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Abstract

This paper presents and describes a pattern recognition program with a relatively simple and general basic structure upon which has been superimposed a rather wide variety of techniques for learning, or self-organization. The program attempts to generalize n-tuple approaches to pattern recognition, in which an n-tuple is a set of individual cells or small pieces of patterns, and each n-tuple is said to characterize an input pattern when these pieces match it, as specified.

The program allows n-tuples to match when only some of their parts match, and it allows these parts to match even though they are not precisely positioned (See Uhr, 1969b, for some simple example programs). It further learns, in a variety of ways: It searches for good weights on its characterizers' implications, byre-weighting as a function of feedback. It generates and discovers new characterizers (and can therefore begin with no characterizers at all), and discards characterizers that prove to be poor (See Uhr and Vossler, 1961, and Prather and Uhr, 1964). It also uses a set of characterizers of characterizers, to search for good parameter values that newlygenerated characterizers should have.

A detailed flow-chart-like "precis" description of the program is given, along with an actual listing. It is thus possible to examine exactly what the program does, and how it does it, and therefore to see how a wide variety of learning mechanisms have been implemented in a single pattern recognition program. But because it was coded in a "high-level" patternmatching and list-processing language the program runs too slowly for extensive tests to be practicable. Therefore only a brief listing of output is given, to show that the program, works and begins to learn.

Descriptors: Learning, self-organization, induction, discovery, pattern recognition, learning to learn, n-tuple recognition, characterizing characterizers.

Introduction

Programs that have used n-tuples as their characterizers appear to perform with the very best of pattern recognition programs (for discussions, see Uhr, 1963, 1969a; for a good recent example, see Andrews, Atrubin, and Hu, 1968). This is not surprising, for n-tuples are easily handled by the digital computer. And although

they may appear simple, any possible characterizer can be described as a sufficiently complex and detailed n-tuple. What we don't know is whether the n-tuple description of sufficiently powerful characterizers would avoid being overly cumbersome and ridiculously wasteful of storage space and processing time.

Programs that use n-tuples either have them designed by human beings and pre-programmed in (e.g. , Andrews, Atrubin, and Hu, 1968), or randomly generate a fixed set of fixed-n-size ntuples (e.g., Bledsoe and Browning, 1959). An interestingly simple generalization of this is the following: Let the program begin with no characterizers, but have it generate new characterizers that are as simple as possible, and only when needed. Thus the program might start by generating one 1-tuple, continue generating more 1-tuples as it finds itself continuing to choose wrong names to assign to input patterns, and at some point begin generating n+1-tuples. It further should be assessing how well each characterizer is working, by in effect conducting a running experiment that examines its successes and failures. This information should be used a) to weight the importance of this characterizer¹s implications in combining them for the decisions as to names to choose, b) to decide whether a characterizer is good and should therefore be used, or is bad and should therefore be discarded, to be replaced by another, and c) to gather information about general types of characterizers, so that new characterizers are generated that are similar in important parameter values to characterizers that have proved themselves good.

This paper describes a program that is a first approximation to this simple, but hazy, scheme of generating as few characterizers as needed, keeping them as simple as possible, but using what has been learned about characterizers to direct the generation of new characterizers, so that they will be similar in their characteristics to good characterizers that have been generated in the past.

The program has a second general purpose to puch deeper into techniques for learning characterizers.

The basic structure of this program seems to us extremely simple - the generation, when needed, of the best new specific n-tuple of the best general type possible, and the learning of as much as possible. But when the program is described or given in detail, as in the following

pages, it inevitably sounds more complex - for indeed it is more complex when forced to the level of code for a discrete digital computer. In order to get flexibility into our n-tuples so that they need not be precisely positioned and can be considered to match even though all parts do not always match, extra details must be added to the code. These in turn suggest additional learning mechanisms that will search for good values for this allowed wobbling and threshold matching .

There are also several points at which we simply evade quite subtle decisions that should be made by the program: Should the program spend more time adjusting the weights of its present set of characterizers, or should it generate one or more new characterizers ? This we handle by having the program generate one new characterizer per pattern, up to a fixed maximum (also discarding characterizers found to be bad, to make room for more). When the program generates a new characterizer, should it be of the same size n, or of size n + 1? This we handle by treating n-size as Just another parameter, so that, as described below, the program will choose the n for a new tuple as a function of the goodness of the tuples of different n-size that have been generated so far. Thus n is initialized to equal 1; the program will keep tabs on the goodness of each n-size and will generate tuples with an n-size that reflects this goodness, but with some probability will occasionally generate a new tuple of size $n + 1$. This procedure is used for all parameters of characterizers .

Precursors

As an introduction to the structure of our program, let us consider the Bledsoe-Browning pattern recognition program (1959), which was among the first to use n-tuples randomly selected from the input grid to recognize typed or handwritten characters. For each n-tuple, the possible pattern names having the same state as the unknown input pattern are added into a comparison tally. After all tuples are considered, the name that matches the unknown pattern most closely (i.e., having the highest sum of same-state n-tuples) is chosen as the name of the input pattern.

Using the string manipulation language SNOBOL, Uhr (1969b) coded a somewhat extended version of the Bledsoe-Browning program. Uhr's short program uses weighted implications, rather than merely tallying them, and it allows varying sizes for the n-tuples and for the individual pieces of the n-tuples.

There are several weaknesses in this type of program: It does not learn, so its performance remains only as good as the n-tuple

characterizers it starts with. N-tuples are rigidly positioned, and must match exactly and entirely .

A Basic N-Tuple Pattern Recognition and Learning Program

Let's try to generalize the basic n-tuple program. For example, the characterizer tuples will be looked for one part at a time, instead of all at once. Each tuple piece of the characterizer n-tuple will contain pertinent information about its expected location within the pattern grid, its size, and the specific configuration that should be found. Optionally, a tuple part will have no particular position specified, signaling the program to look anywhere (presently meaning from its current position on down) for this tuple part. If a characterizer is matched, its implied pattern names are put on a list of found implications. When the same name is implied by several characterizers, the separate weights of implications are added together. The tuples are allowed to be non-exclusive, so that grid points in important locations (such as, perhaps, the left edge of the grid) may reappear in several characterizers .

This basic program will also have the ability to learn from its experience, by comparing its chosen answer with the feedback giving the correct pattern name. If the program gave the right answer, the memory is left as is, since it produced satisfactory results. But a wrong answer calls for reweighting of implications in the characterizers whose tuple configurations were matched. The weights of implications of the wrongly chosen name are decreased, and impli cations of the feedback name are increased. If the answer was wrong the program will also generate a new characterizer using this wrongly named input pattern. To do this, a random ntuple is extracted (n is chosen to reflect the distribution of weights attached to the generated values of n) from the input and assembled into a characterizer which implies the correct feedback name. Each run has an upper limit to the number of characterizers generated, to prevent saturation of memory or unnecessary slowing of processing time. Poor characterizers are discarded, making room for new ones, when the weights of all their implications fall below a minimal acceptable level.

Characterization Over Variations

Presented with only standard, non-varying instances (in a single type font, perhaps) of its repertoire of patterns, it is no great problem for a pattern recognition program to learn to recog nize a set of characters. But if patterns can vary, even slightly, in position or shape from time to time, then problems mushroom. Our

program tries to handle this in several ways.

Wobbly Patterns

Each part of a tuple is allowed to wobble a given horizontal distance to either side. (A somewhat more limited capability for handling vertical wobbling is the "anywhere" search mentioned previously, plus the fact that all tuple part addresses are given relative to the last position, wherever that may be. Uhr (1969b) presents programs that also allow vertical wobble.) In each characterizer tuple part there is an explicitly given wobble which tells the program just how big a hunk of the grid row it can look in for the desired configuration. This allowable wobble may vary from tuple piece to piece, as learning has indicated was needed for good performance. Thus if a desired configuration was not found within the specified wobble, but would have been found were the wobble slightly larger, then the program remembers how it almost found this characterizer. When feedback shows it chose the wrong name, if the program finds that this almost-matched characterizer would have implied the right answer, it increases the wobble allowance to improve performance .

Threshold Characterizers that Can Partially Match

Suppose that three parts of a 4-tuple were found, but the other part was not. We would like to allow use of the implications of this nearly matched characterizer even though the program did not find a perfect match. In order to do this the program uses threshold matching, where each part of a tuple has its own weight to add into the tuple's sum of "foundness." Each implication of the characterizer is preceded by a threshold requirement which must be met by the tuple sum before the implication may be merged into the list of possible pattern names. Thus one implication may require all but one part of the tuple's configuration to be found, where another implication of the same characterizer might require a perfect match of all parts.

Compound Characterizers

Besides having a primitive sort of tuple consisting of a set of 0-1 configurations to be looked for at certain points on the pattern grid, our program can also use compound characterizers, where one or more of the tuple parts is itself the name of another characterizer. The program looks in the stated position (or else 'anywhere") for the name of the desired component characterizer and treats this tuple part just as any other. Now the program must add the names of found characterizers to the input that it is processing.

Compound characterizers are currently generated from primitive characterizers that are on the list of characterizers found for this input. There must be two or more such component characterizers in order to generate a compound characterizer. When the program decides to generate a compound characterizer, it chooses the maximum number of parts to give the tuple. Then the parts are pulled off the list of characterizers found in this input, and the characterizer is assembled as initially implying only the feedback.

These compound characterizers are more general than primitive characterizers in that a more sophisticated set of pattern characteristics can be represented by one tuple. Indeed, with compound characterizers we approach a method for learning stroke or feature recognition, where primitive characterizers might represent the various primary curves and lines, and the compound characterizers could form the desired combinations of strokes to imply the various patterns. For example, if CHAR1 is the tuple describing a small open-left curve, CHAR2 is a long vertical line, and CHAR3 is a large open-left curve, then CHAR4 compounding CHAR2 and CHAR1 could imply the pattern "P" and CHAR5 coupling CHAR2 and CHAR3 could imply "D".

Parameters That Characterize Characterizers

An important part of learning in humans is generalization. In order to enable our program to, in effect, "generalize" on what it has learned and thus perform better, we have given it an expandable set of parameters or characterizer traits. For each trait (such as the number of parts, or their closeness, or their maximum horizontal spread), a value can be computed for every characterizer. With every characterizer there is associated a list of this characterizer's value for each trait. In addition we keep a common traits list of all traits and all values that have been generated and used for them. A weight is associated with each value for each trait. For example, suppose the program gives a wrong name for an input pattern on the basis of found characterizer N. Then after the implication weight of the wrong name in CHAR N is decreased, the program goes through the trait list of CHAR N and, for every trait, downweights CHAR N's value for that trait in the common trait list. In particular, if CHAR N's value for VERTSPRED (vertical point spread) is "1" , then our program will look for the value "1" under the trait VERTSPRED in the general characterizer traits list, and decrease the "goodness weight" of the value "1".

When upweighting a good characterizer's trait values, the program also enters (if not

already there) on each trait value list a slightly larger parameter value. In this way it broadens the range of parameter values that will be used to generate new characterizers. The value and goodness weight information in the general traits list is used when a new characterizer is generated. The program tries to generate the new characterizer tuple within the framework of what the program has already learned; currently it uses the three traits necessary to control the basic generation (tuple size, piece size, wobble) plus a fourth chosen randomly from the other possible traits (currently, these are horizontal spread, vertical spread, average closeness of parts, number of parts on the edge of the grid, and compound or primitive). A desired value for the new characterizer is chosen with a probability that reflects the weights associated with the various possible values of the trait. The program tries several times to find a randomly positioned tuple which will have this same value. Thus the program generalizes on what it has learned, in that if a value of "6" for VERTSPRED has been upweighted several times, the program may decide that this is a good value to try for in a new characterizer. (For further details, see functions TRAITWT and PROBCHOOSE and the section labeled PRIMITIVE in the precis and the code.)

The Complete Program

The preceding sections describe independent features, any or all of which could be added to a basic learning program to create a complete program. The final program containing all the features is described at the end of this section. As might be expected, the characterizers for this final program have become fairly complex. As an example,

CHARO = "D=0.1.1*0-2,5.3.4*01-1,/" "I=3*I.2, $1 * T$.1, /" "P=CHAR4,/T=TRO/L=5.4/"

means the following:

"Description=at row 0, column 1 look in the next 1 position for the string "0", adding 2 to the tuple sum of weights on success; 5 rows down and 3 cols, over look in the next 4 positions for the string "01" , adding 1 to the tuple sum on success/Implications=if sum ≥ 3 then imply I with weight 2; if sum ≥ 1 imply T with weight l/CHARO is £art of the compound CHAR4/Trait list name=TRO/Last tuple part's absolute address is row 5 , col. $4/$ ".

An outline of the program's operation follows.

Discussion

This paper briefly describes the various features of-our program. It then gives a detailed flow-chart-like "precis" that refers by number to the actual program statements being described. The program itself is given in the Appendix. Thus the reader can examine exactly what has been done to implement any of the aspects of the program about which he is curious. This seems to us of crucial importance: if the program can be used to document itself there is no need for lengthy and usually misleading descriptions and discussions.

The program listing is too long and complex to be followed with ease, even by someone who knows SNOBOL; but it should give an idea of what's going on to the casual observer, and those parts in which the reader is interested enough to make some effort should become understandable. SNOBOL is a very simple language in its basic conception, for its programs are built up from sets of production and replacement statements (of the sort "Let A = B; Look for C on A and, if it's found, replace it by B), tied together by labels and gotos. A brief description of SNOBOL is given in the Appendix.

This program was written to examine whether a wide variety of learning methods could be implemented together in a single pattern recognition program. Using the language SNOBOL allowed us to code a relatively powerful, yet short, program. However, the program runs too slowly to make extensive tests of its abilities to learn and achieve interesting asymptotic performance levels. We therefore give only a brief listing of a short run, to indicate that the program works, and that it at least begins to learn. The program will be recoded in a faster language if we decide to make more extensive tests.

Further developments might be to have the program try to learn good weights of characterizer tuple parts and the thresholds required to imply a pattern name. We would also like it to generate new parameters with which to characterize its characterizers (see Uhr, 1969b).

Summary

The program described in this paper attempts to combine a very simple basic pattern recognition scheme with a wide variety of powerful learning mechanisms. The program attempts 1) to generate its own n-tuple characterizers as needed, and to adjust their weights as a function of feedback, 2) to decide what type of characterizer to generate, and 3) to learn what are good general characteristics of characterizers. It can further decide 4) whether and how to modify any particular characterizer that it is evaluating. These decisions are all made within the framework of a program that tries to recognize patterns with as small a set of characterizers that are as simple as possible. It therefore starts out with no characterizers, and generates other characterizers which are as simple as it has been able to get away with and which fall within the range of what the program conjectures to be optimal values for the characteristics of characterizers. In terms of characterizer size, this means the program starts out generating 1-tuples and then, to the extent that feedback indicates that it must improve upon its performance, 2-tuples, 3-tuples, and n+1-tuples.

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Appendix

A Brief Description of SNOBOL

SNOBOL is a "pattern matching" language that turns out to be quite convenient for handling list structures and networks of information, using push-down stacks, indirection, and recursive programming. Its syntax is extremely simple, as follows:

SNOBOL programs are built up of two basic types of statements:

1) Assignment statements that assign a name to a pattern of strings,

- e.g. DESCRIPTION = '001100'
	- CHARACTERIZER = DESCRIPTION ' = ' IMPIiEDS '/ '

2) Replacement statements that find patterns on a string and (if they are found) replace them by

another pattern,
e.g. **FOUND THIS** '-' $*SUM*$ ',' = e.g . THIS $'$ -' SUM + '1' ','

These statements have several components: a) the "name" of the string to be processed, b) the "pattern" which is a sequence of 1) "names" (e.g. IMPUEDS, FOUND, THIS) which refer to and stand for their contents, 2) "literals $(e.g. "='")$ which stand for themselves, and 3) "variable names" (e.g. "*SUM*"), which are assigned contents during the execution of the statement, if the program succeeds in matching the pattern somewhere in the named string. A variable name can be subscripted with a number that fixes its length (e.g. $\#THIS/2 \neq or$ ♦THIS/SIZE* where SIZE contains an integer).

In the two examples of assignment state ments above, DESCRIPTION is made the name of the string whose literal contents are '001100', and then 001100 is put at the beginning of the string named CHARACTERIZER, since the name DESCRIPTION refers to its contents. If another assignment statement, $001100 = 'EDGE'$, were coded, then the indirect reference symbol dollarsign (\$) preceding the name \$ DESCRIPTION would put EDGE, not 001100, on CHARACTERIZER.

The end of the pattern-to-be-matched is marked by the equal sign $(=)$ without quotes around it, and this also marks the beginning of the replacement pattern. The first string of a statement is always the name; all subsequent strings up to the equal sign form the patternto-be-matched, and all strings after the equal sign form the replacement pattern (if the lefthand pattern succeeded).

A statement can be surrounded by "labels " and 'tjotos" which control the flow of the program. A 'label" is a string that always begins in column 1. A "goto" comes after the statement, is sig naled by a slash, and is of the form /(INPUT) or /S(INPUT) or /F(INPUT) or /S(INPUT)F(PROCESS), where S means transfer on success. F means transfer on failure, and no letter after the slash means unconditional transfer. (The goto must, of course, always refer to a label.) When there are no gotos, the program goes to the next statement in sequence.

Arithmetic is performed within these statements by using \dots , \dots , and / (and ** for exponentiation). Numbers must be referred to either as literals or as contents of lists (as in $SUM + '1'$ above, which will add one to the number stored in SUM). A number of built-in functions can be used to test for inequalities: $G T(A, B)$, $LT(A, B)$, $GE(A, B)$, $LE(A, B)$, .EQ(A,B) and EQUALS(A,B) (which is string matching equality). The command ".READ" will read in one data card, and ". $PRINT = "$ will

print out the pattern that follows.

An asterisk (*) in column 1 denotes a comment card, which the compiler will ignore. A period (.) in column 1 indicates that this card continues the statement on the preceding card (statements can use only 72 columns, whereas the data cards that follow the program can use all 80 columns). A program ends with an END card (END starts in column 1) that also contains the label of the first statement to be executed.

The basic pattern match goes from left to right. The compiler looks for the next match of each element of the pattern (ignoring variable names, which will be assigned to the strings that lie between the matched elements - the literals and names with contents). If no match is found, it backtracks to break the assignment of the previously matched element, and looks for its next match, continuing this until either the last element matches or the first element fails. Success or failure in the gotos is contingent upon either this match or one of the functions. The programmer can define and code his own functions, and do a number of other powerful things not discussed here.

A simple program for information retrieval follows .

♦EXAMPLE PROGRAM. A SIMPLE PROGRAM TO ♦ DO 'INFORMATION RETRIEVAL" FOLLOWS:

RIVERS, SPAIN, MOUNTAINS, THE RIVERS, SPAIN, MOUNTAINS,

 $((Query to be input, on data card))$

♦ PRECIS - AN ENGLISH DESCRIPTION OF

♦ABOVE INFORMATION RETRIEVAL PROGRAM.

- GO Let DOCUMENTS contain the de- MI scriptors, followed by pertinent documents.
- IN READ in the next QUERY (which is 1 a list of descriptors)
- ASK Get the next DESCRIPTOR from the 2 QUERY. (If no more, Fail to ASK.) From DOCUMENTS, get PERTINENT 3 ones if the DESCRIPTOR is found. PRINT out the DESCRIPTOR and the 4 PERTINENT documents.

END GO

Figure 1. Program Flowchart

 \bullet

```
* CALCULATE MAX COLS. HETWEEN LEFTMOST AND RIGHTMOST PARTS OF TUPLE
   HOROSPRED COPY = DESCH
                                                                                           219
             COPY AXA F.F ALEFTA F.F AXA F.F =
                                                                                           550
             HT = LEF1-221NEXT = LEFT
                                                                                          222
             COPY PAR F.F. RNOWP. F.F. PXR F.F. = /F(T6)
   T۹.
                                                                                           223
             NEXT # HINW + NEXT
                                                                                           224
             RT = GEENEXT.HT) NEAT ZS(T5)
                                                                                           225
             LEFT = WLTINEATWLEFT) NEAT Z(T5)
                                                                                           226
   Ть
             VAL = R1 - LEFT / (sHET)227.
   * CALCULATE MAX HOWS BETWEEN TOPMOST AND BOTMOST PARTS OF TUPLE.
   VERTSPRED UESCH PX# #+# PLOPY#
                                                                                          228
             VAL = 707229
   \mathbf{L}COPY WHEATH F.F. PXM F.F. = /F (SHET).
                                                                                          230
              VAL = VAL + NEXT /(17)
                                                                                        -231-*CALCULATE NUMBER OF POINTS IN TUPLE WHICH LIF ON EDGE OF PATTERN
   * VAL MORMALIZED OVER 10
   GRIDEDGE COPY = DESCR
                                                                                          232
             HEANK *HUW* *COL*
                                                                                           233
             vAL = \neq 0 \neq-234Tų
             COPY MROW. As # MCOM. As # MXM As # # /F(19R)
                                                                                          235
             ROW = HUW + PQ236
             VAL = \text{LU}(\text{ROM} \neq \emptyset) VAL + \neq \emptyset /S(T9)
                                                                                         237
             VAL = stu(RUW+CULSIZE = #1#) VAL + #1# /S(T9)
                                                                                         238
             COL = COL + CU23a
             VAL = "LE(CUL+#0#) VAL + #1# /S(T9)<br>VAL = «GE(COL + PC + #2# * WAL+ROWSIZE) VAL + #1# /(T9)
                                                                                         -240...241
             VAL = (VaL \triangleq 10\neq) / TUP / (SRET)
  TYR
                                                                                           242
   *CALCULATE SUM OF ARSOLUTE DIFFERENCES HETWEEN CORRESPONDING DIGITS
   # IN ALL FOSSIBLE PAIRS
   PROXIM
             CUPY = UESCR--243 -
             VAL = \neq(\neq244
             COBY #BO# - #T# #CO# - #Y# #Y# #Y# = \E(@MEL)<br>HEVVK #BO# > #COF2# - #BO<sup>N</sup># #OOE#<br>COBY #BO# - #T# #CO# - #Y# #Y# #Y# = \E(@MEL)
                                                                                           245
   Tio
                                                                                           246
             RUN = RO<sub>n</sub> + RO247
             COL = COL + CO24B
             CROW = POWS
                                                                                           249.
                                                                 the companies of the companies
             CROW #NEXT# #+# = /F(T12)
   711250
             VAL = VAL + ABSVAL(HUW = NEAT) / (T11)251
   T_{12}COU = COUS252
             CCOL *NEAT* \neq1* * /f (T14)
                                                                                           253
   TIз
             VAL = vAL + AHSVAL(COL = NEXT) /(T13)
                                                                                           254
             -255- - - - <del>114</del>
             COLS = COLS COL \neq \bullet \neq \neq (\uparrow \downarrow 0)256
   * CHECKS TO SEE IF CHAR IS COMPOUND
   COMPOUND DESCR ##C# /5(T15)
                                                                                           257
             VAL = *NO \neq \sqrt{(8 + EI)}258
   Щħ
        259.
   0.49.4**FUNCTIONS
   \bullet* FUNCTION TRAITWI(TN*DX) ADDS DX (* INC OR DEC) TO THE WEIGHT IN
   * CHTRAITS FOR EACH TRATT IN THE TN=TH TRAIT LIST
  The copy = SIZIRE. INL.<br>
The copy = SIZIRE. INL.<br>
The copy = TRAITS FRAIT = f = f = f (HEIURN)<br>
CHTRAITS TRAIT = f = f = f = f = f = f = f = f = f = f = f = f = f = f = f = f = f = 
                                                                                          260
                                                                                          261
                                                                                       - 262
             VLIST #+# VAL #=# #wT# #+# = #+# VAL #=# WT + DX #+#
                                                                                         263
             /S(T4)F(T3)
             VLIST \bullet \neq \bullet \neq264
   12
             VLIST = VLIST VAL ### DX #+#
                                                                                          265
   T 3
```


 $\label{eq:2.1} \frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac{1}{\sqrt{2}}\sum_{i=1}^n\frac$

 $\mathcal{L}^{\text{max}}_{\text{max}}$ and $\mathcal{L}^{\text{max}}_{\text{max}}$

Performance at Start of Run (No Characterizers in Memory)

INITIAL MEMORY **INPUT PATTERN** $\mathcal{L} = \mathcal{L} \times \mathcal{L}$ 0011111100 0011111100 ~ 100 0000110000 0000110000 ... بوليتين ستداع للمستخدم التحالية 0000110000 0000110000 0000110000 0000116000 0011111100 -0.011111100 ... the state of the **Contract** <u>. He seems a community of the comm</u> FEEUHACK = 1 IT IS UNKNOWN REAFIGHTED CHARACTERIZERS WOUBLE-ADJUSTED CHARACTERIZERS NEW CHARACTERIZER CHARL = 0=3.6.1*0-1.6. -5.1*u-1./1=2*1.5.1P=/I=TR1/L=9.1/____ an ber installer in the same INPUT PATTERN 1109000011 **Contact** 1100000011 1100000011 α , α , α , α 110000011 1111111111 \sim \sim \sim <u>a completive and the completion of</u> 1111111111 1100000011 1100000011 1100000011 1100000011 **FELDBACK = H** ستنسخ الهيفات الدا .
And a complete the complete of the complete and analyzed complete the complete state of the complete state of IT IS UNKNOWN REWEIGHTED CHARACTERIZERS. #OUHLE=ANJUSTED CHARACTERIZERS NEW CHARACTERTZER $CMAR2 = D = 2.01 + 1.1 - 1.15 - 5.1 + 0.1 + 1.1 = 2.11 - 5.17 = 7.17 + 7.51$. INPUJ PATTERN and the component of the component of the component would be a component of the component of the component of 0011111100 0111111110 1110000111 1190000011 11-0000011

Tlenovauli 1100000011 1110000111 0411111119 and the same and a seriously and 0011111100 FELDBACK = 0 IT IS H REWEIGHTED CHARACTERIZERS. $CHARI = 0 = 3.614(-116.75140711/17280557291551/17177/1761/17)$ CHARZ = 0=2.0.1*1-1.5.5.1*0-1./1=2*0.5.2*H.4./D=/I=IRZ/L=7.5/ WONHLE- IDJUSTED CHARACTERTZERS **UEW CHARACTERTZER** $CHAR3 = D = 1.1.141 - 1.15.7.141 - 1.717.740.507 - 5.7777777371 - 6.67$ INPUT PATTERN. 1111111111 1111111111 $\frac{1}{2}$ 110000cope 1180006000 11(1)10000 1111115000 11.000 avec ~ 1160000000 $\mathcal{L}=\mathcal{L}^{\prime}$, \mathcal{L}^{\prime} , \mathcal{L}^{\prime} \sim . $\omega = 1$. 11111111111 1111111111 FELDMACK = F IT IS 0 REWEIGHTED CHARACTEPIZERS. $LHARZ = 0 = 2 + 0 + 191 + 115 + 5 + 190 = 1 + 71 = 29 + 5 + 290 + 4129 + 16417 = 771 = 771 = 771 = 100$ WOHELE-ADJUSTED CHARACTERTZERS. **NEW CHARACTERTZER** $CHAR6 = DE(1,7,19)-1*3*71*1*0*3*71*2*0*7F*7F*7R4/L*3*67$ INPUT PATTERN 0000110000 0001111000 α , and α , and α ω . The second contract ω 0011601160 0011001100 0110006116 0111111116 0111111110 -14.49000011 $\Delta \phi = 0.01$, where ϕ the contract of 1100000011 1100000011 FELUBACK = A LT IS UNKNOWN REMEIGHTEN CHARACTERLZERS NEW CHARACTERIZER CHARS = $D = 0.941*0*1*0*1*1*1*1*1*7*2*4*5*7P*7T*TR57L=6*87$ **TNPUT PATTERN** 0001111110 $\omega_{\rm{max}}$ 0001111100 .0000011000... 0000110000 auuntlaune 0001100000 0001100000 $\sim 10^7$ 0001100000 0111110000 - ----0111110000 FELOHACK = I IT IS E REWEIGHTED CHARACTERIZERS CHAR4 = D=0.7.1º1-1.3.-1.1*U=1./1=2*I.5.2*E.4./P=/T=TR4/L=3.6/

 $\sim 10^{-11}$

 $\bar{\mathcal{L}}$

LUBRIT. L 11 - 1 J, 7 ο. υ. -10 v -11/1 - 2 . . π. 31/F,

..1100600011.. ..1100000011.. \ldots $-111111111...$ **Carl Control** \sim \sim $-1100000011...$ $...1100000011...$ $-11000000011...$ $...$ 1100000011. $FEEDBACK = F$ 11150 \sim $-$. the first construction and the contract of REWEIGHTED CHARACTERIZERS. $CHAR3 = D*J*J*J*J*J*J*J*J*J*J*J*Z*H*5*2*0*5*/P*CHARH*/T*TR3/LE6*R/$ CHAR32 = C=7.5.7*CHAR2-1.2.-4.7*CHARH-1.0.4.A*CHAR10-1./I=2*I.5.2*A.5.2*E.4.2* 0.3.2*H.5.2*\$CHAR2.2*\$CHAR10.2*\$CHAR8./P=/T=TH12/L=9.5/ CHAR19 = C=7.1.10*CHAR1+-1.0.1.10*CHAR17-1.2.7.10*CHAR13-1./I=2*H.5.2*E.5.2*SC HARL4+2#3CHAR17+2*5CHAR13+/P=/T=TR19/L=9.9/ WOBHLE-ADJUSTED CHAPACTERIZERS NEW CHARACTERIZER CHAR20 = C=1+8+6*11-1+2+=5+8*4000-1+3+-1+8*n000-1+1+7+5*1-1+/I=2*H+5+/P=/T=TR2 $0/1 = 7.9/$ INPUT PATTERN $\frac{1}{2}$ $\frac{1}{2}$ **Contractor** فتقتضيهما الطائف المائي المتعاط لقرب $...$ ⁰111111110.. $...1110000111...$ $\omega_{\rm{eff}}=2.0$ km $... 1) 00000011...$ $-1100000011...$ $-1100000011...$ ~ 100 **Service** the company of the state of the $\frac{1}{2}$ and $\frac{1}{2}$ and $\frac{1}{2}$ the continuum companies are all the companies of the context of the cont $-1110000111...$ $-011111110...$ $1.0011111100...$ FELOBACK = 0 IT IS H AREMEIGHTED CHARACTERIZERS And all and a the control of the CHAR20 = C=1+d+6#11-1+2+=5+8#u0UU=1+d+=1+R#genn=1+1+7+5#1=1+/I=2#0+5+2#H+4+/P= /t=1R20/L=7.9/ $ChAR12 = Cz7.5.7*CMAR2-1*2.***$ 7*CHAR8-1+0.4.8*CMAR10-1+/I=2*I.5+2*A.5+2*E.4+2* $0.412*H.412*SCHA R212*2SSOH A H1 u+2SSOH A R81/P=77*TR12/L=9.57$ CHARI9 = D=7.1.10*CHARI4-1+0.1.10*CHARI7-1+2.7.10*CHARI3-1./I=2*0.5.2*H.4.2*E. WOBHLE-ADJUSTED CHARACTERIZERS INFUT PATTERN $... 1 1 1 1 1 1 1 1 1...$ $... 1 1 1 1 1 1 1 1 1 1...$ $-1109000000...$ $... 1111110000...$ $-111110000...$ and a series of the con- $-1100000000...$ $............$ $... 1 1 1 1 1 1 1 1 1...$ FEEDHACK = E 11150 $\mathbf{L} = \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} = \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L} \mathbf{L}$ REWEIGHTED CHARACTERIZERS … …… CHAR2C ≈ C*l+d+6*ll−l+2+=5+d*6000−l+3+=l+8*0000−l+l+7+5+l=l+/I#2*E+5+2*O+4+2*H $.4$,/p=/1=TR20/L=7.9/ CHAH12 = C=7.5.7*CHAR2-1+2.-*.7*CHARU=1+0.4.8*CHAR10-1+/1=2*1.5+2+A_5+2*E_5+2* 0.3 +2*H.4+2*\$CHAP2+2*\$CHAHiU+2*\$CHARB+/P=/T=TR12/L=9+5/ CHAR19 = C=7.1.10*CHAR14-1:0.1.10*CHAR17-1:2.7.10*CHAR13-1:/1=2*0.4.2*H.4.2*E. 6.2*sCHAR14.2*SCHAR17.2*SCHAR13./P=/T=TR19/L=9.9/ WOBBLE=ANJUSTED CHARACTERIZERS INPUT PATTERN

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Memory After Given Feedback
for 134 Instances


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li-l./l=2*l.4+2*0.l+2*5.7+2*E.5+/P=/T=TR22/La9.7/
  CHAR23 = D=5.1.9*00011-1.2.7.6*Il-1.1.-6.9*11111-1.0.2.9*11111-1.1.0.9*11
     lll=l∘/I=2ªI∘4+2ªE∘4+2ª∪∙3+2ªS∙6+/P=/T=TR23/L=9,4/
INPUT PATTERN
 I1MEX = 12\rightarrow...0011111100...... 0011111100......0000110000...
      ... 0000110000...... 0000110000......0000110000...
      ... 0000110000...... 0000110000...... 0011111100......0011111100...
FELUBACK = I
II ISS
REWEIGHTED CHARACTERIZERS
  CHAR14 = D=5.0.6*c000-l+0.3.6*01Lu-1+2.2.6*1000-l+2+2.5*000-l+/I=2*S.4+2*
     A.Š+2#E.2,2#0.4,2#I.6,2#T.5,/P#/T=TR14/L=9.7/
  CHAR15 = D=3,1.6*^001-1.2.2.b*0110-1.1.-1.6*0011-1.0.7.3*0-1./I=2+A.4.2*S
     .4+2*T.6+2*I.6+/P=/T=TR15/L=6.9/
  CHAR21 = Da0.1.9*ullli-l=0.8.5*0-l=3.w8.9*l0000-l=0.7.6*il=1+5.w5.9*11111
    -1+/[=2*H_4+2*A_5+2*T_3+2*i_5+2*5_3+2*E_5+2*O_5+/H=/T=TR21/L=8,3/
  CMAR22 = D=2.3.9*00000-1.3.3.3.3*0*0000-1.4.5-6.9*11111-1.0.6.8*1111-1.0.1.7*111-1,/I=2=1.5,2=0,1,2=5.6,c=E.5,/P=/T=TR22/L=9,7/
  CHAR23 = D=5.1.9*00011-1+2.7.6*11-1+1.-6.9*11111-1+0.2.9*11111-1+1.0.9*11
    <u>111-1,/1=2+1,5,¿*E,4,2*U,3,2+S,5,/P=/T=TRZ3/L=9,4/</u>
  CHARIF = D=2.5.7*CHAR5-1.7. **. 7*CHAR4-1.0.0.8*CHARIB-1.0.0.0.8*CHARI6-1./I=
    24A.6.24I.4.24T.4.24E.3.24U.5.24H.5.24S.3.24SCHAR4.2aSCHAR5.24SCHAR1B.2
    *SCHARl6,/P=/T=TR19/L=9.1/
  \textsf{CMAR11} = \textsf{DzS-1+5+CHAR9=1+1-3+5+CHAR8=1+3-5+6+CHAR10=1+71+2+0+6+2+H}_2∘3∘2⇔T∘5∘2⇔S∘4∘2∞A∘2∘£≈4∘2∞$6µAKd∘2∞$CHAR9∘2⇔$CHAR10∘/P=CHAR16∘/T=TR1
    1/L = 9.17WOBBLETADJUSTED CHARACTERIZERS
INPUT PATTERN
 IIMEX = 115... 1100000011...... 1100000011...... 1100000011...... 1100000011......111111111......111111111...... 1100000011...***1100000011***
     ...1100000011...
     ...1100000011...
FEEUBACK = H
11 IS H
INPUT PATTERN
 I/MEX = 145...0011111100......0111111110......1110000111......1100000011...... 1100000011...... 1100000011...... 1100000011......1110000111...
     ... 0111111110...
     ...0011111100...
FELUBACK = 0
IT IS 0
                                                   ÷.
INPUT PATTERN
 IIMEX = 184
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 $...111111111...$1111111111... $... 1100000000...$ $... 1100000000...$...1111110000... $...1111110000...$ $... 11000000000...$ $...1100000000...$ $...111111111...$ $...$ 1111111111... FELDBACK = E IT IS E INPUT PATTERN **TIMEX = 196** $... 0000110000...$ $... 0001111000...$ $-0.0011001100...$ $... 0011001100...$ $...0110000110...$... 0111111110... $... 011111111...$ $... 1100000011...$ $...1100000011...$ \ldots 1100000011... FELOHACK = A IT IS A
INPUT PATTERN TIMEX = 206 $...0001111110...$ $... 00011111100...$ $... 00000011000...$...0000110000... ...0000110000... ...0001100000... ...0001100000... $... 0001100000...$ $...0111110000...$...0111110000... FELDBACK = I IT IS I
INPUT PATTERN $IIMEX = 218$ $...0110000110...$ $...0110000110...$ $...0110000110...$ $...0110000110...$ $... 0110000110...$... 0111111110... ... 01111111110... ...0110001110... $...0110001110...$ $... 0110001110...$ **IT 15 H** INPUT PATTERN TIMEX # 229 ...0011111000... $... 0110001100...$...0110000110... ...0110000110... $...0110000110...$...0110000110... ...0110000110... ...0110000110...

 $... 1100000011...$ $... 11000000011...$ $... 11000000011...$ $...1100000011...$ $...1110000111...$... 01111111110... ...00111111100... FELUBACK = IT 1S 0 INPUT PATTERN TIMEX = 296 11111111111... $...1100000000...$ $... 1100000000...$...1111110000... ...1111110000... $... 11000000000...$ $... 1100000000...$ $...111111111...$ FELDBACK = IT IS E **INPUT PATTERN** TIMEX = 307 $... 0000110000...$ $... 0001111000...$...0011001100... $... 0011001100...$ $...0110000110...$ $...0111111110...$... 0111111110... ...1100000011... $...1100000011...$ $... 1100000011...$ FELDBACK = IT IS A
INPUT PATTERN TIMEX = 317 ...0011111100... $...0011111100...$ $... 0000110000...$...0000110000... $... 0000110000...$ $... 0000110000...$ $... 0000110000...$ $... 0000110000...$...0011111100... ... 00111111100... FELUBACK = I IT is I INPUT PATTERN $TIMEX = 328$ $...1100000011...$ $...1100000011...$ $...1100000011...$ $... 1100000011...$ $...1111111111...$ $......11000000011...$ $...1100000011...$ $...1100000011...$ FELUBACK = H

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