## PUTTING THEORIES TOGETHER TO MAKE SPECIFICATIONS

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order not significant

We have been developing a language in which you can give structured descriptions of theories.

Why are we interested in theories? Because you need a theory to specify a problem before you can develop a program to solve it, whether you intend to develop the program intuitively or to synthesise it mechanically by rule. It only makes sense to say 'We want a program which can invert a matrix' in the context of some theory about matrices and the operations on them such as multiplication.

Why are we interested in structured descriptions of theories? Because people find it very hard to understand anything at all unless they have a well-structured description of it; as for machines, twenty years work in Artificial Intelligence has taught us to beware of letting them loose on an unstructured description.

What would an unstructured description of a theory be like? Imagine 217 axioms in Predicate Calculus telling you how to find your way around SRI, or 217 semantic equations describing the language Klugegol78. Minsky (1975) protests about 'attempts to represent knowledge as collections of separate simple fragments'. No-one could approve of such monsters as these.

Now consider the analogous situation with programs. They are structured by statements, iterations and procedures. For large programs these have proved inadequate (217 LISP functions!), and SIMULA classes, CLU clusters and ALPHARD forms have been devised to ward off the threatened chaos (Dahl et. al 1970, Liskov 1975, Wulf et al 1976). They all introduce abstract data structures by giving the collections of procedures which define the primitive operations on them. They separate the part of the program which implements a structure from other parts which use it but have no concern with its representation. Similarly in Al Minsky's frame notion (Minsky 1975) offers a way of bundling together LISP functions into some meaningful entities. Indeed one reason for the move away from a 'logical' representation of knowledge to a procedural one may be that we have some skill at structuring programs but hardly any at structuring theories.

Our work on theories derives from our attempts to clarify and generalise the above methods of building up programs in terms of abstract data structures. Tackling problem specifications rather than programs turned out to use the same mathematical tools but to be rather less difficult. It is also an area overdue for illumination. The present paper sets forth in
an informal way our first, tentative, proposal for a language in which one may describe theories. This language, called 'Clear', is intended primarily as a tool for program specification, but it might also serve to represent knowledge in a machine manipulable form. We have largely worked out the mathematical semantics of Clear, but we have not attempted to implement it.

We will first explain our notion of theory in general terms, then discuss possible areas of application. After this we will describe our theory language and give some simple illustrations of its use.

## What we mean by a theory

The notion of theory is a loose intuitive one in mathematics. There should be axioms, rules of inference and theorems, but the language in which they are expressed is open to choice. A popular choice of a formal language would be first order predicate calculus, or more boldly a higher order calculus. Some people, like the predicate calculus programmers (Kowalski 1974), would use a more restricted calculus, say Horn clauses with free variables but no explicit quantifiers. We have chosen an algebraic notion of theory, due to Lawvere (1963), making it many-sorted (Goguen, Thatcher and Wagner 1977) and with provision for errors (Goguen 1977).

A many-sorted algebraic theory is given by naming a set of sorts, a set of operators over those sorts and a set of laws which those operators must satisfy. The laws take the form of equations with free variables but no quantifiers. Since we may introduce truth values as a sort and two no-argument operators (constants) true and false, we can introduce predicates as operators producing a truth value as result (just like LISP).

Here are two examples:-
Vector spaces The sorts are scalar and vector.
The operators are scalar addition and multiplication, scalar zero and one, vector addition, vector negation, vector zero, and vector-byscalar multiplication. The laws are associativity and commutativity for scalar addition, identity for scalar zero with addition and so on.
GPS (General Problem Solver) The sorts are states, actions, action-sequences, state descriptions, attributes, values and differences. (In GPS attributes of states have values, which give rise to differences between states.)
The operators are (i) apply, taking an action and a state to a state, (ii) descriptionof,
taking a state to a description, (iii) valueof, taking a description and an attribute to a value, (iv) undefined, a constant for a state, and so on.
There are some laws, for example:apply(a,undefined) = undefined, concatenation of action sequences is associative.
Lawvere showed how such a theory description can be taken to denote a more abstract algebraic structure, namely a collection of operators susceptible to 'composition' (substitution) and 'tupling'. This is important because he was able to develop some theory about 'theories' (if you can have a theory about 'groups' you can have a theory about 'theories'), and his work enables us to give a mathematical basis to our language for denoting theories. It is not appropriate to go into thi3 mathematics here, but it is a comfort to us that we have managed to outline a proper semantics for our language; we hope to develop this and write it up soon for publication*

Not only is it relatively easy to reason about algebraic theories, but there is evidence that it is relatively easy to reason within an algebraic theory, indeed that is just the domain which was tackled very successfully by Boyer and Moore (1975) with their LISP theorem prover, subsequently enhanced to deal with many sorts by Aubin (1976).

We already have some encouraging experience of using algebraic theories (but not structured ones) as a specification tool (Goguen 1976, Goguen, Thatcher and Wagner 1977).

The use of algebraic techniques for specifying abstract data types has been studied extensively by Zilles (1974) and by Guttag, Horowitz and Musser (Guttag 1975, Guttag et al 1976) who give examples of program verification using such specifications.

We should remark that although we have chosen to use algebraic theories rather than predicate logic or lambda calculus theories, the methods we have used to combine them are rather general and may well apply to other kinds of theory.

We have not written out the above examples of theories' in full because they would be long and hard to understand; even eight operators and a dozen laws is a lot to swallow in one bite. A mathematics book would scarcely present the concept of vector space without some preparation on semigroups, groups and fields. Indeed most of the structure can be explained by saying that the scalars form a field and the vectors a group. We then have to impose some extra conditions (e.g. commutativity of vector addition) and enrich the structure with an extra operator, multiplication of vectors by scalars, which is distributive, etc.

Similarly GPS becomes much easier to understand if we first describe a state-action system, then say that action-sequences are just strings of actions whose effect is the composition of the effect of the component actions. We can independently enrich the idea of state with attributes
and values, saying that descriptions are justarrays (finite functions) from attributes to values. Only then can we put it all together and introduce the notion of the differences reduced by an operator.

This then is intuitively what we mean by building up a theory in a structured way: any good textbook does it all the time. Luckily Lawvere's notion of the category of theories supplies the mathematical correlate of this informal exposition and enables us to apply known mathematical methods ('colimits') to the task of constructing theories by using other theories as ingredients.

One may view a theory as a natural generalisation of the notion of abstract data type. Such a type is characterised by the operations which create its elements or apply to them. A theory may consist of several such types with the operations between them, thus avoiding the difficulty of arbitrarily assigning an operation from A's to B's to type A or to type B. Analogous to a group of procedures which realise a data-type, as in SIMULA, CLU or ALPHARD, would be a group of procedures which realise a theory. We learned recently that Nakajima, Honda and Nakahara (1977) had also been working on this idea and had designed a programming language to incorporate it. Their use of theories in a programming language is close to what we had in mind. We hope that the mathematical methods we have for structuring specifications can be adapted to give semantics for such a programming language (see our tentative remarks about programs as theory morphisms later on).
Specifications required for -program verification, transformation and synthesis
Program verification has been a continuing concern since McCarthy's classic paper (1963). Recently there has been considerable interest in synthesising programs from their specifications (Manna and Waldinger 1971, 1975), Dijkstra (1975), Darlington (1975, 1976), one promising method being to take a very naive program as the specification and transform it into an acceptably efficient one (Darlington and Burstall 1976, Burstall and Darlington 1977, Arsac 1977). All of these techniques for obtaining correct programs must start from a specification. Verification, whether by hand or by machine, makes heavy weather even of non-trivial 'text-book' programs and still seems impractical for the much longer programs met with in practice. This comparative lack of success of verification techniques has obscured the fact that for large programs not only are we unable to carry through a correctness proof, but usually we cannot even specify the problem which the program is supposed to solve.* Similar remarks apply to program synthesis.

* For an overview of specification techniques, with many references, see Liskov and Berzins (1977).

There are exceptions. To specify a compiler, and hence verify it, you need to define the source language and the target machine. Scott and Strachey (1971 and subsequent papers) battled valiantly to give us precise semantic definitions of programming languages. Unfortunately, for large languages the specifications are very hard to understand (Robert Milne had one for Algol-68 which he declined to publish on the grounds that no-one would read it). We surmise that a good part of the trouble may be the lack of structure in such a formal definition, the structure that the writer of an informal manual for a language must be very careful to make clear.*

Thus we feel that a better grip on the way to structure the theory in terms of which specifications are made is a prerequisite for raising verification and synthesis techniques above the toy problem level.

## Specifying AI problems

In Al research, as in other disciplines dealing with complex programs, there is a tendency to write the program but never get around to specifying the problem. Further any large program must be composed of subprograms, and these cannot be understood without a clear specification of the subproblems they are supposed to solve. Thus better tools for problem specification are a pressing need in AI.

Not only Slould the theories used in specifying these problems and subproblems be well structured, they should also be sufficiently abstract. They should be concerned with the abstract nature of the data and the operations to be performed rather than the particular problem domain or the specific machine representation of the data. For example Walts's (1975) work is about the abstract notion of networks of relations, rather than just about blocks and shadows or about LISP S-expressions; its full utility can only be exploited if this is kept in mind (see Mackworth 1977). Our theory language must be able to handle such abstraction and enable us to hide unnecessary detail.

## Representing knowledge within an AI program

Al programs are commonly conceived to embody knowledge, whether as program or as data. Procedural embedding of knowledge may promote efficiency, and it may enable one to use existing program structuring techniques to impose some order on the embedded knowledge. However procedural embedding has disadvantages of inflexibility, and it makes it difficult to incorporate new knowledge, whether input or from inductive learning. Much of the disquiet with knowledge held as data seems to us to stem from its lack of structure, a large collection of axioms or facts unorganised, slowing processing down with irrelevant information.

Again we are exhorted to consider our commonsense knowledge of the world as composed of a large number of micro-theories about particular

* Mosses (1977) makes a start in this direction.
aspects. But we are left largely in the dark as to how to put these micro-theories together. This question of 'putting theories together' is close to the heart of our concern.

Thus although we cannot yet speak from experience, we very much hope that our theorybuilding techniques may eventually give some fresh insight into the appropriate organisation of knowledge in AI programs. A way of presenting theories so that people can understand them might help us to see how machines can make use of them.

## Theories

We start our exposition of the language Clear by looking more closely at the notion of many-sorted algebraic theory. Our theories will also make provision for errors, like division by zero, but we will defer consideration of this until we have the basic ideas straight.

First we need the notion of a signature, that is a vocabulary of operators with given sorts.

A signature is a set of sort names and a set of operator symbols, each with a given sequence of 3orts for its arguments and a sequence of sorts for its results (possibly more than one result). We write $w: s_{1}, \ldots, s$-> $\mathrm{sj}, \ldots \ldots, \mathrm{s}_{\mathrm{n}}$ ' to show that
w is an operator with input 30 rts $\mathrm{s}_{1}, \ldots, \mathrm{~s}_{\mathrm{m}}$ and output sorts $\mathrm{s}_{1}{ }^{\prime}, \ldots, \mathrm{s}^{\prime}{ }_{\mathrm{n}}$.*
Example 1 Natural numbers
sorts nat, bool
operations
zero : -> nat
succ : nat -> nat
iszero: nat -> bool
true : -> bool
false : -> bool
not : bool -> bool
or : bool, bool -> bool
Example 2 Geometry (a fragment)

| sorts | line, point, | bool |
| :---: | :---: | :---: |
| operations | .join | point, point -> line |
|  | intersection: | line, line -> point |
|  | colinear | point, point, point->bool |
|  | true | -> bool |
|  | false | -> bool |
|  | not | bool -> bool |

A theory presentation is a signature together with a set of equations using the operators of the signature and respecting their input and output sorts. The equations have variables which are implicitly universally quantified.
Example 1 (continued)

```
variables m,n: nat
equations iszero(zero) = true
    iszero(succ(n)) = false
    not(true) = false
    not(false) = true
```

* for multi-result operators we could use a syntax like "...a...r... where $<q, r>=$ quotient and -remainder(m,n)", but we will not need them.

Example 2 (continued)

A theory is a signature together with a set of equations closed under inference by reflexivity, transitivity and symmetry of equality and by substitution. For example 'false $=$ iszero(succ(succ (zero)))' is an equation in the theory defined by the presentation above.

Thus each theory presentation gives rise to a theory but the same theory can be presented in more than one way by choosing different sets of 'axiom' equations to generate it, (The notion of Theory is more basic than Theory Presentation in the sense that one would like to talk about the theory of groups,for example,irrespective of any particular axiomatisation of it,)*

The interpretations of a theory are algebras, where an algebra is a collection of sets, one for each sort, with a function over these sets assigned to each operator of the theory. These functions must obey the equations of the theory. In practice for theories containing bool we will only be interested in 'consistent' interpretations in which true $\varnothing$ false.

## Theory-building operations

In the last section we were just writing down theories explicitly one at a time. As soon as they get to be interesting they become incomprehensible. We wind up with a large set of equations that no-one can understand and which are almost certainly wrong. So we must build our theories up from small intelligible pieces. For this we need
(i) the ability to write (small!) explicit theories, as above, thus

```
theory sorts ...
        opns ...
        eqns ... endth
```

(ii) four operations on theories, combine enrich. induce and derive, which enable us to build up theory expressions denoting complex theories.
We will explain these operations informally, using examples.
First we define two explicit theories which will be useful
The theory Nato

## theory sorta nat

opns 0 : -> nat suce: nat $\rightarrow$ nat
eqne
ondth

Technically we should call this a 'theory with signature' rather than just a 'theory' because the choice of a particular set of operators is irrelevant to the abstract notion, just as is the choice of particular axioms (see Lawvere 1963 or Manes 1976).

The theory BoolO

```
theory sorts bool
    onns true : -> bool
            false: -> bool
                7: bool -> bool
                A: bool, bool -> bool
    gons T true = false
        7false = true
        false A p = false
        true ^ p=p endth
```

(Strictly we ought to insert 'variable p: bool' before 'eqns'. but we will assume that undeclared single letter identifiers are variables; their type will be obvious. We will also allow ourselves to use traditional infixed symbols like A.)

## Combine

This operation is dull but plays its part in the larger scheme of things. We simply take two theories and add them together. The sorts of the resulting theories are the union of the sorts of the given theories, the operators are the union of their operators, and the equations are the union of their equations. We use the + sign for the combine operation.

For example BoolO + NatO could be written explicitly as

```
theory
    gortg bool, nat
        oona true : -> bool
            false: -> bool
                7: bool -> bool
                A : bool, bool -> bool
                    0: -> nat
            suce: nat -> nat
        egns 7 true = false
            7false = true
            falge A p = falae
        true A p =p endth
```

We will see later that combine does not necessarily produce the disjoint union of two theories; it allows for sharing of common subtheories.

## Enrich

Suppose that we want to build up a useful theory of the natural numbers,including operators for ordering and for equality. The operators < and eq belong neither to BoolO nor NatO, but they can be added to their combination to obtain a new theory

## The theory Nat 1

## enrich Bool0 + NatO by

 eq: nat, nat -> bool
anns $\begin{aligned} & 0<r=\text { true } \\ & \text { succ }(\mathrm{m})\end{aligned}$ suce $(m) \leq \operatorname{succ}(n)=m \leq n$ eq $(m, n)=m \leq n \wedge n \leq m$ enden
This whole expression denotes the new enriched theory.

In general one may add new sorts as well, thus


The enriched theory inherits all the sorts. operators and equations of the orifinal one. The new operators can have es input and output sorts the original sorts or the new sorts.

Given the enrichment operstion we could just start with the empty theory, say $\Phi$, and regard any explicitly written theory as an enrichment of面。

## Induce

The theory Nati has an operator eq which satisfies not only the three equations explicit.ly given but also by substitution, the equations

```
\(a(0,0)=\) true
eq \((\operatorname{succ}(0), \operatorname{succ}(0))=\) true
\(\operatorname{eq}(\operatorname{succ}(\operatorname{succ}(0)), \operatorname{succ}(\operatorname{succ}(0)))=\operatorname{true}\)
```

and so on. But the equation
$\theta(n, n)=$ true
is not inferable by subatitution and is not purt. of the theory.

We would like to be able to extend the equatione of a theory so that an equation holds for a variable, $n$, if it holds for every equation obtained by substituting a constant, that is a variablefree term, for $n$. So we have an operation induce on a theory which does just this.* Thue in the theory induce Nat 1 , which we will call Nat, the oquations

$$
\begin{array}{ll}
\text { eq }(n, n)=\text { true } & \text { reflexive } \\
\text { eq }(m, n)=\text { eq }(n, m) & \text { symmetric } \\
\text { eq }(1, m) \wedge \text { eq }(m, n) \wedge \neg \text { eq }(1, n)=\text { false } & \text { transitive }
\end{array}
$$

all hold.
To find equations holding in a theory crented by induce we may prove by induction on the structure of terms, using the equations of the original theory, that a certain form of equation holds for every variable-free term; we may then assert that the form with a variable must hold in the induced theory. (Such methods of inference will not in eeneral be complete however.)

In Boolo every variable-free term is equivalent to true or false by using the equations for 7 and $A$, so it suffices to show that an equation holds for both true and false to aee that the general equation holds in induce Boolo. Induction here just amounts to case analysi $\bar{s}$. For exemple 77 true $=$ true and 77 false $=$ false both hold in Bool0, so $77 \mathrm{p}=\mathrm{p}$ holds in induce Boolo. We call induce BoolO sumply Bool.

## Derive

The third operation derive enables us to take a more complex theory than we need, perhaps built by combining and enriching some familiar theories, and then to select out from it just those sorts

* Technically, induce $T$, is the theory of the initial algebra of T7
and operations which we require. For example, if we only need eq from Nat (and not < or zero or succ) we may write


## The theory Natequal <br> derive

sorts element, bool
opns equal, true, false
from Nat by
element is nat
bool is bool
equal is eq
true is; true
false is, false endde

This denotes a new theory with two sorts and three operators. The equations governing the new operator, equal, are not specified. Indeed we have only given the signature of the new thonry. but. the properties of equel are given implicitly by the correspondence equal is eq. Notiee- thet the equations for eq use the auxiliary operator $\leq$. In general an operator of the derived theory may correspond to a $\lambda$ defined operator of the original theory, thus "plus2 is $\lambda$ n.succ(succ(n))".

For brevity we will omit pairs of the form ' $x$ is $x$ ', such as 'true is true'. Also if we already have a theory T we may write'signature T ' to denote its signature.

We use derive when we want to define a theory in terms of some other theories with which we are already familiar but which, taken together, are too rich for our purpose. We are making a construction from familiar mathematical objects, but the details of the construction are discarded in the more abstract result. An analogy would be the construction of the natural numbers in terms of the sets $\varnothing,[\varnothing],\{\varnothing,[\varnothing]\}, \ldots$. The operations we need on the natural numbers are, say, zero, successor and <, Other possible operations on these sets, such as cartesian product of two sets, are not meaningful for numbers. In programming work it is well-known that the operations on an abstract data type are defined in terms of those on a more concrete type which represents it; but at the abstract program level the more concrete operationsshould not be available.

## Procedures for theory-building

We have some primitive operations on theories. The next step is to enable the user to define his own operations using these. For this we introduce procedures - no self-respecting language could be without them.

We shall introduce the simplest mechanisms which provide tolerably convenient facilities, namely
(i) Theory constants, enabling us to give a name to a theory
(ii) Theory procedures, taking theories as their parameters and producing a theory as a result. Their bodies use the primitive operations already defined and may call other theory procedures (but we eschew recursion])

Local theory definitions, permitted in the bodies of theory procedures, thus:let $T=\ldots$ in …

These facilities would be very similar whatever domain we were working in. Let us introduce them in the familiar domain of numbers and truthvalues as a warming up exercise. We will assume the primitives * (multiply), /(divide) and if... then...else...

A constant declaration, .just assigning a fixed value to an identifier pi, would be
constant pi - 22/7
A procedure declaration for a procedure producing a number as result would be
procedure $f(x$ : number, $b$ : boolean $)=$ if $b$ then $\mathrm{pi}^{*} \mathrm{x}$ else 0
A procedure declaration with an auxiliary local variable $z$ would be
procedure $g(y$ : number) $=$ let $z=f(y$ * $y$, true) in $s$ * $z$ * $z$
Now if we evaluate $g(2), 7$, takes the value $f\left(2^{*} ?\right.$, true), i.e. $(22 / 7)^{*} 2^{*} 2$, and $g(2)$ is the cube of this value.

Now the same definitional methods and syntax will apply to theories, using the theory-building operations instead of *,if-then-else etc. (we do not need conditional expressions for theories). We will need the type specification for parameters, as in x: number, since it turns out that there is notion of type for theory parameters.

There is one major difference however between numbers and theories as a domain. Two theories may share some common subtheory. For example the theory of natural numbers has Bool as a subtheory since it has predicates like <, so does the theory of character strings which has predicates like isempty. We may want to enrich the combination of these two theories to allow operators like
length: string -> nat
In this new theory we want the truthvalues produced by < to be the same as those produced by isempty. We want one copy of Bool not two. Thus Bool is a shared subtheory.

Where have we met this situation before? In LISP or any other language with pointers we have shared substructures. Let us see how the definitional mechanisms we have introduced would behave with shared lists. We will then be ready to tackle theories. We need atoms "A, "B etc., the list constructor cons, the selectors car and cdr and, crucially, the predicate eq which tests whether two lists are equal in the sense of starting with the same list cell, not just having the same shape. We will not use LISP syntax, but we intend LISP semantics, passing parameters by pointer than than copying the list structure. Let us look at examples (the intended values of the expression are given on the right)
(i) eq(cons("A,"B),cons("A,"B)
false

```
(ii) constant ab = cons("A,"B)
    eq(ab,ab)
    true
(iii)
constant ab = cons("A, "'B)
    eq(cons(ab,"c),cons(ab,"C)).... f alse
eq(car(cons(ab,"c)) ,car(cons(ab, "c))) ....
                                    true
(iv) procedure }P(I; list) = eq(I,I
P(cons("A,"B))
                                    true
(v) procedure P(I: list) -
            let m - cons(l,"C) in e1(m,m)
P(cons(A,"B))
true
```

Thus every use of a constant, parameter or local variable refers to the same list, to within eq, but writing down an explicit expression twice using cons refers to a different list (i). Two different lists can share a common sublist (iii).

Now our theory-making operations, explicitly writing a theory and enriching one, behave ju3t like cons. But by using theory constants or variables we can arrange for the theories we create to contain shared sub-theories- One of our main technical problems was to make this remark precise, since for theories we do not have the addre3s/value storage model as we do for data structures. In fact the category theory ideas of "diagram" and its "colimit" give a rather general notion of shared substructure. We hope that the reader's intuition using the LISP analogy will give him a reasonably good grip on the intended semantics. Those who wish to know the precise method for determining the denotation of our specifications must await the mathematical semantics in the paper which we are preparing.

## The specification language Clear

We will call our proposed specification language "Clear". A specification in Clear consists of a sequence of constant and procedure declarations followed by an expression. The expression denotes a theory, not explicitly but using the theory-building operations and the declared constants and procedures.

Clear can be viewed as a language for communicating a precise specification of a problem to people, such as programmers- It could also be implemented on a machine so that 'evaluation' of a Clear specification yielded an explicit representation of the theory it denotes- A more useful implementation however would be to link Clear to an equatinnal theorem prover which would try to prove that a given equation held in this theory without producing the theory explicitly. Or it could be incorporated in a system which tried to show that a given program implemented some operations of this theory. This raises interesting, but still unanswered questions, about the relation between specification structure and program structure.

We will explain Clear by example. Let us start by building up the theory Nat of natural numbers using the constant facility and the let facility, thus repeating in succinct form the more fragmentary development of Nat above. We start with Bool, the theory of truth values.
(const is short for constant)
const Bool $=$
induce theory
sorts bool
opng true. false: $\rightarrow$ bool
7 : bool -> bool
人: bool,bool -> bool
vars $p:$ bool
egns 7 true $=$ false $7 \mathrm{false}=$ true true $\wedge p=p$
false $\wedge p=$ falge endth
The constant Bool now denotes the theory of trutt. values. Since we applied the induce operntion it also has equations such as $77 p=p$ obtained by case analysis.

## const Nat $=$

induce let Nato $=$
theory zorts nat opns o: nat suce: nat -> nat endth
in enrich Nato + Bool by
opns
vars $\mathrm{m}, \mathrm{n}$ : nat
corns $0 \leq r-1 . r u e$ $\operatorname{succ}(m) \leq 0=$ frise $\operatorname{succ}(m) \leq \operatorname{succ}(n)=m \leq n$ $\theta q(m, n)=m \leq n \wedge n \leq m \quad$ ender
The constant Nat now denotes the theory of natural numbers. It is built up by first making a local definition of the simple theory NatO with just zero and suec. We then combine this with Bool, enriching the combination with extra predicates < and eq. finally induce applied to the whole expression ensures that the theory contains general equations like eq(m,m) - true-

## Procedures in Clear

We often build one theory on top of another. Suppose for example that we have some partially ordered set, then we can form strings from its elements and define the predicate 'ordered' for strings- This is just what we would have to do if we wanted to specify some sorting task. A theory of ordered strings can be developed for any partially ordered set (poset) of elements and the latter can be regarded as a theory parameter (compare Form parameters in ALPHARI)). We can write a procedure using the theory-building operations to construct the theory of ordered strings from this parameter. Now we can apply this procedure to any theory which has a 'less than or equal' operator satisfying the reflexivity, transitivity and antisymmetry laws, for example the theory Nat- Thus the procedure can only accept as parameter a certain sort of theory; we had better call it a 'meta-sort' to avoid confusion with the sorts within theories. This metasort is itself a theory, in this case the theory of partial orderings-

A degenerate example would be a theory procedure which can take any set as parameter and does not need any operators, for example the procedure which, given a set of elements, produces the theory of 3 tring 3 of those elements. The
nieta-sort here is the trivial theory with one sort and no operators.

## const Triv $=$ theory sorts element endth

The theory procedure to make strings is then (proc being short for procedure)
proe Strings ( x : Triv) $=$
induce enrich $X$ by
sorts $\overline{\text { s.t. }}$ trine.
opns' unit: element $\rightarrow$ string
$\Lambda:->$ blring

- : strine, strine $\rightarrow$ string
eqns $\boldsymbol{\Lambda}=\mathrm{a}$
$\mathrm{s} . \boldsymbol{A}=\mathrm{s}$
(s.t).u $=s_{0}\left(t_{0}, u\right)$ enden

As an example we can apply this procedure to Nat to get strings of natural numbers, but we need to associate the sorts and operators of the metasort (Triv)of the formal parameter with those of the actual parameter (Nat), that is we need a sort to sort function and an operator to operator function just as in derive. We write these in brackets after the actual parameter, thus

## Strings (Nat [element is nat])

We may omit pairs of the form ' $x$ is. $x$ '-
The actual parameter theory must include all the equations of the meta-sort theory as rewritten under this operator to operator function. We must prove this for every procedure applicationUnlike conventional type checking it is not in general decideable.

Now to do ordered strings we need the theory of partial order for use as a meta-sort.
const Poset $=$

$$
\begin{aligned}
& \text { enrich Rool by } \\
& \text { sort.s alement } \\
& \text { opns } \leq \text {, eq: element, element } \rightarrow \text { bool } \\
& \text { eans } x \leq x=\text { true } \\
& x \leq y \wedge y \leq z \wedge 7(x \leq z)=\text { false } \\
& \text { (transitivity) } \\
& e q(x, y)=x \leq y \wedge y \leq x \text { enden }
\end{aligned}
$$

We can now write the procedure for ordered strings. We use the procedure Strings defined above.

```
proe Orderedstrings (P: Poset) =
    inducc enrich Strings (E) by
        opns ordered: string -> bool
        egng ordered(A)= true
        ordered(unit(x)) = true
        ordered(unit(x),unit(y)) = I \leq y
        ordered(s.t.u) = ordered(s.t)
            A ordered(t.u) enden
```

Use of a theory as a meta-sort is rather distinct from its use in defining some data structure such as natural numbers- It enables us to state the presuppositions for some task which we wish to specify, and we are interested in any interpretation of the theory rather than some particular canonical one.

## Shared subtheories

We observed already that just as two lists may share substructure so may two theories; this
in accomplished by having the same variable appear in both the expressions denoting these theories. The details, which follow, are a little technical and may be skipped if desired.

Suppose that we have a theory variable T ei ther a formal parameter or bound by a let," Then the theory "enrich T by...enden" contains this theory T as a subthe~ory, and so do " $\mathrm{T}+\ldots$... and "Induce T". The theory 'derive aigrigture T1 from T? by, .Tendde" contains T as a subtheory if TInjontains it. Should T2. also contain $T_{-}$as a subtheory then the "..." had better map its operators identically (if they both contain Bool, "true is false" would not be welcome). Now it we combine two theories T1_ and T2 which both have T as a subtheory then TT+ ${ }^{-}$2 "only contains T once". The same rules hold IT T Ts not a variable but is introduced by "const $\mathrm{T}=\ldots$...". All this enables us to have Bool, say, as"a subtheory of several
theories without proliferating many copies of it. Sometimes we do need a fresh copy of a theory $\mathrm{T}_{\text {, }}$, so we let "copy T" denote one, to save writing it out again explicitly.

When we apply a procedure P to an argument _ $\top$ the result always includes $T$ just as if we had written $P(T)+T$ instead of $P(T)$. For example String (Nat) is a theory whic has not only string operators but also the operators like succ defined in Nat, Of course when we are writing the definition of the procedure String these latter operators are not available; the importance of such 'insulation' mechanisms has been pointed out by Wulf and others.

## Errors and conditionals

Before going on to look at examples of specifications written in Clear we will incorporate two USEFU features: errors and conditionals.

Some applications of ar operator to its arguments will, not give a meaningful result, for example dividing by zero or popping an empty stack. Thus we need to consider errors, a topic which is often glo33ed over in algebraically oriented work, but whose proper treatment is essentialfor a realistic specification language. It is important too that the different levels of abstraction provided by our language should not become confused as soon as an error is encountered; we do' not want a stack underflow to produce an error message 'array subscript out of bounds'. Gtoguen (1977) studies this topic in depth, defining error algebras and error theories. We will confine ourselves to an informal, glance at error theories.

The idea is to extend each sort by a set of error elements of that sort, and to have error operators which produce these elements. Thus the theory of stacks might have an error operator
underflow: -> stack
and the theory of arrays might have an error operator
notdefinedfor: index -> value
meaning that there is no value for this index in
the array. The term 'notdefinedfor(7)' would serve as an informative error result.

To say when an error occurs or to equate two different error expressions we need to use error equations, thus

$$
\begin{array}{ll}
\text { pop(empty) } & =\text { underflow } \\
\text { pop(underflow) } & =\text { underflow }
\end{array}
$$

We call the non-error elements of a 3ort "OK elements", the non-error operators "OK operators" and the non-error equations "OK equations". Now we can write a presentation of a theory with a set of erroropns in addition to the previous (OK)opns, and a set of erroregns in addition to the previous (OK)eqns. An interpretation of such a theory is an 'error algebra', that is an algebra some of whose elements are designated error elements. This designation must obey the following rules:-
(0 Error operators always produce an error element.
(?) OK operators produce an error element if any of their arguments is an error element.

Now for an error algebra to satisfy the theory an OK equation or an error equation does not have to hold for all values of the variables. Only the following must be the case
(1) An OK equation must hold if both sides evaluate to an OK element.
(2) An error equation must hold if either side evaluates to an error element.

## For example

theory sorts nat opns zero: -> nat
succ: nat -> nat
pred: nat -> nat
erroropns neg: -> nat eqns $\operatorname{pred}(3 \operatorname{ucc}(n))=n$ erroreqns pred(zero) $=$ neg succ(neg) $=$ neg pred(neg) $=$ neg endth
Further examples, stack, array and symbol table, are given later.

It often happens that two expressions are equal only under a certain condition, thus

$$
f(x)-g(x) \text { if } p(x)
$$

Now we can permit such a conditional equation by regarding it as an abbreviation for

$$
\text { if }(p(x), f(x), g(x))=g(x)
$$

where 'if' is the usual conditional operator defined for each type by the equations

$$
\text { if (true, } y, z)=y \quad \text { if (false, } y, z)=z
$$

Conditional axioms have been studied using a different approach by Thatcher, Wagner and Wright (1977).

Notice that the fact that our OK equations automatically do not apply to error values often saves us from adding a condition such as
"... If s \# underflow".

## Notation

We should mention some small further points
about notation. If we are naming sorts in a context where several theories are present, the same sort name, s, may appear in two different theories, T1 and T2, making a reference to s ambiguous. We then simply refer to "s of TV" or "s of T2.". A similar notation "f of TT"" will disambiguate operators.

Often a theory has a particular sort which is so to speak its raison d'etre, for example sort nat in theory Nat (even though Nat also has sort bool). To enable us to distinguish such a sort we define the principal sort of a theory to be the first sort mentioned in its definition, thus in 'theory sorts $\mathrm{s}, \mathrm{t} .$. endth' s is the principal sort and similarly in 'enrich T by sorts $\mathrm{s}, \mathrm{t} \ldots$ enden'. Now a helpful convention is to allow the theory name, in lower case, to denote its principal sort. Also when we specify the correspondence between sorts in a derive operation we may omit a pair 's is $t$ ' if $s$ and $t$ are the principal 3orts of their respective theories; similarly for the [... notation used for actual parameters of procedures, thus 'Strings (Nat)' is acceptable for 'Strings (Nat [element is nat])'.

## Examples of specification

We will give two illustrations to show how Clear can be used to build up theories from pieces in a systematic way:-
(i) a theory to specify a symbol table such as one might need in an Algol compiler (an example given by Guttag et al_ 1976)
(ii) a theory to specify a problem solving system for a two dimensional blocks world.
These are, of course, rather small, simple examples, but we hope that they are .just complex enough to give the reader some idea of the modular structure that we wish to see in specifications. We hope the reader can grasp this structure without poring over every equation. The whole Clear description denotes a theory which does not itself have this structure, sc that the implementer would be at liberty to organise his program in some other way..,3 (Just as we might describe the number 19683 as 3, but you are free to store it in the machine in any way you like, 3uch as binary.) Indeed by using derive we 'throw away' many of the operators introduced in our Clear description of the theory, so that they do not appear in the final theory and need have no corresponding procedures in the program which implements it. For example we describe a symbol table in terms of a stack of arrays, because stack and array are familiar concepts, but our specification does not demand that it be implemented in this way.

Here is our plan of campaign showing the main procedures or constants we will define and which other ones will use them.


We will use the thoory Set of sets without derining it. The definitionshould be fairly obvious. We will also use expressions of the form $\{f(x): x \in X \wedge p(x)\}$ instead of defining such sets by explicit equations.

## Stack

Since we can put any kind of element on a stack we take as a parameter theory a trivial theory, one with a single sort and no operators. This describes the 'values' which go on the stack. The operators, such as push and pop, are wellknown. Notice that no 'side-effects' are allowed. We explicitly produce a new stack from push and pop.

```
proc Stack (Value: Triv) =
    induce enricn पद्ध_uब +' Bool by
        gorta atack
            opns nilstack: -> stack
                    push : value,stack->stack
                    empty : stack -> bool
                    pop : stack -> stack
            top : stack ->> value
            erroropng underflow: -> stack
                undef : -> value
    ggna empty(nilstack)= true
            empty(push(v,s))= false
            pop(push(v,s)) =s
            top(push(\nabla,s))=}
            erroregns pop(empty) = underflow
                    top (empty) = undef
                    pop(underflow) = underflow
                        enden
```


## Array

We define arrays with any kind of element as indices, not just integers. However the indices must have an equality relation defined over them in order for us to 'look up' indices in the array, so we have a parameter theory of meta-sort Id., a theory of identifiers with one sort besides bool and an equivalence operator $==$ over that sort.
We write the array access function as a[i] instead of, say, get(a,i).

## const Id $=$

enrich Bool by
sorte identifier
opng $=$ : identifier, identifier $\rightarrow$ bool
eqns $i=i=$ true
$i=\mathrm{i}=\mathrm{j}=\mathrm{j}=\mathrm{i}$
$(i=j) \wedge(j=-k) \wedge\rceil(i=k)=$ false enden

```
proc Array (Index: Id, Value: Triv)=
    induce enrich Index + VElue by
    s0rts EMrav
    Opn⿴ nilarray: -> array
                put : index,value,array->array
                ...[...]: array,index m value
                in : index,urrey m bool
    erroropng undef: index -> value
    eqng put(il,v,e)[i] =v if i==i1
    put(i1,v,a)[i] =a[iT if' i i=mil
    In(i,nilarray) = false
    in(i,put(i|,v,a))={i==il or in(i,a)
    put(i,v,put(il,v1,a)mput(i1,vi,
                                    put(i,v,a))
                            if7 i==i1
    erroregns nilarray[i] = undef(i) enden
```

Symbol table

A compiler needs to maintain a symbol table relating each identifier to a value such as a machine address or an address plus a type．In an Algol－like language with blocks each block introduces new identifiers which may or may not have occurred before．It associates new values with them，and these override any previous values until the end of the block is encountered and the table reverts to its prior state．Thus we need a theory with sorts：symbol，value，table；it has operators：nilst－an empty table，extend－ used to mark entry to a new block，put－to add a symbol value pair，get（written－，．［．．．］）－to retrieve a value，contract－used when the end of the block is reached．Guttag e，t al＿（1976）have already given an equational specification of a symbol table as an abstract data structure．In contrast to their direct specification we will build up ours from the familiar concepts of stack and array，then use derive to extract just those operations which are required for a symbol table．

```
proc Symtap (Symbol: Id, Value: Triv) :
    Let Trble Stack (Array (Symoof Value)) in
    let \(\frac{1 a b 161}{\text { abrich Iable by }}\)
        opns extend: tablér table
            putst : symbol, value, tabla \(\rightarrow\) table
            ... [...7: table, symbol \(\rightarrow\) value
            nilst : \(\rightarrow\) table
    erroropns undef: swhol \(->\) value
    eqns extend \((t)=\) push (nilarray, \(t\) )
    putgif(s,v,t) \(=\) push \((\operatorname{put}(s, v, \operatorname{top}(t)), p o p(t))\)
            \(t[s]=\operatorname{top}(t)[s]\) if in(i,top \((t))\)
            \(t\left[a^{-}\right]=\operatorname{pop}(t)[s]\) if in \((i, \operatorname{top}(t))\)
    erroreqna underflow[g] \(=\) undef(s) in
    let \(T=\) enrich Symbol + Value by
    Borts table
    opns nilst: \(\rightarrow\) table
            extend: table \(\rightarrow\) table
            put皿t: symbol, value, table \(\rightarrow\) table
            ...[...]: table, symbol \(\rightarrow\) value
            contract: table \(->\) table
        erroropns undef: symbol \(\rightarrow\) value onden in
derive gignature \(T\) from Tabled by
            nilat i霊 nilatack
            contract is pop ende
```


## Tabletop and Blocks World

Now let us specify a very crude model of a set of blocks on a tabletop together with some commands for moving them．We will stick to two
dimensions and assume square blocks all of the same size．We can do this in terms of a one－ dimensional array indexed by places on the table， each element of the array is a stack of blocks． We enrich this array of stacks theory with some extra operations：create an empty array of stacks， put a block on the stack at a given place，move a block from the stack at a place onto the stack at another place．We now use derive to get rid of the unwanted operations on stacks and arrays，just retaining these operations on an array of stacks， which we rename a tabletop．We do however need an equality for tabletops，because later we want to do problem solving and see whether we have the required goal tabletop．For this we use a theory procedure Stackeg（Value：Id）of stacks with equality（＝＝：stack，stacic $->$ bool）．Its defin－ ition from Stack（Value：Triv）by enrichment is left as an easy exercise．Similarly for Arrayeg（index：Id，Value：Id）．

```
proc Tabletop (Block: Id, Place: Id.) =
    let Stackofblocka - Stackeq (Block) in
    let ArravofstacTcs" = Arraveq (Place,StackofblocksX"
    let T = enrich Array of stacks by
            opns empty: -> arrayofst
```

                put: place,block,arrayofst->arrayofst
                    move: place,place, arrayofst->arrayofst
            erroropns error: -> arrayofst
            eqns empty[p] = nilstack
                    \(\operatorname{put}(p, b, a)=\operatorname{put}(p, \operatorname{push}(b, a f p]), a)\)
                    move(p, \(\left.p^{\prime}, p u t(p, b, a)\right)-p u t\left(p^{\prime} b . a\right)\)
            erroregns move \((p, p, a)=\) serror if isemptv \((a[p])\)
                                    enden in
    derive signature enrich Block + Place by
    sorts tabletop
        opns empty: -> tabletop
            put : place,block,tabletop \(->\) tabletop
            move : place, place,tabletop \(->\) tabletop
            \(=\) - : tabletop, tabletop \(\rightarrow\) bool
        erroropas euror: -> tabletop
    from \(T\) by. tabletop is, arrayofst endde
        The problem solver will seek a string of
    actions to transform one tabletop to another.. To
provide these actions we define some commands,
just expressions of the form "makemove(place1,
place2)" using an operator "makemove" with no
equations (like succ for numbers). Now we can
define a dynamic Blocks World, in which you can
execute commands to change the tabletop,

enden
State-action system and Problem Solver
Quite separately from the Blocks World, but
later to be combined with it, we define a Problem
Solver theory for some arbitrary system with
states and actions. First we define the state-
action system alone with just these two sorts, then we have a procedure Iterate to enrich any state-action system to give the" effect of a whole string of actions. A problem solver is then defined for such a system, with an operation solve which must attain any reachable set of goal states- Note that we do not say how solve is to be programmed, just specify its desired result.
const State-action-system $=$
Let State $=$ CDOX $\frac{10}{}$ In tet Action $=$ copy Id in enrich State + Rotion + Sat (Action) by opns do: action,state $->$ state acts: $\rightarrow$ get(action) erroropns error: -> state enden
proc Iterate (Sas: State-action-syotem) $=$ Let action s.tring $=$ tring (Sas [element is action]) ancich SAS+ACtion-string by
opns do: action-strine, state -> state
eqns $d o(n i l, s)=g$

$$
\mathrm{do}(a s . \operatorname{unit}(a), s)=\mathrm{do}(\mathrm{a}, \mathrm{do}(\mathrm{as}, \mathrm{~s})) \text { enden }
$$

proc Problem-aolver (Sas: State-action-system) $=$ enri Ch Iteritu (Sas) +Nat oy
onns rachable: nat, ifate $\rightarrow \operatorname{set}($ atate $)$ solve : nat,state, set (state) $\rightarrow$ action-string
erroropns error: $\rightarrow$ action-string eqns reachable $(0, s)=\{ \}$
reachable $(n+1, s)=\{\alpha 0(a, s 1) \mid a \in \operatorname{acts}$ $\wedge$ s1 $\in$ readable $(n, s)\}$
do(solve $(n, s, 3), s) \in S=$ true
erroreqns solve(n.s,s) $=$ error
if readnable $(n, s) n S==\{ \}$
enden

## Blocks World Problem Solver

We now put this all together by deriving the required operations for a state-action system from the Blocks World, and applying the theory producing procedure Problem-Solver to it. The resulting theory specifies the notion of solving a problem for our Blocks World, that is finding a sequence of suitable moves to get from one state to a specified set of states. (In practice we would have to add extra operators to describe the start and goal states.) We choose to represent blocks and places by natural numbers, but we leave as a parameter the set of natural numbers determining just which places are involved.
 enden
proc Blocks-problem-solver (S: Setofnumbers) $=$
let Sas $=$ derive giphature State-action-system from Elocksworl (Nat, Nat) ${ }^{7} \underline{\underline{S}}$ state is tabletop action is commend acts is luove $\left(p^{1}, p 2\right): p 1 \in$ nset p2 $\varepsilon$ nset $\}$
do is execute endde in

## Problem-solver (Sas)

Some open questions
A number of questions arise from these
examples.
(i) The language pays for the extra structure and localness by being rather cumbersome. Is this inevitable? We tried to moderate the longwindedness by 3ome conventions, but feared to sprinkle too much 3Ugar lest the reader lose sight of the basic mechanisms.
(ii) Should we distinguish two kinds of enrichment (a) adding new sorts and operators and equations about them, but without constraining existing operators further, (b) imposing further equations on the existing operators?
(iii) Could we improve on the rather clumsy way sharing is indicated in derive?
(iv) The induce operation is rather different from the others, a little mysterious. We stuck it in whenever we were talking about a particular data structure. Could it be inserted more systematically? Perhaps we should distinguish between theories used as metasorts, which generally do not need induce, and other theories, which generally do. Does induce allow us to make all the inductive inferences we need?
(v) Is our transfer of the LISP sharing paradigm to theories the best approach? Can we make good our claim to understand its semantics?

## Programs and theory morphisms

In this section we discuss in a tentative way how programs, as opposed to specifications, might fit into our algebraic framework. For this we will need to define a 'morphism' between theories, which represents one theory in another. (The theories and their morphisms form a category, Lawvere 1963). The idea is that a program is essentially a means of representing one theory (the specification) in another theory (the machine), that is a morphism from one to the other.

We can often represent operators of one theory by operators of another, to be precise by derived operators of the other theory. By a derived operator of a theory we mean one which can be expressed in terms of the primitive operators. In a theory with primitives 'not' and 'and' the operator

## $\lambda x y .7(\neg \times \wedge\urcorner y)$

is a derived operator ('or'). In general we may build any term in the primitive operators using suitable variables, using the familiar $\boldsymbol{\lambda}$ notation to bind these variables. These operators include miliary ones, that is constant terms. An operator may be represented by more than one derived operator of the other theory. Since our theories may involve several sorts we must also represent each sort of the first theory by a sort of the second.

Now the operators of the first theory obey certain equations, so naturally the same equations must be true of the corresponding derived operators of the second theory.

We call such a connection between two
theories a theory morphism. Here is the definition.*

A theory morphism from a theory T to a theory $\mathrm{T}^{\prime}$ is
(i) A function $f$ from the sorts of $T$ to the sorts of $T$. Ve write $s$ is $s$ to mean $f(s)=s^{1}$.
(ii) A function $g$ from the operators of $T$ to nonempty sets of derived operators of T , such that any equation of $T$ gives rise to an equation of $T^{\prime}$ when each operator $\boldsymbol{W}$ of $T$ is replaced by any operator in $g(\boldsymbol{\omega})$ - The input and output sorts of an operator in $g(\boldsymbol{\omega})$ must be the f-images of those of $\boldsymbol{\omega}$ - We write $\boldsymbol{\omega}$ is $\boldsymbol{\omega}^{\prime}$ to mean $g(\boldsymbol{\omega})$ - $\boldsymbol{\omega}^{\prime}$.
By the obvious extension, the* theory morphiam maps each derived operator of $T$ to a set of derived operators of T '; this holds in particular for nullary operators i.e. constant terms.

Consider for example Id., 'the theory of identifiers with an equivalence operator, and Nat the theory of natural numbers. We can definēa morphism from Id to Nat by


Suppose that we enrich Nat with a multiplication operator to get, say, Naymlt. Then we cou have a morphism from Bool to Netmit
sorta bool is nat.
opna false is
true is $\left\{\begin{array}{l}0,2,4, \ldots\}\} \\ 1,3,5, \ldots\}\end{array}\right.$
7 18 suce $\}$
A is $\{*$
Representing sets by strings and stacks by array-index pairs are other well-known examples.

As a matter of fact such theory morphisms play an essential role in our mathematical semantics for Clear. But here we are concerned with their connection with programs. It seems that if we restrict ourselves to an applicative language (without assignment) our theory morphisms are the mathematical correlate of a SIMULA class, CLU cluster or ALPHARD form, with the theory T playing the (generalised) role of the newly defined data type and the theory T ' being the existing data type used to represent it. The derived operators in the morphism from T to T ' are the procedures in the class, cluster or form declaration.

We do need one generalisation however since in the programming case the procedures may well be recursive. Fortunately Wright, Thatcher, Wagner and Goguen (1976) have defined a notion of rational theories and their morphisms** allowing recursively

* Our theory morphisms are different from Lawvere's which represent an operator by a single derived operator.
** We would also need rational theories to make Clear deal properly with infinite data, such as infinite trees, defined inductively.
derived operations (not just $\boldsymbol{\lambda}$ but recursion too); this seems to model the real programming situation (always provided that we regard an imperative program as a notational variant of an applicative one!).

Now we see that a specification is just a theory, a machine (or more abstractly the primitive operators and sorts of a programming language) is another theory, and a program to realise the specification is just a (rational) morphism from the specification theory to the machine theory.

Of course we should not describe this morphism in an unstructured way, indeed there should be a programming language analogous to the specification language Clear, but describing morphisms not theories.** This would be the correlate of SIMULA etc. or more closely of the iota language of Naka.jima et al, and of Parnas' (197?) method of programming with modules. We have worked on such a language but decided to first get straight the rather easier case of a specification language.

How would the structure of such a program relate to the structure of the specification which it implements? The degree of closeness would be up to the implementer, but it would be natural to use the various theories defined for specification purposes to define the task of subparts of the program. In general one would expect the specification would be simpler than the program, and to specify parts of the program one would need to elaborate the theories used in the specification with new sorts and operators. For example one might decide to use the GPS method to solve the blocks world problem, and one would have to enrich the state-action theory with new sorts like 'difference' and operators like 'reduces'.

A speculative conclusion: the main intellectual task of programming is elaborating the theories which describe all the concepts used in the actual program. Writing the code (defining the morphisms) is a much more humdrum business.

Ah well! This is all delightfully vague and a great deal of work needs to be done. But it does promise to be interesting.

## Conclusions

The main point of this paper is that it is possible to specify complex tasks provided that we do not try to write the specifications in an unstructured way. Our particular language proposal is only important in bringing into fbcus the problem of devising structured descriptions of specifications and suggesting the kind of operations which should be used to build them up. The basic ideas developed for data abstraction in programming languages should guide us in this task, and we firmly believe that the mathematical ideas about the category of theories can help us to grasp the rather deep concepts involved-

[^0]
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## References

Arsac, J. (1977) Program transformations as a programming tool. Research Report, Institut de Programmation, University de Paris VI.
Aubin, R. (1976) Mechanising structural induction. Ph.D. thesis. Depts. of Artificial Intelligence and Computer Science, University of Edinburgh.

Boyer, R.S. and Moore, J S. (1975) Proving theorems about LISP functions. JACM, 22, 1, 129-144.

Burstall, R.M. and Darlington, J. (1977) A transformation system for developing recursive programs. JACM, 14, 1, 44-67.
Burstall, R.M. (1977) Program proof, program transformation, program synthesis for recursive programs. Lecture notes at Summer School, Erice, Sicily, 1976. To appear in Information the Journal of the Italian Association for Computer Science.
Dahl, O-J., Myhrhaug, B. and Nygaard, K. (1970) The SIMULA 67 Common Base Language. Publication S22. Norwegian Computing Centre, Oslo.

Darlington, J. (1975) Application of program transformation to program synthesis. Proc. of International Symposium on Proving and Improving Programs, Arc-et-Senans, France, pp. 133-144.
Darlington, J. (1976) The use and implementation of very high level specifications. Invited paper at IFIP WG 2.3 Conference on Software Specifications. St. Pierre-de-Chartreuse, France.

Darlington, J. and Burstall, R.M. (1976) A system which automatically improves programs. Acta Informatica, 6, 41-60.
Dijkstra, E.W. (1975) Guarded commands, nondeterminacy and formal derivation of programs. CACM, 18, 8, 453-457.

Goguen, J.A. (1976) Correctness and equivalence of data types. Proc. of 1975 Conference on Algebraic Systems, Udine, Italy, pp. 352-358. Springer-Verlag.

Goguen, J.A. (1917) Abstract errors for abstract data types. To appear in Proc. of IFIP Working Conference on the Formal Description of Programming Concepts, New Brunswick, N.J.

Goguen, J.A. and Tardo, J. (1977) OBJ-O Preliminary Users Manual, Semantics and Theory of Computation Report, UCLA, Los Angeles.
Goguen, J.A., Thatcher, J.W. and Wagner, E.G. (1977) An initial approach to the specification, correctness and implementation of abstract data types. To appear in Current trends in programming methodology, Vol. 3. Data Structuring (ed. R.T. Yeh) Prentice Hall.

Guttag, J.V. (1975) The specification and application to programming of abstract data types. Computer Systems Research Technical Report CSRG-59, University of Toronto.

Guttag, J.V., Horowitz, E. and Musser, D.R. (1976) Abstract data types and software validation. Report ISI/RR-76-48, Information Sciences Institute, Marina del Rey, California.

Kowalski, R. (1974) Predicate logic as a programming language. Proc. of IFIP Congress '74, pp 569-574, North Holland.
Lawvere, F.W. (1963) Functional semantics of algebraic theories. Proc. of National Academy of Science. 50, pp. 869-872.

Liskov, B.H. (1975) A note on CLU. MAC-TR, MIT, Cambri dge, Mass•

Liskov, B.H. and Berzins, V. (1977) An appraisal of program specifications. Computation Structures Group Memo 141-1, MIT, Cambridge, Mass.

Mackworth, A.K. (1977) Consistency in networks of relations. Artificial Intelligence, 8, 1_, 99-118.

Manes, E.G. (1976) Algebraic theories. Springer Verlag.
Manna, Z. and Waldinger, R. (1971) Toward automatic program synthesis. CACM, 14, 3. 151-165.
Manna, Z. and Waldinger, R. (1975) Knowledge and reasoning in program synthesis. Artificial Intelligence, 6, 2, 175-208.
McCarthy, J. (1963) A basis for a mathematical theory of computation. Computer Programming and Formal Systems (eds. P. Braffort and D. Hirschberg) North Holland.

Minsky, M. (1975) A framework for representing knowledge. The Psychology of Computer Vision (ed. P. Winston) McGraw-Hill: New York.

Mosses, P. (1975) Making denotational semantics less concrete. To appear in Proc. of the Bad Honnef Workshop on Semantics of Programming Languages.

Nakajima, R., Honda, M. and Nakahara, H. (1977) Programming and verification schemes in the iota system. To appear in Proc. of IFIP Working Conference on the Formal Description of Program--ing Concepts, New Brunswick, N.J.
Parnas, D.L. (1972) A technique for module specification with examples. CACM, 15, 5, 330-336.
Scott, D. and Strachey, C. (1971) Towards a mathematical semantics for computer languages. Technical Monograph PRG 6, Computing Laboratory, Oxford University.
Thatcher, J.W., Wagner, E.G. and Wright, J.B. (1977) Specification of abstract data types using conditional axioms. Report IBM Laboratories, Yorktown Heights, N.Y.
Waltz, D. (1975) Understanding line drawings of scenes with shadows. The Psychology of Computer Vision (ed. P. Winston) MoCraw Hill: New York.

Wright, J.B., Thatcher, J.W., Wagner, E.G. and Goguen, J.A. (1976) Rational algebraic theories and fixed point solutions. Proc. of IEEE 17th Symposium on Foundations of Computer Science, Houston, pp. 147-158.
Wulf, W.A., London, R.L. and Shaw, M. (1976) Abstraction and verification in ALPIIARD. ISI/RR-76-46, Information Sciences Institute, Marina del Rey, California. Also as a CarnegieMellon Computer Science Report.
Zilles, S. (1974) Algebraic specification of data types. Computation Structures Group Memo 119, MIT, Cambridge, Mass.


[^0]:    ** We have a base for such development in the equational languages we have already implemented OBJ (Goguen and Tardo 1977) and NPL (Burstall 1977).

