

## Unit 8: Advanced Production Techniques

In this unit we will describe two additional mechanisms which can be used in the procedural system of ACT-R. They are called procedural partial matching and dynamic pattern matching. These capabilities allow for a lot more flexibility in the procedural system, and they can make it easier to create models which are able to work in situations where all of the details of the task are not known in advance and thus cannot be explicitly encoded within the model.

### 8.1 Procedural partial matching

Procedural partial matching is very similar to the partial matching of declarative memory as was described in unit 5 of the tutorial. When procedural partial matching is enabled by setting the **:ppm** parameter to a number, a production may be selected to fire even when its conditions do not perfectly match the current buffer contents. This mechanism applies to all productions being tested and it modifies the conflict resolution process used when multiple productions match under this looser definition of matching. Other than that however it does not change any of the other operations of the procedural system and all other procedural functionality is as described in the previous units.

#### 8.1.1 Condition testing with procedural partial matching

When procedural partial matching is enabled the slot tests for the buffer chunk's values are slightly relaxed, but most of the conditions in a production are still tested explicitly. These conditions must still be true for the production to match: if the production tests a buffer then that buffer must contain a chunk, all queries must be true as specified, all inequality tests on slots (negations, less-than, and greater-than comparisons) must be true, and all special conditions specified with eval or bind operators must be true. The only tests which do not have to be true are equality tests for the slots of the chunk in a buffer i.e. tests that specify a specific value for a slot or tests with variables which are comparing two or more slot values. If all of the equality tests are true, then the production matches just as it would without procedural partial matching enabled. If some of the tests are not true the production may still be considered a match under procedural partial matching.

If a value specified for a slot in the production does not match the current value of that slot for the chunk in the buffer, then in order for it to be considered a match under procedural partial matching the mismatching values must be similar. Similarity here is defined in the same way that it is for declarative memory. Thus they must be chunks for which a similarity value has been specified through the set-similarities command or the modeler must provide a similarity hook function which specifies a similarity between the items whether or not they are chunks as was done for numbers in the unit 5 assignment. The only difference between the procedural partial matching and declarative partial matching is that for procedural partial matching two items are only considered to be similar if they have a similarity value which is greater than the current minimum

similarity (as set with the :md parameter). That additional constraint on the similarities is done for practical reasons because by default, all chunks have a similarity of the :md value to all other chunks. Without that constraint, any chunk could potentially be a partial match to any other in the production matching. By disallowing procedural partial matching from using the default minimum similarity value it allows the modeler to control which items are allowed to be partial matched in productions. If one wants all chunks to potentially match to any other then a simple similarity hook function can be defined that returns a value greater than :md for all chunk to chunk similarities.

### 8.1.2 Conflict resolution with procedural partial matching

If only one production matches then it is selected and fired. When there is more than one production which matches (including partially matched productions) the production with the highest utility is the one selected and fired as described before. The difference when procedural partial matching is enabled is that productions which are not a perfect match receive a reduction to their utility. The equation for the utility of production  $i$  when procedural partial matching is enabled is:

$$Utility_i(t) = U_i(t) + \varepsilon + \sum_j ppm * similarity(d_j, v_j)$$

**$U_i(t)$ :** Production  $i$ 's current true utility value.

**$\varepsilon$ :** The noise which may be added to the utility.

**$j$ :** The set of slots for which production  $i$  had a partially matched value.

**$ppm$ :** The value of the :ppm parameter.

**$d_j$ :** The desired value for slot  $j$  in production  $i$ .

**$v_j$ :** The actual value in slot  $j$  of the chunk in the buffer.

A production which has one or more partially matched slot tests has its utility decreased by the similarity of each mismatch multiplied by the :ppm setting. That adjusted utility value is only used for the purposes of conflict resolution. It does not affect the  $U_i(t)$  value used in the utility learning equation or the utility values used during production compilation learning.

### 8.1.3 Simple procedural partial matching model

The simple-ppm-test model included with the tutorial unit shows a very simple example of procedural partial matching. If you open that model you will see that it has only three productions and there is no Lisp code for an experiment. Everything there except the

:ppm and :cst parameters has been described in previous units, so it should be easy to understand. The **goal** buffer starts with a chunk which looks like this:

```
TEST0-0
  VALUE  SMALL
```

and there are three productions which simply test the value slot of the goal chunk and then output the value from that slot:

<pre>(p small   =goal&gt;     isa test     value small     value =val   ==&gt;     !output! =val   -goal&gt;)</pre>	<pre>(p medium   =goal&gt;     isa test     value medium     value =val   ==&gt;     !output! =val   -goal&gt;)</pre>	<pre>(p large   =goal&gt;     isa test     value large     value =val   ==&gt;     !output! =val   -goal&gt;)</pre>
---	---	---

If you load the model and run it as it is, with procedural partial matching disabled, you will see a trace like this:

```
> (run 1.0)
0.000  PROCEDURAL  CONFLICT-RESOLUTION
(P SMALL
  =GOAL>
    VALUE SMALL
    VALUE SMALL
  ==>
    !OUTPUT! SMALL
  -GOAL>
)
Parameters for production SMALL:
:UTILITY 0.000
:U 0.000
0.000  PROCEDURAL  PRODUCTION-SELECTED SMALL
0.000  PROCEDURAL  BUFFER-READ-ACTION GOAL
0.050  PROCEDURAL  PRODUCTION-FIRED SMALL
SMALL
0.050  PROCEDURAL  CLEAR-BUFFER GOAL
0.050  PROCEDURAL  CONFLICT-RESOLUTION
0.050  -----  Stopped because no events left to process
```

As expected the production small is selected and fired. Before describing the results with procedural partial matching enabled the additional output in the trace will be described.

### 8.1.3.1 The conflict set trace parameter

The :cst parameter which is set to **t** in the model is the conflict set trace parameter. It is a model debugging aid similar to the activation trace parameter used with the declarative memory module. If it is set to **t** then during every conflict resolution occurrence it will

display the instantiation of each production which matches along with its current utility parameters. That set of matching productions is referred to as the conflict set. In this case that is only the production small, and because there is no utility learning on or any noise in the system that production has a utility and  $U(t)$  of 0:

```
(P SMALL
  =GOAL>
    VALUE SMALL
    VALUE SMALL
  ==>
    !OUTPUT! SMALL
    -GOAL>
)
Parameters for production SMALL:
:UTILITY 0.000
:U 0.000
```

### 8.1.3.2 Turning on ppm

If you change the model to enable procedural partial matching by setting the :ppm parameter to 1 (you can make that change in the file and reload it or reset the model and then make the change at the Lisp prompt) then run it you will see a trace like this:

```
> (run 1.0)
0.000 PROCEDURAL CONFLICT-RESOLUTION
(P SMALL
  =GOAL>
    VALUE SMALL
    VALUE SMALL
  ==>
    !OUTPUT! SMALL
    -GOAL>
)
Parameters for production SMALL:
:UTILITY 0.000
:U 0.000
(P MEDIUM
  =GOAL>
    VALUE [MEDIUM, SMALL, -0.5]
    VALUE SMALL
  ==>
    !OUTPUT! SMALL
    -GOAL>
)
Parameters for production MEDIUM:
:UTILITY -0.500
:U 0.000
0.000 PROCEDURAL PRODUCTION-SELECTED SMALL
0.000 PROCEDURAL BUFFER-READ-ACTION GOAL
0.050 PROCEDURAL PRODUCTION-FIRED SMALL
SMALL
0.050 PROCEDURAL CLEAR-BUFFER GOAL
0.050 PROCEDURAL CONFLICT-RESOLUTION
0.050 ----- Stopped because no events left to process
```

Again we see the production small being selected and fired, but now we see that the production medium was also a member of the conflict set. For a partially matched

production the instantiation of the production will show additional information about the partial match. Here is the instantiation for the production medium from the trace:

```
(P MEDIUM
  =GOAL>
    VALUE [MEDIUM, SMALL, -0.5]
    VALUE SMALL
  ==>
    !OUTPUT! SMALL
  -GOAL>
)
```

In the comparison for the value slot, instead of just seeing medium as was specified in the production, we see a set of items in brackets (the red text above). That indicates that the test was not a perfect one. The first item in the brackets was the value specified in the production. The second item is the buffer chunk's value for that slot, and the third item is the similarity between those items.

Another important thing to notice is that the binding for the variable =val in that production is small (the blue text above). That is because that is the actual content of that slot in the chunk in the buffer -- the variable bindings come from the slots of the buffer's chunk and not values specified in the production.

After the instantiation of medium we see its current utility values:

```
Parameters for production MEDIUM:
:UTILITY -0.500
:U 0.000
```

The  $U(t)$  value for medium is 0 just as it is for small. The utility used for deciding which production to fire however is not 0 because it was not a perfect match. The similarity between small and medium is set to -0.5 in the model and the :ppm value was set to 1. So, the utility of medium is:  $0 + 1 * (-0.5) = -0.5$ .

### 8.1.3.3 The large production

Why isn't the production large also considered in the conflict set as a partial match? The reason is because there is no similarity set between the chunks small and large in the model. Thus, those chunks have the minimum similarity value and a test for the chunk large will not be considered a partial match to the chunk small in a production.

### 8.1.3.4 Adding noise

If the :egs parameter is set to a value greater than 0 then occasionally the medium production will be selected over the small production because of the noise added to the utilities. Here is a run where :egs was set to 1 showing medium being selected:

```
> (run 1.0)
0.000 PROCEDURAL CONFLICT-RESOLUTION
(P SMALL
 =GOAL>
   VALUE SMALL
   VALUE SMALL
 ==>
   !OUTPUT! SMALL
   -GOAL>
)
Parameters for production SMALL:
:UTILITY -0.713
:U 0.000
(P MEDIUM
 =GOAL>
   VALUE [MEDIUM, SMALL, -0.5]
   VALUE SMALL
 ==>
   !OUTPUT! SMALL
   -GOAL>
)
Parameters for production MEDIUM:
:UTILITY 0.453
:U 0.000
0.000 PROCEDURAL PRODUCTION-SELECTED MEDIUM
0.000 PROCEDURAL BUFFER-READ-ACTION GOAL
0.050 PROCEDURAL PRODUCTION-FIRED MEDIUM
SMALL
0.050 PROCEDURAL CLEAR-BUFFER GOAL
0.050 PROCEDURAL CONFLICT-RESOLUTION
0.050 ----- Stopped because no events left to process
```

### 8.1.4 Building Sticks Task alternate model

To see procedural partial matching used in an actual task this unit contains a slightly different model of the Building Sticks Task from unit 6 of the tutorial. The main difference between this model and the one presented in unit 6 is that instead of having separate productions to force and decide for both the over and under strategies, this model only has a decide production for each strategy.

There are several minor differences between this model and the previous version with respect to how the encoding is performed to enable the simpler test, but we will only be looking in detail at the two major differences between them. Those differences are in how the strategy is initially chosen and how the model computes the difference between the current stick's length and the goal stick's length.

#### 8.1.4.1 Strategy choice

In this model these are the productions which decide between the overshoot and undershoot strategies:

```
(p decide-over
  =goal>
    isa      try-strategy
    state    choose-strategy
  - strategy over
  =imaginal>
    isa      encoding
    goal-length =d
    b-len     =d
  ==>
  =imaginal>
  =goal>
    state    prepare-mouse
    strategy over
  +visual-location>
    isa      visual-location
    kind      oval
    screen-y 60)

(p decide-under
  =goal>
    isa      try-strategy
    state    choose-strategy
  - strategy under
  =imaginal>
    isa      encoding
    goal-length =d
    c-len     =d
  ==>
  =imaginal>
  =goal>
    state    prepare-mouse
    strategy under
  +visual-location>
    isa      visual-location
    kind      oval
    screen-y 85)
```

They are essentially a combination of the force and decide productions from the previous model for each strategy. Because they test the current strategy value they still operate as a forcing production when the model fails with its first choice and has to choose the other strategy, but when there is no current strategy either one can be potentially chosen and the utilities will determine which one is chosen.

Procedural partial matching is enabled for this task and a similarity between numbers is set up for this model with these parameter settings in the model:

```
(sgp :ppm 40 :sim-hook number-sims)
```

The :ppm value of 40 was estimated to produce a good fit to the data.

The similarities between numbers (the line lengths in pixels) are computed by the number-sims function specified and are set using a simple linear function to scale the possible differences into the default similarity range of 0 to -1:

$$\text{Similarity}(a,b) = -\frac{\text{abs}(a-b)}{300}$$

Unlike the previous model of this task, this one does not need to compute the difference between the goal stick's length and the b and c sticks' lengths explicitly to determine whether overshoot or undershoot should be used. Now that happens as a result of the partial matching in the **imaginal** buffer test of those productions. Whichever stick is closer to the goal stick's length will bias the utility toward that choice.

The initial utilities of the decide-over and decide-under productions are set at 10 in the model. Given that, we can look at how utility is determined when those productions are competing on the first problem which has stick lengths of a=15, b=250, c=55, and a goal of 125. The chunk in the **imaginal** buffer at that time will look like this:

```
CHUNK0-0
  A-LOC  VISUAL-LOCATION8-0-0
  B-LOC  VISUAL-LOCATION9-0-0
  C-LOC  VISUAL-LOCATION10-0-0
  GOAL-LOC VISUAL-LOCATION11-0-0
  GOAL-LENGTH 125
  B-LEN  250
  C-LEN  55
```

The length of the goal, b, and c sticks are the important tests for the decide productions in the imaginal buffer tests:

```
(p decide-over
...
  =imaginal>
    isa      encoding
    goal-length =d
    b-len     =d
  ==> ...)
```

```
(p decide-under
...
  =imaginal>
    isa      encoding
    goal-length =d
    c-len     =d
  ==> ...)
```

Each production is checking to see if the desired stick and the goal stick are the same length, and the procedural partial matching will adjust the utilities of those productions based on the similarity between the compared sticks. Here are the instantiations of those productions showing the similarities as computed from the number-sims function:

```
(P DECIDE-OVER
  =GOAL>
    STATE CHOOSE-STRATEGY
```



```

- STRATEGY OVER
=IMAGINAL>
  GOAL-LENGTH 125
  B-LEN [125, 250, -0.41666666]
==>
=IMAGINAL>
=GOAL>
  STATE PREPARE-MOUSE
  STRATEGY OVER
+VISUAL-LOCATION>
  KIND OVAL
  SCREEN-Y 60
)

(P DECIDE-UNDER
=GOAL>
  STATE CHOOSE-STRATEGY
  - STRATEGY UNDER
=IMAGINAL>
  GOAL-LENGTH 125
  C-LEN [125, 55, -0.23333333]
==>
=IMAGINAL>
=GOAL>
  STATE PREPARE-MOUSE
  STRATEGY UNDER
+VISUAL-LOCATION>
  KIND OVAL
  SCREEN-Y 85
)

```

The effective utility of decide-over is -6.666666 (10 + 40 \* -0.41666666) and the effective utility of decide-under is 0.666667 (10 + 40 \* -0.23333333). Knowing that the noise for utilities is set at 3 in the model we can compute the probabilities of choosing over vs under on the initial trial using the equation presented in unit 6:

$$Probability(i) = \frac{e^{U_i / \sqrt{2}s}}{\sum_j e^{U_j / \sqrt{2}s}}$$

$$Probability(over) = \frac{e^{-6.666 / 4.24}}{e^{-6.666 / 4.24} + e^{.666 / 4.24}} \approx .15$$

$$Probability(under) = \frac{e^{0.666 / 4.24}}{e^{-6.666 / 4.24} + e^{.666 / 4.24}} \approx .85$$

Thus, the model will pick undershoot about 85% of the time for the first problem.

As in the unit 6 model of the task, this model is also learning utilities based on the rewards it gets. So, the base utility values of the strategies will be adjusted as it progresses. Here are the results from running the unit 6 model of the task showing the average learned utility values for the four productions it needs to make the decision:

```
> (bst-experiment 100)
CORRELATION: 0.803
MEAN DEVIATION: 17.129

Trial 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
      23.0 60.0 59.0 70.0 91.0 42.0 80.0 86.0 59.0 34.0 33.0 22.0 54.0 72.0 56.0

DECIDE-OVER : 13.1506
DECIDE-UNDER: 11.1510
FORCE-OVER : 12.1525
FORCE-UNDER : 6.5943
```

Here are the results of running this new model of the task:

```
> (bst-experiment 100)
CORRELATION: 0.851
MEAN DEVIATION: 14.839

Trial 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15
      16.0 69.0 49.0 74.0 89.0 31.0 67.0 93.0 66.0 33.0 31.0 23.0 57.0 64.0 43.0
DECIDE-OVER : 11.7534
DECIDE-UNDER: 6.9756
```

We see a similar shift in the utilities with over gaining utility and under losing utility and overall this model produces a slightly better fit to the data.

#### 8.1.4.2 *Attributing actions to the imaginal module*

Before moving on to the other new procedural mechanism there is one other new capability to look at in the new Building Sticks model. In the previous model of the task the productions computed the difference between the current stick length and the goal stick length to decide whether to select stick a or stick c for each of the actions after the strategy choice had been made using a `!bind!` action in the production to do the math and then place that value into a slot of the **imaginal** buffer:

```
(p calculate-difference
  =goal>
    isa      try-strategy
    state    calculate-difference
  =imaginal>
    isa      encoding
    length   =current-len
  =visual>
    isa      line
    width    =goal-len
  ==>
    !bind! =val (abs (- =current-len =goal-len))
  =imaginal>
    length   =val
  =goal>
    state    consider-next)
```

In many models abstractions like that are easy to justify and do not cause any issues for data comparison. However, if one is interested in more low-level details, often when comparing model data to human data collected from fMRI or EEG studies, then

accounting for the timing of such actions and attributing them to an appropriate module are important. In the case of the imaginal module, there is a built in mechanism that allows the modeler to assign user defined functionality to the imaginal module and this version of the Building Sticks task does so instead of using a !bind! action for computing the difference. The details of how that is done are in the experiment code description text for this unit.

## 8.2 Dynamic Pattern Matching

Dynamic pattern matching is a powerful mechanism which allows the model to test and extend its representations based on the current context without that specific information having to be explicitly encoded into the model. It is particularly important for tasks where instruction or example following are involved, but can also be useful in other situations where flexibility or context dependence are necessary.

### 8.2.1 Basic Operation

The distinguishing feature between dynamic pattern matching and the standard pattern matching which has been used so far in the tutorial is that with dynamic pattern matching one can use variables to specify the slots in the conditions and actions of the productions. Other than that, a dynamically matched production operates just like the productions that have been used throughout the tutorial. Thus, whether standard or dynamic the following things still apply: only one production can be selected and fired at a time, the production which is selected will be the one that has the highest utility among those that match the current state, it takes 50ms to fire the production, utility learning applies to all productions which have fired when a new reward is received, and if production compilation is enabled every pair of successive productions which fire may be combined into a single new production.

In previous versions of ACT-R special commands were required to create productions which used dynamic pattern matching, but as of ACT-R 6.1 those commands are no longer required. Variablized slots can be used in productions created with the p command just like any other production which you have written.

There are two things which dynamic pattern matching allows that cannot be done with standard pattern matching and there is one capability which can be done with or without dynamic pattern matching but which is not recommended without dynamic pattern matching. Those three topics will be described in the following sections. For those descriptions we will be using a very simple model found in the simple-dynamic-model file. It has three productions which demonstrate those capabilities, and it is a very simplified version of something that is often done in a model that is following a set of declarative instructions. All the model does is update the chunk in the **imaginal** buffer based on information it retrieves from declarative memory. Because all the components of this model are known in advance it is not actually necessary to use dynamic pattern

matching, but that should make it easier to understand since it can be compared to the static productions which would perform the same operations in this case.

### 8.2.2 Arbitrary slots in conditions

The first thing that dynamic pattern matching allows is the ability to test arbitrary slots in the conditions of a production. The conditions of the productions start and retrieve-first-step from the example model show this:

```
(p start
  =goal>
    isa      fact
    context  =context
    =context =x
  ?imaginal>
    state    free
    buffer   empty
  ==>
  =goal>
    context  destination
  +imaginal>
    isa      result
    data1    =x
  +retrieval>
    isa      step
    step     first)

(p retrieve-first-step
  =goal>
    isa      fact
    context  =slot
    data     =x
  =imaginal>
    isa      result
    data1    =x
  =retrieval>
    isa      step
    =slot    =target
    step     first
  ==>
  =goal>
    data     11
  =imaginal>
    =target  =x
  +retrieval>
    isa      step
    step     second)
```

The slot tests in red above are instances of dynamic pattern matching. By using a variable to name a slot in a condition that test now depends on the contents of a buffer at the time of the test instead of specifying the slot name in advance. That means that the same production could test different slots based on the current context.

First we will look at the production start. The only thing different in that production relative to those seen previously is the last test in the **goal** buffer's condition:

```
=goal>
```

```

isa      fact
context  =context
=context =x

```

That means that the slot being tested will be the one which corresponds to the binding of the variable =context. The variable =x will be bound to the value of that slot. The =context variable is bound to the value of the context slot of the chunk in the **goal** buffer in the same way that you have seen in other productions.

Before running the model we will look at the contents of the **goal** buffer and see how this will apply for pattern matching. [If you want, you could run the model using the ACT-R Environment's stepper in tutor mode as was used in unit 1 and try to instantiate the production yourself before continuing.]

Here is the initial chunk placed in the **goal** buffer in the model:

```

FACT0-0
  CONTEXT DATA
  DATA 10

```

The =context variable is bound to the value in the context slot, which is data. Then the slot which corresponds to the binding of =context, which is data, is used to bind the variable =x. Thus, =x gets bound to 10 since that is the value of the data slot of the chunk in the **goal** buffer. If the binding of =context did not correspond to a slot of the chunk in the buffer then the production would not match. The rest of the start production operates just like all the other productions that have been seen previously in the tutorial and thus should not need further explanation.

When we run the model with the :cst parameter on to show the instantiation of matching productions this is what the start production looks like:

```

(P START
  =GOAL>
    CONTEXT DATA
    DATA 10
  ?IMAGINAL>
    STATE FREE
    BUFFER EMPTY
  ==>
    =GOAL>
      CONTEXT DESTINATION
    +IMAGINAL>
      DATA1 10
    +RETRIEVAL>
      STEP FIRST
)

```

That instantiation looks just like productions that you have seen previously, but the important thing to remember is that the instantiation of a dynamic production may have instantiated variables in both the slot value and slot name positions.

The retrieve-first-step production also has a dynamic test in its conditions:

```

(p retrieve-first-step
  =goal>
    isa    fact
    context =slot
    data    =x
  =imaginal>
    isa    result
    data1   =x
  =retrieval>
    isa    step
    =slot  =target
    step   first
  ==>
  ...)

```

In this case, that test involves multiple buffers. The value for the =slot variable is bound from one buffer and used to test a slot in a different buffer. Again, you may want to step through that in tutor mode with the ACT-R Environment and instantiate it yourself to get a better feel for how this works before looking at the instantiation below.

After the start production fires, the **goal** buffer's chunk looks like this:

```

FACT0-0
  CONTEXT  DESTINATION
  DATA    10

```

Thus, in the **goal** buffer condition of retrieve-first-step the =slot variable will be bound to the value destination and the =x variable will be bound to 10.

The chunk created by the start production in the **imaginal** buffer looks like this:

```

CHUNK0-0
  DATA1   10

```

That matches the condition for the **imaginal** buffer in retrieve-first-step since =x is bound to 10.

The chunk which is in the **retrieval** buffer at that time looks like this:

```

A-0
  STEP  FIRST
  DESTINATION  DATA2

```

The =slot variable is bound to destination from the **goal** buffer, and thus the variable =target will be bound to the value of the destination slot from the chunk in the **retrieval** buffer, which is data2. If there was not a slot named destination in the chunk in the **retrieval** buffer then this condition would not have matched and the production would not be selected.

Here is the instantiation of that production from the trace:

```

(P RETRIEVE-FIRST-STEP

```

```

=GOAL>
  CONTEXT DESTINATION
  DATA 10
=IMAGINAL>
  DATA1 10
=RETRIEVAL>
  DESTINATION DATA2
  STEP FIRST
==>
=GOAL>
  DATA 11
=IMAGINAL>
  DATA2 10
+RETRIEVAL>
  STEP SECOND
)

```

Though not shown in these examples, the dynamic conditions may also be used with any of the modifiers for a slot test as well as multiple times within or across buffer conditions. Thus, this set of conditions would be valid:

```

=goal>
  context =context
=imaginal>
  > =min-s 0
  =min-s =min
  > =max-s =min
  =context current
=retrieval>
  - =context complete
  max-slot =max-s
  min-slot =min-s

```

However, there are some constraints imposed on the use of dynamic conditions and those will be described in a later section.

### 8.2.3 Arbitrary slots in actions

The actions of the retrieve-first-step production show how dynamic pattern matching can be used to specify an action based on the current context. In its modification of the **imaginal** buffer we see this:

```

=imaginal>
  =target =x

```

As with the conditions, that means that the slot of the chunk in the **imaginal** buffer that will be modified will be the one bound to the variable =target. From the previous section we saw that that was the value data2, and that the =x variable was bound to 10. Thus this action will modify the chunk in the **imaginal** buffer so that its data2 slot has the value 10.

Here is what the chunk in the **imaginal** buffer looks like after retrieve-first-step fires.

CHUNK0-0

DATA1 10

DATA2 10

A variable may be used to specify a slot in any modification, modification request, or request action of a production. However, because such values are only determined when the production actually matches, it is possible that the production may attempt to make a modification or request with a slot that was not previously defined for the indicated chunk-type or any chunk-type if the production does not declare a chunk-type in the action. In the event of buffer modification actions there is a special mechanism which handles that, as described in the next section. For requests, if a previously unspecified slot is used that will usually lead to a warning and the failure to execute the request, but could also result in errors occurring during the run depending on the details of the module which handles the request. Thus, if slots of requests are specified dynamically, care should be taken to ensure the productions perform other tests, either in that production, or elsewhere in the sequence of productions, to protect against invalid requests.

### 8.2.4 Extending chunks with new slots

The final production in the test model, retrieve-second-step, shows the final new capability which dynamic pattern matching allows. Here is the production:

```
(p retrieve-second-step
  =goal>
    isa      fact
    context  =slot
    data     =x
  =imaginal>
    isa      result
  =retrieval>
    isa      step
    =slot    =target
    step     second
  ==>
  =imaginal>
    =target =x)
```

Other than specifying that the step slot of the retrieved chunk is the value second the conditions of this production are exactly the same as they are for the retrieve-first-step production, and the action of this production is a modification to the chunk in the **imaginal** buffer which looks exactly the same as the one from the retrieve-first-step production.

The significant difference between retrieve-first-step and retrieve-second-step is not in the specifications of the productions, but the contents of the buffers when they are selected. Retrieve-first-step was described in the previous section, and essentially the same matching process holds true for retrieve-second-step. However, the bindings for the



variables are now different. Here are the chunks from the **goal** and **retrieval** buffers after retrieve-first-step fires which match the retrieve-second-step production:

```
GOAL: FACT0-0
FACT0-0
  CONTEXT  DESTINATION
  DATA   11

RETRIEVAL: B-0 [B]
B-0
  STEP     SECOND
  DESTINATION DATA3
```

The variable bindings from the conditions of the production are: =slot is bound to destination, =x is bound to 11, and =target is bound to data3. Given those bindings, the instantiation of the action of this production will look like this:

```
=imaginal>
  data3 11
```

While that doesn't look all that different from the modification performed by the previous production the interesting thing to note is that none of the chunk-types specified for this model have a slot named data3:

```
(chunk-type fact context data)
(chunk-type step step destination)
(chunk-type result data1 data2)
```

As we have seen previously in the tutorial, modifications to a buffer add slots when the chunk does not have the slot indicated. When a dynamically determined modification action specifies a slot which does not exist in any of the chunk-types for the model that will be indicated in the trace by an extend-buffer-chunk action before the mod-buffer-chunk action:

```
0.350  PROCEDURAL  PRODUCTION-FIRED RETRIEVE-SECOND-STEP
0.350  PROCEDURAL  EXTEND-BUFFER-CHUNK IMAGINAL
0.350  PROCEDURAL  MOD-BUFFER-CHUNK IMAGINAL
```

Here is the result for the chunk in the **imaginal** buffer after that occurs:

```
CHUNK0-0
  DATA1  10
  DATA2  10
  DATA3  11
```

This mechanism allows the model to build its chunk representations as needed instead of requiring all possible slots be specified up front.

It is also possible to extend the available slots without dynamic pattern matching in a modification action, but such a change will happen as part of the model definition and

will also generate a warning. For example, if we were to add this production to this model:

```
(p change-new-slot
  =goal>
  ==>
  =goal>
  new-slot 10)
```

That will result in this warning when the model is loaded:

```
#|Warning: Production CHANGE-NEW-SLOT uses previously undefined
slots (NEW-SLOT). |#
```

Which indicates that a slot which was not specified in the chunk-type definitions is used. That will add a slot named new-slot to the chunk in the **goal** buffer if it does not already have one when the production fires, but it does not report the extend-buffer-chunk action since the extension of the chunk-types occurred at model loading time. Such a practice is not recommended and all slots specified explicitly in productions should be declared in the chunk-type definitions.

## 8.2.5 Constraints on dynamic pattern matching

Dynamic pattern matching adds a lot of flexibility to the specification of productions, and this flexibility allows for a lot more powerful productions to be created. However, since ACT-R is intended to be a model of human cognition, there are two constraints imposed upon how dynamic pattern matching works to maintain the plausibility of the system.

### 8.2.5.1 No Search

The first constraint on dynamic pattern matching is that it does not require searching to find a match. All productions which use dynamic pattern matching must be specified so that all variables are bound directly based on the contents of slots. The procedural module will not allow the creation of a production which has only a condition like this:

```
(p not-allowed
  =goal>
  isa example
  =some-slot desired-value
  ==>
  ...)
```

which requires finding a slot which has a particular value. If search like that were allowed then the matching of a production could become an NP complete task.

### 8.2.5.2 One level of indirection

The other constraint on dynamic pattern matching is that it only allows one level of indirection. All of the variables which are used as slot indicators must be bound to slots which are specified as constants. Thus, one cannot use a dynamically matched slot's value as a slot indicator like this:

```
(p also-not-allowed
  =goal>
    isa example
    first-slot =s1
    =s1        =next-slot
    =next-slot value
  ==>
  ...)
```

Allowing an unbounded level of indirection is not plausible, thus some constraint needed to be determined for the indirection. A single level was chosen as the constraint because that was all that was necessary to provide the abstractions needed and such a mechanism appears to be realizable within the human brain.

### 8.2.6 Example Models

There are two example models which use dynamic pattern matching included with this unit and both are variations of previous models seen in the tutorial. The first is an expanded version of the semantic model from unit 1 and the other is a refinement of the paired associate experiment model which performed the task based on instructions as presented in unit 7. Both models operate similarly to how they did before, and therefore will not be described in full detail here. Only the significant differences related to dynamic pattern matching will be discussed.

#### 8.2.6.1 Semantic Model

In unit 1 the model used a rather cumbersome representation of the knowledge in declarative memory specifying slots named attribute and value instead of just using slots and values:

```
(p1 ISA property object shark attribute dangerous value true)
(p2 ISA property object shark attribute locomotion value swimming)
(p3 ISA property object shark attribute category value fish)
```

The reason for that representation at the time was because without dynamic pattern matching the model would have required specifying separate productions for each of the attributes which one wanted to lookup. With dynamic pattern matching it will be easier to write productions which can search the knowledge using a more natural representation of the chunks:

```
(p1 ISA property object shark dangerous true)
(p2 ISA property object shark locomotion swimming)
(p3 ISA property object shark category fish)
```

To go along with that the model specifies the property chunk-type as having all the possible attributes used:

```
(chunk-type property object category dangerous locomotion edible
      breathe moves skin color sings flies height wings)
```

That is not necessary, because just as with productions, specifying new slots when creating chunks in the model definition will automatically extend them and print a warning. For example if we add this property to the model's add-dm call:

```
(p25 isa property object shark teeth sharp)
```

We get this warning when the model is loaded and when it is reset:

```
#|Warning: Invalid slot TEETH specified when creating chunk P25 with
type PROPERTY. Extending chunks with slot named TEETH. |#
```

However, as was recommended with productions, all slot names used as constants in the model should be declared in advance. Of course, if this model also included a means to acquire new facts in some way instead of having them all specified in the definition it could create those new slots through dynamic modifications in the productions.

Instead of only being able to chain through category tests this model is now able to search for any attribute and value and will search back through the categories as necessary to try and find it. Here are some goal chunks which the model starts out with as options to test:

```
(g1 ISA test-attribute object canary attribute category value bird)
(g2 ISA test-attribute object canary attribute wings value true)
(g3 ISA test-attribute object canary attribute dangerous value true)
```

The goal chunks now contain slots for attribute and value to indicate what is being searched for and here are the productions which use that information dynamically to request a retrieval of the desired fact and to verify when it has been successfully retrieved:

```
(p retrieve-attribute
  =goal>
    ISA      test-attribute
    object   =obj
    attribute =attr
    value    =val
    state    nil
  ==>
  =goal>
    state attr-check
  +retrieval>
    ISA      property
    object   =obj
    - =attr  nil)
```

```

(P direct-verify
  =goal>
    ISA      test-attribute
    original  nil
    object    =obj
    attribute =attr
    value     =val
    state     attr-check
  =retrieval>
    ISA      property
    object    =obj
    =attr     =val
  ==>
  =goal>
    answer    yes
    state     done)

```

The retrieve-attribute production requests the retrieval of a chunk which has a value in the slot with the named attribute, and then the direct-verify production matches if that retrieved chunk has the requested value in that slot. You may wonder why we don't just request the retrieval of the specific slot value desired in retrieve-attribute, and the reason is that the model may contain a contradictory fact which would fail to be retrieved if that were the case and it would then search through the other categories to try and find the matching chunk. For example, if asked whether ostriches fly with the goal:

```
(g1 ISA test-attribute object ostrich attribute flies value true)
```

A model which requested that specific slot value combination “flies true” would fail for the ostrich object, but when it chained up to bird it would succeed and then incorrectly indicate that an ostrich can fly. This is very similar to the fan model in how it operates and as a general strategy it is almost always better for the model to retrieve something than to rely on retrieval failure.

There are several other productions which handle failure to retrieve, retrieving a contradictory fact, and chaining up through the categories to continue searching which you can investigate further on your own.

One final thing to note about this model is that when it finds a matching fact in a parent category it adds that specific fact to the model so that future searches will not require going through the categories. Here are the traces of two successive runs asking for the same fact:

```

> (goal-focus g2)
G2
> (run 10)
0.000 GOAL      SET-BUFFER-CHUNK GOAL G2 REQUESTED NIL
0.000 PROCEDURAL CONFLICT-RESOLUTION
0.050 PROCEDURAL PRODUCTION-FIRED RETRIEVE-ATTRIBUTE
0.050 PROCEDURAL CLEAR-BUFFER RETRIEVAL
0.050 DECLARATIVE START-RETRIEVAL

```

```

0.050  PROCEDURAL  CONFLICT-RESOLUTION
0.100  DECLARATIVE RETRIEVAL-FAILURE
0.100  PROCEDURAL  CONFLICT-RESOLUTION
0.150  PROCEDURAL  PRODUCTION-FIRED MISSING-ATTR
0.150  PROCEDURAL  CLEAR-BUFFER RETRIEVAL
0.150  DECLARATIVE START-RETRIEVAL
0.150  PROCEDURAL  CONFLICT-RESOLUTION
0.200  DECLARATIVE RETRIEVED-CHUNK P14
0.200  DECLARATIVE SET-BUFFER-CHUNK RETRIEVAL P14
0.200  PROCEDURAL  CONFLICT-RESOLUTION
0.250  PROCEDURAL  PRODUCTION-FIRED CHAIN-FIRST-CATEGORY
0.250  PROCEDURAL  CLEAR-BUFFER RETRIEVAL
0.250  PROCEDURAL  CONFLICT-RESOLUTION
0.300  PROCEDURAL  PRODUCTION-FIRED RETRIEVE-ATTRIBUTE
0.300  PROCEDURAL  CLEAR-BUFFER RETRIEVAL
0.300  DECLARATIVE START-RETRIEVAL
0.300  PROCEDURAL  CONFLICT-RESOLUTION
0.350  DECLARATIVE RETRIEVED-CHUNK P18
0.350  DECLARATIVE SET-BUFFER-CHUNK RETRIEVAL P18
0.350  PROCEDURAL  CONFLICT-RESOLUTION
0.400  PROCEDURAL  PRODUCTION-FIRED INDIRECT-VERIFY
0.400  PROCEDURAL  CLEAR-BUFFER RETRIEVAL
0.400  PROCEDURAL  CONFLICT-RESOLUTION
0.450  PROCEDURAL  PRODUCTION-FIRED RECORD-RESULT
0.450  PROCEDURAL  CLEAR-BUFFER IMAGINAL
0.450  PROCEDURAL  CONFLICT-RESOLUTION
0.650  IMAGINAL    SET-BUFFER-CHUNK IMAGINAL CHUNK0
0.650  PROCEDURAL  CONFLICT-RESOLUTION
0.700  PROCEDURAL  PRODUCTION-FIRED CREATE
0.700  PROCEDURAL  CLEAR-BUFFER IMAGINAL
0.700  PROCEDURAL  CONFLICT-RESOLUTION
0.750  PROCEDURAL  PRODUCTION-FIRED RESPOND
CANARY WINGS TRUE ANSWER IS YES
0.750  PROCEDURAL  CLEAR-BUFFER GOAL
0.750  PROCEDURAL  CONFLICT-RESOLUTION
0.750  -----    Stopped because no events left to process

> (goal-focus g2)
G2
> (run 10)
0.750  GOAL        SET-BUFFER-CHUNK GOAL G2 REQUESTED NIL
0.750  PROCEDURAL  CONFLICT-RESOLUTION
0.800  PROCEDURAL  PRODUCTION-FIRED RETRIEVE-ATTRIBUTE
0.800  PROCEDURAL  CLEAR-BUFFER RETRIEVAL
0.800  DECLARATIVE START-RETRIEVAL
0.800  PROCEDURAL  CONFLICT-RESOLUTION
0.850  DECLARATIVE RETRIEVED-CHUNK CHUNK0-0
0.850  DECLARATIVE SET-BUFFER-CHUNK RETRIEVAL CHUNK0-0
0.850  PROCEDURAL  CONFLICT-RESOLUTION
0.900  PROCEDURAL  PRODUCTION-FIRED DIRECT-VERIFY
0.900  PROCEDURAL  CLEAR-BUFFER RETRIEVAL
0.900  PROCEDURAL  CONFLICT-RESOLUTION
0.950  PROCEDURAL  PRODUCTION-FIRED RESPOND
CANARY WINGS TRUE ANSWER IS YES
0.950  PROCEDURAL  CLEAR-BUFFER GOAL
0.950  PROCEDURAL  CONFLICT-RESOLUTION
0.950  -----    Stopped because no events left to process

```

### 8.2.6.2 Paired-learning Model

The first difference between this version of the model and the one from the previous unit is in the representation of the chunks which it uses. For the operator chunks, instead of having two generic slots named `arg1` and `arg2` which get used differently for different subtasks it uses appropriately named slots for each operation:

```
(op1 isa operator pre start action read label word
      post stimulus-read)
(op2 isa operator pre stimulus-read action retrieve required word
      label number post recalled)
(op3 isa operator pre recalled slot number success respond
      failure wait)
(op4 isa operator pre respond action type required number post wait)
(op5 isa operator pre wait action read label number post new-trial)
(op6 isa operator pre new-trial action complete-task post start)
```

It also does not specify a chunk-type for the result. Instead, it just creates an empty chunk that gets the appropriate slots added to it such that the resulting chunks for the trials will look like this:

```
CHUNK0-0
  WORD "tent"
  NUMBER "5"
```

Those slot names are encoded in the instructions in the label slot of operators `op1` and `op5` above.

The label slot of the action specifies the name of the slot into which the item should be stored in the **imaginal** buffer and is handled by the read and encode productions:

```
(p read
  =goal>
    isa      task
    step      retrieving-operator
  =retrieval>
    isa      operator
    action    read
    label     =destination
    post      =state
  =visual-location>
    isa      visual-location
  ?visual>
    state    free
  ?imaginal>
    buffer    full
  ==>
  +visual>
    isa      move-attention
    screen-pos =visual-location
  =goal>
    context  =destination
    step      process
    state     =state)
```

```
(p encode
  =goal>
    isa      task
    step      process
    context   =which-slot
  =visual>
    isa      text
    value     =val
  =imaginal>
  ?imaginal>
    state     free
  ==>
  *imaginal>
    =which-slot =val
  =goal>
    step      ready)
```

The read production saves the value of the label slot in the **goal** buffer's context slot and requests a shift of visual attention to the item. When the item is attended the encode production can fire and place the value of the text which was read into that slot of the chunk in the **imaginal** buffer. If the chunk in the buffer does not have a slot by that name then that modification request will extend the chunk to have such a slot.

That makes this set of instruction following productions more general than the previous ones because the representation does not have to be encoded in the model's chunk-types and could have any number of slots in the representation based on the instructions. The model also does not need to have a separate production to set each possible slot that is used in the representation. Of course, since the instructions are specifically encoded in this particular model's definition that generality is not necessary since the representation is known in advance. However, these same productions could be used for other tasks without changing them, or they could be used with an even more general version of the model which had other productions for reading the instructions themselves.

Similarly, we see that by using dynamically matched productions this new version of the model can also perform the retrieval based on a slot specified in the instructions:

```
(p retireve-associate
  =goal>
    isa      task
    step      retrieving-operator
  =imaginal>
    =target   =stimulus
  =retrieval>
    isa      operator
    action    retrieve
    required  =target
    label     =other
    post      =state
  ==>
  =imaginal>
  +retrieval>
    =target   =stimulus
  =goal>
    step      retrieving-result
    context   =other
    state     =state)
```



and also respond using an arbitrary slot specified in the instructions:

```
(p type
  =goal>
    isa      task
    step     retrieving-operator
  =imaginal>
    =slot    =val
  =retrieval>
    isa      operator
    action   type
    required =slot
    post     =state
  ?manual>
    state    free
==>
  =imaginal>
  +manual>
    cmd      press-key
    key      =val
  =goal>
    state    =state
    step     ready)
```

### 8.2.6.3 Dynamic matching and production compilation

As in the previous version of this task, this model uses production compilation to learn specific productions for doing the task as it is repeatedly following the instructions. There is no difference in how the production compilation mechanism works with dynamically matched productions. It still combines successive productions which are fired into a single production when possible using the rules described in unit 7. However, it is worth looking at a couple of examples to see how that applies when dynamically matched productions are involved. When one or both of the productions being composed together contain dynamically matched components, the resulting production may retain some of those dynamic components or they may be replaced with statically matched values. They will be replaced by static values in the same way that other variables are replaced – when a retrieval request and harvesting are removed between the productions.

We can see examples of this very early in the model's trace with the :pct parameter set to t. When the encode and retrieve-operator productions are combined the result still has the dynamic component from the encode production:

```
(P PRODUCTION1
  "ENCODE & RETRIEVE-OPERATOR"
  =GOAL>
    CONTEXT =WHICH-SLOT
    STEP PROCESS
    STATE =STATE
  =IMAGINAL>
  =VISUAL>
    TEXT T
    VALUE =VAL
  ?IMAGINAL>
    STATE FREE
```

```

==>
=GOAL>
  CONTEXT NIL
  STEP RETRIEVING-OPERATOR
+RETRIEVAL>
  PRE =STATE
*IMAGINAL>
  =WHICH-SLOT =VAL
)

```

However, when the retrieve-operator and retrieve-associate productions are combined the instantiation of the variables used from the retrieved chunk results in a production with no dynamic components:

```

(P PRODUCTION2
  "RETRIEVE-OPERATOR & RETIREVE-ASSOCIATE - OP2"
  =GOAL>
    STATE STIMULUS-READ
    STEP READY
  =IMAGINAL>
    WORD =STIMULUS
==>
  =IMAGINAL>
  =GOAL>
    CONTEXT NUMBER
    STATE RECALLED
    STEP RETRIEVING-RESULT
+RETRIEVAL>
  WORD =STIMULUS
)

```

#### 8.2.6.4 Data fit

Despite the model being more general, it still performs the task the same way as the previous version of the model does, and with production compilation enabled provides a similar fit to the data using the same parameter settings.

Here are the results from the unit 7 model:

Latency:

CORRELATION:	0.991							
MEAN DEVIATION:	0.089							
Trial	1	2	3	4	5	6	7	8
	0.000	2.040	1.948	1.831	1.698	1.630	1.584	1.555

Accuracy:

CORRELATION:	0.993							
MEAN DEVIATION:	0.046							
Trial	1	2	3	4	5	6	7	8
	0.000	0.405	0.642	0.799	0.863	0.899	0.941	0.942

and here are the results from the model from this unit:

Latency:

CORRELATION:	0.989							
MEAN DEVIATION:	0.105							

Trial	1	2	3	4	5	6	7	8
	0.000	2.059	1.929	1.806	1.730	1.663	1.628	1.589

Accuracy:

CORRELATION: 0.996

MEAN DEVIATION: 0.034

Trial	1	2	3	4	5	6	7	8
	0.000	0.432	0.657	0.788	0.873	0.927	0.943	0.957

### 8.3 Assignment

The assignment for this unit will be to use both of the new production techniques described above to create a model which can perform a simple categorization task. The experiment this model will be performing is a simplification of an experiment which was performed by Robert M. Nosofsky (which was based on an experiment performed by Stephen K. Reed) that required participants to classify schematic face drawings into one of two learned categories.

In the experiment the participants first trained on learning 10 faces each of which belonged to one of two categories. The faces themselves were varied along four features: eye height, eye separation, nose length, and mouth height. Then there was a testing phase in which they were presented with both old and new faces and asked to specify to which category the face belonged. The data collected was the probability of classifying the face as a member of each category in the testing phase. For this assignment we will not be modeling the whole task, nor will we be trying to fit all of the data from the experiment because a thorough model of this task would require a lot more work than is reasonable for an assignment.

Here is the general description of the task which the model for this assignment will have to perform. It will be presented with the attributes of a stimulus one at a time, indicating the name of a feature and its value (it will not be visually interpreting a face image). It must collect those attributes into a single chunk which represents the current stimulus. Using that chunk, it can then retrieve a best matching example from declarative memory. Based on that retrieved chunk, it will make a category choice for the current stimulus. The model will not be performing the initial training phase, thus it will not require using any of the ACT-R learning mechanisms. Each trial will be completed separately with the model being reset before each one. This is similar to how the fan experiment model from unit 5 worked, with the training information pre-encoded in declarative memory and the model only needing to perform one trial of the task. The details of how those steps are to be performed are described below.

The primary part of the exercise is the first step – creating the stimulus representation from the individual attributes. The important aspect of the assignment will be on how to perform this task in a general way because that sort of encoding is something which can be applicable to many different tasks. Overall, this should be a very small model, only requiring around 5 productions to do the task, but will require using both of the new mechanisms described in this unit.

### 8.3.1 The Stimulus Attributes

The attributes of the stimulus to categorize will be presented to the model one at a time through the **goal** buffer. The experiment code will set the **goal** buffer to a chunk which uses the slots specified for the chunk-type named goal:

```
(chunk-type goal state name value)
```

The state slot will be set to the value add-attribute, the name slot of the chunk will contain a symbol specifying the name of the attribute being presented. The value slot will hold a value for that attribute in the current stimulus which will be a number. Thus, a goal chunk at the start of a trial may look like this:

```
CHUNK1-0
  NAME  EH
  VALUE 0.704
  STATE  ADD-ATTRIBUTE
```

What the model must do is convert that numeric value into a symbolic description which will be stored in a slot of the **imaginal** buffer. The reason for doing so is because the example chunks which the model has stored in declarative memory that it will be retrieving look like this:

```
EXAMPLE1
  CATEGORY 1
  EH  MEDIUM
  ES  SMALL
  NL  LARGE
  MH  MEDIUM
```

Those chunks provide a more general representation of the stimuli instead of just recording explicit measurements or distance values. By converting the attributes as they are encoded the model will be able to create a similarly structured chunk in the **imaginal** buffer. In a more complete model of the task a similar process would take place during the training phase of the experiment to strengthen and learn the examples, and we want to maintain that same representational aspect even if it is not currently being modeled.

For this task all of the attributes can be classified as either small, medium, or large, and to make things easier, the numeric values of the attributes used have all been scaled to the same range based on data also collected by Nosofsky for this task. To perform that conversion from numeric value to descriptive name, procedural partial matching should be used by the model. The starting model has a similarity function provided that assigns a similarity score between the attribute values and the labels small, medium, and large. Thus, one can have competing productions which test the value for each of those labels and the production which specifies the most similar label will be the one selected.

The specific range of values used should not be explicitly encoded into the model, and in fact this unit will not describe how the similarity values are computed between the labels and the numbers. Thus, your model should not explicitly test the values against any particular numbers, but should be able to work with any value given relying on the similarity function to provide the comparison to the appropriate labels. Thus, a production like this is **not** a good thing to use in this model:

```
(p bad-way-to-test-medium
  =goal>
    isa attribute
    > value -.5
    < value .5
  ...
)
```

After determining what the appropriate label for the attribute is, the model must record that value in the chunk in the **imaginal** buffer. When the first attribute is presented, the **imaginal** buffer will be set to a chunk which only has the value unknown in the category slot:

```
CHUNK0-0
  CATEGORY UNKNOWN
```

It does not have any slots for holding the specific attributes of the task. This is where dynamic pattern matching will need to be used. The model will need to add a slot to the chunk based on the name of the attribute provided. Thus, the complete encoding of the attribute shown above should result in the **imaginal** buffer looking something like this when done (because of noise it may not always categorize that particular value as large):

```
CHUNK0-0
  CATEGORY UNKNOWN
  EH LARGE
```

Again, it is important that the model be general in how it performs that modification to the **imaginal** buffer's chunk. The model should be able to encode any attribute name which is provided, and should not have any specific attribute names mentioned in the productions. Thus this action in a production is **not** the way that it should be handled:

```
(p bad-imaginal-action
  ...
  ==>
    =imaginal>
      eh =value
  ...)
```

As with the values, the unit will not be specifying the names that the attributes will have. The experiment code will guarantee that the example chunks created in declarative memory have the same attributes as those that are presented to the model, and the model should be able to work with any attribute names it is given.

After updating the **imaginal** buffer, the model should stop and wait for the next attribute to be provided. An easy way to do that would be to make sure that all of the productions which are processing the attribute test the **goal** buffer chunk in their conditions (which is likely to occur since it contains the information needed) and then clear the chunk from the **goal** buffer after the attribute has been processed. Thus, the model should be able to process any number of attributes for a stimulus. The result will be a chunk in the **imaginal** buffer which has a slot for each of the attributes that was provided and the value in each of those slots is a label (small, medium, or large) as determined through procedural partial matching based on the numeric value from the attribute.

### 8.3.2 Model Response

After all of the attributes have been provided to the model a different goal chunk will be set to indicate that it is time for the model to retrieve an example and classify the stimulus that is currently encoded in the **imaginal** buffer. That goal chunk will have the state slot set to the value categorize:

```
CHUNK5-0
  STATE  CATEGORIZE
```

To make a response, the model needs to do two things. First, it must retrieve a chunk from declarative memory which is similar to the chunk in the **imaginal** buffer. The model will have 10 examples already encoded in declarative memory which have their features set based on the examples from the original experiment. Half of the examples are in category 1 and the other half are in category 2, and here are two examples:

```
EXAMPLE5
  CATEGORY  2
  EH  LARGE
  ES  SMALL
  NL  SMALL
  MH  SMALL
```

```
EXAMPLE4
  CATEGORY  1
  EH  SMALL
  ES  MEDIUM
  NL  LARGE
  MH  LARGE
```

Because the names of the slots to specify in the retrieval request are not known in advance the easiest way to perform the retrieval request is using an indirect request with the chunk from the **imaginal** buffer, as was shown in the siegler model from unit 5 of the tutorial. That will look like this as an action in the production:

```
(p
...
```

```
==>
+retrieval> =imaginal
...)
```

and is equivalent to specifying all of the slots and values from the chunk that is in the **imaginal** buffer explicitly in the request.

Declarative partial matching is also enabled for this model, and that will allow for the retrieval of a chunk which has values close to the requested values in the event that there is not a perfectly matching example. The other declarative parameters for the model are set such that if the chunk in the **imaginal** buffer is created correctly there should always be a chunk retrieved in a reasonable amount of time.

After the model retrieves a chunk, the final step it needs to do is to set the category slot of the chunk in the **imaginal** buffer to be the same as the category value of the chunk that was retrieved. After that happens the model should again stop because it is then done with the trial.

### 8.3.3 Running the experiment

There are three commands provided for running the task. The first is present-one-attribute which takes two parameters, an attribute name and an attribute value. It can be used to test the model's encoding ability. The attribute name can be any symbol and the value should be a number between -1 and 1. It will generate an attribute goal chunk for the model with the name and value slots set using the values provided and a state slot value of add-attribute then run the model to perform the encoding. Thus, it could be called like this:

```
(present-one-attribute size -1)
```

Which would create this chunk in the **goal** buffer:

```
CHUNK1-0
  NAME  SIZE
  VALUE -1
  STATE ADD-ATTRIBUTE
```

and should result in the model having a chunk like this in the **imaginal** buffer when it is done:

```
CHUNK0-0
  SIZE  SMALL
  CATEGORY UNKNOWN
```

That's because a value of -1 is most similar to the small label (though sometimes noise in the utility calculations could cause one of the other labels to also be applied). You should work with this command only until your model is able to do that part of the task reliably.

Once the model is able to properly encode attributes you can test its ability to retrieve examples based on a stimulus with multiple attributes using the `present-one-stimulus` command. It requires four parameters which should each be a number in the range of -1 to 1. It will reset the model, generate the attribute goal chunks for the model (using a default set of names for the attributes) and run it with each of the values specified then generate a categorize goal and run the model to make the response. The return value will be the category which the model has set in the **imaginal** buffer's chunk or **nil** if it does not properly set a category. Here is an example of calling it and showing it responded with category 1:

```
(present-one-stimulus -1 .5 -.2 0)
1
```

Once you have a model which can handle individual trials with `present-one-stimulus` you should then test it on the experiment data using the `categorize` command. It requires one parameter which is the number of times to repeat the experiment. It will run the model over the 14 stimuli from the experiment as many times as specified and print out the proportion of times that each item was classified as category 1 along with the experimental data, number of responses the model made, and the model's fit to the experimental data:

```
> (categorize 10)
CORRELATION: 0.880
MEAN DEVIATION: 0.209
P(C=1)
  ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10) ( 10)
data 0.975 0.850 0.987 1.000 0.963 0.075 0.138 0.087 0.050 0.025 0.937 0.544 0.988 0.087
model 0.700 0.800 0.800 0.900 0.700 0.100 0.200 0.400 0.100 0.100 1.000 0.900 0.900 0.500
```

The numbers in parentheses should all be the same as the number of trials that were run indicating that the model always responds. We will discuss the data fit and other running options below.

### 8.3.4 Fitting the data

If your model works as described above, then it should produce a fit to the data similar to this using the default parameters in the model:

```
> (categorize 100)
CORRELATION: 0.948
MEAN DEVIATION: 0.174
P(C=1)
  (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100) (100)
data 0.975 0.850 0.987 1.000 0.963 0.075 0.138 0.087 0.050 0.025 0.937 0.544 0.988 0.087
model 0.960 0.750 0.950 0.950 0.870 0.200 0.280 0.420 0.190 0.070 0.920 0.830 0.940 0.470
```



If the correlation and deviation are significantly worse than that, then you will want to go back and make sure your model is doing all of the steps described above correctly.

Because fitting the data is not the focus of this exercise it should not be necessary to adjust the parameters to improve that fit, but if you would like to explore the parameters for improving the fit then the ones that are recommended to be changed would be these four from the model:

```
(sgp :mp 1 :ppm 1 :egs .25 :ans .25)
```

Those are the partial matching scale parameters for declarative and procedural partial matching and the noise values for those mechanisms. Through adjusting those parameters the reference model was able to achieve this fit which improves the deviation slightly:

```
> (categorize 500)
CORRELATION: 0.948
MEAN DEVIATION: 0.142
P(C=1)
(500) (500) (500) (500) (500) (500) (500) (500) (500) (500) (500) (500) (500) (500)
data 0.975 0.850 0.987 1.000 0.963 0.075 0.138 0.087 0.050 0.025 0.937 0.544 0.988 0.087
model 0.992 0.780 0.978 0.988 0.918 0.118 0.052 0.130 0.050 0.030 0.966 0.798 0.986 0.534
```

### 8.3.5 Generality

If your model fits the data adequately then the final thing to test is to make sure that it is doing the task in a general way. The categorize command takes optional parameters which can be used to modify the attribute names and the range of values it uses. Providing a second number to categorize will shift the attribute values provided to the model by that amount and also shift the similarities to the labels accordingly. Thus, the model should be unaffected by that change and produce the same fit to the data regardless of such a shift:

```
> (categorize 100 4.5)
CORRELATION: 0.968
MEAN DEVIATION: 0.161
```

In addition to that, one can also specify the four names to use for the attributes. Those provided names will be used to generate the examples in declarative memory and to provide the attributes to the model. The names can be any Lisp symbols other than category, since the example chunks already have such a slot. To specify different names they must be passed to categorize after the offset value. Here is an example with no effective offset to the values (a shift of 0) and new names for the attributes:

```
> (categorize 100 0 slot-1 b other name)
CORRELATION: 0.975
MEAN DEVIATION: 0.161
```

Here is what an example from declarative memory looks like in that case:

```
EXAMPLE0  
NAME SMALL  
CATEGORY 1  
SLOT-1 SMALL  
B LARGE  
OTHER MEDIUM
```

and the chunk created in the **imaginal** buffer to encode a stimulus should look similar (the values of the attribute slots will differ based on the attributes that are presented).

Again, this change should not affect the model's ability to do the task if it has been written to perform the task generally. The best test of the model is to provide both a non-zero shift to the attribute values and new attribute names. A good model for the assignment will still provide the same fit to the data under those circumstances:

```
> (categorize 100 -3 a b c d)  
CORRELATION: 0.936  
MEAN DEVIATION: 0.162
```

## References

Nosofsky, R. M. (1991). Tests of an exemplar model for relating perceptual classification and recognition memory. *Journal of Experimental Psychology: Human Perception and Performance*. 17, 3-27.

Reed, S. K. (1972). Pattern recognition and categorization. *Cognitive Psychology*. 3, 382-407.