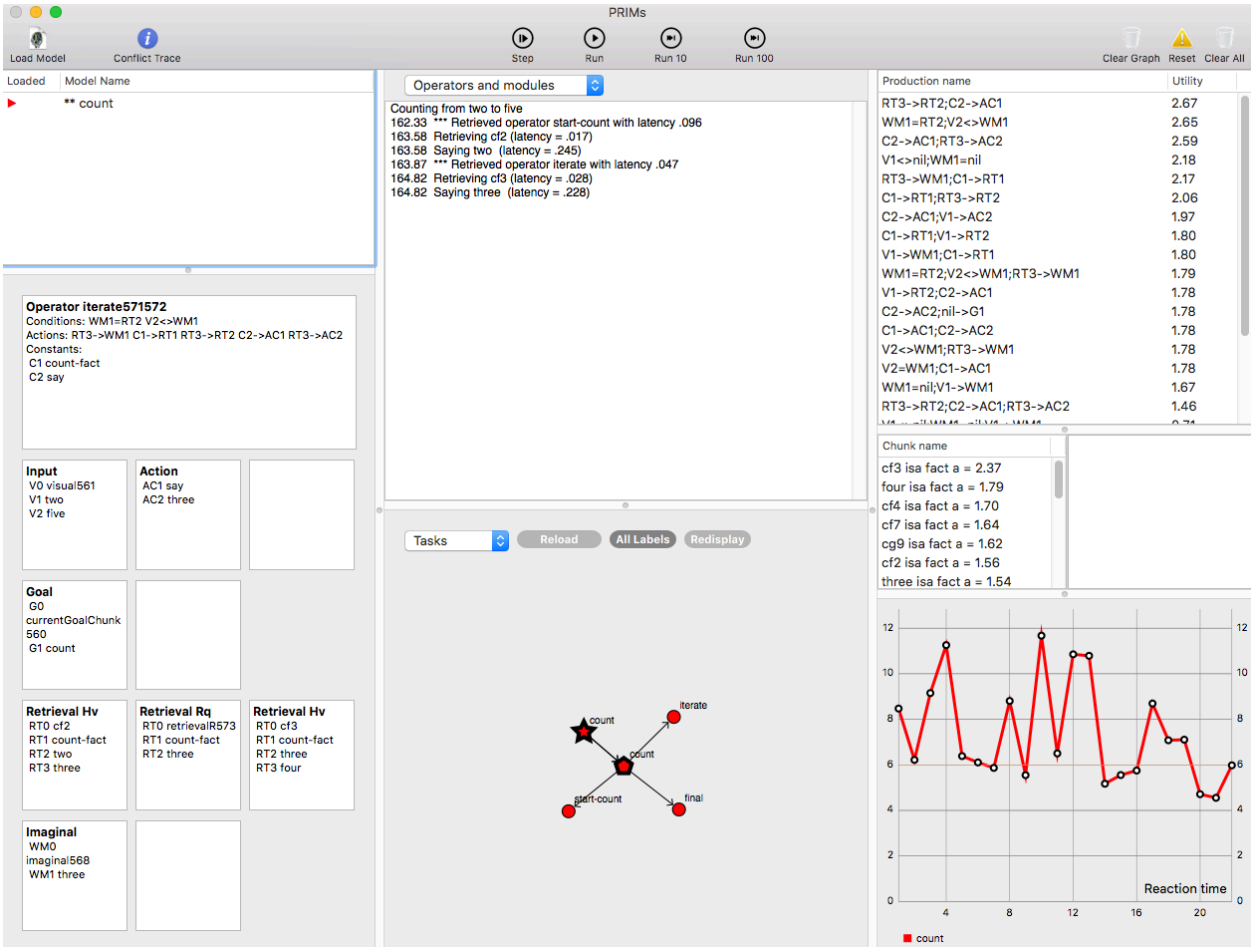
## Running a model

To run the count model, start the PRIMs application, and use the "Load Model" button or "Open..." menu option to load the file. Select `count.prims`, after which the top-middle panel will show some information about what is loaded. If there is an error in the model, it will show up in that panel, you will find it in that panel (unless the program crashed first.... Not everything is fool-proof yet).

Once the model has loaded, you can run it with the four buttons in the menu bar (Step, Run, Run 10, Run 100). Various other parts of the window can help you make sense of what is going on in the model. Let us have a look after the model has run a couple of times (Figure 1).

This model window has the following panels:

- The top-left panel shows a list of tasks that the system currently knows, and are proceeded by a colored triangle if the associated model is actually loaded. The color of the triangle also identifies the task in some of the other panels. The task with ** is the currently active task, clicking a different task activates it.
- The bottom-left panel shows the contents of the different buffers when the model is running. Shown are the currently selected operator, the contents of several buffers before the operator is executed (left column), how buffers are changed by the operator (middle column), and how buffers are changed by module actions (right column).




- The top-center panel typically shows the model trace. We will discuss this in a little more detail in a moment. The pop-up menu at the top of this panel can be used to select the desired amount of detail in the trace. For now, select “Operators and productions”.

- The bottom-center panel shows a graph of the tasks, showing tasks as stars, skills as hexagons, and operators as colored circles. The pop-up menu allows you to look at this in a bit more detail: if you select "PRIMs", it will show the individual PRIMs that make up the operators, and potentially their overlap. If multiple tasks are loaded, items will be shows in different colors, and PRIMs that are used by multiple tasks will receive a yellow halo. The popup menu can be used to make graphs of others aspects of the models.
- The top-right panel shows learned production rules with their utilities. Production rules are always combinations of PRIMs.
- The middle-right panel shows all the chunks in declarative memory with their activation. If you click on one, it will show in more detail on the right.
- Finally, the bottom-right panel shows a graph of model results. In the example, the model has run about 20 times, and has improved its speed considerably. Multiple graphs can show after running multiple models.
- The buttons on the top-right of the window do the following: Clear Graph clears the graph on the bottom-right. Reset removes all models from memory and reloads the one that is selected on the top-left (Note: it doesn't actually reload it from the file, just from a stored representation, so if you have changed the model you should load it back explicitly). Clear All removes everything. If you click Conflict Trace, an extra window will open in which you can see how operators and memory items compete. This is not a big thing yet in the Count model, but it will be later on.

Once you have loaded the model, you can step through it with the Step button, run it all the way with the Run button, or run it 10 times with the Run 10 button (no trace will show in that case). The trace will show detail of what is going on. You can select several levels of detail with the popup menu. Let the Count run model once, and select "Operators and productions" in the popup-menu. The trace will show something like:

```
Counting from two to four
0.00  *** Retrieved operator start-count with spread 3.0
0.00  Firing V1<>nil
0.05  Firing WM1=nil
0.35  Firing V1->WM1
0.65  Firing C1->RT1
0.95  Firing V1->RT2
1.25  Firing C2->AC1
1.55  Firing V1->AC2
1.85  Retrieving cf2 (latency = 0.0457923987659046)
1.85  New imaginal chunk imaginalN6  (latency = 0.2)
1.85  Saying two  (latency = 0.363782)
2.22  *** Retrieved operator iterate with spread 2.0
2.22  Firing WM1=RT2
2.27  Firing V2<>WM1
```

```
2.57  Firing RT3->WM1
2.87  Firing C1->RT1
3.17  Firing RT3->RT2
3.47  Firing C2->AC1
3.77  Firing RT3->AC2
4.07  Retrieving cf3 (latency = 0.0868078620404207)
4.07  Saying three  (latency = 0.339786)
       4.42  *** Retrieved operator start-count with spread 2.0
       4.42  Firing V1<>nil
       4.47  Firing WM1=nil
       4.77  Operator start-count15 failed
4.78  *** Retrieved operator iterate with spread 1.5
4.78  Firing WM1=RT2
4.83  Firing V2<>WM1
5.13  Firing RT3->WM1
5.43  Firing C1->RT1
5.73  Firing RT3->RT2
6.03  Firing C2->AC1
6.33  Firing RT3->AC2
6.63  Retrieving cf4 (latency = 0.0693551797048966)
6.63  Saying four  (latency = 0.230098)
       6.88  *** Retrieved operator start-count with spread 2.0
       6.88  Firing V1<>nil
       6.93  Firing WM1=nil
       7.23  Operator start-count23 failed
7.23  *** Retrieved operator final with spread 2.0
7.23  Firing V2=WM1
7.28  Firing C1->AC1
7.58  Firing C2->AC2
7.88  Firing nil->G1
8.18  Saying stop  (latency = 0.380044)
```

The number in the left column represents time. We can see that at time `0`, the model retrieves the `start-count` operator. It will then start carrying out that operator by firing a production rule for each individual PRIM. After the last PRIM has been carried out, modules do their actions in parallel. In this case, three modules become active: the retrieval module retrieves `cf2`, the action module says two, and the imaginal (working memory) module makes a new chunk to store the count. They each have their own latency, but the longest counts (in this case 0.36 seconds for saying two). Note that anything in the trace that is indented belongs to an operator that failed, so it has no impact on execution, except for taking up time. As we can see, the model is pretty slow to count from two to four, taking about eight seconds.

The popup menu at the top of the panel can be used to change the level of detail. For example, selecting All will reveal:

```
Counting from two to four
0.00  Conflict Set
0.00    start-count A = 5.6670079060538
0.00    iterate A = 5.52215155396268
0.00    final A = 4.90347259519914
0.00  *** Retrieved operator start-count with spread 3.0
```

```
0.00  Firing V1<>nil
0.05  Firing WM1=nil
0.05  Compiling V1<>nil;WM1=nil
0.35  Firing V1->WM1
0.35  Compiling WM1=nil;V1->WM1
0.65  Firing C1->RT1
0.65  Compiling V1->WM1;C1->RT1
0.95  Firing V1->RT2
0.95  Compiling C1->RT1;V1->RT2
1.25  Firing C2->AC1
1.25  Compiling V1->RT2;C2->AC1
1.55  Firing V1->AC2
1.55  Compiling C2->AC1;V1->AC2
1.85  Retrieving cf2 (latency = 0.0457923987659046)
1.85  New imaginal chunk imaginalN6  (latency = 0.2)
1.85  Saying two  (latency = 0.363782)
```

For each retrieved operator it will show all the competing operators with their activations. Of those competing operators, only those will be tried in which the first production that checks conditions matches. Initially, the only productions are productions that check or execute a single PRIM. But the learning mechanism of production compilation will learn productions that execute combinations of PRIMs.

## Production Compilation

The trace also shows production compilation in action. After `V1<>nil` and `WM1=nil` have been checked, a rule is learned that makes both comparisons in one step. This rule will not be used right away. The reason is that all rules have a utility value, and the rule with the highest utility value will be used. Initially, there are only rules that each carry out a single PRIM, and they all have a utility of `2.0` (you can give this a different value with the `primU:` parameter). Newly learned productions receive a utility of `0.0` (you can change that as well with the `nu:` parameter). Whenever PRIMs needs to select a production rule, it will add logistic noise to the utility values (varied by the `egs:` parameter, by default `0.05`), and will pick the rule with the highest value.

Whenever a rule successfully leads to the execution of an operator, its utility will be adjusted according to the following equation:

$$U_{t+1} = U_t + \alpha(\text{Payoff} - U_t)$$

Payoff is equal to the Reward parameter (`procedural-reward:`, defaults to `4.0`) minus the time needed after executing the production to finish the operator. The $\alpha$ parameter controls the learning speed (`alpha:` by default `0.1`). Learning is only used for rules that consist of multiple PRIMs: the utility of rules that carry out a single PRIM remains fixed at `2.0` (or whatever value you select for `primU`).

Obviously, a new rule has little chance to compete with the existing rule that it was learned from. Therefore, every time a production is relearned, its utility is increased by the following equation:

$$U_{t+1} = U_t + \alpha(U_{\text{parent}} - U_t)$$

This is the same equation as the regular equation, except that the payoff is replaced by the utility of the parent. This ensure that utility gradually approaches the utility of the parent, increasing the odds that it will eventually be selected (and evaluated).

Production compilation speeds up the execution of the model. Carrying out an operator takes the amount of time needed to retrieve the operator (typically this is very short) and the time needed to fire production rules that carry out the operator. The first of these takes 50 ms to carry out, but each subsequent one takes 300 ms (you can change these values with the `dat:` and `production-prim-latency:` parameters, respectively). After sufficient learning, a production is learned that checks all conditions and carries out all actions with a single rule. Try running the count model often enough to see this (newly learned productions show up in the top-right of the window).

## Modeling Transfer

One of the goals of PRIMs is to model transfer. The general idea of transfer is that productions that are learned for one task can be reused for another task. We therefore need to specify at least one additional model. The example is the Semantic model from unit 1. The goal of the semantic model is to judge relationships between animals and animal categories, and answer questions like "Is a lion an animal"? The facts the model uses are:

```
define facts {
    (sem1  property  lion  mammal)
    (sem2  property  mammal  animal)
    (sem3  property  animal living-thing)
    (sem4  property  plant living-thing)
    (sem5  property  tulip plant)
    (sem6  property  bird animal)
    (sem7  property  tweety bird)
    (sem8  property  robin bird)
}
```

Answering the question involves two steps: first to retrieve that a lion is a mammal, and then that a mammal is an animal. Even though this model is semantically different from count, it shares the same type of iteration. The operators in the model are therefore similar:

```
define skill semantic {
    operator start-semantic {
       V1 <> nil
        WM1 = nil
       ==>
```

```
        V1 -> WM1
        property -> RT1
        V1 -> RT2
        subvocalize -> AC1
        V1 -> AC2
    }

    operator move-up-tree {
       RT2 = WM1
        V2 <> WM1
       ==>
        RT3 -> WM1
        property -> RT1
        RT3 -> RT2
        subvocalize -> AC1
        RT3 -> AC2
    }

    operator say-yes {
       V2 = WM1
       ==>
        say -> AC1
        yes -> AC2
        stop -> G1
    }

    operator say-no {
       V2 <> WM1
        RT1 = error
       ==>
        say -> AC1
        no -> AC2
        nil -> G1
    }
}
```

The first two operators in this model are the same as in the counting model, with the exception that the slot labels are different. But once the operators are translated into declarative memory, the conditions and actions are identical. The last two operators are different. If a match between the target category and the retrieved category is found, the model should answer "yes", which is slightly different from finalizing the count. Also, if the proposition does not hold, the model will hit a retrieval error at some point. On a retrieval error, the first slot of the retrieval buffer will be set to error (which is, in the example, matched by `RT1 = error`).

Here is an example of a run of the model:

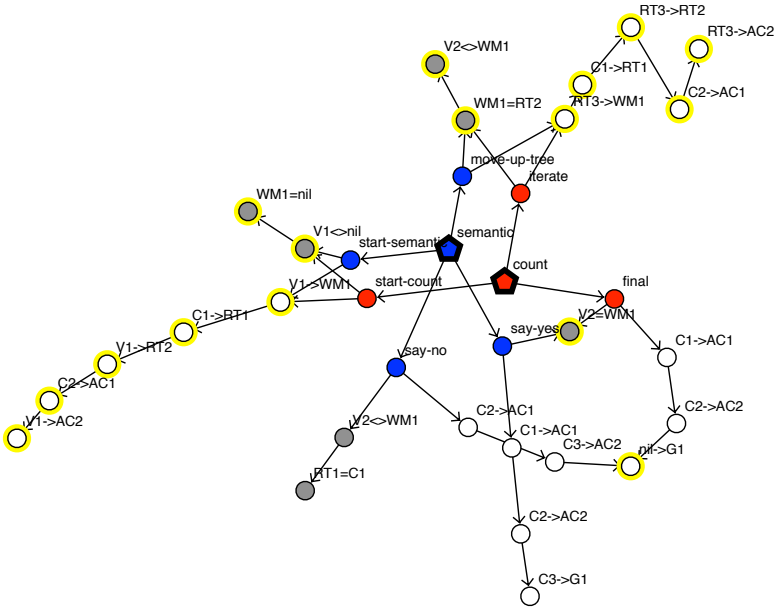
```
0.00  *** Retrieved operator start-semantic with spread 3.0
0.00  Firing V1<>nil
0.05  Firing WM1=nil
0.35  Firing V1->WM1
0.65  Firing C1->RT1
0.95  Firing V1->RT2
```

```
1.25  Firing C2->AC1
1.55  Firing V1->AC2
1.85  Retrieving sem1 (latency = 0.0458280985167914)
1.85  New imaginal chunk imaginalN6  (latency = 0.2)
1.85  Subvocalizing lion (latency = 0.3)
2.15  *** Retrieved operator move-up-tree with spread 2.0
2.15  Firing RT2=WM1
2.20  Firing V2<>WM1
2.50  Firing RT3->WM1
2.80  Firing C1->RT1
3.10  Firing RT3->RT2
3.40  Firing C2->AC1
3.70  Firing RT3->AC2
4.00  Retrieving sem2 (latency = 0.0750171372159093)
4.00  Subvocalizing mammal (latency = 0.3)
      4.31  *** Retrieved operator start-semantic with spread 2.0
      4.31  Firing V1<>nil
      4.36  Firing WM1=nil
      4.66  Operator start-semantic16 failed
      4.67  *** Retrieved operator say-no with spread 2.0
      4.67  Firing V2<>WM1
      4.72  Firing RT1=C1
      5.02  Operator say-no19 failed
5.03  *** Retrieved operator move-up-tree with spread 2.0
5.03  Firing RT2=WM1
5.08  Firing V2<>WM1
5.38  Firing RT3->WM1
5.68  Firing C1->RT1
5.98  Firing RT3->RT2
6.28  Firing C2->AC1
6.58  Firing RT3->AC2
6.88  Retrieving sem3 (latency = 0.0460701809949314)
6.88  Subvocalizing animal (latency = 0.3)
      7.19  *** Retrieved operator start-semantic with spread 2.0
      7.19  Firing V1<>nil
      7.24  Firing WM1=nil
      7.54  Operator start-semantic28 failed
      7.55  *** Retrieved operator say-no with spread 2.0
      7.55  Firing V2<>WM1
      7.60  Firing RT1=C1
      7.90  Operator say-no30 failed
7.90  *** Retrieved operator move-up-tree with spread 2.0
7.90  Firing RT2=WM1
7.95  Firing V2<>WM1
8.25  Firing RT3->WM1
8.55  Firing C1->RT1
8.85  Firing RT3->RT2
9.15  Firing C2->AC1
9.45  Firing RT3->AC2
9.75  Retrieval failure
9.75  Subvocalizing living-thing (latency = 0.3)
11.24  *** Retrieved operator say-yes with spread 2.0
11.24  Firing V2=WM1
11.29  Firing C1->AC1
11.59  Firing C2->AC2
11.89  Firing nil->G1
12.19  Saying yes (latency = 0.3)
```

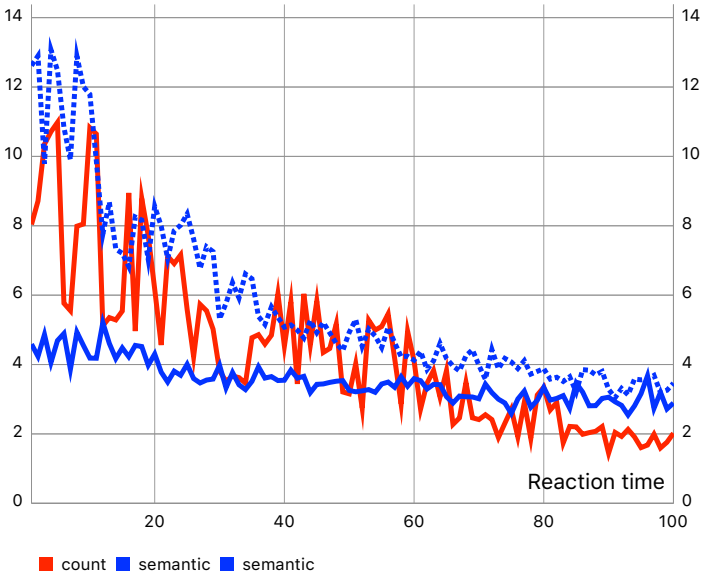
However, if you first run the count model for a while, productions have been compiled that can be reused:

```
1108.01  *** Retrieved operator start-semantic with spread 3.0
1108.01  Firing V1<>nil;WM1=nil;V1->WM1;C1->RT1
1108.06  Firing V1->RT2;C2->AC1;V1->AC2
1108.36  Retrieving sem2 (latency = 0.0557285933220927)
1108.36  New imaginal chunk imaginalN12151  (latency = 0.2)
1108.36  Subvocalizing mammal (latency = 0.3)
      1108.67  *** Retrieved operator say-no with spread 2.0
      1108.67  Firing V2<>WM1
      1108.72  Firing RT1=C1
      1109.02  Operator say-no12156 failed
1109.03  *** Retrieved operator move-up-tree with spread 2.0
1109.03  Firing RT2=WM1;V2<>WM1;RT3->WM1;C1->RT1;RT3->RT2;C2->AC1;RT3->AC2
1109.08  Retrieving sem3 (latency = 0.0922408709785375)
1109.08  Subvocalizing animal (latency = 0.3)
      1109.39  *** Retrieved operator say-no with spread 2.0
      1109.39  Firing V2<>WM1
      1109.44  Firing RT1=C1
      1109.74  Operator say-no12166 failed
1109.75  *** Retrieved operator move-up-tree with spread 2.0
1109.75  Firing RT2=WM1;V2<>WM1;RT3->WM1;C1->RT1;RT3->RT2;C2->AC1;RT3->AC2
1109.80  Retrieval failure
1109.80  Subvocalizing living-thing (latency = 0.3)
1111.29  *** Retrieved operator say-yes with spread 2.0
1111.29  Firing V2=WM1
1111.34  Firing C1->AC1
1111.64  Firing C2->AC2
1111.94  Firing nil->G1
1112.24  Saying yes (latency = 0.3)
```

How do we assess transfer between these two models? A first option is to look at the overlap of PRIMs between the two models. The figure to the right gives an impression of this overlap (all the yellow halos), which is considerable (this figure can be obtained by selected the PRIMs option in the center-bottom panel).




To get a real sense of the amount of transfer, we have to run the model. We first run the Count model a number of




times, and then the Semantic model. Then we run the Semantic model without prior training.

To do this in a simple way, do the following. Load in both the Count and Semantic model. Click on the count model in the top-left panel to activate it. Click the "Run 10" button ten times to run the model for 100 times. You will see the learning curve in the right bottom corner. Now activate semantic, and run it 100 times. The new curve will show semantic after learning count. Now push the Reset button, and run the semantic model again for 100 times. Your graph should look something like the one here.

The top blue curve is semantic without transfer from count, and the bottom curve is the one with transfer.

We can also collect this type of data by automatizing this. Choose the "Run Batch..." option from the Run menu, and select the "testbatch.bprims" as input in the file dialog. Then choose a filename of your choice as output. The system will now run what we just did by hand ten times. It will also generate a datafile that we can analyze with R, Excel or any other packages that takes data tables.

## Perception and Action

PRIMs uses a simplified version ACT-R's perception and motor modules. This means that some of the precision is lost, but on the other hand that it is easier to program the experiment part of the model.

For the current assignment, we are going to build two models of addition by counting. The first one will be done through mental operations, but the second model assumes that one of the two counters that has to be maintained through the use of fingers. The assumption of the model is that each time we say a number, we also stick up an additional finger, and the total number of fingers is available to perception. In order to do this we need a somewhat more elaborate script that changes perception on the basis of actions:

```
define script {
       digits =
["zero","one","two","three","four","five","six","seven","eight","nine","ten"]
    num1 = random(4) + 1
    num2 = random(4) + 1
    print("Adding",digits[num1],"and",digits[num2])
    screen(digits[num1],digits[num2])
    done = 0
    fingers = 0
    while (!done) {
              run-until-action()
              ac = last-action()
              if (ac[0] == "say") {
                     fingers = fingers + 1
                     screen(digits[num1],digits[num2],digits[fingers])
              }
              if (ac[0] == "answer") {
                     done = 1
              }
       }
    issue-reward()
    trial-end()
}
```

This script picks two random numbers between one and four, and displays them to the model. It will start a loop that ends when the model uses "answer" as an action. More in particular, the `run-until-action()` function will run the model until it takes any action. The `last-action()` function then returns an array with the last action the model took. If the first element in this array is "say", it means we need to put up an extra finger, and add this to the input (it goes into `V3`). If the first element is "answer", it means we are done (the script language has no Booleans, but uses `0` as false and any non-zero number as true).

## Assignment

The assignment is to add a model of addition by counting to the existing two models, and to assess transfer between counting and addition.

There are two possible solutions to explore. The first involves keeping track of two numbers in WM. The two numbers to be added are perceptual input, and two `WM` slots are needed to hold the current count and the current sum.

Your first operator has to initialize the process by putting the first addend (which is in `V1`) into `WM1`, and zero in `WM2`. It then has to make a retrieval request for the a count-fact about the number in `V1`.

The second operator harvests a retrieval count-fact that matches `WM1`, updates the number in `WM1`, and issues a count-fact retrieval request for `WM2`.

A third operator harvest a count-fact retrieval that matches `WM2`, checks whether `WM2` is not equal to the second addend (in `V2`), and issues a count-fact retrieval for a count-fact about `WM1`. It also updates `WM2`.

A fourth operator checks whether the count in `WM2` equals `V2`, and gives the contents of `WM1` as an answer.

Implement this model, and check whether it works. The script is a more simple version of the one above: replace `done = 0, finger = 0` and the `while` loop by `run-until-action("answer")`. Make sure the last action of your model is "answer"! Although we haven't yet gone over the details of the script (they are in the appendix to this unit), it should be relatively easy to understand and edit.

Once you have made sure the model works, you can check how fast it learns. You can then also see how much transfer there is from the count model, using the same method as with semantic. If you want to use the method with the batch file, you should edit the `.bprims` file so that it uses your new model instead of semantic (hopefully the structure of the batch file speaks for itself).

You will probably conclude that transfer between counting and this addition model is limited. You can therefore try to build an alternative model using fingers. This model only requires three operators, and should show more transfer than the "standard" model.

## Details of Declarative Memory

The standard ACT-R equation for calculating the activation of a chunk is as follows:

$$A_i = B_i + \sum_{k}^{\text{sources}} \sum_{j}^{\text{slots}} S_{ji} W_k + \text{noise}$$

In this equation $B_i$ is the base-level activation that reflects how often the chunk has been recreated in the past. The double summation calculated the spreading activation from the different buffers (sources) in the workspace. Each of these buffers can spread activation, the amount of which is represented by the $W_k$ parameter that is set as a global parameter (e.g., `:imaginal-activation` for the imaginal buffer, see the list of PRIMs parameters).

Each buffer has a number of slots, and the chunk in each slot is the potential source of spreading, assuming it has a non-zero strength of association ($S_{ji}$). This strength of association can be set explicitly in the model, but also receives a value by default whenever a chunk in the buffer is in one of the slots of a chunk in declarative memory. For example, if the chunk `three` has a positive association with the chunk that represents `3 + 4 = 7`, because the `three` chunk is in one of the slots of `3 + 4 = 7`.

The base-level activation is calculated using the standard base-level activation formula:

$$B_i(t) = \ln \sum_{k} (t - t_k)^{-d}$$

In this equation, the $t_k$'s are all the moments in time that the chunk was created or accessed, and $d$ is a decay parameter that is 0.5 by default. In standard ACT-R, both a recreating of a chunk or a retrieval from memory reinforces the chunk. In PRIMs, only recreating a chunk in the working memory buffer reinforces it. However, if the `retrieval-reinforces:` parameter is set to `t`, retrieval also reinforces the activation.

Because the standard formula is not very efficient computationally, an optimized version can be used (and is in fact the default, controlled by the `ol:` parameter):

$$B_i(t) = \ln(\frac{n}{1-d}) - d \ln(t - t_0)$$

In this version of the equation, $t_o$ is the creation time of the chunk, and $n$ is the number of accesses it has had during its lifetime.

As mentioned above, the strength of association ($S_{ji}$) can be set by hand in the model. It is zero by default, except when chunk $j$ is in a slot of chunk $i$. In that case the value is calculated by the following equation:

$$S_{ji} = S - \ln(\text{fan}_j)$$

$S$ is the maximum associative strength parameter (`:mas`), and $\text{fan}_j$ is the number of chunks in which chunk $j$ appears. The idea behind this is that as chunk $j$ is less unique for chunk $i$ (because it appears in many other chunks), its association is weaker.

Whenever the total activation of a chunk drops below the retrieval threshold $\tau$, retrieval fails. If retrieval succeeds, the time required for a retrieval is:

$$t_{\text{retrieval}} = Fe^{-A_i}$$

$F$ is a global parameter (`:lf`). In the case of a retrieval failure, the time spent on that failure is:

$$t_{\text{retrieval}} = Fe^{-\tau}$$

PRIMs adds a few things to the standard activation equations. First, it handles the spreading activation of skills slightly different from standard ACT-R. We will discuss this in a later unit, but the equation is:

$$A_i = B_i + \sum_k^{\text{buffers}} \sum_j^{\text{slots}} S_{ji} W_k + \sum_k^{\text{skills}} S_{ki} A_k + \text{noise}$$

The basic idea is that every active skill spreads an amount of activation that is equal to its own activation.

Furthermore, PRIMs adds the convenience of a "default activation". In most models you add facts that you assume are more or less permanently available to the model. In the count model you don't want the model to forget the count-facts. The default activation puts a lower bound on the activation of a chunk. If that activation is well over the retrieval threshold, and the noise in your model is not too large, you can be sure that the chunk will always be retrieved successfully. Here is how this is integrated into the equations:

$$B_i(t) = \ln(e^{\text{fixed}} + \sum_k (t - t_k)^{-d})$$

$$B_i(t) = \ln(e^{\text{fixed}} + \frac{n}{1-d}) - d \ln(t - t_0)$$

## PRIMs parameters

imaginal-delay:

Time it takes to put a new chunk in the imaginal buffer (default 0.2)

egs:

Utility noise (default 0.05)

alpha:

Learning parameter for production compilation (default 0.1)

procedural-reward:

Reward for procedural learning (default 4.0)

nu:

Utility for newly compiled productions (default 0.0)

primU:

Utility of productions that handle a single PRIM (default 2.0)

dat:

Default time to fire the first production to handle an operator (default 0.05)

production-prim-latency:

Default time to fire subsequent productions to handle an operator. The idea is that this takes longer because it also involves retrieving a (PRIM)-chunk from memory. The current implementation doesn't actually do this, but the time this would take should be accounted for. The consequence is that a fully proceduralized operator only takes de default action time (dat:) to carry out, but if multiple productions have to fire it takes substantially longer. (default 0.3)

bll:

Base-level decay (d) (default 0.5)

ol:

Optimized learning (default t). Set to nil for the standard equation.

mas:

Maximum associative strength (default 3.0)

rt:

Retrieval Threshold (default -2.0)

lf:

Latency Factor (default 0.2)

mp:

Mismatch Penalty (default 5.0).

pm:

Use partial matching to retrieve facts. Off by default (nil), switch to t to use.

blending:

Use blending to retrieve facts. Off by default, switch to t to use.

ans:

Activation noise (default 0.2)

ga:

Spreading activation (W) from the goal (default 1.0)

input-activation:

Spreading activation (W) from the input (default 0.0)

retrieval-activation:

Spreading activation (W) from the retrieval buffer (default 0.0)

imaginal-activation: or wm-activation:

Spreading activation (W) from working memory (default 0.0)

default-activation:

In most models, the chunks you specify as part of the model can be assumed to exist for a while, so they probably have reasonable stable activation values. When you give a value to default-activation, that value becomes the lower-bound of baselevel activation for all chunks you specify in the model (including operators). The default for the parameter is 0.0. In addition to giving this parameter a different value, you can set it to nil, so that all chunks are susceptible to decay.

default-operator-assoc:

$S_{ji}$ between an operator and the skill it is defined in. This ensures that operators relevant to one of the skills in the goal buffer are more likely to be retrieved instead of other operators. (default 4.0)

goal-chunk-spreads:

Normally, the amount of spreading from the goal is equal to the ga parameter divided by the number of chunks is the goal. If you set this parameter to t, the amount of

spreading will be equal to the activation of the goal, allowing you to give goals more or less priority. (default nil)

default-inter-operator-assoc:
: $S_{ji}$ between an operator and other operators for the same goal. Make it more likely that an operator that is associated to the same goal as the previous operator is selected. (default 1.0)

default-operator-self-assoc:
: $S_{ji}$ between an operator and itself. Should be negative to make it less likely that an operator will fire repeatedly. (default -1.0)

perception-action-latency:
: Default time for any action that is not defined explicitly (default 0.2)

retrieval-reinforces:
: In standard ACT-R, each time you retrieve a fact from memory it receives an extra reference, increasing its baselevel activation. In PRIMs this is not the case by default. If you want standard ACT-R behavior, set this parameter to t. (default: nil)

skill-operator-learning:
: Experimental mechanism for a task to find its own operators. When set to t (true), the mechanism will be active. The mechanism tries to learn associations between the skills in the goal buffer and operators it retrieves using reinforcement learning. Whenever the model successfully completes a task, all the operators responsible are updated. The next four parameters also need to be specified. (default: nil)

operator-bll:
: When set to true, each operator that led to a reward will get an additional reference, increasing its baselevel activation. This only works when skill-operator-learning: is also set to t. (default: nil)

inter-operator-learning:
: In addition to learning associations between skills and operators, associations between operators can also be learned. Setting this to t will enable this (default: nil). If this is switched on, the inter-operator associations in the model will all be set to 0 initially, and the learning will converge towards the default-inter-operator-assoc: parameter.

beta:
: Learning speed for skill-operator learning (similar to alpha). (default: 0.1)

reward:

Reward used in skill-operator learning. The reward also puts a maximum on the time that the model will try to complete the task (default is 0.0, which switches it off, so if you want to use it you have to give it a sensible value, i.e., something slightly longer than the time necessary to reach the goal).

explore-exploit:

Skill-operator learning adds extra noise to skill-operator combinations it hasn't tried very often yet. This parameter scales how fast noise on the skill-operator association is reduced with more experience. A higher value corresponds to a longer period of exploration (default 0.0). Still very experimental, so off by default.

context-operator-learning:

Further extension of skill-operator-learning. When set to t (true), the model learns associations between any chunk in any bufferslot and the retrieved operator based on reinforcement learning.

time-to:

PRIMs also implements ACT-R's time perception module. This parameter sets the to parameter in that module (default: 0.011)

time-a: The a parameter in the temporal module (default: 1.1)

time-b: The b parameter in the temporal module (default: 0.015)

bindings-in-dm:

When set to t (true), anytime a binding is created (see later chapters on bindings), it will be added to dm with a cost of the imaginal-delay parameter. If a binding is instantiated, it is retrieved from memory with the usual costs (retrieval time), and possibility of failure.

## Script Syntax

The scripting language has the following types: integers, reals, strings and arrays. Arrays can hold items of different types. Types are all implicit. There is no boolean type, but instead the integer 0 is used for false, and all other integers for true.

A script consists of a sequence of statements. Statements can be an assignment, a while loop, a for loop, and if clause, or a function call.

## Assignment

An assignment assigns a value to a variable, or to an element in a arrays. Examples of the former are:

```
a = (10 + 5) * 8
b = [“letter”, 8, 4.5, random(10)]
```

Examples of the latter are:

```
b[2] = 10
b[3] = [1, 1, 2, 3, 5, 8]
```

Arrays always start at index `0`. If an assignment is made to an array element that is out of bounds, the array is automatically expanded. For example, the following loop creates an array with 5 random numbers:

```
a = []
for i in 0 to 4 {
       a[i] = random(10)
}
```

## If, While and For

If statements are very similar to most programming languages. The syntax is

`if (`*`condition`*`) { `*`then-statements`*` } else { `*`else-statements`*` }`

The else statement is optional, but both parentheses and braces are required. The condition can be a combination of comparisons, using `&&` for and, `||` for or, and `!` for negation.

New variables within an if or else clause are local to that clause.

While statements have the following syntax:

`while (`*`condition`*`) { `*`statements`*` }`

Like with the if-clause, parentheses and braces are required, and new variables within the loop are local.

Finally, there are two kinds of for loops, one that iterates over an integer from a starting to an ending value, and one that iterates over an array:

`for `*`index`*` in `*`startindex`*` to `*`endindex`*` { `*`statements`*` }`

Iterates *index* from *startindex* to *endindex* (both inclusive).

`for `*`index-variable`*` in `*`array`*` { `*`statements`*` }`

Iterates over all elements in *array*.

### Function calls

The script module has a set of functions calls that can be used to inspect, change and run the model, and several miscellaneous purposes. The functions are all detailed in the next section.

## Script types

Each model has a main script that defines what happens when you push the run button. Optionally, a model can have a second script that is run when the model is loaded, an initialization script. This can be useful to add larger amounts of knowledge to declarative memory, or other things that only need to be done once. For example, an alternative means to add facts to declarative memory in the counting model would be to add the following script:

```
define init-script {
    print("Init script: Adding count-facts to memory")
    digits = ["one","two","three","four","five","six","seven",
    "eight","nine","ten"]
    for i in 0 to 8 {
        name = random-string("count-fact")
        add-dm(name, "count-fact", digits[i], digits[i + 1])
        set-activation(name, 1.0)
    }
 }
```

## Script Functions

### Running the model

run-step()

Run the model for one operator.

run-until-action(values to be compared to slot values in action)

Run until the model takes a certain action. Only the slots compared in the call are compared, so run-until-action("say") will stop at any "say" action. run-until-action() will run until any action.

run-relative-time(time)

Run the model for a specified number of seconds.

run-absolute-time(time)

Run the model until a particular time. The function time() provides the current model time.

run-relative-time-or-action(time, values to be compared to slot values in action)

Runs until either the specified action is taken by the model, or the specified amount of time has elapsed.

run-absolute-time-or-action(time, values to be compared to slot values in action)

Same as previous, but now until a particular time.

### Perception and Action

screen(items)

Put the specified items in the input buffer. First argument is put into `V1`, second in `V2`, etc. The argument can also be a single chunk in the visicon, we will explain this in a later Unit.

last-action()

Returns an array with the last action (`AC1` is the first item, `AC2` the second, etc.). If there is no last action, it returns an array with a single empty string (this is useful in any of the run functions that runs until a time or an action).

### Run Control of the Model

trial-start()

Set the start-time of the model back to zero. You only need to call this if you run multiple trials in a single script run.

trial-end()

Indicates the end of a trial. Sets the model up for the next trial, and writes a line to the output file in the case of batch running. Always include this.

issue-reward(optional number)

Give the model a reward that it can use to reinforce connections to successful operators. Gives the reward set in the main parameters of the model if no value is specified, or the amount specified in the parameter.

sleep(amount of time in seconds)

Move the model time forward for the specified amount of time without running the model. This mainly affects memory decay.

### Modification and inspection of the model

time()

returns the current model time

add-dm(chunk-name, slot values)

Add a chunk to memory in the same way as add-fact does this. The first parameter is the name of the chunk, and the remaining are values to be put in slots slot1..slotn. Use the function random-string to generate chunk-names if necessary.

set-activation(chunk-name, value)

Set the lower-bound default activation of a chunk to value.

set-sji(chunkj, chunki, value)

Set the Sji value between two chunks

sgp(parameter, value)

Set a global parameter to a certain value. Example: `sgp("lf:", 0.3)`

batch-parameters()

Returns an array with parameters passed on by the batch script. This can be useful if you want to run several different conditions in the same model. Returns "NA" when not running in batch.

add-binding(variable-nane, value)

Add a binding to memory. Skills can have general parameters that are instantiated in the script, or by the model. Will be discussed in a later unit.

purge-bindings()

Remove all bindings from dm. This is only necessary if bindings-in-dm is true, which can prevent dm from being filled with useless bindings.

set-buffer-slot(buffer, slot, value)

Set the slot in buffer to value. Example: set-buffer-slot("input", "slot1", "nine").

get-buffer-slot(buffer, slot)

Returns the value of slot in buffer.

## Other commands and functions

print(arguments)

Print the arguments in the trace field

shuffle(array)

Returns an array with the elements of the given array in random order.

length(array)

Returns the number of elements in the array

set-data-file-field(number between 0 and 3, name)

The lines in the datafile have a number of extra fields that you can put values in, in case your run multiple different conditions in the model, or want to put other information in the datafile. There are four columns for this, and you can set the value in the column with this command, e.g., `set-data-file-field(0,"control")`

random-string(optional prefix)

Generate a unique string starting with the optional prefix. If none is given, the prefix is "fact".

str-to-int(string)

Converts a string into an integer.

set-graph-title(string)

The graph shows by running time (reaction time) by default, but you can change this in the script, for example to accuracy or whatever you want to plot. You can change the name title of the graph with this command.

plot-point(number)

Plot a custom point in the graph

set-average-window(number)

Sometimes you want to smooth the data in the graph, for example when displaying accuracies. The number you supply here is the size of the smoothing window.

# UNIT 2

*Variable Binding, Multiple Skills, the Multilevel Architecture*

## Variable binding in skills

In the examples we have looked at in Unit 1, any specific values such as "say" and "count-fact" have been part of the operator. This disadvantage of this approach is that this makes operators quite specific, and therefore less suitable for reuse. To make operators more general, we can also bind the specific values at the level of the skill, keeping operators more general.

For example, in the example of Count and Semantic in Unit 1, the conditions and actions of some of the operators were identical, but each still required a separate operator node because their specific values were different. We can generalize this by building a more generic operator, such as:

```
operator start-iteration {
     V1 <> nil
     WM1 = nil
     ==>
     V1 -> WM1
     *fact-type -> RT1
     V1 -> RT2
     *action -> AC1
     V1 -> AC2
}
```

For the counting task, we can then instantiate `*fact-type` with `count-fact`, and `*action` with `say`, while in the semantic task we instantiate it with `property` and `subvocalize`. Notice the notation convention here: if we precede the name of a constant by an asterix, it means that we are looking for a name that is bound to the active skill.

We can do this binding in the script. In the case of the counting, we can give the skill a more generic name such as `iterate`, and the bind the different variables to values:

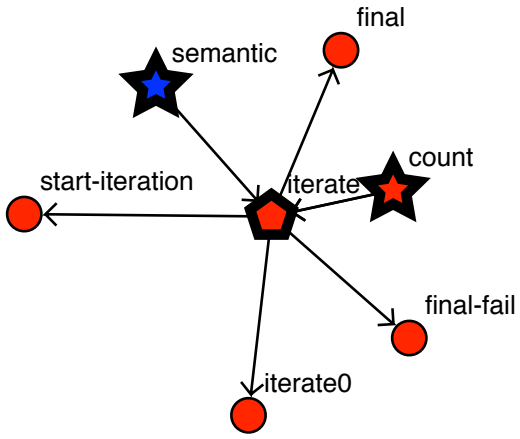
```
add-binding("fact-type","count-fact")
add-binding("action","say")
add-binding("final-action","say")
add-binding("final-response","stop")
```

By default, bindings are "perfect", in the sense that they do not have an associated time cost or chance of failure. However, if you set `bindings-in-dm` to `t`, bindings will be stored and retrieved from declarative memory with the associated costs and probability of failure.

We can then instantiate the same skill for the `semantic` task:

```
add-binding("fact-type","property")
add-binding("action","sub-vocalize")
add-binding("final-action","say")
add-binding("final-response","yes")
add-binding("final-response-negative","no")
```

In the unit 2 folder you can find the updated version of count and semantic (`count-rev1.prims` and `semantic-rev1.prims`). If you load both, you can see that each task uses the same skill.




Although we have now unified the two models, the result is still not entirely satisfactory, because the iterate skill is still very limited in utility. Suppose you want to use the result of the iteration for something else, or the source of your iteration is not in the input buffer, but the result of something else? To make a more plausible model with reusable skills, we need to break down the task in several skills, and connect these together.

## Tasks consisting of multiple skills

We encounter new tasks every day, many of which we can carry out without instruction or training. The probable reason is that these new tasks are combinations of things that we already know how to do. Up to now, tasks have corresponded to a single skill. However, a task may consist of several skills, possibly parallel or with some imposed control structure. In this section unit we will examine the option to have multiple skills.

In the earlier examples, the skill was stored in slot `G1`. However, we can also store skills in subsequent slots `G2` and up. Each of these skills can be associated with its own set of operators. Skills in slots in the goal buffer spread activation to associated operators (the Sji for this association is `default-operator-assoc`). Operators for a particular skill are also associated with each other (with an Sji of `default-inter-operator-assoc`). This increases the likelihood of using an operator for the same skill as long as there are any applicable. Finally, in most models we don't want the same operator to fire repeatedly, so operators are negatively associated with themselves (by `default-operator-self-assoc`). Operators can put new skills in G slots (e.g., `count-one --> G2`), and can also remove them (by putting nil into them, e.g. `nil -> G2`). By making goals variable themselves., we can connect skills together in a flexible way (e.g., `*next-skill -> G2`).

If we want to start the model with a number of skills already active, we can add these to the `initial-skills:` declaration: the first in the list is place into `G1`, the second into `G2`,

To explore this, we will take the count and semantic examples, and break up the iterate skill into three skills: `read`, `iterate`, and `respond`. You can find the example in the file `count-rev2.prims`. The read and respond skills are quite simple, but achieve the goal of decoupling the iterate skill from perception and action.

The task declaration has the following line:

```
  initial-skills: (read)
```

The initial skill in this model is to read the two numbers. The read skill consists of two operators:

```
define skill read {
       operator read-for-two-items {
              V1 <> nil
              V2 <> nil
              WM1 = nil
       ==>
              V1 -> WM1
              V2 -> WM2
       }
       operator switch-to-next-skill {
              V1 = WM1
       ==>
              *next-skill -> G1
       }
}
```

The first operator just transfers the two items in the input buffer to working memory. The second operator transfers control to the next skill by placing it into `G1`. In this particular case, the read skill transfers control to the iterate skill, because we specified this in the script:

```
       add-binding("next-skill","iterate")
```

Because we have made this only a temporary binding, we can use the read skill for different purposes as well. Indeed, we can expand the skill to improve its usability to let it read an arbitrary number of words, one at a time.

The iterate skill now does not carry out an action itself, but transfers control to one of two other skills, one in the case of success, and one in the case of failure. The count goal only needs a success skill:

```
       add-binding("action","say")
       add-binding("fact-type","count-fact")
       add-binding("final-action-skill","respond")
```

The respond skill is very simple: it just carries out an action:

```
define skill respond {
	operator carry-out-action {
		G1 <> nil // Operators require at least one condition
		==>
		*action -> AC1
		*arg -> AC2
		nil -> G1
	}
}
```

This action is instantiated with:

```
	add-binding("respond-action","say")
	add-binding("respond-arg","stop")
```

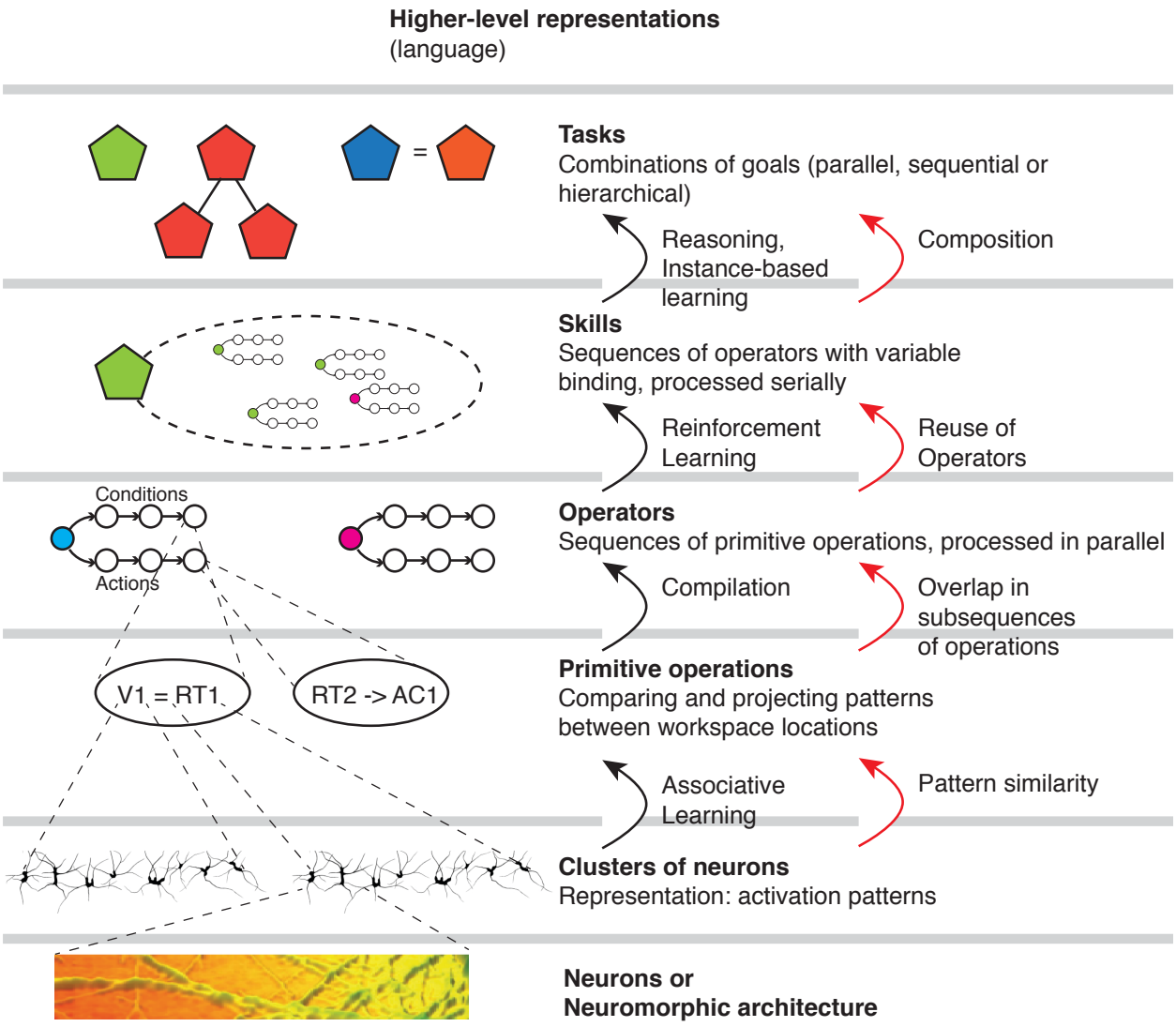
We can now reuse all these skills for the semantic example. For this example we do need to specify a fail-skill. It this point, we would like to instantiate the respond skill twice, once for saying "yes", and once for saying "no". However, now we run into trouble, because we can only add a binding for a particular variable once. We really would like two "copies" of the respond skill. This is a typical subproblem of the binding problem, which we are solving relatively crudely here by making an additional copy of the responds skill:

```
define skill alt-respond {
	operator carry-out-action {
		G1 <> nil // Operators require at least one condition
		==>
		*alt-respond-action -> AC1
		*alt-respond-arg -> AC2
		nil -> G1
	}
}
```

Now we can change the bindings to fit the semantic task:

```
	add-binding("next-skill","iterate")
	add-binding("action","sub-vocalize")
	add-binding("fact-type","property")
	add-binding("final-action-skill","respond")
	add-binding("fail-skill","alt-respond")
	add-binding("respond-action","say")
	add-binding("respond-arg","yes")
	add-binding("alt-respond-action","say")
	add-binding("alt-respond-arg","no")
```

The interesting aspect about the semantic model is that we only have to add the copy of the respond skill, and can reuse all the other skills from the count model. This means that we have, more or less, a higher-level means of building cognitive models. If we have the set of skills we need already encoded in memory, the only thing we need to do is to connect them together, and provide the appropriate instantiations. One of the goals of PRIMs is to




provide multiple levels of abstraction in modeling. We have started, in Unit 1, with a relatively traditional abstraction level that is similar to ACT-R. But now we see that we can also build models at a higher level of abstraction.

The figure on the this page illustrates the basic idea behind the multi-level architecture: knowledge has different levels of abstraction, which also means we can have learning and transfer on multiple levels of abstraction. We have already seen that transfer can occur on three levels: by overlapping PRIMs (we have seen that in Unit 1), by overlapping operators (our first example in this Unit), or by overlapping skills (the last example).

In future units we will examine an even higher level of abstraction, in which the model itself creates the representation of the skill, and a lower level of abstraction, where the model has to discover which combinations of PRIMs lead to a reward in a very simple task.

## Assignment

The iteration skill in the count/semantic example is still limited to performing an action on the particular item that we iterate over. However, we might want to do more with an item than just a primitive action. In `count-rev3.prims`, control is handed over to another skill on each iteration by the following operator:

```
operator do-sub-skill {
   RT1 = *fact-type
   ==>
   RT3 -> WM3
   *sub-skill -> G1
  }
```

This operator switches to a different skill after retrieving a next fact, and placing it in `WM3`. After the sub-skill has done something with the contents of WM3, and has returned control to the iterate skill, it can proceed with the next item (assuming we are not done yet):

```
  operator retrieve-next {
    RT1 = nil
    WM3 <> nil
    WM2 <> WM3
   ==>
    *fact-type -> RT1
    WM3 -> RT2
  }
```

In the count example, say the number is still the only thing we do, so the actual sub-skill is pretty simple:

```
define skill do-action {
       operator do-action-on-WM3 {
              WM3 <> nil
       ==>
              *action -> AC1
              WM3 -> AC2
              *main-skill -> G1
       }
}
```

Of course, we need to tie everything together when we instantiate the skills:

```
       add-binding("next-skill","iterate")
       add-binding("action","say")
       add-binding("fact-type","count-fact")
       add-binding("final-action-skill","respond")
       add-binding("respond-action","say")
       add-binding("respond-arg","stop")
       add-binding("sub-skill","do-action")
       add-binding("action","say")
       add-binding("main-skill","iterate")
```

Here we specify that `do-action` is the sub-skill of `iterate`, and `iterate` is the skill to return to when done with `do-action`.

So far, the model still does exactly the same thing as the original count model. A possible new use for this new way of specifying the skill is to extend the semantic model. Up to now, we have only been able to ask very category questions. However, we would also like to ask question such as "Can a robin fly?", where flying is a an attribute of bird. We can accomplish this by switching to a sub-skill that checks whether the current item in the iteration has the property.

Check the file `semantic-rev3.prims`. It has a number of attributes in its list of facts, and a number of additional questions to answer in the script. Furthermore, it has an additional skill defined that does the fact checking (called `attempt-retrieve`). The attempt-retrieve skill will try to retrieve a fact based on `WM3` and `WM2`, and will switch to one skill if it is successful, and to another skill if it fails.

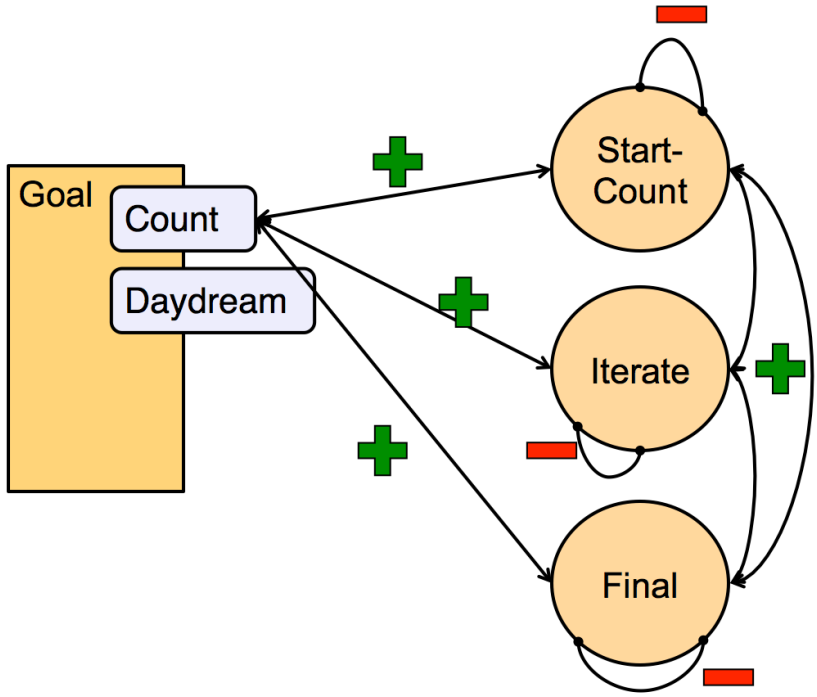
The assignment is to finish the model. The only thing you need to do is instantiate the skills in the script.

# UNIT 3

*Operator Selection*

## Competition between operators

An operator is a chunk in declarative memory, so just like any other chunk it has a base-level activation, and strengths of association with other chunks. Just like any other chunk, these activations correspond to the odds that we need the operator in the current context. This means that the decision of which operator to use is based on how much spreading activation it receives from the current context.




The key associations that determine the selection process are illustrated in the figure above. The first, and most important, is an association between a skill and an operator. If a skill is active, it will favor operators with which it is associated. A second association is the between operators, typically related to the same skill. This promotes sticking to a particular skill instead of switching to another. A final association is a negative self-association, that discourages using the same operator twice in a row.

In the models we have looked at up to this point, these associations were automatically set: all operators receive a positive association with the skill within which they are defined (the

Sji for this association is `default-operator-assoc:`, default 3.0), and all operators within a skill have a positive association with one another (with an Sji of `default-inter-operator-assoc`, default 1.0). All operators are negatively associated with themselves (by `default-operator-self-assoc`, default -1.0).

PRIMs does not necessarily choose to execute operators that are linked to one of the active skills. If none of the operators linked to a skill have matching conditions, another operator may be chosen. Or, another operator may be chosen if another source of spreading activation is stronger than the spreading activation from the goal. For example, certain strong perceptual input (e.g., someone calling your name) can activate operators to attend that input.

## Learning New Skills

A different case in which other operators have to be chosen, is when we have to learn a new skill that has to be composed from existing operators. In that case we need to learn the association between the skill and the operator.

Is a skill is in a situation in which there are no associated operators, any matching operator can be tried. If that leads to success, the operator will receive an additional reference, increasing its baselevel activation. In addition, the association between the operator and the goal will be strengthened using reinforcement learning. The equation for the update is:

$$\Delta S_{ji} = \beta(\text{payoff} - S_{ji})$$

in which

$$\text{payoff} = \max S_{ji} * (\text{reward} - \text{timeToReward})/\text{reward}$$

If the operator does not lead to a reward, it is penalized:

$$\text{payoff} = \max S_{ji} * (0 - \text{timeToReward})/\text{reward}$$

In these equations, reward, beta and MaxSji are parameters that are set by the model (see example above). MaxSji is the `default-operator-assoc` parameter.

As a first demonstration, we will let the count model adopt operators from the semantic model. We will use the `count-learn.prims` and `semantic.prims` files from Unit 3, and a new model: `daydream.prims`.

Here is the parameter declaration of `count-learn.prims`:

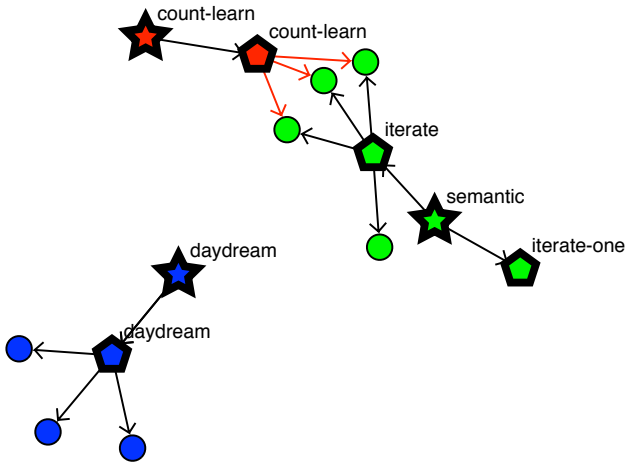
```
define task count-learn {
    initial-skills: (count-learn)
```

```
    default-activation: 1.0
    ol: t
    rt: -2.0
    lf: 0.2
    default-operator-self-assoc: 0.0
    goal-operator-learning: t
    operator-bll: t
    reward: 5.0
    beta: 0.1
}
```

The `goal-operator-learning` parameter switches on the learning mechanisms for operators. The `operator-bll` parameter switches on baselevel learning, which means that successful operators receive additional references (if you switch it off, only associations will be learned. The `reward` parameter sets the reward in units of time (seconds). This means that a positive reward corresponds to reaching the goal within that amount of time (5 seconds in the example).

The key associations that need to be learned are the associations between goals (like count and daydream), and operators. The assumption is that these associations are initially set to 0, but increase if an operator is successful in accomplishing the goal involved.

If we run the count-learn model, nothing will happen, because there are no operators. But luckily, another model can supply all the necessary operators. So, also load `semantic.prims`, and now try to run count-learn. It will now run successfully, and will learn associations between the semantic operators and the count goal.

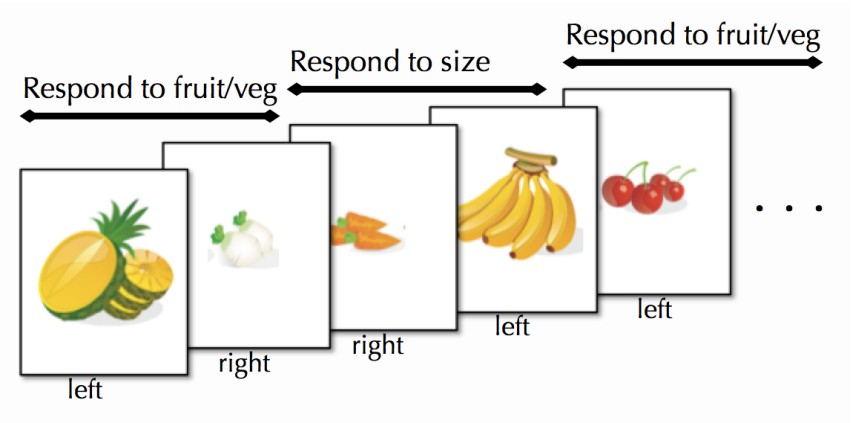



Just `semantic` and `count-learn` can hardly go wrong. Load in a third model, daydream, and try again. You will see that the model will initially make some mistakes, but will learn the right operators fairly quickly. If you reload the task graph, you can see that the associations have been learned between count-learn and three of the semantic operators (red arrows).

## Far Transfer

Karbach and Kray have shown in an experiment that training on task-switching transfers to several other control tasks, among which the Stroop task. You can load in both models, and check the overlap. The key aspect to modeling transfer here is not so much that there is a

large overlap between the two tasks (which there isn't), but that task switching, at least this particular version, trains a single skill that is useful for picking the better strategy for Stroop.




In the particular version of task switching, subjects have to keep track of the current task themselves: there is no external cue. The stimuli consist of either pictures of fruit or vegetables, which can be either small or large. For the first two stimuli, subjects have to respond to fruit/vegetable, the next two large/small, the next two fruit/vegetable, etc. The structure of this version of task switching forces a strategy the prepares for the upcoming stimulus (other versions of task switching also allow a more reactive policy, so training on them may not always have the desired result).

In the model this means that after a response has been made on an item, it is not sufficient to wait for the next item: it has to prepare for what to do with that next item. But it should only prepare once.

Although this task should probably be broken down in a number of smallers skills, we restrict ourselves to two skills: a skill that carries out the choice-reaction task, and a skill that determines what the next property (food or size) to respond to is (prepare-next).

The following operator, part of the main `choice-reaction` skill, will switch to the `prepare-next` skill:

```
operator prepare-for-stimulus {
    V1 = fixation
    G2 = nil
    ==>
    *prepare -> G2
}
```

We use a variable `*prepare` here, which we instantiate with the `prepare-next` skill in the script:

```
add-binding("prepare","prepare-next")
```

The current task is represented in the *property variable, which is initially set to food.

While looking at the fixation cross, the prepare-for-stimulus operator places the prepare-next skill in G2. This skill now has to decide what the task will be. To keep track of this, it will keep a counter in WM1. The first time the slot will be empty, so it places one in that slot, and will then remove itself (meaning that the food will remain *property):

```
operator set-first-task {
     V1 = fixation
     WM1 = nil
    ==>
     one -> WM1
     nil -> G2
     wait -> AC1
 }
```

wait is a special action in PRIMs: it will let the model wait until the next perceptual action happens. Although this is convenient, we have to keep in mind that in reality our thinking never stops, and people probably fill any mental slack time with other thoughts.

After the task has been carried out (you can check the model yourself to see whether you can figure out how it works), the model needs to check what it has to do next. It therefore uses the prepare-for-stimulus operator again that reinstates the prepare-next goal. The following operator, which is also part of the prepare-next goal, starts determining the next task:

```
operator determine-next-task-retrieve-count {
    V1 = fixation
    RT1 = nil
    WM1 <> nil
    ==>
    count-fact -> RT1
    WM1 -> RT2
}
```

If the retrieved count-fact gives two as the next number, it means we have to do the same task one more time, but if is three, it means we have to change to the other task. You can check that the appropriate operators are there to handle this.

Whereas the task switching model has no choice whether to prepare, the Stroop model does have a choice. The idea is that the model can just wait for a stimulus to appear, or that it can prepare by being ready to just focus on the color and ignore the word. If the model just attends the stimulus, both the word and the color will be put in slots in the input buffer,

but if the focus is on color only, only the color will be represented. In the case of a conflict trial and a regular attend action, spreading activation will both increase and decrease activation of the response, while in a congruent trial spreading activation only increases activation. But if the focus is just on color, the difference disappears.

Preparation in the Stroop model is done by the following operator:

```
    operator prepare-for-stimulus {
        V1 = fixation
        G2 = nil
        ==>
        *prepare -> G2
    }
```

This the same operator as in the task-switching model, but now "prepare" is instantiated with "focus-color":

```
      add-binding("prepare","focus-color")
```

While watching the fixation cross, the model sets up a second skill to focus on just the color when the stimulus appears. This skill has just a single operator, `attend-just-color`, which carries out the `attend-color` action that will put the color of the ink in `V2`.

```
define skill focus-color {
    operator attend-just-color {
        V1 = stim
        V2 = nil
        ==>
        attend-color -> AC1
    }
}
```

The preparation strategy competes with the more default `just-wait` strategy:

```
    operator just-wait(activation=1.5) {
    "Just wait for the stimulus"
        V1 = fixation
        ==>
        wait -> AC1
    }


    operator attend(activation=1.5) {
        V1 = stim
        V2 = nil
        ==>
        attend -> AC1
    }
```

The `attend` action will attend both the color of the ink (which will appear in `V2`) and the identity of the word (which appears in `V3`). If both attributes are attended, the identity of the word will interfere with the color of the ink, but if only the color of the ink is attended, interference will be absent.

The `(activation=1.5)` addition to more default operators means they have a higher base-level activation than the `prepare` operator, so they would normally win the competition most of the time. However, the `prepare-for-stimulus` operator also appears in the task-switching model. Training on task-switching will therefore increase the activation of that operator, making it more likely that it will be chosen after switching to Stroop.

Try running the Stroop model, and try running it after first running the Task-switching model for a number of trials (± 100 should do it). Observe the different choice of operators.

## Running models in batch mode

The PRIMs interface is fine to observe your model, and see some qualitative evidence for learning and transfer, but if you want to fit actual data you need to be able to run the model hundreds of times, and average over the results.

To support this, PRIMs has an option to run a simple external script. The script has the extension .bprims, and contains simple commands to run one or more models multiple times. The script (in `taskswitchstrooptransfer.bprims`) is as follows:

```
repeat 10
reset
run stroop stroop-control 100
reset
run task-switching task-switching 300
run stroop stroop-transfer 100
```

The first line always starts with "repeat" and a number, indicating how often the rest of the script has to be run. A "reset" puts the models back into their starting state. The run command has (at least) three arguments. The first is the name of the task. Make sure that the name matches both the filename with the model (e.g., `stroop.prims`), and the name of the task within that file (so the task has to be called `stroop`, and not `my-stroop` or anything else). The second argument is a label that is placed in the output file. This is useful for later processing of the output: in this example you want to distinguish running stroop without prior experience (`stroop-control`) from running stroop after taskswitching (`stroop-transfer`). The fourth number is the number of times that you run the model.

Instead of `run`, you can also use `run-time`. This works the same as `run`, except that the model will run for a certain amount of (simulated) time. As a fourth argument give the time in seconds that you want the model to run.

With `run` and `run-time` you can also pass parameters to the model. Any parameter that you put after the fourth will be made available to the script. The script function `batch-`

`parameters()` will return a string array with anything you put after the fourth parameter. This is useful if you want to change parameters or pass particular arguments to your model.

To run the script, choose "Run batch..." in the "Run" menu in PRIMs, enter the `bprims` file name, then give an output file name, and wait until the simulation finishes. You can then analyze the output file (which is just a big table in a text file) with any program you like (we typically use R for this).

You can try this out by running this by hand and observing the choice of strategy (and the resulting latencies), or by running the provided batch script (`taskswitchstrooptransfer.bprims`). A simple R-script is provided to extract the results out of the data file. `TSStroop.R` is an example R-file that analyses the output.

## Assignment: Bottom-up learning

The learning we have looked at up to this point is about operators within a skill. But how are operators themselves learned? Operators are composed of PRIMs, so we need some sort of learning story for how operators are learn out of PRIMs.

You can find an initial experiment with this idea in the "bottom-up learning" subfolder of the Unit 3 folder. Look at the `primitives.prims` file. In it, you see a large collection of PRIMs encoded as small operators. For example, the `V1 -> RT1` PRIM is encoded as:

```
operator V1toRT1 {
    V1 <> nil
==>
    V1 -> RT1
    nil -> V1
}
```

All the other models in the folder only specify the task, but not the knowledge necessary to carry them out. Your task is to experiment with these tasks, and look at what is learned. In addition to the associative strength learning between operators and the skill, the models use an experimental form of *operator compilation*. When the model successfully reaches a reward, it will try to compile pairs of operators into new operators. For example if you try to learn the paired-associative task, the model might compile the following two operators:

```
operator V1toRT2 {
    V1 <> nil
==>
    V1 -> RT2
    nil -> V1
}
```

```
operator C1toRT1 {
      G1 <> nil
==>
      *fact-type -> RT1
}
```

into:

```
operator V1toRT2+C1toRT1 {
       V1 <> nil
       G! <> nil
==>
       V1 -> RT2
       *fact-type -> RT1
       nil -> V1
}
```

A property of this new operator is that it retrieves exactly the right chunk, whereas both `V1toRT2` and `C1toRT1` can (and will) retrieve wrong chunks (if you check the paired-associative model you can see that several alternative facts have been supplied in memory with that property).

The assignment is to try out the different tasks that are in the folder, and see how fast they learn, and what is learned. Try to identify the combinations of tasks among which there is transfer. Can you identify the operators that are instrumental in that transfer?

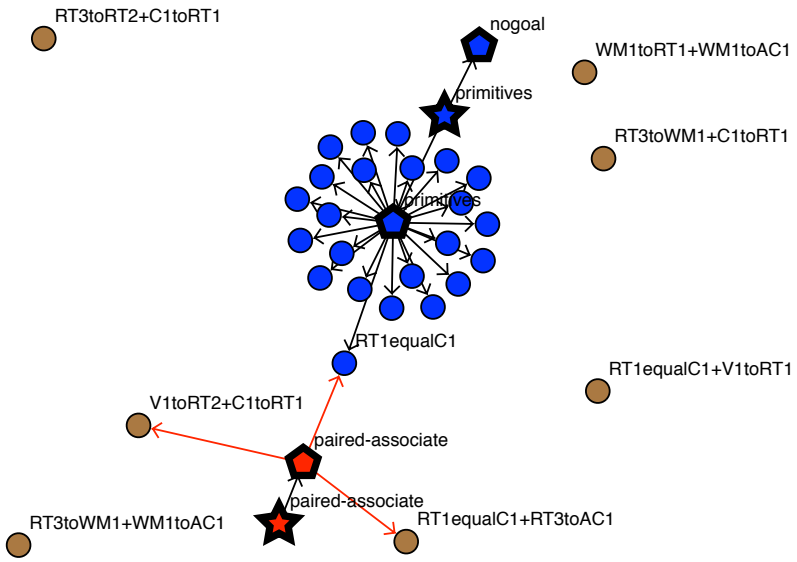



Figure: Learning the paired-associate task. The model has learned several new operators (brown), two of which are useful for the task.

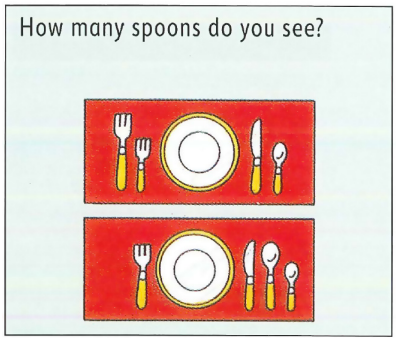
# UNIT 4

*Extended Vision*

One of the limitations of the global workspace/buffer model is that the amount of information that you have access to is very limited, and probably too limited. The currently available alternative, arbitrary search in an unlimited working memory, is computationally intractable, and even when restricted involves too much search to be plausible as a model of human intelligence. In this, and the subsequent unit, we will explore an alternative. Given that a chunk in a buffer is a node in a large network, we can allow operators to access chunks that are connected to the chunks in the buffers. For example, if a chunk representing 3 + 4 = 7 is in one of the slots of working memory, we should be able to access the individual elements of that chunk (3, 4 and 7). To do this we will have to introduce a few new PRIMs.

Note that the representations presented here are preliminary, and serve as a first approximation. They may change in future versions of PRIMs.

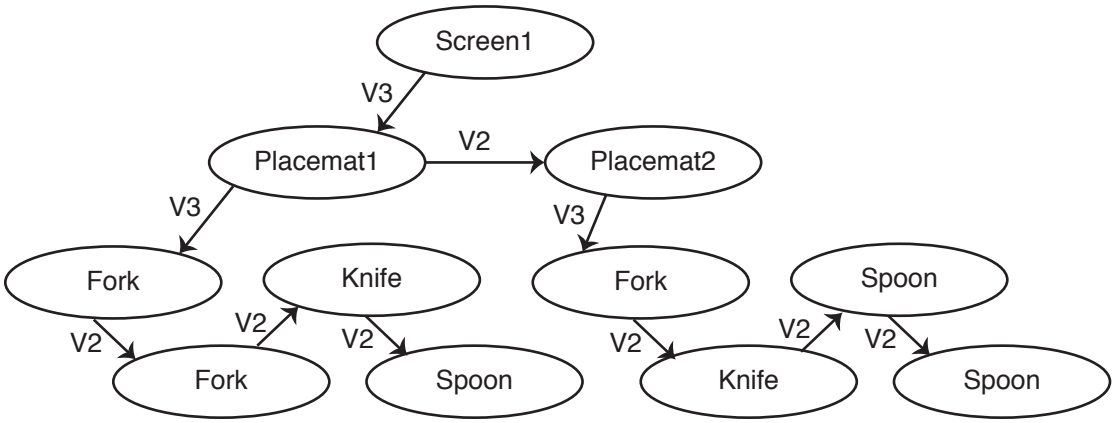
In the next unit we will introduce this idea in its full extent. In this unit, we will use these ideas to expand the perceptual capabilities of PRIMs.




## More complex screens

Up to this point we have only looked at screens that are represented in a single chunk. To allow a slight more complex, but also not overly complex representation, PRIMs allows a more hierarchical representation of structure. Consider the following example:

This picture consists of two placemats, each of which has a number of items, each of which has properties. We can represent this picture hierarchically as follows:



In this diagram, each oval is a chunk that can be placed in the visual buffer. A V3 link goes down a level of abstraction, whereas a V2 link points to the next item at the same level.

In the model we define this as:

```
define visual {
    (screen1 screen nil placemat1)
    (placemat1 placemat placemat2 item1)
    (placemat2 placemat nil item5)
    (item1 utensil item2 nil fork)
    (item2 utensil item3 nil fork)
    (item3 utensil item4 nil knife)
    (item4 utensil nil nil spoon)
    (item5 utensil item6 nil fork)
    (item6 utensil item7 nil knife)
    (item7 utensil item8 nil spoon)
    (item8 utensil nil nil spoon)
}
```

This representation is very similar to the one that defines facts, and, in fact, it produces chunks that are similar to facts. However, these are not placed in declarative memory, but in a separate visual store. The idea is that one of these chunks is in the visual buffer, starting with the top-level chunk (`screen1` in this case), and that we can use "perceptual action PRIMs", to shift attention to details within that top-level chunk. In the Unit 4 folder, `more-spoons.prims` performs the task. The script sets the screen to the top-level chunk in visual with

```
screen("screen1")
```

If you look at the operators, you will see two new PRIMs, the >> and << operations. The >> operations shift focus down by replace the chunk in the visual buffer by the chunk in the slot that appears after the >>. For example, if the current chunk in the visual buffer is the `screen1`, then a >>V3 operation will shift attention to the chunk in V3, which is `placemat1`. The first operator in the model actually performs this action twice, first shifting attention to `placemat1`, and then to `item1`:

```
operator init-count-spoons {
     WM1=nil
     V1=screen
     ==>
     >>V3  // shift to the first container (placemat)
     >>V3 /// shift to first item in the container
     zero -> WM1
 }
```

The << operation is the opposite of >>: it shifts attention up to the parent chunk. For example, if the model is done counting the spoons in one placemat, it will shift attention back up.

```
operator skip-item-up {
        V1 = item-type
        V4 <> target
        V2 = nil
        ==>
        V<<
}
```

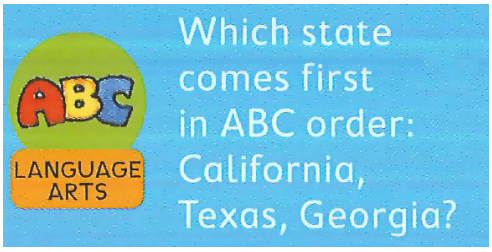
Important: in order to know what the parent is of a certain item, the implementation assumes that you use `V2` to specify the next item in the hierarchy. This is important ensure that `V<<` brings you back to the right chunk.

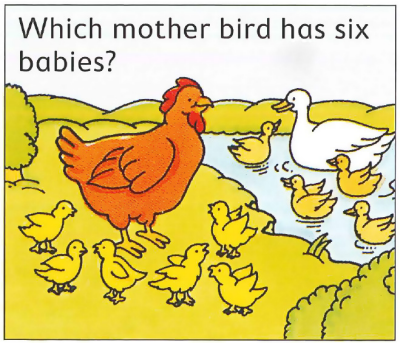
## Assignment

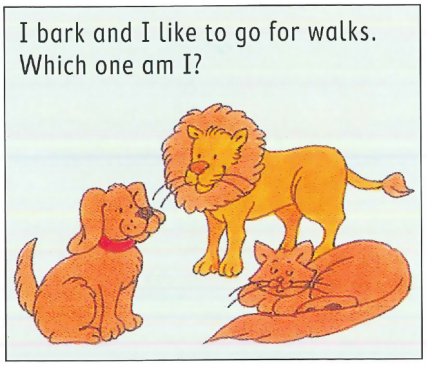
The "how many spoons" example is a card from an educational game called BrainQuest. In the past, we have written several PRIMs models of these cards, and it is interesting to look at the transfer between them. In the next Unit, we are going to look into more detail how to do this in order to maximize transfer, because the current example model is not very generally applicable.

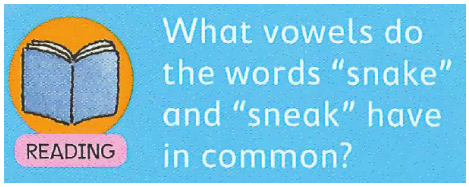
The assignment is to choose another BrainQuest card and write a model for that card. If you have time you can create models for several cards, and check the transfer between them (and the spoons example).

Some cards:



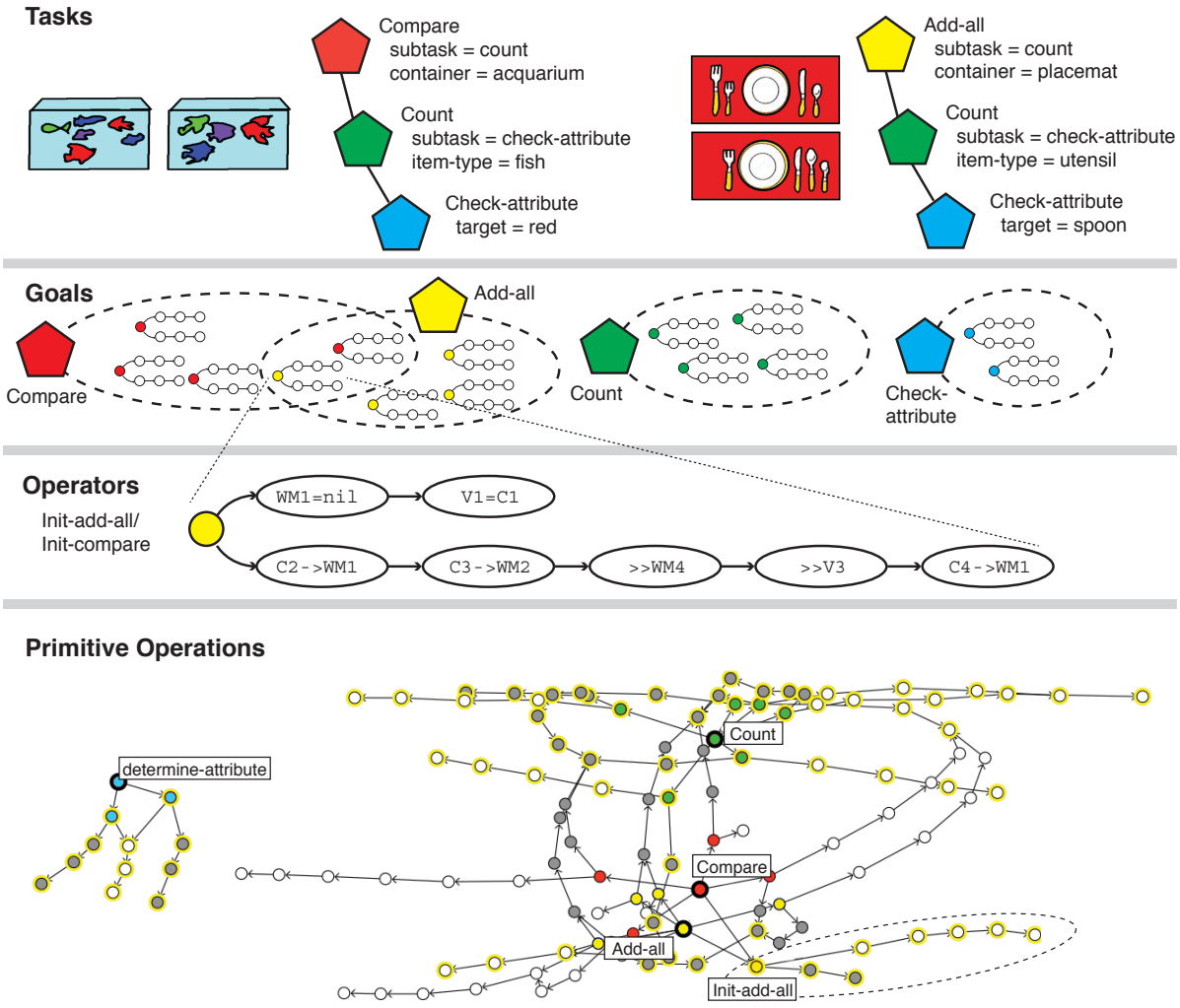



More in separate files cards1.pdf and cards2.pdf.

# UNIT 5

## *Composable Goals*

One of the goals of PRIMs is to be able to compose new task representations using existing skills. Key components for this are the option to have multiple active goals, and to be able to bind variables within that goal, which we have discussed in Unit 2. What we want is a model can explain how the task of solving the simple BrainQuest cards from Unit 3 can be solved by composing and instantiating a number of existing goals. The figure below shows and example.




We have almost all the necessary puzzle piece to achieve that, except for one: how do the goals that are composed to perform the two tasks pass information to one another? The obvious place is working memory, but in the current implementation working memory is limited to a number of fixed slots. To pass results between goals, each goal should ideally

have its own working memory. However, our previous research has shown that people do not have an unlimited working memory. The current solution is to adapt the same method that we have used for vision, and use this for working memory, and also for memory retrieval.

## The new >> and << operations

The new PRIM operations introduced in Unit 3 can be used for different purposes than just visual input. For each buffer they have a slightly different result. We have already looked at input/visual, so let us look at retrieval and working memory.

### Retrieval buffer

If there is something in the retrieval buffer, we can examine chunks that are connected to that chunk. For example, we can check whether a retrieval has the appropriate type of chunk in one of the slots. The conditions of an operator could therefore be something like:

```
operator example {
     RT1 = count-fact
     >>RT2
     RT1 = number
     RT<<
   ==>
     RT3 -> WM1
}
```

This operator checks whether the chunk retrieval buffer has `count-fact` in `RT1`, then shifts towards the chunk in the `RT2` slot (so now that chunk is in the retrieval buffer), checks whether its `RT1` is `number`, then shift back up to the count-fact. If that all matches (there also no match if `RT2` is empty or contains a non-chunk value), the contents of `RT3` (the `RT3` in the count-fact) is copied to `WM1`. Shifts in the retrieval buffer are always about the chunk that has just been retrieved, and never about the new retrieval request.

### Working memory buffer

The >> and << operations allow us to create a working memory representation that larger than a single chunk, but in which all elements still are connected. This is consistent with the idea that in larger tasks we build up memory representations that go beyond a single chunk. But even in understanding a single sentence a single chunk is probably not enough. This means that it is quite likely that people are quite capable of handling larger structures.

The new >> and << operations can be used to traverse such a structure. This keeps matching memory tractable, but still gives us more flexibility.

Whereas the retrieval buffer can be used to traverse existing memories, working memory allows us to create and navigate through new memories. The key new aspect is that if we perform a >> operation on a slot in the working memory buffer that is empty, this creates a new, empty chunk that will then be put in the working memory buffer. If there is already an existing chunk in the slot, attention will shift to it, just like in the retrieval buffer.

These new PRIMs are very helpful in creating communication between goals. The `count-spoons` and `more-fish` examples in the Unit 4 folder show examples. Let us have a look at the count-spoons example.

Instead of having one goal, the new version of count-spoons has three goals with instantiations as in figure at the start of this unit. The first of these goals, `add-all`, starts off with the following operator:

```
operator init-add-all {
        WM1=nil
        V1=screen
        ==>
        >>V3  // shift to the first container (placemat)
        overall-total -> WM1
        zero -> WM3 // that is the current total
        >>WM4 // this creates a new chunk that is placed in WM4,
              // and shifts focus to that chunk
        total-count -> WM1
        push-goal -> AC1
        subtask -> AC2
    }
```

This operator does several things. First, it shifts attention to the first container, just as in the model from the previous unit. Then it sets up a chunk in the working memory buffer to represent the eventual answer: it puts `overall-total` in `WM1`, and initializes `WM3` with `zero`.

The idea is that `add-all` goal now shifts control to a goal that does the actual counting (`subtask`, which is instantiated by `count-goal`). However, that goal needs its own working memory chunk. The `init-add-all` operator therefore creates a new, empty chunk in `WM4` (the `>>WM4` PRIM), shifts attention to that new chunk, and puts `total-count` in it.

The `push-goal` action places the new chunk in the first available G slot (`G2` in this case)[1]. Now the `count-goal` can start the counting process, using its own working memory chunk. It performs the same trick to determine what it is that needs to be counted:

```
    operator init-countgoal {
```

[1] In the current implementation the push-goal (as well as the remove-goal) action is not yet implemented, and there for the action doesn't do anything. Instead, all three goals are already placed in the Goal buffer at the start of the simulation.

```
    WM1 = total-count
    WM3 = nil
    V1 = container
    ==>
    zero -> WM3
    >>V3 // shift to first item
    >>WM4 // Determine whether this is something that we need to count
    member -> WM1
    push-goal -> AC1
    subsubtask -> AC2
}
```

After these two operators, we are looking at one of the utensils, and can determine whether it has to be counted. The determine-attribute goals takes care of this:

```
operator answer-yes {
    WM1 = member
    V1 = item-type
    V4 = target
==>
    yes -> WM2
    WM<<
    remove-goal -> AC1
}
```

If what we are looking at is a target (i.e., a spoon), we put yes in `WM2`, shift back to the parent WM chunk, and remove the current goal (`determine-attribute`) from the goal buffer. The parent goal now, of course, has to inspect the result.

```
operator retrieve-count-fact-for-countable-item {
    WM1 = total-count
    >>WM4
    WM2 = yes
    WM<<
==>
    count-fact -> RT1
    WM3 -> RT2
    nil -> WM4
}
```

With the `>>WM4`, `WM2 = yes`, `WM<<` sequence the operator checks for a yes-result in the finalized subgoal, and starts incrementing the count if this is found. As similar process is carried out at the level of the add-all goal: each time the count-goal produces an answer, the add-goal adds it to its current total, and outputs the result once it is done.

Once the model is done, the whole working memory structure will be transferred to declarative memory.

## Transfer

The second example, `more-fish`, shares two of the three goals with the count-spoons model. It therefore only needs a single extra goal. As a consequence, there is considerable transfer between the two tasks.

In a broader perspective, we can image that most adults have already mastered all the necessary skills. This means that the only thing they still need to do is instantiate the three goals.

## Disclaimer

The solutions presented in this Unit are still under development, so it is quite likely that details will change!