

AD-A133 447

PROUST: KNOWLEDGE-BASED PROGRAM UNDERSTANDING(U) VALE

1/1

UNIV NEW HAVEN CT DEPT OF COMPUTER SCIENCE

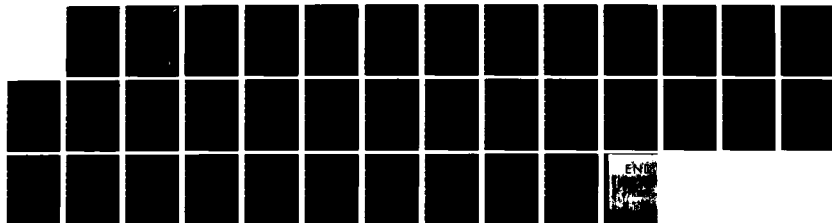
W L JOHNSON ET AL. AUG 83 VALEU/DCS/RR-285

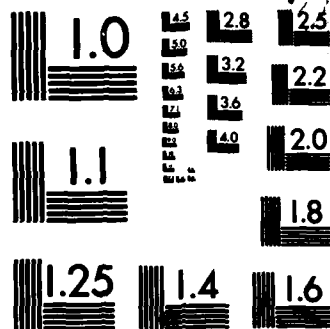
UNCLASSIFIED

N00014-82-K-0714

F/G 9/2

NL





MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

AD-A133447

2



PROUST: Knowledge-Based Program Understanding

W. Lewis Johnson and Elliot Soloway

YaleU/CSD/RR #285

August 1983

DTIC FILE COPY

DTIC
ELECTE
S OCT 12 1983

YALE UNIVERSITY
DEPARTMENT OF COMPUTER SCIENCE

D

DISTRIBUTION STATEMENT A

Approved for public release;
Distribution Unlimited

83 10 12 149

PROUST: Knowledge-Based Program Understanding

W. Lewis Johnson and Elliot Soloway

YaleU/CSD/RR #285

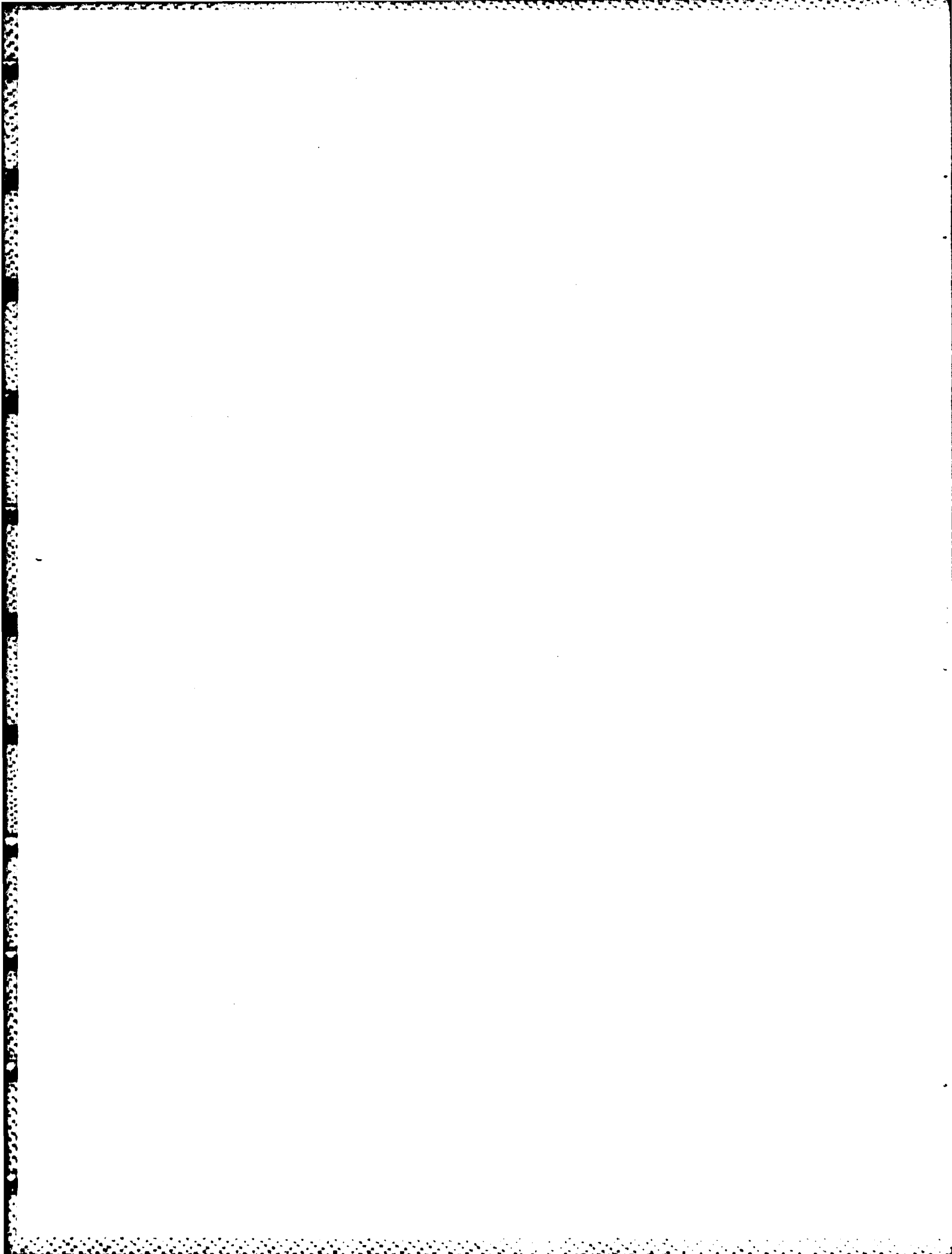
August 1983

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER #285	2. GOVT ACCESSION NO. AD A193447	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) PROUST: Knowledge-Based Program Understanding		5. TYPE OF REPORT & PERIOD COVERED Technical
7. AUTHOR(s) W. Lewis Johnson and Elliot Soloway		6. PERFORMING ORG. REPORT NUMBER
9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Computer Science Yale University New Haven, CT 06520		8. CONTRACT OR GRANT NUMBER(s) N00014-82-K-0714
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research (Code 458) Arlington, VA 22217		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR 154-492
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		12. REPORT DATE August 1983
		13. NUMBER OF PAGES 23
		15. SECURITY CLASS. (of this report) unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE
16. DISTRIBUTION STATEMENT (of this Report) Approved for public release; distribution unlimited		
17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)		
18. SUPPLEMENTARY NOTES		
19. KEY WORDS (Continue on reverse side if necessary and identify by block number) Artificial Intelligence Debugging Aids Expert Systems Programming Plans Automatic Program Understanding Tutoring Systems		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) This paper describes a program called PROUST which does on-line analysis and understanding of Pascal programs written by novice programmers. PROUST takes as input a program and a non-algorithmic description of the program requirements, and finds the most likely mapping between the requirements and the code. This mapping is in essence a reconstruction of the design and implementation steps that the programmer went through in writing the program. A knowledge base of programming plans and strategies, together with common bugs associated with them, is used in constructing this mapping. Bugs are discovered in the process of		

relating plans to the code; PROUST can therefore give deep explanations of program bugs by relating the buggy code to its underlying intentions.

Accession For	
NTIS GRA&I	☒
DTIC TAB	☐
Unannounced	☐
Justification	
By _____	
Distribution/	
Availability Codes	
Dist	Avail and/or Special
A	





PROUST: Knowledge-Based Program Understanding

W. Lewis Johnson

Elliot Soloway

July 1983

Yale University

Computer Science Department

New Haven, Ct. 06520

203-436-0606

This work was co-sponsored by the Personnel and Training Research Groups, Psychological Sciences Division, Office of Naval Research and the Army Research Institute for the Behavioral and Social Sciences, under Contract No. N00014-82-K-0714, Contract Authority Identification Number, Nr 154-492. Approved for public release; distribution unlimited. Reproduction in whole or part is permitted for any purpose of the United States Government.

Abstract

This paper describes a program called PROUST which does on-line analysis and understanding of Pascal programs written by novice programmers. PROUST takes as input a program and a non-algorithmic description of the program requirements, and finds the most likely mapping between the requirements and the code. This mapping is in essence a reconstruction of the design and implementation steps that the programmer went through in writing the program. A knowledge base of programming plans and strategies, together with common bugs associated with them, is used in constructing this mapping. Bugs are discovered in the process of relating plans to the code; PROUST can therefore give deep explanations of program bugs by relating the buggy code to its underlying intentions.

1. Introduction: Motivation and Goals

Our goal is to build a tutoring system which helps novice programmers to learn how to program. This system will have two components: a *programming expert* which can analyze and understand buggy programs, and a *pedagogical expert* that knows how to effectively interact with and instruct students. We have focused our attention on the first component, with the objective of building a system that can be said to truly understand (buggy) novice programs.¹ In this paper, we will describe the theory and processing techniques by which our analysis system, PROUST, understands buggy and correct programs.

Bugs in programs are sections of code whose behavior fails to agree with the program specification. Although the presence of bugs may be indicated by various kinds of anomalous program behavior, in general bugs are not properties of programs, but rather *are properties of the relationship between programs and intentions*. [9, 10] For example, consider the program in Figure 1-1. The programmer has written a program that reads in a number and then computes the average of all the numbers between it and 99999, in integer increments. This is not what the stated problem requires; presumably the programmer was trying to solve the problem, but a bug has altered the program's behavior. How do we determine what this bug is? Note that the programmer first does a Read into the variable New, and then increments it by 1. Based on our theory of programming knowledge, [17, 12, 18, 1] we would hypothesize that the student thought that incrementing the variable New would return the next value of New; if incrementing Count gets the next INTEGER value, then incrementing New should get the next input value! The student has thus made an overgeneralization: adding one to a variable returns the next value of that variable. The key element of the above analysis is the construction of a relationship from a piece of code to a problem goal; the mechanism for that construction was knowledge about how

¹Miller's SPADE-0 [11] is another example of a programming tutor; unlike PROUST, it constrains the program construction process so that less machinery is required for understanding and more effort can be devoted to pedagogy.

programs are typically constructed, together with knowledge about novice misconceptions.

Problem: Read in numbers, taking their sum, until the number 99999 is seen. Report the average. Do not include the final 99999 in the average.

```

1  PROGRAM Average( input, output );
2  VAR Sum, Count, New, Avg: REAL;
3  BEGIN
4      Sum := 0;
5      Count := 0;
6      Read( New );
7      WHILE New <> 99999 DO
8          BEGIN
9              Sum := Sum+New;
10             Count := Count+1;
11             New := New+1
12         END;
13     Avg := Sum/Count;
14     Writeln( 'The average is ', avg );
15 END;
```

PROUST output:

It appears that you were trying to use line 11 to read the next input value. Incrementing NEW will not cause the next value to be read in. You need to use a READ statement here, such as you use in line 6.

Figure 1-1: Example of analysis of a buggy program

While we have not built a pedagogical expert yet, it would certainly need the type of information produced in the above analysis. That is, an intelligent tutoring system would need to know:

- what the bugs in the student's program are, and where they occur;
- what the student was intending to do with the buggy code;
- what misconceptions the student might have which would explain the presence of the bugs.

What is an appropriate method for deriving information such as this from a program? One way might be to compare the input-output behavior of the program against the expected input-output behavior. The information which this approach would provide is insufficient, particularly with larger programs, because a number of bugs might result in the same input/output behavior.²

²BIP [21] makes use of input/output behavior in its program analysis; consequently it only deals with small programming problems.

For example, many different bugs can cause a program to go into an infinite loop, so simply knowing that a program goes into an infinite loop is insufficient for determining what the bug is. Enhancing input-output analysis with dataflow analysis, or other compiler analysis techniques, will not help in cases where the code does not have any obvious structural anomalies,³ such as in the preceding example.

What is missing in the above methods is a *detailed understanding of the relationship between the program text and the program's intentions*. We suggest that a method for building such a description involves (1) recreating the goals that the student was attempting to solve (i.e., what problem the student thought he was solving), (2) identifying the functional units in the program that were intended to realize those goals. In effect, *the programming expert needs to analyze the buggy program by reconstructing the manner in which it was generated*. The claim is that the trace generated by the programming expert does actually correspond to what the student was thinking, although not necessarily to the utmost detail; the pedagogical expert would then use that trace in subsequent tutoring activity.⁴ In this paper, we briefly highlight the theoretical basis for reconstructive program analysis, and we detail how PROUST goes about building the reconstruction.

2. The Role of Plans in Program Understanding

Knowledge about what implementation methods should be used in programming is codified in PROUST in the form of *programming plans*. A programming plan is a procedure or strategy for realizing intentions in code, where the key elements have been abstracted and represented explicitly. It is our position that expert programmers make extensive use of programming plans, rather than each time building programs out of the primitive constructs of a programming language. This claim is based on a theory of what mental representations programmers have and use in reading and writing programs. In [17, 6, 19, 20] we describe various empirical experiments which support our theory. Thus, PROUST is directly based on a plausible, psychological theory of the programming process. Note that codifying programming knowledge in terms of plans is not unique to PROUST: the Programmer's Apprentice, [12] for example, also makes extensive use of plans.⁵

Figure 2-1 is an illustration of how plans are realized in programs. The figure shows a correct

³One area in which many compilers do a reasonable job is analyzing *syntactic* errors. Although it would be worthwhile to construct a parser which produces error reports aimed at novices, this is outside of the scope of our current work.

⁴Most intelligent tutoring systems at least tacitly assume such a correspondence. [7, 8, 3]

⁵Sniffer [15] is a prototype of a debugging system which is based upon the Programmer's Apprentice.

implementation of the problem shown in Figure 1-1, together with four plans that this program uses. Two of them, the RUNNING TOTAL VARIABLE PLAN and the COUNTER VARIABLE PLAN, are *variable plans*, i.e. they are plans which generate a result which is usually stored in a variable. Such plans typically have an initialization section and an update section, and carry information about what context they must appear in, e.g. whether or not they must be enclosed in a loop. The other two plans, the RUNNING TOTAL LOOP PLAN and the VALID RESULT SKIP GUARD, are *control plans*; their main role is not to generate results but to regulate the generation and use of data by other plans. The RUNNING TOTAL LOOP PLAN is a method for constructing a loop which controls the computation of a running total; in this program it also controls the operation of the COUNTER VARIABLE PLAN. The VALID RESULT SKIP GUARD plan is an example of a skip guard, i.e. a control plan which causes control flow to skip around other code when boundary conditions occur. In this case it prevents the average from being computed or output when there is no input.

Problem: Read in numbers, taking their sum, until the number 99999 is seen. Report the average. Do not include the final 99999 in the average.

		PROGRAM Average(INPUT, OUTPUT);	
		VAR Sum, Count, New, Avg: REAL;	
		BEGIN	
Counter Variable Plan		-----> Count := 0;	
		---> Sum := 0;	Running Total Loop Plan
		Read(New); <-----	
Running Total Variable Plan		WHILE New <> 99999 DO <-----	
		BEGIN	
		-----> Sum := Sum + New; <-----	
		-----> Count := Count + 1;	
		Read(New); <-----	
		END;	Valid Result Skip Guard
		IF Count > 0 THEN <-----	
		BEGIN <-----	
		Avg := Sum/Count; <-----	
		WriteIn(Avg); <-----	
		END <-----	
		ELSE <-----	
		WriteIn('no legal inputs'); <-----	
		END.	

Figure 2-1: Programming Plans

Recognition of plans in programs forms the basis of our approach to program understanding. But plan recognition alone is insufficient. Novices often use plans that would never occur to an expert, because they do not have a good sense of what is a good plan and what is not. PROUST's knowledge base of plans has therefore been extended in order to include many stylistically dubious plans.⁶ Unfortunately, the more alternative plans there are in the system, the harder it

⁶The process of collecting novice programs and analyzing them is described in [2], [9], and [10].

is to determine which plans the programmer was using. Furthermore, program behavior depends not only upon what plans are used, but how they are organized; it is thus possible for a program to use correct plans yet still have bugs. In order to cope with these problems a method is needed for relating plans to other plans, and to the programmer's underlying intentions. This process, and the way it is used to search for the right interpretation of the program, is described in Section 4.

3. A Typical Problem in PROUST's Domain

PROUST's knowledge base is currently tailored to analyze the programming problem in Figure 3-1.⁷ This problem (hereafter referred to as the Rainfall Problem) is a more complex version of the averaging problem shown in Figure 1-1. Among other computations, a program that solves this problem must

1. count the number of valid inputs (i.e., days on which there was zero or greater rainfall), and
2. count the number of positive inputs (i.e., days on which rain fell).

Novices attempt to realize these two goals in a variety of correct and buggy ways. Since coping with variability is one of PROUST's main objectives, examining how PROUST handles this specific set of goals should be illustrative. Thus, in what follows, we will focus on PROUST's techniques for processing fragments of code that implement these goals.

Noah needs to keep track of rainfall in the New Haven area in order to determine when to launch his ark. Write a program which he can use to do this. Your program should read the rainfall for each day, stopping when Noah types "99999", which is not a data value, but a sentinel indicating the end of input. If the user types in a negative value the program should reject it, since negative rainfall is not possible. Your program should print out the number of valid days typed in, the number of rainy days, the average rainfall per day over the period, and the maximum amount of rainfall that fell on any one day.

Figure 3-1: The Rainfall Problem

4. Relating Goals to Code via Plans

In order to relate the plans in a program to the program requirements, PROUST makes explicit the *goal decomposition* underlying the program. A goal decomposition consists of

- a description of the hierarchical organization of the subtasks in a problem.
- indications of the relationships and interactions among subtasks, and
- a mapping from subtask requirements (goals) to the plans that are used to implement them.

⁷We are currently extending PROUST to handle a range of introductory programming problems.

The plans which a goal decomposition specifies are matched against the program; this results in a mapping from program requirements to individual statements.

In attempting to understand all except the most trivial programming problems, two issues must be squarely faced:

- the goal decomposition of a *problem* may not be unique, and
- one *program* may be associated with more than one goal decomposition.

We deal with each issue in turn in the next two sections.

4.1. The Space of Goal Decompositions and Programs

Figure 4-1 illustrates how alternative goal decompositions can lead to different program implementations. A single problem description, at the top, can result in several different goal decompositions, which in turn result in a number of different programs, depending upon which plans are used. Some of these programs may be correct, others buggy. Buggy programs are either derived from incorrect goal decompositions or from incorrect implementations of correct goal decompositions. Each path from the problem description down to an individual program is a *program interpretation*; we call this set of possible derivation paths the *interpretation space* associated with a problem.

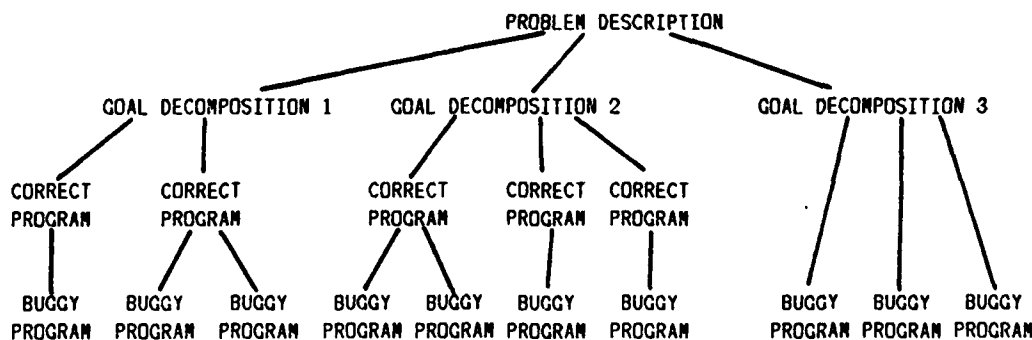


Figure 4-1: Search space of possible programs

Figures 4-2 and 4-3 illustrate two different solutions of the Rainfall Problem (Figure 3-1) and their corresponding goal decompositions. We focus here on two specific aspects of the problem:⁸ (1) counting the valid inputs (daily rainfall greater than or equal to zero), and (2) counting the number of rainy days (daily rainfall strictly greater than zero).

Figure 4-2 shows a fragment in which these two goals are realized directly. First, a COUNTER VARIABLE PLAN is used to count the valid inputs; this is realized in the code that computes the

⁸There are other differences in the goal decompositions of these programs besides the ones mentioned here. However, we will not analyze them in this discussion.

value of the variable `Valid`. Second, the GUARDED COUNTER VARIABLE PLAN is used for counting the positive inputs; the variable `Rainy` is used in this plan.

While the program in Figure 4-3 also prints out the number of valid inputs and the number of positive inputs, the goal decomposition in this program is different. Instead of the two goals of counting the valid inputs and counting the positive inputs, the program in Figure 4-3 uses three goals to achieve the same end: (1) count the zero inputs, (2) count the positive inputs, and (3) add these two counters together to derive the valid day total. The goal of counting the positive inputs is implemented with a GUARDED COUNTER VARIABLE PLAN, operating on the variable `Rainy`. The goal of counting the zero inputs is also implemented with a GUARDED COUNTER VARIABLE PLAN, operating on the variable `Dry`. The counters are combined with an ADD PARTIAL RESULTS PLAN, resulting in the variable `Valid`.

4.2. Resolving Ambiguous Interpretations

If the mapping from problem descriptions to programs is to be rich enough to generate a sufficiently wide variety of programs, ambiguity is an unavoidable consequence, i.e. two different paths in the interpretation space can lead to the same program. This situation is exacerbated when buggy programs are allowed: bugs add uncertainty to the analysis. For example, if one encounters a statement `New := New+1` in a correct program, one can be fairly certain that it is part of a counter plan. But if the program is buggy, as in Figure 1-1, one must also consider the possibility that this statement is intended to input new values; the only way of determining which is the proper role is by looking at the program as a whole and determining which interpretation is more consistent with the interpretations of the other parts of the program. The ability to enumerate and evaluate alternative interpretations is a key processing technique for a system that attempts to understand buggy programs.

In Figure 4-4 we give an example of the results of PROUST's attempt to resolve ambiguous interpretations. Figure 4-4 shows a fragment of code which might appear in a novice solution to the Rainfall Problem in Figure 3-1. We have focused on the counter variables in the program, `Valid` and `Rainy`; the rest of the main loop of the program is shown so that the surrounding context may be seen. Instead of counting the positive inputs (`Rain>0`) and the valid inputs (`Rain>=0`), this program counts the positive inputs and the zero inputs, and does not count the valid inputs.

There are two possible interpretations for this code, each of which results in a different explanation for the bugs. According to one interpretation, shown on the left side of the figure, the programmer intended to implement the valid input goal and the positive input goal directly. The plans used are COUNTER VARIABLE PLAN and GUARDED COUNTER VARIABLE PLAN; the resulting variables are `Valid` and `Rainy`, respectively. `Valid` appears to count only the the zero

Plans

Goal Decomposition

Plan: RUNNING TOTAL LOOP PLAN

1. Get input, stopping at 99999
2. Check that input is non-negative

Plan: COUNTER VARIABLE PLAN

6. Count valid inputs

Plan: GUARDED COUNTER VARIABLE PLAN

7. Count positive inputs

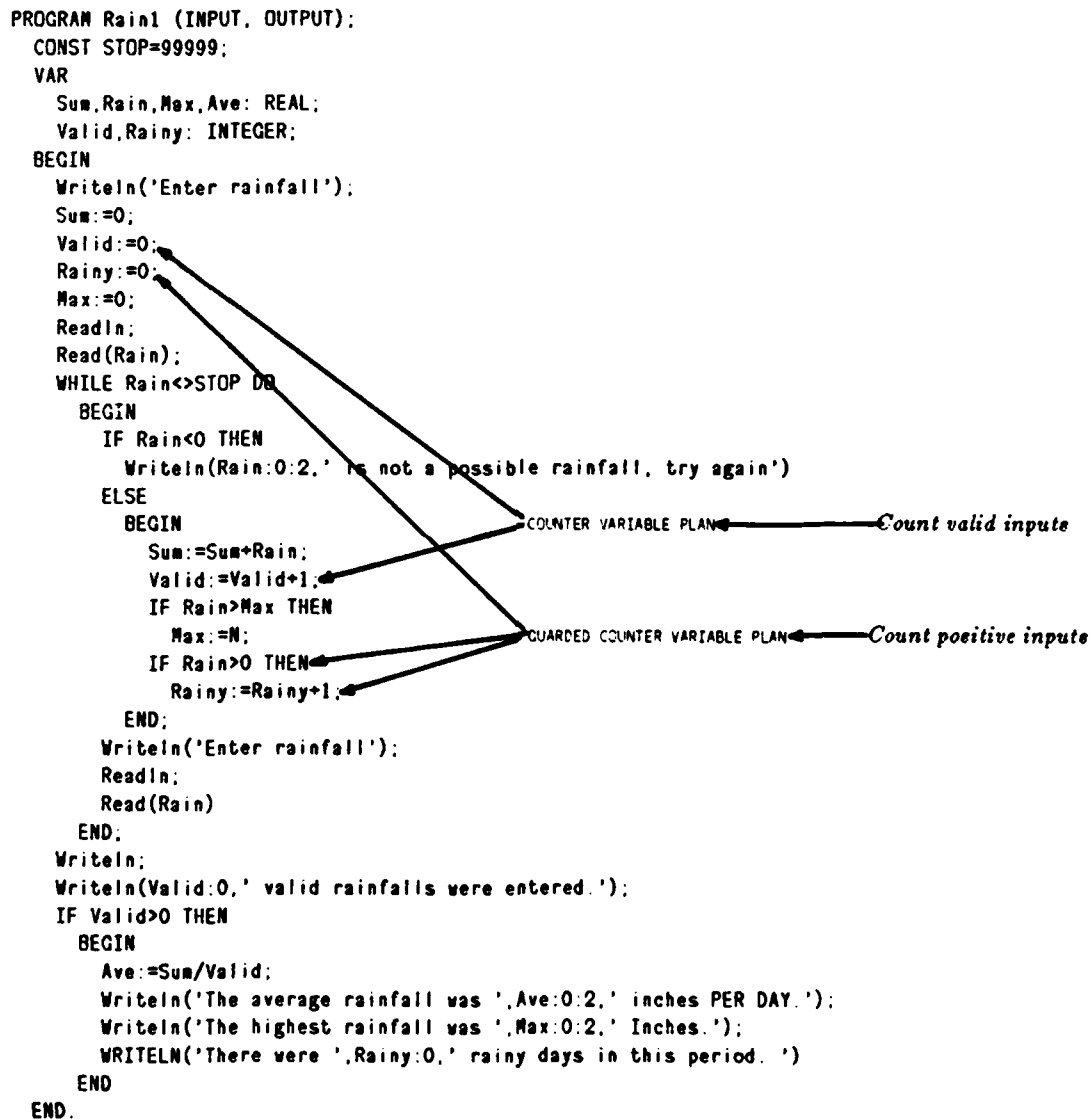


Figure 4-2: Simple goal decomposition

Plans

Goal Decomposition

Plan: RUNNING TOTAL LOOP PLAN

1. Get input, stopping at 99999
2. Check that input is non-negative

Plan: COUNTER VARIABLE PLAN

6. Count zero inputs
7. Count positive inputs
8. Combine counters

Plan: GUARDED COUNTER VARIABLE PLAN

```

PROGRAM Rain2 (INPUT, OUTPUT);
CONST STOP=9999;
VAR Sum,Rain,Max,Ave: REAL;
    Valid,Rainy,Dry: INTEGER;
BEGIN
    Sum:=0;
    Dry:=0;
    Rainy:=0;
    Max:=0;
    Writeln('Enter rainfall');
    Readln;
    Read(Rain);
    WHILE Rain<0 DO
    BEGIN
        Writeln(Rain:0:2,' is not a possible rainfall, try again');
        Read(Rain);
    END;
    WHILE Rain<>STOP DO
    BEGIN
        Sum:=Sum+Rain;
        IF Rain=0 THEN
            Dry := Dry+1
        ELSE
            Rainy:=Rainy+1;
        IF Rain>Max THEN Max := Rain;
        Valid := Rainy+Dry;
        Writeln('Enter rainfall');
        Readln;
        Read(Rain);
        WHILE Rain<0 DO
        BEGIN
            Writeln(Rain:0:2,' is not a possible rainfall, try again');
            Read(Rain);
        END;
    END;
    Writeln;
    Writeln(Valid:0,' valid rainfalls were entered. ');
    IF Valid>0 THEN
    BEGIN
        Ave:=Sum/Valid;
        Writeln('The average rainfall was ',Ave:0:2,' Inches per day. ');
        Writeln('The highest rainfall was ',MAX:0:2,' Inches. ');
        Writeln('There were ',Rainy:0,' rainy days in this period. ')
    END
END.

```

Diagram illustrating the goal decomposition of the Rain2 program. Arrows point from specific code lines to the goals in the Goal Decomposition section:

- Line 25: `IF Rain=0 THEN Dry := Dry+1` points to Goal 6: *Count zero inputs*.
- Line 26: `ELSE Rainy:=Rainy+1` points to Goal 7: *Count positive inputs*.
- Line 27: `Valid := Rainy+Dry` points to Goal 8: *Combine counters*.
- Line 28: `Writeln('Enter rainfall')` points to Goal 1: *Get input, stopping at 99999*.
- Line 29: `Readln` points to Goal 2: *Check that input is non-negative*.

Labels for the plans are also present near the code:

- `GUARDED COUNTER VARIABLE PLAN` is labeled near lines 25 and 26.
- `ADD PARTIAL RESULTS PLAN` is labeled near line 27.

Figure 4-3: Alternative goal decomposition

Buggy Program Fragment

```

WHILE Rain <> 99999 DO
  BEGIN
    IF Rain < 0 THEN
      WriteIn( 'Input not valid' )
    ELSE
      BEGIN
        IF Rain = 0 THEN
          Valid := Valid + 1
        ELSE
          BEGIN
            Rainy := Rainy + 1;
          END;
        Sum = Sum + Rain;
      END;
    WriteIn( 'Enter next value' );
    Read( Rain );
  END;

```

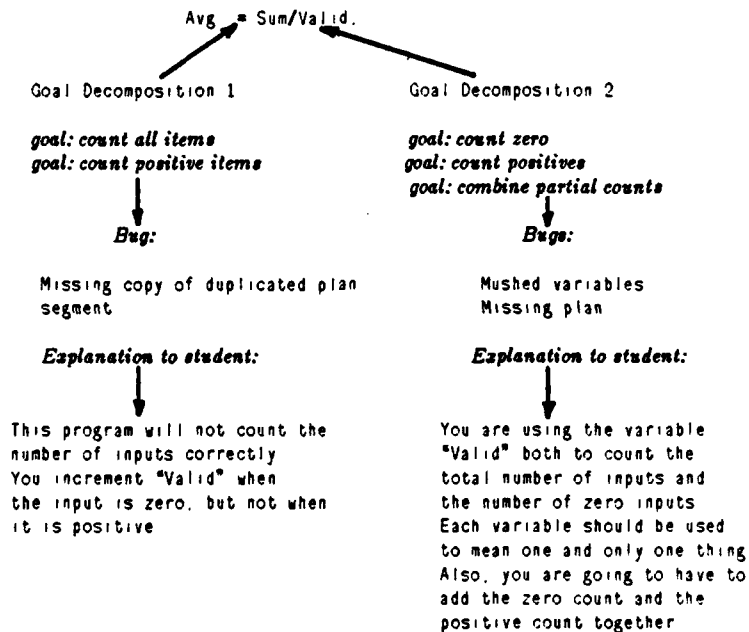


Figure 4-4: Alternative explanations for bugs

inputs, because the programmer intended to *modify* the COUNTER VARIABLE PLAN so that a copy of the counter update appears in both the THEN branch and the ELSE branch of the inner IF statement, and then left out one of the copies. The failure to update Valid in both branches thus appears to be a low-level slip, such as a mistake in editing the source file.

In the other interpretation, on the right side of the of the figure, the program is assumed to arise from a goal decomposition where the positive values and the zero values are counted separately and then added together. The programmer uses the variable Valid to refer to the count of zero values and Rainy to refer to the count of positive values. The plan to add Valid and Rainy together is missing. We could claim that the plan is missing because of an editing slip.

However, the context in which the counter plans appear weighs against this hypothesis: the average computation uses *Valid* in the denominator of the division, implying that *Valid* is the valid input counter as well as the zero input counter. We call variables which are used in contradictory ways such as this *mushed variables*. Mushed variables are very serious bugs; they reflect radical deficiencies in the programmer's ability to design programs. Therefore this goal decomposition is less highly valued than the previous goal decomposition. PROUST has a number of heuristics for deciding among alternative interpretations such as these.

5. The Understanding Process: An Example Of PROUST In Action

In the preceding sections, we (1) described what difficulties a program understanding system must overcome in order to analyze a program accurately, and we (2) gave an example of the *results* of PROUST's analysis. In this section, we will illustrate PROUST's *processing* capabilities. First we will describe the overall strategy by which PROUST searches through the space of potential interpretations for one that best accounts for the student's program, and then we will describe how PROUST actually produces the analysis already depicted in Figure 4-4.

5.1. Searching the Interpretation Space

Clearly, one can't possibly enumerate beforehand the space of program interpretations: there are just too many ways to construct correct and buggy programs. Rather, starting with the problem specification and a database of correct and buggy plans, transformation rules⁹, and bug-misconception rules, PROUST constructs and evaluates interpretations for the program under consideration. In effect, the goal decomposition and the plan analysis of the program evolve simultaneously. To constrain the generation process, PROUST employs heuristics about what plans and goals are likely to occur together.

The evaluation process is *prediction driven*: based on the current candidate interpretation for the program, how well do *other parts of the program conform to PROUST's expectations*? For example, if, in a program that attempts to solve the Rainfall Problem, PROUST has assumed that the variable *Count* is keeping track of the number of valid days, PROUST would expect to see *Count* in the denominator of the average daily rainfall calculation. If this expectation is confirmed, then PROUST is more confident of its interpretation, and vice versa. PROUST employs heuristics that evaluate matches, near-misses, and misses of its expectations. Examples of construction and evaluation processes will be given in the next section.

The fact that PROUST constructs and evaluates interpretations anew for each program, and

⁹These entities will be explained shortly.

does not rely on a prestored set of possible interpretations, provides it with an important capability: PROUST readily generates interpretations for programs that it (and we) have not seen previously. That is, unlike some diagnostic systems that effectively choose a fault from a set of predefined faults, [16, 4] PROUST actively constructs diagnoses. Given the variability in programs, PROUST needs such a capability in order to be effective.¹⁰

5.2. Putting It All Together: Two Examples

```

Sum := 0;
Rainy := 0;
Valid := 0;
Max := 0;
Read( Rain );
WHILE Rain <> 99999 DO
  BEGIN
    IF Rain < 0 THEN
      Writeln( 'Input not valid' );
    ELSE
      BEGIN
        IF Rain = 0 THEN           (a)
          Valid := Valid + 1;      (b)
        ELSE
          BEGIN
            Valid := Valid + 1;    (c)
            Rainy := Rainy + 1;
          END;
        Sum := Sum + Rain;
        IF Rain > Max THEN
          Max := Rain;
        END;
        Writeln( 'Enter next value:' );
        Read( Rain );
      END;
    Avg := Sum / Valid;
  
```

Figure 5-1: Excerpt of Rainfall Program

In this section we will illustrate how PROUST actually goes about analyzing a program. We will show two examples; one is a correct program and the other is a buggy program.

5.2.1. Analysis of a correct program

Our first example, in Figure 5-1, is an excerpt from a correct solution to the Rainfall Problem in Figure 3-1; it is based on the program fragment shown in Figure 4-4. Although this program functions correctly, there is one construction which is unusual; the valid input counter *Valid* is updated in two places instead of one. That is, *Valid* is updated in each branch of the conditional

¹⁰FALOSY [14] is also capable for recognizing novel faults; however, it assumes that there is only one fault, which the programmer must describe beforehand.

statement at (a); the update at (b) is executed when Rain is zero, and the update at (c) when Rain is positive. The program in this figure illustrates the variability possible in programs; coping with this type of situation requires additional machinery, as will be seen shortly.

Assume that PROUST has carried out a partial plan analysis of this program already, and has made the following tentative assumptions:

- the variable Sum is the running total variable,
- the variable Valid keeps tracks of the number of valid days,
- the update on Valid should be in the loop, embedded inside a test for negative rainfall (IF Rain < 0 THEN....).

The processing that continues from this point is illustrated in Figure 5-2. PROUST maintains an agenda of goals that remain to be worked on; at this point in the analysis the agenda includes the Count goal for valid inputs, the Sum goal, and the Count goal for positive inputs, to name a few. PROUST selects the first goal on the agenda, as shown at (a), checks that it is ready for analysis, and then determines whether or not it needs to be decomposed. The entry in the knowledge base for Count stipulates that it is most commonly implemented in an undecomposed fashion, so Proust consults the plan database looking for appropriate plans for realizing this goal. It finds only one plan plan: the COUNTER VARIABLE PLAN (b). It then makes tentative bindings for the plan variables, and determines where each segment of the plan should be found. The resulting structure, shown at (c), can then be matched against the student's program.

Figure 5-3 shows the results of matching the instantiated plan against the code. There is a unique match for the initialization step of the plan, but instead of there being one match for the update step, there are *two* matches. Furthermore, PROUST expects the update to be at "top level" inside the loop, i.e. it should not be enclosed inside code which might disrupt its function. Instead it discovers that each update is enclosed in an IF statement which restricts its application. PROUST treats the plan as a near-match for the program, but the plan cannot be accepted until the match discrepancies are accounted for.

PROUST has a number of different methods for explaining a plan difference; one of them is to use *transformation rules* to relate the code to the plan. One such transformation is shown in Figure 5-4.¹¹ Each transformation rule has a test part and an action part. The test part consists of a conjunction of micro-tests, each testing various aspects of the program; the action part usually indicates how to modify the code in order to nullify the effect of the transformation. In this case the Distribution Transformation Rule applies. This is a rule for recognizing plans in situations where a set of computations have been divided into parts using a CASE statement or an

¹¹PROUST currently has 15 such transformations in its database. Some rules, such as the Distribution Transformation Rule, are quite general; others, such as the transformation which changes Valid<>0 into Valid<>0 if Valid is a counter variable, are plan specific.

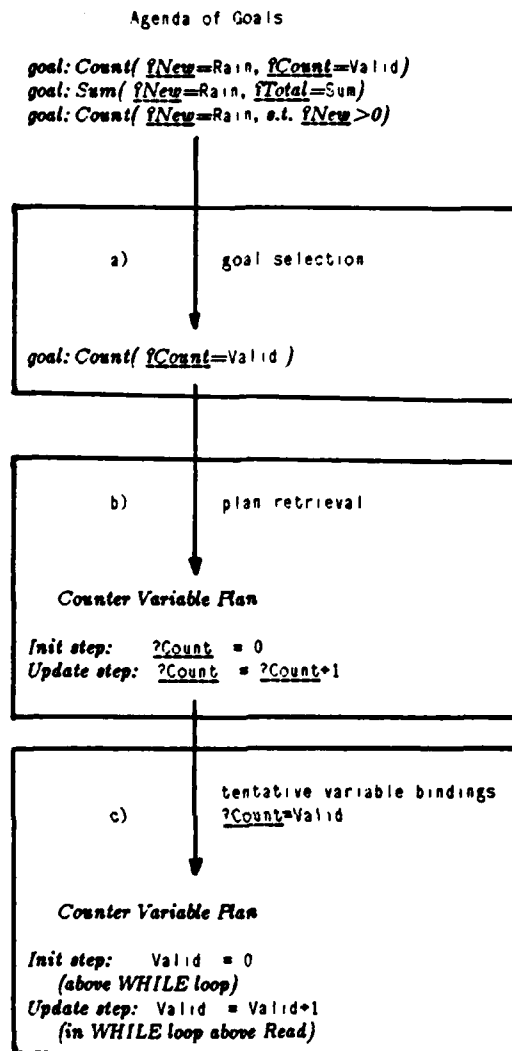


Figure 5-2: Simple mapping from goals to instantiated plans

IF-THEN-ELSE construct, and where the plan update is duplicated so that a copy appears in each branch. The control flow branches in this case are the two branches in the IF-THEN-ELSE construction which test for $Rain=0$ and $Rain>0$. The rule checks to see whether there is exactly one $Valid:=Valid+1$ statement for each possible branch of the test. It then combines the two updates and moves the result to an appropriate place outside of the test. Once this is done the counter plan matches successfully.

5.2.2. A buggy example

We will now show how PROUST analyzes the buggy program shown in Figure 4-4; a more complete version is given in Figure 5-5. When PROUST analyzes buggy programs such as this, it goes through much the same process that it goes through in analyzing correct programs; the main difference is that PROUST must consider more alternative interpretations in order to find the most

```

Sum := 0;
Valid := 0; ← Valid := 0  Init step:
Rainy := 0;      EXACT MATCH
Max := 0;
Read( Rain );
WHILE Rain <> 99999 DO
  BEGIN
    IF Rain < 0 THEN
      WriteLn( 'Input not valid' )
    ELSE
      BEGIN
        IF Rain = 0 THEN
          Valid := Valid+1; ← Valid := Valid+1  Update step:
        ELSE
          BEGIN
            Valid := Valid+1;
            Rainy := Rainy+1;
          END;
        Sum := Sum+Rain;
        IF Rain > Max THEN
          Max := Rain;
        END;
        WriteLn( 'Enter next value:' );
        Read( Rain );
      END;
    Avg := Sum/Valid;
  
```

TWO MATCHES; BOTH EMBEDDED INSIDE UNEXPECTED CODE

Figure 5-3: Plan matching

<pre> IF Rain=0 THEN Valid := Valid+1; ELSE BEGIN; Valid := Valid+1; Rainy := Rainy+1; END; </pre>	<pre> Valid := Valid+1; IF Rain=0 THEN {} ELSE BEGIN; {} Rainy := Rainy+1; END; </pre>
--	--

Figure 5-4: Program transformation

plausible explanation for the bug.

Figure 5-6 shows what happens when the COUNTER VARIABLE PLAN is matched against this program. This time there is one good match for the counter update; unfortunately it is inside of an unexpected IF statement. The Distribution Transformation Rule is invoked to explain the plan difference, but it predicts that there should be two updates, so it does not fully explain the problem. PROUST therefore looks for another rule which will explain the difference between the prediction made by the Distribution Transformation Rule and the observed code. A rule applies which states that if a single instance of duplicated code is missing, it is explainable as a low-level slip. This completes the mapping from the plan to the code.

Whenever an interpretation presumes the presence of a bug, it is necessary to make sure that

```

Sum := 0;
Rainy := 0;
Valid := 0;
Max := 0;
Read( Rain );
WHILE Rain <> 99999 DO
  BEGIN
    IF Rain < 0 THEN
      Writeln( 'Input not valid' )
    ELSE
      BEGIN
        IF Rain = 0 THEN
          Valid := Valid + 1
        ELSE
          BEGIN
            Rainy := Rainy + 1;
          END;
          Sum := Sum + Rain;
          IF Rain > Max THEN
            Max := Rain;
          END;
          Writeln( 'Enter next value:' );
          Read( Rain );
        END;
      END;
    Avg := Sum / Valid;
  
```

Figure 5-5: A buggy program

there are no other interpretations which presume fewer or less severe bugs. PROUST therefore goes back and looks for another way of implementing the *Count* goal. PROUST has in its knowledge base an alternative method for decomposing *Count* goals, namely to implement counters for particular intervals and then combine the partial counts. One of these subgoals can be unified with the *Count positives* goal that already exists in the agenda. The two *Count* goals are thus transformed into a set of three goals. Plans can then be chosen and instantiated for each of these goals, as was done in Figure 5-2. The result plans, and the results of matching them, is shown in Figure 5-7. This time two match errors are found. First, *Valid* is the counter for zero values; but the average predicts that *Valid* is the main counter; *Valid* is a mushed variable. Second, the ADD PARTIAL RESULTS PLAN is missing altogether. PROUST ranks bugs according to their severity; missing plans that do not pertain to some boundary condition are moderately severe bugs, and mushed variables are extremely severe bugs. Therefore this interpretation is less highly valued, and the analysis involving the transformation holds.

```

Sum := 0;
Valid := 0; ← Valid := 0 Init step:
Rainy := 0;      EXACT MATCH
Max := 0;
Read( Rain );
WHILE Rain <> 99999 DO
  BEGIN
    IF Rain < 0 THEN
      Writeln( 'Input not valid' )
    ELSE
      BEGIN
        IF Rain = 0 THEN
          Valid := Valid + 1 ← Valid := Valid + 1 Update step:
                                predicted by distribution transformation
        ELSE
          BEGIN
            Rainy := Rainy + 1;      Valid := Valid + 1 Update step:
                                     ??? condition for transformation violated
            Sum := Sum + Rain;        EXPLANATION: low-level slip
            IF Rain > Max THEN
              Max := Rain;
            END;
            Writeln( 'Enter next value:' );
            Read( Rain );
          END;
        END;
      END;
    Avg := Sum / Valid;
  
```

Figure 5-6: Transformation with bugs

6. Performance -- Preliminary Results

As a preliminary test of PROUST's capabilities, we tested PROUST on 206 different novice solutions to the Rainfall Problem shown above. We collected these programs by modifying the Pascal compiler used by the students in an introductory programming course so that each syntactically correct version of the program was stored on tape [2]. We ran PROUST on the first syntactically correct version from each student, so that we could see how PROUST behaves when faced with a large number of bugs.

In Table 6-1 we see how PROUST performed on this corpus of programs. Of the 206 programs in the sample, PROUST only commented on 137 of them (67%). The remaining 33% PROUST decided that it didn't understand the program well enough to make a reasonable assessment of the bugs. Thus, rather than venturing a guess, PROUST remained silent. On those programs that it did feel confident of its analysis, it was correct almost¹² 94% of the time! In an educational setting, we felt that no advice was better than bad advice. Thus, we built into

¹²There were still 32 "false alarms:" cases where PROUST said there was a bug, but there really wasn't.

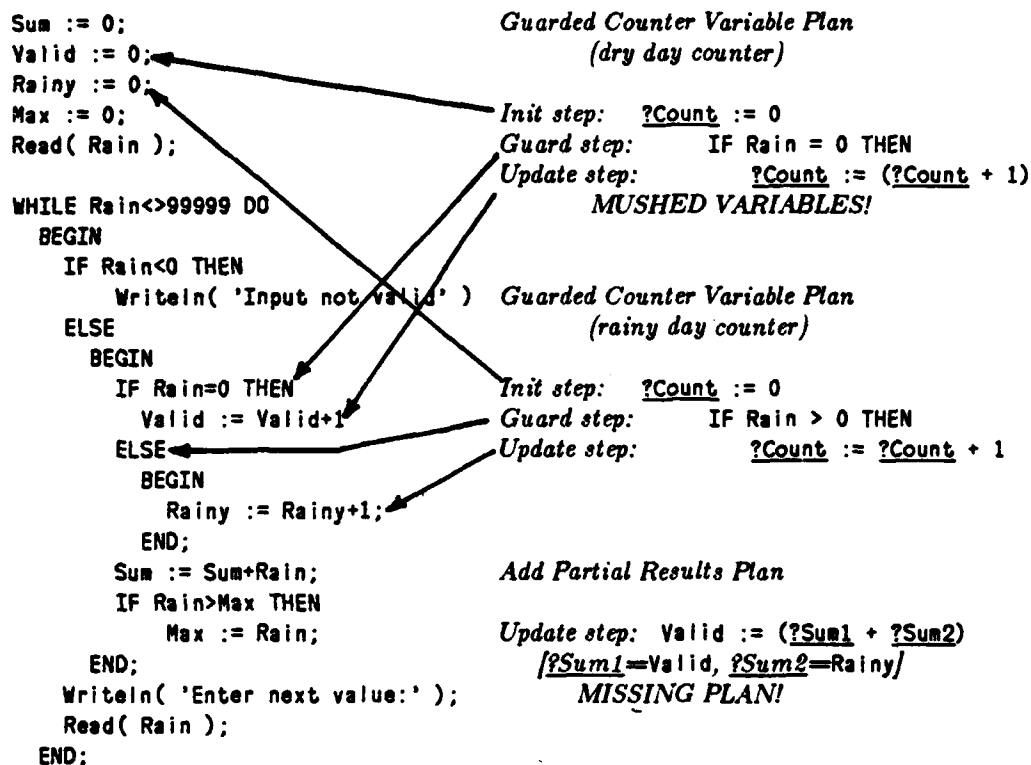


Figure 5-7: Matching alternate plans

PROUST a number of heuristics that it would use to assess its confidence in its analysis. From the data in Table 6-1, it seems that when PROUST thought it had a good analysis, it was indeed correct.

Total number of programs: 206

PROUST actually gave complete bug reports for 137 programs (67%)

Total number of bugs (from 137 programs)	444
Bugs recognized correctly:	419 (94%)
Bugs not reported:	25 (6%)
False alarms:	32

Table 6-1: Preliminary results

Clearly, the next stage is to improve PROUST's overall performance. Moreover, in looking at the cases where PROUST failed, we see no fundamental obstacle to getting PROUST up to the 80% overall correct rate. However, we can characterize the kinds of programs which will *always* cause problems for PROUST as follows: 1) very unusual bugs, which occur too infrequently to justify inclusion in PROUST's knowledge base, 2) programs which contain novel plans which PROUST has no means for predicting, 3) ambiguous cases which can only be resolved through dialog with the student. For these cases, we would suggest that the student see

a human teacher.

7. Concluding Remarks

Is all the machinery described in this paper necessary in order to understand buggy and correct programs -- programs that are only about 1 page in length? The answer, in our minds at least, is: undeniably yes. If anything, PROUST is the minimum that is required! The basis for this conclusion is twofold:

1. In Artificial Intelligence research, systems have been built to understand stories of moderate length that require machinery similar to that employed by PROUST. [13, 5] Certainly, programs are as complicated an entity as are stories.
2. We attempted to build a bug finding system that used a database of bug templates in a *context-independent* fashion to analyze programs similar to those analyzed by PROUST. That system, MENO, [16] failed miserably: in order to cope with the variety and variability in actual programs, a system must be able to understand how the pieces of the program fit together -- which is a highly *context-dependent* process.

Finally, all programmers intuitively know that the mapping from problem specifications to code is a complex process. What PROUST has done -- which we feel is its major contribution -- is lay that mapping process open to inspection: since PROUST constructs a program in its attempt to understand the program under analysis, we can "see" the programming process in action. By making the programming process explicit, our work joins with that of the software engineering community to change programming from an ethereal art to an object of scientific inquiry.

I. Proust's analysis of a sample program

```

1  PROGRAM RAINFALL  (INPUT ,OUTPUT);
2
3  CONST
4    SENTINEL = 99999;
5
6  VAR
7    RAINFALL, VALID, HIGHEST, AVERAGE, TOTAL : REAL;
8    RAINDAY : INTEGER;
9  BEGIN
10 (*INFORMATION IS ENTERED INTO THE TERMINAL*)
11   WRITELN('PLEASE ENTER THE AMOUNT OF RAINFALL FOR EACH DAY SEPERATLY');
12   WRITELN('THIS PROGRAM WILL THEN FIGURE OUT THE AVERAGE, HIGHEST, TOTAL');
13   WRITELN('NUMBER OF RAINY DAYS, AND THE NUMBER OF VALID RAINY DAYS ENTERED');
14   WRITELN('PLEASE MAKE SURE THE NUMBERS ARE POSITIVE');
15   WRITELN('ENTER RAINFALL');
16   READLN;
17   READ(RAINFALL);
18
19   (*TEST FOR INVALID ENTRY*)
20   IF RAINFALL < 0 THEN
21     WRITELN('THE DATA IS IMPOSSIBLE PLEASE CHECK AND REENTER DATA');
22     WRITELN('PLEASE REMEMBER THE NUMBERS MUST BE POSITIVE');
23     READLN;
24     READ(RAINFALL);
25
26   (*IDENTIFICATION AND CALCULATIONS*)
27
28   BEGIN
29     WHILE RAINFALL <> SENTINEL DO
30       IF RAINFALL > HIGHEST THEN
31         HIGHEST := RAINFALL;
32         TOTAL := RAINFALL + TOTAL;
33       IF RAINFALL >= 0 THEN
34         VALID := VALID + 1;
35       IF RAINFALL > 0 THEN
36         RAINDAY := RAINDAY + 1;
37     END;
38   REPEAT
39     UNTIL RAINFALL = SENTINEL;
40
41   (*FIND AVERAGE*)
42   AVERAGE := (TOTAL / VALID);
43
44   (*PRINTS OUTPUT*)
45   WRITELN(' ', VALID:2, 'VALID RAINFALLS WERE ENTERED. ');
46   WRITELN('THE AVERAGE RAINFALL WAS', AVERAGE:8:2, 'INCHES PER DAY');
47   WRITELN('THE HIGHEST RAINFALL WAS', HIGHEST:8:2, 'INCHES');
48   WRITELN('THERE WERE', RAINDAY:2, 'RAINY DAYS IN THIS PERIOD')
49 END.
```

Bug Report

1. The WHILE statement at line 29 and the BEGIN statement at line 29 are reversed. The BEGIN should come after the WHILE.
2. Your main loop is missing a READ statement. As it stands your loop will process the same input value over and over. Perhaps you intended line 24 to serve this purpose. If so, there may be a bug there.
3. You left out the initialization for the variable VALID.
4. You left out the initialization for the variable TOTAL.
5. You left out the initialization for the variable RAINDAY.
6. You left out the initialization for the variable HIGHEST.
7. You need a test to check that at least one valid data point has been input before line 42 is executed. The average is not defined when there is no input.
8. You need a test to check that at least one valid data point has been input before line 46 is executed. The average is not defined when there is no input.
9. You need a test to check that at least one valid data point has been input before line 47 is executed. The maximum is not defined when there is no input. Perhaps you intended line 33 to serve this purpose. If so, there may be a bug there.
10. Your test for valid input at line 20 won't work, because it's outside the main loop. Remember that you have to test ALL the input for validity.
11. The loop at line 39 doesn't do anything; it will loop forever. In particular, it will not make the program loop back to the beginning, if that is what you had in mind.

References

- [1] Bonar, J. and Soloway, E.
Uncovering Principles of Novice Programming.
1983.
SIGPLAN-SIGACT Tenth Symposium on the Principles of Programming Languages, in press.
- [2] Bonar, J., Ehrlich, K., Soloway, E.
Collecting and Analyzing On-Line Protocols from Novice Programmers .
Behavioral Research Methods and Instrumentation 14:203-209, 1982.
- [3] Brown, J. S., Burton, R. R., and de Kleer, J.
Pedagogical, Natural Language and Knowledge Engineering Techniques in SOPHIE I, II, and III.
In Sleeman, D. and Brown, J. S. (editors), *Intelligent Tutoring Systems*. Academic Press, New York, 1981.
- [4] Clancey, W. J., Bennett, J. S., and Cohen, P. R.
Applications-oriented AI Research: Education.
Technical Report HPP-79-17, Stanford Heuristic Programming Project, July, 1979.
- [5] Dyer, M.
In-Depth Understanding.
Technical Report 219, Computer Science Department, Yale University, May, 1982.
- [6] Ehrlich, K., Soloway, E.
An Empirical Investigation of the Tacit Plan Knowledge in Programming.
1983.
in *Human Factors in Computer Systems* , J. Thomas and M.L. Schneider (Eds.), Ablex Inc., in press.
- [7] Genesereth, M. R.
The Role of Plans in Intelligent Teaching Systems.
In Brown, J. S. and Sleeman, D. (editors), *Intelligent Tutoring Systems*. New York, 1981.
- [8] Goldstein, I. P.
The Genetic Graph: a Representation for the Evolution of Procedural Knowledge.
Int. J. of Man-Machine Studies 11:51-77, 1979.
- [9] Johnson, L., Draper, S., and Soloway, E.
An Effective Bug Classification Scheme Must Take the Programmer into Account.
1983.
SIGPLAN/SIGSOFT Workshop on High-Level Debugging, in press.
- [10] Johnson, L., Draper, S., and Soloway, E.
Classifying Bugs is a Tricky Business.
1983.
NASA Workshop on Software Engineering, in press.

- [11] Miller, M. L.
A Structured Planning and Debugging Environment for Elementary Programming.
Int. J. of Man-Machine Studies 11:79-95, 1978.
- [12] Rich, C.
A Formal Representation for Plans in the Programmer's Apprentice.
In *Proc. of the Seventh Int. Joint Conf. on Artificial Intelligence*, pages 1044-1052.
ICJAI, August, 1981.
- [13] Schank, R. and Abelson, R.
Scripts, Plans, Goals, and Understanding.
Lawrence Erlbaum, Hillsdale, New Jersey, 1977.
- [14] Sedlmeyer, R. L. and Johnson, P. E.
Diagnostic Reasoning in Software Fault Localization.
In *Proceedings of the SIGSOFT Workshop on High-Level Debugging*. SIGSOFT,
Asilomar, Calif., 1983.
- [15] Shapiro, D. G.
Sniffer: a System that Understands Bugs.
Technical Report AI Memo 638, MIT Artificial Intelligence Laboratory, June, 1981.
- [16] Soloway, E., Rubin, E., Woolf, B., and Bonar, J.
MENO-II: An AI-CAI Programming Tutor.
1983.
Journal of Computer-Based Instruction, in press.
- [17] Soloway, E., Ehrlich, K., Bonar, J., and Greenspan, J.
What do Novices Know about Programming.
In A. Badre and B. Shneiderman (editor), *Directions in Human-Computer Interactions*.
Ablex Inc., Norwood, New Jersey, 1982.
- [18] Soloway, E., Ehrlich, K., Bonar, J.
Tapping Into Tacit Programming Knowledge.
In *Proceedings of the Conference on Human Factors in Computing Systems*. NBS,
Gaithersburg, Md., 1982.
- [19] Soloway, E., Ehrlich, K., and Gold, E.
Reading a Program Is Like Reading a Story (Well, Almost).
In *Proceedings of the Cognitive Science Conference, 1983*. Cognitive Science Society.
Rochester, N.Y., 1983.
- [20] Soloway, E., Bonar, J., and Ehrlich, K.
Cognitive Strategies and Looping Constructs: An Empirical Study.
1983.
Communications of the ACM, in press.
- [21] Wescourt, K. T., Beard, M., Gould, L., and Barr, A.
Knowledge-based CAI: CINS for Individualized Curriculum Sequencing.
Technical Report 290, Stanford Institute for Mathematical Studies in the Social Sciences.
Psychology and Education Series, October, 1977.

-- OFFICIAL DISTRIBUTION LIST --

Army		Private Sector	
Technical Director U S Army Research Institute for the Behavioral and Social Sciences 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Michael Genesereth Department of Computer Science Stanford University Stanford, California 94305	1 copy
Mr. James Baker Army Research Institute 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Dedre Gentner Bolt Beranek & Newman 10 Moulton Street Cambridge, Massachusetts 02138	1 copy
Dr. Beatrice J. Farr U S Army Research Institute 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Robert Glaser Learning Research & Development Center University of Pittsburgh 3939 O'Hara Street Pittsburgh, Pennsylvania 15260	1 copy
Dr. Milton S. Katz Williams Technical Area U S Army Research Institute 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Joseph Goguen SRI International 333 Ravenswood Avenue Menlo Park, California 94025	1 copy
Dr. Marshall Narva U S Army Research Institute for the Behavioral & Social Sciences 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Bert Green Johns Hopkins University Department of Psychology Charles & 34th Street Baltimore, Maryland 21218	1 copy
Dr. Harold F. O'Neill, Jr. Director, Training Research Lab Army Research Institute 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. James G. Greeno LRDC University of Pittsburgh 3939 O'Hara Street Pittsburgh, Pennsylvania 15213	1 copy
Commander, US Army Research Institute for the Behavioral & Social Sciences Attn: PERI-BR (Dr. Judith Orasanu) 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Barbara Hayes-Roth Department of Computer Science Stanford University Stanford, California 95305	1 copy
Joseph Psotka, Ph.D. Attn: PERI-IC Army Research Institute 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Frederick Hayes-Roth Teknowledge 525 University Avenue Palo Alto, California 94301	1 copy
Dr. Robert Sasmor U S Army Research Institute for the Behavioral and Social Sciences 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Glenn Greenwald, Ed Human Intelligence Newsletter P O Box 1163 Birmingham, Michigan 48012	1 copy
Dr. Robert Wisher Army Research Institute 5001 Eisenhower Avenue Alexandria, Virginia 22333	1 copy	Dr. Earl Hunt Department of Psychology University of Washington Seattle, Washington 98105	1 copy
		Dr. Marcel Just Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy

Air Force

U S Air Force Office of Scientific Research Life Sciences Directorate, NL Bolling Air Force Base Washington, DC 20332	1 copy	Dr David Kieras Department of Psychology University of Arizona Tucson, Arizona 85721	1 copy
Dr Earl A Alluisi HQ AFHRL (AFSC) Brooks AFB, Texas 78235	1 copy	Dr Walter Kiatsch Department of Psychology University of Colorado Boulder, Colorado 80302	1 copy
Bryan Dallman AFHRL/LRT Lowry AFB, Colorado 80230	1 copy	Dr Stephen Kosslyn Department of Psychology The John Hopkins University Baltimore, Maryland 21218	1 copy
Dr Genevieve Maddad Program Manager Life Sciences Directorate AFOSR Bolling AFB, DC 20332	1 copy	Dr Pat Langley The Robotics Institute Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy
Dr John Tangney AFOSR/NL Bolling AFB, DC 20332	1 copy	Dr Jill Larkin Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy
Dr Joseph Yasutake AFHRL/LRT Lowry AFB, Colorado 80230	1 copy		
Marine Corps		Dr Alan Lesgold Learning R&D Center University of Pittsburgh 3939 O'Hara Street Pittsburgh, Pennsylvania 15213	1 copy
H William Greenup Education Advisor (E031) Education Center, MCDEC Quantico, Virginia 22134	1 copy	Dr Jim Levin University of California at San Diego Laboratory for Comparative Human Cognition - 0003A La Jolla, California 92093	1 copy
Special Assistant for Marine Corps Matters Code 100M Office of Naval Research 800 N Quincy Street Arlington, Virginia 22217	1 copy	Dr Michael Levine Department of Educational Psychology 210 Education Bldg University of Illinois Champaign, Illinois 61801	1 copy
Dr A L Slafkosky Scientific Advisor (Code RD-1) HQ, U S Marine Corps Washington, DC 20380	1 copy	Dr Marcia Linn University of California Director, Adolescent Reasoning Project Berkeley, California 94720	1 copy
Department of Defense		Dr Jay McClelland Department of Psychology MIT Cambridge, Massachusetts 02139	1 copy
Defense Technical Information Center Cameron Station, Bldg 5 Alexandria, Virginia 22314 Attn TC	12 copies	Dr James R Miller Computer Thought Corporation 1721 West Plano Highway Plano, Texas 75075	1 copy
Military Assistant for Training and Personnel Technology Office of the Under Secretary of Defense for Research & Engineering Room 3D129, The Pentagon Washington, DC 20301	1 copy	Dr Mark Miller Computer Thought Corporation 1721 West Plano Highway Plano, Texas 75075	1 copy
Major Jack Thorpe DARPA 1400 Wilson Blvd Arlington, Virginia 22209	1 copy		

Navy		Dr. Tom Moran	1 copy
Robert Abers	1 copy	Xerox PARC	
Code N711		3333 Coyote Hill Road	
Human Factors Laboratory		Palo Alto, California 94304	
NAVTRAEQUIPCEN		Dr. Allen Mauro	1 copy
Orlando, Florida 32813		Behavioral Technology Laboratories	
Code N711	1 copy	1845 Elena Avenue, Fourth Floor	
Attn: Arthur S. Blaines		Redondo Beach, California 90277	
Naval Training Equipment Center		Dr. Donald Norman	1 copy
Orlando, Florida 32813		Cognitive Science, C-015	
Liaison Scientist	1 copy	Univ. of California, San Diego	
Office of Naval Research		La Jolla, California 92093	
Branch Office, London		Dr. Jesse Orlansky	1 copy
Box 38		Institute for Defense Analyses	
FPO New York, New York 09510		1801 N. Beauregard Street	
Dr. Richard Cantone	1 copy	Alexandria, Virginia 22311	
Naval Research Laboratory		Professor Seymour Papert	1 copy
Code 7510		20C-109	
Washington, DC 20375		MIT	
Chief of Naval Education and Training	1 copy	Cambridge, Massachusetts 02139	
Liaison Office		Dr. Nancy Pennington	1 copy
Air Force Human Resource Laboratory		University of Chicago	
Operations Training Division		Graduate School of Business	
WILLIAMS AFB, Arizona 85224		1101 E. 58th Street	
		Chicago, Illinois 60637	
Dr. Stanley Collier	1 copy	Dr. Richard A. Pollak	1 copy
Office of Naval Technology		Director, Special Projects	
800 N. Quincy Street		MECC	
Arlington, Virginia 22217		2354 Hidden Valley Lane	
CDR Mike Curran	1 copy	Stillwater, Minnesota 55082	
Office of Naval Research		Dr. Peter Polson	1 copy
800 N. Quincy Street		Department of Psychology	
Code 270		University of Colorado	
Arlington, Virginia 22217		Boulder, Colorado 80309	
Dr. John Ford	1 copy	Dr. Fred Reif	1 copy
Navy Personnel R&D Center		Physics Department	
San Diego, California 92152		University of California	
Dr. Jude Franklin	1 copy	Berkeley, California 94720	
Code 7510		Dr. Lauren Resnick	1 copy
Navy Research Laboratory		LRDC	
Washington, DC 20375		University of Pittsburgh	
Dr. Mike Gaynor	1 copy	3939 O'Hara Street	
Navy Research Laboratory		Pittsburgh, Pennsylvania 15213	
Code 7510		Mary S. Riley	1 copy
Washington, DC 20375		Program in Cognitive Science	
Dr. Jim Hollan	1 copy	Center for Human Information Processing	
Code 14		University of California, San Diego	
Navy Personnel R&D Center		La Jolla, California 92093	
San Diego, California 92152		Dr. Andrew Rose	1 copy
Dr. Ed Hutchins	1 copy	American Institutes for Research	
Navy Personnel R&D Center		1055 Thomas Jefferson Street, NW	
San Diego, California 92152		Washington, DC 20007	

Dr Norman J Kerr Chief of Naval Technical Training Naval Air Station Memphis (75) Millington, Tennessee 38054	1 copy	Dr Ernst Z Rothkopf Bell Laboratories Murray Hill, New Jersey 07974	1 copy
Dr James Lester ONR Detachment 495 Summer Street Boston, Massachusetts 02210	1 copy	Dr William B Rouse Georgia Institute of Technology School of Industrial & Systems Engineering Atlanta, Georgia 30332	1 copy
Dr William L Maloy (02) Chief of Naval Education and Training Naval Air Station Pensacola, Florida 32508	1 copy	Dr David Rumelhart Center for Human Information Processing University of California, San Diego La Jolla, California 92093	1 copy
Dr Joe McLachlan Navy Personnel R&D Center San Diego, California 92152	1 copy	Dr Michael J Samet Perceptronics, Inc 6271 Varrel Avenue Woodland Hills, California 91364	1 copy
Dr William Montague NPRDC Code 13 San Diego, California 92152	1 copy	Dr Roger Schank Yale University Department of Computer Science P O Box 2158 New Haven, Connecticut 06520	1 copy
Library, Code P201L Navy Personnel R&D Center San Diego, California 92152	1 copy	Dr Walter Schneider Psychology Department 603 E Daniel Champaign, Illinois 61820	1 copy
Technical Director Navy Personnel R&D Center San Diego, California 92152	1 copy	Dr Alan Schoenfeld Mathematics and Education The University of Rochester Rochester, New York 14627	1 copy
Commanding Officer Naval Research Laboratory Code 2627 Washington, DC 20390	6 copies	Mr Colin Sheppard Applied Psychology Unit Admiralty Marine Technology Est Teddington, Middlesex United Kingdom	1 copy
Office of Naval Research Code 433 800 N Quincy Street Arlington, Virginia 22217	1 copy	Dr H Wallace Sinsko Program Director Manpower Research and Advisory Service Smithsonian Institution 801 North Pitt Street Alexandria, Virginia 22314	1 copy
Personnel & Training Research Group Code 442PT Office of Naval Research Arlington, Virginia 22217	6 copies	Dr Edward E Smith Bolt Beranek & Newman 50 Moulton Street Cambridge, Massachusetts 02138	1 copy
Office of the Chief of Naval Operations Research Development & Studies Branch OP 115 Washington, DC 20350	1 copy	Dr Richard Snow School of Education Stanford University Stanford, California 94305	1 copy
LT Frank C Petho, MSC, USN (Ph D) CNET (N-432) NAS Pensacola, Florida 32508	1 copy	Dr Kathryn T Spoehr Psychology Department Brown University Providence, Rhode Island 02912	1 copy
Dr Gary Poock Operations Research Development Code 55PK Naval Postgraduate School Monterey, California 93940	1 copy		

Dr. Gil Ricard Code M711 NTEC Orlando, Florida 32813	1 copy	Dr. Robert Sternberg Department of Psychology Yale University Box 11A, Yale Station New Haven, Connecticut 06520	1 copy
Dr. Worth Scanland CNET (N-5) NAS, Pensacola, Florida 32508	1 copy	Dr. Albert Stevens Bolt Beranek & Newman 10 Moulton Street Cambridge, Massachusetts 02238	1 copy
Dr. Robert G. Smith Office of Chief of Naval Operations OP-987H Washington, DC 20350	1 copy	David E. Stone, Ph.D. Hazeltine Corporation 7680 Old Springhouse Road McLean, Virginia 22102	1 copy
Dr. Alfred F. Snodde, Director Training Analysis & Evaluation Group Department of the Navy Orlando, Florida 32813	1 copy	Dr. Patrick Suppes Institute for Mathematical Studies in the Social Sciences Stanford University Stanford, California 94305	1 copy
Dr. Richard Sorensen Navy Personnel R&D Center San Diego, California 92152	1 copy	Dr. Kikumi Tatsuoka Computer Based Education Research Lab 252 Engineering Research Laboratory Urbana, Illinois 61801	1 copy
Dr. Frederick Steinheiser CNO - OP115 Navy Annex Arlington, Virginia 20370	1 copy	Dr. Maurice Tatsuoka 220 Education Bldg 1310 S. Sixth Street Champaign, Illinois 61820	1 copy
Roger Weissinger-Baylon Department of Administrative Sciences Naval Postgraduate School Monterey, California 93940	1 copy	Dr. Perry W. Thoradyke Perceptronics, Inc. 545 Middlefield Road, Suite 140 Menlo Park, California 94025	1 copy
Mr. John H. Wolfe Navy Personnel R&D Center San Diego, California 92152	1 copy	Dr. Douglas Towne University of So. California Behavioral Technology Labs 1845 S. Elena Avenue Redondo Beach, California 90277	1 copy
Dr. Wallace Wulfek, III Navy Personnel R&D Center San Diego, California 92152	1 copy	Dr. Kurt Van Lehn Xerox PARC 3333 Coyote Hill Road Palo Alto, California 94304	1 copy
Private Sector		Dr. Keith T. Wescourt Perceptronics, Inc. 545 Middlefield Road, Suite 140 Menlo Park, California 94025	1 copy
Dr. John R. Anderson Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy	William B. Whitten Bell Laboratories 2D-610 Holmdel, New Jersey 07733	1 copy
Dr. John Annett Department of Psychology University of Warwick Coventry CV4 7AJ ENGLAND	1 copy	Dr. Mike Williams Xerox PARC 3333 Coyote Hill Road Palo Alto, California 94304	1 copy
Dr. Michael Atwood ITT - Programming 1088 Oronoque Lane Stratford, Connecticut 06497	1 copy		
Dr. Alan Baddeley Medical Research Council Applied Psychology Unit 15 Chaucer Road Cambridge CB2 2EF ENGLAND	1 copy		

Dr. Patricia Baggett Department of Psychology University of Colorado Boulder, Colorado 80309	1 copy	Civilian Agencies Dr. Patricia A. Butler NIE-BRM Bldg. Stop #7 1200 19th Street NW Washington, DC 20208	1 copy
Ms. Carole A. Bagley Minnesota Educational Computing Consortium 2354 Hidden Valley Lane Stillwater, Minnesota 55082	1 copy	Dr. Susan Chipman Learning and Development National Institute of Education 1200 19th Street NW Washington, DC 20208	1 copy
Dr. Jonathan Baaron 80 Glenn Avenue Berwyn, Pennsylvania 19312	1 copy	Edward Esty Department of Education, OERI MS 40 1200 19th Street, NW Washington, DC 20208	1 copy
Mr. Avron Barr Department of Computer Science Stanford University Stanford, California 94305	1 copy	Edward J. Fuentes Department of Education 1200 19th Street, NW Washington, DC 20208	1 copy
Dr. John Black Yale University Box 11A, Yale Station New Haven, Connecticut 06520	1 copy	TABE, TAK National Institute of Education 1200 19th Street, NW Washington, DC 20208	1 copy
Dr. John S. Brown XEROX Palo Alto Research Center 3333 Coyote Road Palo Alto, California 94304	1 copy	Dr. John Mays National Institute of Education 1200 19th Street, NW Washington, DC 20208	1 copy
Dr. Bruce Buchanan Department of Computer Science Stanford University Stanford, California 94305	1 copy	Dr. Arthur Melmed 724 Brown U. S. Dept. of Education Washington, DC 20208	1 copy
Dr. Jaime Carbonell Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy	Dr. Andrew R. Molnar Office of Scientific and Engineering Personnel and Education National Science Foundation Washington, DC 20550	1 copy
Dr. Pat Carpenter Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy	Everett Palmer Research Scientist Mail Stop 239-3 NASA Ames Research Center Moffett Field, California 94035	1 copy
Dr. William Chase Department of Psychology Carnegie-Mellon University Pittsburgh, Pennsylvania 15213	1 copy	Dr. Mary Stoddard C 10, Mail Stop B296 Los Alamos National Laboratories Los Alamos, New Mexico 87545	1 copy
Dr. Micheline Chi Learning R & D Center University of Pittsburgh 3939 O'Hara Street Pittsburgh, Pennsylvania 15213	1 copy	Chief, Psychological Research Branch U. S. Coast Guard (G-P-1/2/TP42) Washington, DC 20593	1 copy

Dr. William Clancey
Department of Computer Science
Stanford University
Stanford, California 94306

1 copy

Dr. Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, Massachusetts 02138

1 copy

ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, Maryland 20014

1 copy

Mr. Wallace Feurzeig
Department of Educational Technology
Bolt Beranek and Newman
10 Moulton Street
Cambridge, Massachusetts 02238

1 copy

Dr. Dexter Fletcher
WICAT Research Institute
1875 S. State Street
Orem, Utah 22333

1 copy

Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, Massachusetts 02138

1 copy

Dr. Frank Withrow
U. S. Office of Education
400 Maryland Avenue SW
Washington, DC 20202

1 copy

Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

1 copy

