

1 Sound Notional Machines

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3 A notional machine is a pedagogical device that abstracts away details of the semantics of a programming
4 language to focus on some aspects of interest. A notional machine should be *sound*: it should be consistent
5 with the corresponding programming language, and it should be a proper abstraction. This reduces the risk
6 of it introducing misconceptions in education. Despite being widely used in computer science education,
7 notional machines are usually not evaluated with respect to their soundness. To address this problem, we first
8 introduce a formal definition of soundness for notional machines. The definition is based on the construction
9 of a commutative diagram that relates the notional machine with the aspect of the programming language
10 under its focus. Derived from this formalism, we present a methodology for constructing sound notional
11 machines, which we demonstrate by applying it to a series of small case studies. We also show how the
12 same formalism can be used to analyze existing notional machines and find inconsistencies in them as well
13 as propose solutions to these inconsistencies. The work establishes a firmer ground for research in notional
14 machines by serving as a framework to reason about them.

15
16 CCS Concepts: • Social and professional topics → Computing education; • Software and its engineering
17 → Formal language definitions; Context specific languages.

18 Additional Key Words and Phrases: notional machines, programming education

19 1 INTRODUCTION

20 Learning to program involves learning how to
21 express a program in a programming language,
22 but also learning what the semantics of such
23 a program is. For novices, the semantics of a
24 program is often not obviously apparent from
25 the program itself. Instructors then often use a
26 *notional machine* [Fincher et al. 2020] to help
27 teach some particular aspect of programs and
28 programming languages, and also to assess stu-
29 dents' understanding of said aspect. This aspect
30 is the notional machine's focus. For example,
31 showing expressions as trees (the ExPTREE no-
32 tional machine), as depicted in Figure 1, brings
33 out the internal structure of lambda-calculus ex-
34 pressions [Marceau et al. 2011] and can help to
35 explain the step-by-step evaluation of such ex-
36 pressions. Notional machines are used widely
37 in computer science education; Fincher et al.
38 [2020] interviewed computer science teachers
39 to build up a collection of over 50 notional machines¹.

40 1.1 Unsound Notional Machines

41 Given the extensive use of notional machines, and their intended use as devices to help students
42 when learning, it is important to look at their quality. To begin with, one should make sure that the
43 notional machine is *sound*: it is faithful to the aspect of programs it is meant to focus on. Anecdotal
44 evidence of using unsound representations in education goes back a long way. In 1960, education

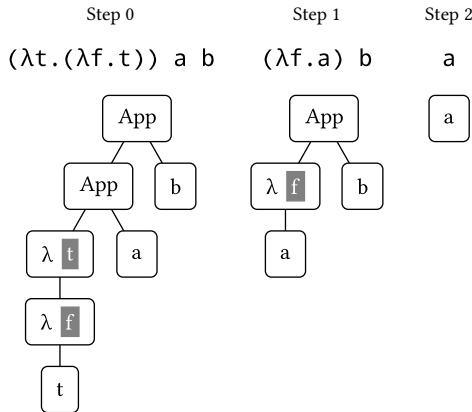


Fig. 1. Evaluation of the term $(\lambda t.(\lambda f.t)) a b$ shown with the notional machine ExPTREE.

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47
48¹<https://notionalmachines.github.io/notional-machines.html>

50 pioneer Jerome Bruner wrote that “the task of teaching a subject to a child at any particular age is
 51 one of representing the structure of that subject in terms of the child’s way of viewing things”, that
 52 this “task can be thought of as one of translation”, but that ideas have to be “represented *honestly*
 53 [...] in the thought forms of children” [Bruner 1960]. Bruner’s use of the term “honestly” can be
 54 seen as a call for soundness of such representations. Decades later, Richard Feynman eloquently
 55 stated [Feynman 1985], after reviewing “seventeen feet” of new mathematics schoolbooks for the
 56 California State Curriculum Commission:

57 [The books] would try to be rigorous, but they would use examples (like automobiles
 58 in the street for “sets”) which were almost OK, but in which there were always some
 59 subtleties. The definitions weren’t accurate. Everything was a little bit ambiguous.
 60

61 Ambiguously specified notional machines and notional machines with imperfect analogies
 62 to programming concepts are a problem. Educators may mischaracterize language features and
 63 students may end up with misconceptions [Chiodini et al. 2021] instead of profoundly understanding
 64 the language.

65 For example, Fincher et al. [2020] describe
 66 the “Array as Row of Spaces in Parking Lot”
 67 notional machine. Figure 2 shows part of their
 68 card summarizing it. Notice the parallels be-
 69 tween the programming language (PL) and the
 70 notional machine (NM). Consider Java, a lan-
 71 guage commonly used in programming courses.
 72 In Java, when an array of objects is allocated,
 73 all its slots contain **null**, which means these
 74 slots don’t contain a reference to any object.
 75 This would be reasonably represented in the
 76 notional machine as an empty parking lot. But if
 77 instead of an array of objects, we have an array
 78 of **ints**, for example, then when we instantiate
 79 an array, all its slots contain **0**, which is not
 80 the absence of a number but a number like any
 81 other. A student could also reasonably question
 82 whether one can park a car in a slot that is al-
 83 ready occupied by another car, or whether one
 84 has to remove a car from a spot to park another
 85 car in the same spot. In fact, the authors point out that, “the effectiveness of the analogy depends
 86 on [...] how well that models the semantics of the programming language.”

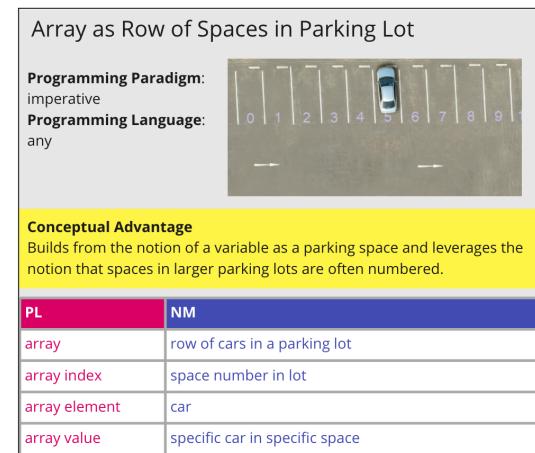


Fig. 2. The “Array as Row of Spaces in Parking Lot” notional machine captured by Fincher et al. [2020].

87 1.2 Soundness of Notional Machines via Simulation

88 To avoid these issues, we need to make sure that a notional machine is indeed an accurate ab-
 89 straction. Although the more general view of notional machines as “pedagogic devices to assist
 90 the understanding of some aspect of programs or programming” [Fincher et al. 2020] makes no
 91 direct reference to programming languages, programs are expressed in programming languages
 92 so we will look at these “aspects of programs” through the lens of how they are realized by some
 93 programming language. If a notional machine represents a part of the operational semantics of a
 94 programming language, for example, then this representation should be sound, in the sense that
 95 steps in the notional machine correspond to steps in the operational semantics of the programming
 96 language.
 97

Showing the soundness of a notional machine amounts to demonstrating that the notional machine *simulates* (in the sense described by Milner [1971]) the aspect of programs under the focus of the notional machine. This property can be given in the form of a commutative diagram. Milner’s simulation was also used by Hoare [1972] to establish a definition of the correctness of an ‘abstract’ data type representation with respect to its corresponding ‘concrete’ data type representation. Cousot and Cousot [1977] use a similar commutative diagram to simulate concrete computations in their abstract interpretation framework. This interpretation of simulation also captures the relationship between a notional machine and the underlying programming language because a notional machine is indeed an *abstraction* of some aspect of interest.

1.3 Contributions

This paper makes the following contributions:

- A formal definition of sound notional machine based on simulation (Section 2.1.2).
- A methodology for designing notional machines that are sound by construction.
It consists of deriving part of the notional machine by leveraging the relationship between the abstract representation of the notional machine and the abstract syntax of the programming language under its focus.
We demonstrate the methodology by applying it to a combination of various small programming languages, notional machines, and aspects of programming language semantics (Section 2).
- A methodology for analyzing notional machines with respect to their soundness.
It consists of modelling the notional machine and the aspect of the programming language under its focus, relating them via simulation.
We demonstrate the methodology by analyzing existing notional machines, sometimes pointing out unsoundnesses, and suggesting directions for improvement (Section 3).

A brief discussion about the distinction between the abstract and concrete representations of a notional machine follows in Section 4. We then evaluate, in Section 5, the entire framework by comparing the notional machines that appeared in Section 2 and Section 3 to an existing dataset of 37 notional machines. We classify the notional machines in the dataset according to various dimensions and show that the notional machines we analyzed are representative of the design space of notional machines used in practice. Section 6 discusses related work and Section 7 concludes.

2 DESIGNING SOUND NOTIONAL MACHINES

We can only begin to talk about the soundness of a notional machine if we have a formal description of the programming language the notional machine is focused on. We use a set of small programming languages with well-known formalizations described in Pierce’s Types and Programming Languages (TAPL) book [Pierce 2002]. The languages are used to explore different aspects of programming language semantics. Table 1 shows the notional machines we use in this section as well as the corresponding programming language and aspect of the semantics of the programming language that the notional machine focuses on. We use the first example also to introduce the definition of soundness for notional machines.

We model each programming language and notional machine in Haskell. The models are executable, so they include implementations of the programming languages (including parsers, interpreters, and type-checkers), the notional machines, and the relationship between them². The soundness proofs presented in this section are done using equational reasoning [Bird 1989; Gibbons 2002].

²The artifact containing a superset of the examples in this paper is at ANONYMOUS.

Section	Notional Machine	Programming Language	Focus
2.1	EXPTREE	UNTYPEDLAMBDA	Evaluation
2.2	EXPTUTORDIAGRAM	UNTYPEDLAMBDA	Evaluation
2.3	TAPLMEMORYDIAGRAM	TYPEDLAMBDAREF	Evaluation (Refs)
2.4	TYPEDEXPTUTORDIAGRAM	TYPEDARITH	Type-checking

Table 1. Notional machines, programming languages, and aspects of focus used in Section 2.

$$\begin{array}{ccc}
 A_{NM} & \xrightarrow{f_{NM}} & B_{NM} \\
 \alpha_A \uparrow & & \uparrow \alpha_B \\
 A_{PL} & \xrightarrow{f_{PL}} & B_{PL}
 \end{array}$$

$$\alpha_B \circ f_{PL} \equiv f_{NM} \circ \alpha_A \quad (1)$$

Fig. 3. Soundness condition for notional machines shown as a commutative diagram and in algebraic form.

2.1 Isomorphic Notional Machines

As a first straightforward example, let's look at a notional machine for teaching how evaluation works in the untyped lambda-calculus (we will refer to this language as UNTYPEDLAMBDA³). While most research papers discuss the lambda-calculus using its textual representation, textbooks sometimes illustrate it using tree diagrams [Pierce 2002, p. 54]. We use this as an opportunity to define a simple notional machine which we call EXPTREE.

2.1.1 *Illustrative Example.* Figure 1 uses EXPTREE to demonstrate the evaluation of a specific lambda expression, which happens in two reduction steps. The top of the figure shows the terms in the traditional textual representation of the programming language, while the bottom shows the terms as a tree.

2.1.2 *Soundness via Commutative Diagrams.* In general, a notional machine is sound if the diagram in Figure 3 commutes. We call the commutativity of this diagram the *soundness condition* for a notional machine. In this diagram, the vertices are types and the edges are functions. We will explain the diagram while instantiating it for this illustrative example (the result of this instantiation is shown in Figure 4).

The bottom layer (A_{PL}, f_{PL}, B_{PL}) represents the aspect of a programming language⁴ we want to focus on. A_{PL} is an abstract representation of a program in that language. In our example, that is the abstract syntax of UNTYPEDLAMBDA (given by the type $\text{Term}_{U\lambda}$). The function f_{PL} is an operation the notional machine is focusing on. In our example, that would be *step*, a function that performs

³The syntax and reduction rules for UNTYPEDLAMBDA are reproduced in Appendix A.1.

⁴Although we refer to the bottom layer of the diagram as the programming language layer and we restrict ourselves to analyzing aspects of the syntax and semantics of programming languages, for which we have well-established formalizations, that is not an intrinsic restriction of the approach. In principle, the bottom level of the diagram can be whatever aspects of programs or programming the notional machine is focused on.

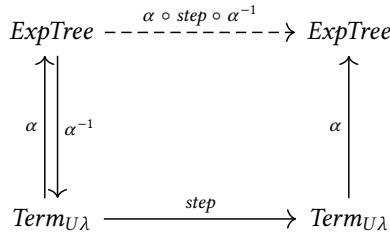


Fig. 4. Instantiation of the commutative diagram in Figure 3 for the notional machine `EXP TREE` and the programming language `UNTYPEDLAMBDA`.

a reduction step in the evaluation of a program according to the operational semantics of the language, which in this case also produces a value of type $\text{Term}_{U\lambda}$.

The top layer of the diagram (A_{NM}, f_{NM}, B_{NM}) represents the notional machine. A_{NM} is an abstract representation of the notional machine (its abstract syntax). In our simple example, that is a type `ExpTree` trivially isomorphic to $\text{Term}_{U\lambda}$ via a simple renaming of constructors. The function f_{NM} is an operation on the notional machine which should correspond to f_{PL} . Connecting the bottom layer to the top layer, there are the functions α_A and α_B from the abstract representation of a program in the programming language to the abstract representation of the notional machine. α is also called an abstraction function.

Definition 2.1. Given the notional machine $(A_{NM}, B_{NM}, f_{NM} : A_{NM} \rightarrow B_{NM})$, focused on the aspect of a programming language given by $(A_{PL}, B_{PL}, f_{PL} : A_{PL} \rightarrow B_{PL})$, the notional machine is *sound* iff there exist two functions $\alpha_A : A_{PL} \rightarrow A_{NM}$ and $\alpha_B : B_{PL} \rightarrow B_{NM}$ such that $\alpha_B \circ f_{PL} \equiv f_{NM} \circ \alpha_A$.

If the abstract representation of the programming language (A_{PL}) is isomorphic to the abstract representation of the notional machine (A_{NM}) , we can construct an inverse mapping α_A^{-1} such that $\alpha_A^{-1} \circ \alpha_A \equiv id \equiv \alpha_A \circ \alpha_A^{-1}$. In that case, we can always define a correct-by-construction operation f_{NM} on A_{NM} in terms of an operation f_{PL} on A_{PL} :

$$\begin{aligned} f_{NM} &:: A_{NM} \rightarrow B_{NM} \\ f_{NM} &= \alpha_B \circ f_{PL} \circ \alpha_A^{-1} \end{aligned}$$

In such cases, the diagram always commutes and therefore the notional machine is sound:

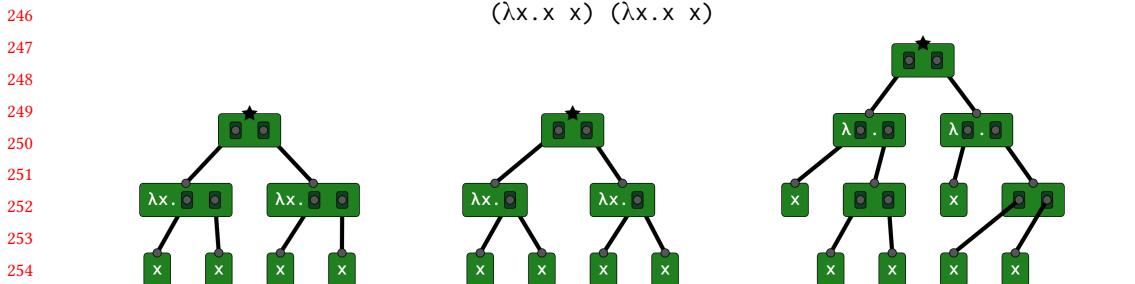
$$f_{NM} \circ \alpha_A \equiv \alpha_B \circ f_{PL} \circ \alpha_A^{-1} \circ \alpha_A \equiv \alpha_B \circ f_{PL} \quad (2)$$

Instantiating the commutative diagram for `EXP TREE` and `UNTYPEDLAMBDA` yields the diagram in Figure 4. A dashed line indicates a function that is implemented in terms of the other functions in the diagram and/or standard primitives.

We call these isomorphic notional machines because they are isomorphic to the aspect of the programming language they focus on (a condition sometimes called *strong simulation* [Milner 1971]). Of course that's a rather strong condition and not every notional machine is isomorphic so throughout the next sections we will move further away from this simple example, arriving at other instantiations of this commutative diagram.

2.2 Monomorphic Notional Machines

Notional machines can also serve as the basis for so-called “visual program simulation” [Sorva et al. 2013] activities, where students manually construct representations of the program execution. This



260 effort often is supported by tools, such as interactive diagram editors, that scaffold the student's
261 activity. Obviously, instructors will want to see their students creating correct representations.
262 However, to prevent students from blindly following a path to a solution prescribed by the tool, the
263 visual program simulation environment should also allow *incorrect* representations.

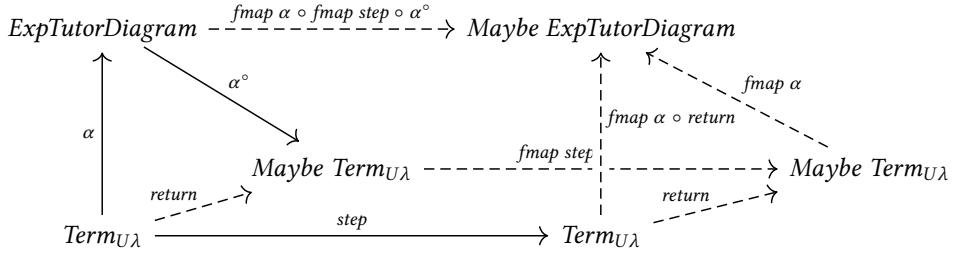
264 ExpressionTutor⁵ is such an educational tool to teach the structure, typing, and evaluation of
265 expressions in programming courses. In ExpressionTutor, students can interactively construct
266 expression tree diagrams given a source code expression. The tool is language agnostic so each
267 node can be freely constructed (by the instructor or the student) to represent nodes of the abstract
268 syntax tree of any language. Nodes can contain any number of holes that can be used to connect
269 nodes to each other. Each hole corresponds to a place in an abstract syntax tree node where an
270 expression would go. Nodes can be connected in a variety of ways, deliberately admitting incorrect
271 structures that not only may not be valid abstract syntax trees of a given programming language
272 but may not even be trees. Even the root node (labeled with a star) has to be explicitly labeled by
273 the student, so it is not guaranteed to exist in every diagram.

274 We define the notional machine EXP TUTOR DIAGRAM, which models the behavior of Expression-
275 tutor. The fact that ExpressionTutor allows students to construct incorrect expression tree
276 diagrams means that the abstraction function α is not bijective, as was the case of EXP TREE's α .
277 Such incorrect diagrams do not correspond to programs, thus α is deliberately not surjective.

278
279 2.2.1 *Illustrative Example.* Figure 5 uses EXP TUTOR DIAGRAM to represent the omega combinator.
280 The top shows the textual form on the level of the programming language. Below that are three
281 different incorrect representations students could produce. The left tree collapses the applications
282 (the terms $x x$) into the enclosing lambda abstraction. The middle tree similarly does this, but it
283 preserves the structure of the lambda abstraction node, while violating the well-formedness of the
284 tree by plugging two children into the same hole. The right tree shows a different problem, where
285 the definition of the name is pulled out of the lambda abstraction and shown as a name use.

286 2.2.2 *Commutative Diagram.* In general, if the mapping α_A , from the abstract representation of
287 the programming language (A_{PL}) to the abstract representation of the notional machine (A_{NM}), is
288 an injective but non-surjective function, we can still define the operations on A_{NM} in terms of the
289 operations on A_{PL} . For this we define a function $\alpha_A^\circ : A_{NM} \rightarrow \text{Maybe } A_{PL}$ to be a left inverse of
290 α_A such that $\alpha_A^\circ \circ \alpha_A \equiv \text{return}$ (we use *return* and *fmap* to refer to the *unit* and *map* operations on
291 monads). Here we modeled the left inverse using a *Maybe* but another monad could be used, for

292
293 ⁵expressiontutor.org

Fig. 6. Instantiation of the commutative diagram in Figure 3 for the notional machine `ExpTUTORDIAGRAM`

example, to capture information about the values of type A_{NM} that do not have a corresponding value in A_{PL} . The top-right vertex of the square (B_{NM}) in this case is the type $\text{Maybe } B'_{NM}$ and the mapping α_B can be implemented in terms of a mapping $\alpha'_B : B_{PL} \rightarrow B'_{NM}$ like so:

$$\begin{aligned} \alpha_B &:: B_{PL} \rightarrow B_{NM} \\ \alpha_B &= \text{return} \circ \alpha'_B \end{aligned}$$

Using the left inverse α_A° and α'_B , we define the operation on A_{NM} as follows:

$$\begin{aligned} f_{NM} &:: A_{NM} \rightarrow B_{NM} \\ f_{NM} &= \text{fmap } \alpha'_B \circ \text{fmap } f_{PL} \circ \alpha_A^\circ \end{aligned}$$

This square commutes like so:

$$\begin{array}{ll} \begin{array}{l} f_{NM} \circ \alpha_A \\ \equiv \{ \text{definition of } f_{NM} \} \\ \quad \text{fmap } \alpha'_B \circ \text{fmap } f_{PL} \circ \alpha_A^\circ \circ \alpha_A \\ \equiv \{ \alpha_A^\circ \text{ is left inverse of } \alpha_A \} \\ \quad \text{fmap } \alpha'_B \circ \text{fmap } f_{PL} \circ \text{return} \\ \equiv \{ \text{third monad law} \} \\ \quad \text{fmap } \alpha'_B \circ \text{return} \circ f_{PL} \end{array} & \begin{array}{l} \alpha_B \circ f_{PL} \\ \equiv \{ \text{definition of } \alpha_B \} \\ \quad \text{return} \circ \alpha'_B \circ f_{PL} \\ \equiv \{ \text{third monad law} \} \\ \quad \text{fmap } \alpha'_B \circ \text{return} \circ f_{PL} \end{array} \end{array}$$

We can use this result to instantiate the commutative diagram of Figure 3 for `ExpTUTORDIAGRAM` and `UNTYPEDLAMBDA`, shown in Figure 6. A_{PL} is defined to be the type `ExpTutorDiagram`, which essentially implements a graph. Each node has a top plug and any number of holes, which contain plugs. Edges connect plugs. That allows for a lot of flexibility in the way nodes can be connected.

The ExpressionTutor tool is language agnostic but we can only talk about soundness of a notional machine with respect to some language and some aspect of that language. In this case, we say the tool implements a family of notional machines, each one for a given aspect of focus and a given programming language. We consider here a notional machine focused on evaluation and the programming language again `UNTYPEDLAMBDA` (denoted again by the type $Term_{U\lambda}$), with f_{PL} equal to `step`.

The construction of a mapping $\alpha :: Term_{U\lambda} \rightarrow ExpTutorDiagram$ is straightforward because a term $t :: Term_{U\lambda}$ forms a tree and from it we can always construct a corresponding ExpressionTutor diagram $d :: ExpTutorDiagram$ (a graph). For each possible term in $Term_{U\lambda}$, we need to define a pattern for the content of the corresponding `ExpTutorDiagram` node which will help the student identify the kind of node. The construction of the left inverse mapping $\alpha^\circ :: ExpTutorDiagram \rightarrow Maybe Term_{U\lambda}$ requires more care. We need to make sure that the diagram forms a proper tree and that the pattern

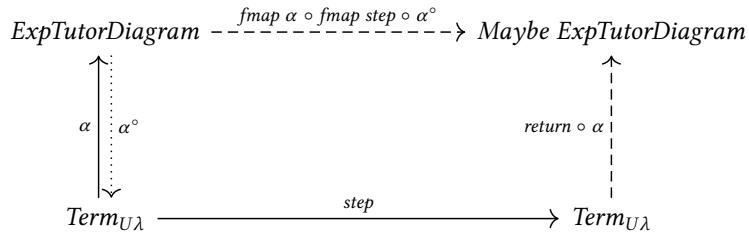


Fig. 7. Simplified version of the commutative diagram for *ExpTutorDiagram* shown in Figure 6.

formed by the contents of each *ExpTutorDiagram* node corresponds to a possible $Term_{U\lambda}$ node, besides making sure that they are connected in a way that indeed corresponds to a valid $Term_{U\lambda}$ tree.

In the next section, we construct another commutative diagram where f_{NM} is defined using f_{PL} and a left inverse mapping α_A° . To emphasize that point and simplify the diagrams, we will depict the left inverse in the diagram as a dotted line pointing from A_{NM} to A_{PL} (even though α_A° is of type $A_{NM} \rightarrow \text{Maybe } A_{PL}$ and not $A_{NM} \rightarrow A_{PL}$) and omit the path via $\text{Maybe } A_{PL}$ as shown in Figure 7.

We call these monomorphic notional machines because there is a monomorphism (injective homomorphism) between the notional machine and the aspect of the programming language it focuses on. This is the case here by design, to allow students to make mistakes by constructing wrong diagrams that don't correspond to programs. In general, this will be the case whenever there are values of A_{NM} (the abstract syntax of the notional machine) that have no correspondence in the abstract representation of the language (A_{PL}). That's often the case in memory diagrams [Dalton and Krehling 2010; Dragon and Dickson 2016; Holliday and Luginbuhl 2004] (notional machines used to show the relationship between programs and memory) because they typically allow for the representation of memory states that cannot be produced by legal programs. We show an example of such a notional machine in the next section.

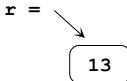
2.3 A Monomorphic Notional Machine to Reason About State

A common use of notional machines is in the context of reasoning about state⁶. An example of the use of a visual notation to represent state can also be found in TAPL [Pierce 2002, p. 155]. In Chapter 13 (“References”), the book extends the simply typed lambda-calculus with references (a language we will refer to as **TYPEDLAMBDAREF**⁷). It explains references and aliasing by introducing a visual notation to highlight the difference between a *reference* and the *cell* in the store that is pointed to by that reference. We will refer to this notation, which we will develop into a notional machine, as **TAPLMEMORYDIAGRAM**. In this notation, references are represented as arrows and cells are represented as rounded rectangles containing the representation of the value contained in the cell. Before designing the notional machine, we need to see the context in which this notation is used in the book.

The book first uses this notation to explain the effect of creating a reference. It shows that when we reduce the term `ref 13` we obtain a reference (a store location) to a store cell containing 13. The book then represents the result of binding the name `r` to such a reference with the following diagram:

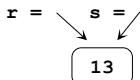
⁶29 of the 57 notional machines presented on <https://notionalmachines.github.io/notional-machines.html> at the time of this writing refer to the concept of *variable* or *array element*.

⁷The syntax and reduction rules for **TYPEDLAMBDAREF** are reproduced in Appendix A.3.



393 In the book, this operation is written as $r = \text{ref } 13$, but as we will see in the next Section, this
 394 form of name binding (name = term) exists only in a REPL-like context which is not part of the
 395 language.

396 The book continues explaining that we can “make a copy of r ” by binding its value to another
 397 variable s (with $s = r$) and shows the resulting diagram:
 398



401 The book then explains that one can verify that both names refer to the same cell by *assigning* a
 402 new value to s and reading this value using r (for example, the term $s := 82; !r$ would evaluate to
 403 82). Right after, the book suggests to the reader an exercise to “draw a similar diagram showing the ef-
 404 fects of evaluating the expressions $a = \{\text{ref } 0, \text{ ref } 0\}$ and $b = (\lambda x:\text{Ref Nat}. \{x, x\}) (\text{ref } 0)$.”
 405 Although we understand informally the use of this diagram in this context, how can we know what
 406 a correct diagram would be in general for any given program? This is what we aim to achieve by
 407 designing a notional machine based on this notation.
 408

409 Let’s see how we would turn that kind of diagram into a sound notional machine. We want
 410 to construct a commutative diagram where A_{PL} is an abstract representation of the state of a
 411 TYPEDLAMBDAREF program execution, A_{NM} is an abstract representation of the diagram presented
 412 in the book, and f_{PL} is an operation that affects the state of the store during program execution.
 413

414 In a first attempt, let’s choose f_{PL} to be an evaluation step and A_{PL} to be modeled as close as
 415 possible to the presentation of a TYPEDLAMBDAREF program as described in the book. In that
 416 case, A_{PL} is the program’s abstract syntax tree together with a *store*, a mapping from a location (a
 417 reference) to a value.
 418

419 **2.3.1 Problem: Beyond the Language.** The first challenge is that the name-binding mechanism
 420 used in the examples above (written as name = term) exists only in a REPL-like context in the
 421 book used for the convenience of referring to terms by name. It is actually not part of the language
 422 (TYPEDLAMBDAREF) so it is not present in this representation of A_{PL} and as a result it cannot be
 423 mapped to A_{NM} (the notional machine). We will avoid this problem by avoiding this name-binding
 424 notation entirely and writing corresponding examples fully in the language. The only mechanism
 425 actually in the language to bind names is by applying a lambda to a term. Let’s see how we can write
 426 a term to express the behavior described in the example the book uses to introduce the diagram
 427 (shown earlier), where we:

- 428 (1) Bind r to the result of evaluating $\text{ref } 13$
- 429 (2) Bind s to the result of evaluating r
- 430 (3) Assign the new value 82 to s
- 431 (4) Read this new value using r

432 Using only the constructs in the language, we express this with the following term:
 433

434 $(\lambda r:\text{Ref Nat}. (\lambda s:\text{Ref Nat}. s := 82; !r) r) (\text{ref } 13)$

435 **2.3.2 Problem: Direct Substitution.** The problem now is that if we model A_{PL} and evaluation as
 436 described in the book, the result of reducing a term $(\lambda x.t_1) t_2$ is the term obtained by replacing
 437 all free occurrences of x in t_1 by t_2 (modulo alpha-conversion), so we don’t actually keep track
 438 of name binding information. What we have in A_{PL} at each step is an abstract syntax tree and
 439

```

442 a = {ref 0, ref 0};
443
444 a = { , }
445
446 b = { , }
447

```

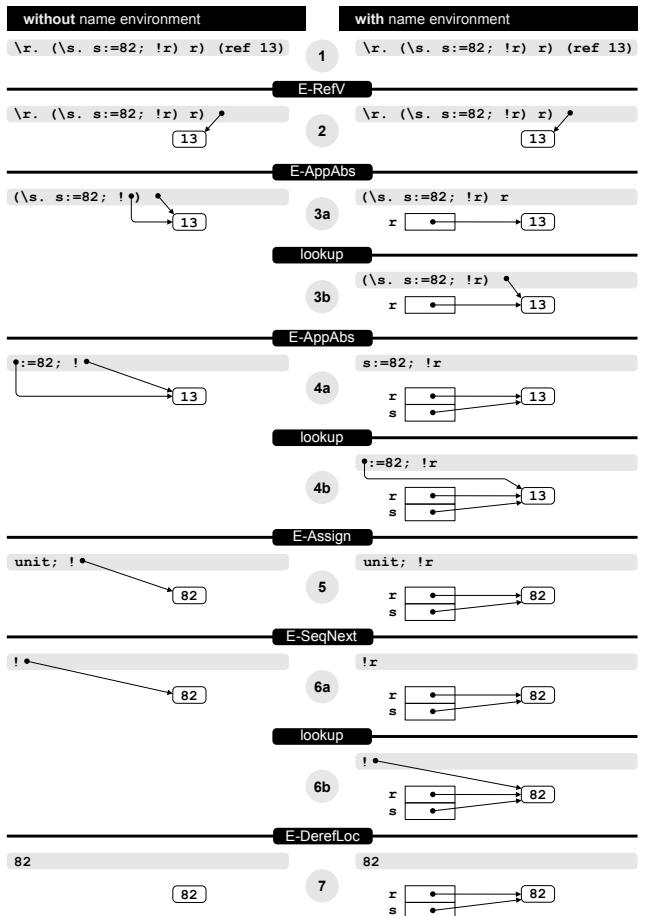
Fig. 9. TAPLMEMORYDIAGRAM for TYPEDLAMBDAREF for TAPL Exercise 13.1.1

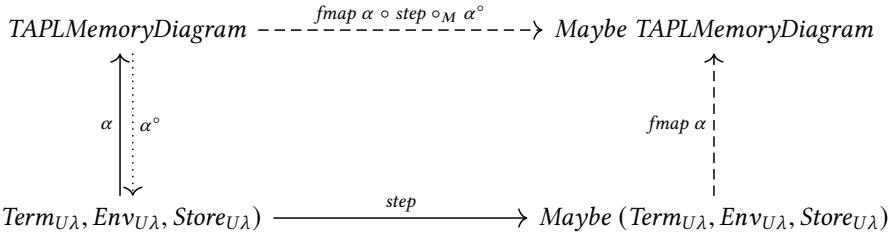
a store, but we have no information about which names are bound to which values because the names were already substituted in the abstract syntax tree. That would be enough to do Exercise 13.1.1, for example, whose solution is shown in Figure 9. But the absence of explicit information mapping names to values makes it less suitable to talk about aliasing, because even though a term may contain, at any given point during evaluation, multiple occurrences of the same location, it is not possible to know if these locations correspond to different names, and one may need to trace several reduction steps back to find out when a name was substituted by a location.

We need to change A_{PL} and step to capture this information, keeping not only a store but an explicit name environment that maps names to values, and only substituting the corresponding value when we evaluate a variable. Like the definition of application in terms of substitution, we have to be careful to avoid variable capture by generating fresh names when needed.

2.3.3 Illustrative Example. Figure 8 shows two variations of the notional machine being used to explain the evaluation of the term we had described before. It shows the state after each reduction step, on the left without an explicit name environment and on the right with an explicit name environment. Between each step, a line with the name of the applied reduction rule is shown. Notice that the representation with a name environment requires extra name lookup steps.

In both variations, the representation of the program (the term) being

Fig. 8. Using TAPLMEMORYDIAGRAM to trace the evaluation of $(\lambda r:\text{Ref Nat. } (\lambda s:\text{Ref Nat. } s := 82; !r) r) (\text{ref 13})$

⁸The syntax and typing rules for TYPEDARITH are reproduced in Appendix A.2.

540 of typed arithmetic expression, which is the simplest typed language introduced in TAPL [Pierce
 541 2002, p. 91]. We describe two designs.

542 In the first design, the data type used for the abstract representation of the notional machine
 543 (A_{NM}) is *ExpTutorDiagram*, used in Section 2.2. We represent a program in *TYPEDARITH* with the
 544 type $Term_{TyArith}$ and the operation we focus on (f_{PL}) is $typeof :: Term_{TyArith} \rightarrow Maybe\ Type_{TyArith}$,
 545 a function that gives the type of a term (for simplicity we use a *Maybe* here to capture the cases
 546 where a term is not well-typed).

547 We then have two abstraction functions:

548 $\alpha_{Term} :: Term_{TyArith} \rightarrow ExpTutorDiagram$

549 $\alpha_{Type} :: Type_{TyArith} \rightarrow Type_{ExpTutor}$

551 The implementation of $f_{TyArith}$, the notional machine operation (f_{NM}) that produces a notional
 552 machine-level representation of maybe the type of a term, is analogous to what is shown in Figure 10
 553 because (1) the abstraction function (α_{Term}) has a left inverse (α_{Term}°) and (2) f_{PL} produces a *Maybe*.
 554

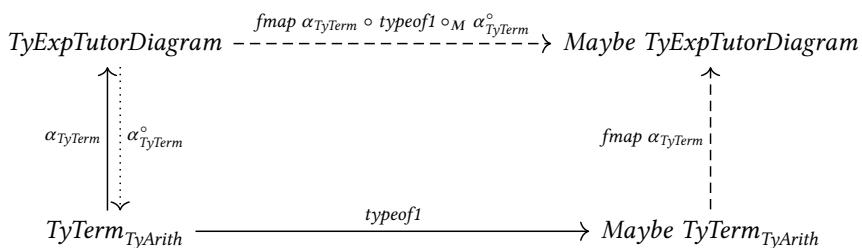
555 $f_{TyArith} :: ExpTutorDiagram \rightarrow Maybe\ Type_{ExpTutor}$

556 $f_{TyArith} = fmap\ \alpha_{Type} \circ\ typeof \circ_M\ \alpha_{Term}^\circ$

557

558 As is, a student may benefit from the notional machine's representation of the program's abstract
 559 syntax tree and that may be helpful to reason about typing but the notional machine doesn't expose
 560 to the student the inner workings of the process of typing a term.

561 The second design, represented in the diagram in Figure 11, tackles this issue by enriching the
 562 notional machine in a way that allows it to go step-by-step through the typing algorithm. The
 563 idea is that f_{NM} now doesn't produce a type but gradually labels each subtree with its type as
 564 part of the process of typing a term. For this, A_{NM} here is *TyExpTreeDiagram*, which differs from
 565 *ExpTreeDiagram* by adding to each node a possible type label. We still want to write f_{NM} in terms
 566 of f_{PL} . The key insight that enables this is to change f_{PL} from *typeof* to *typeof1*. The difference
 567 between *typeof* and *typeof1* is akin to the difference between big-step and small-step semantics:
 568 *typeof1* applies a single typing rule at a time. As a result, we have to augment our representation
 569 of a program by bundling each term with a possible type (captured in type $TyTerm_{TyArith}$). The
 570 abstraction function and its left inverse are updated accordingly. The resulting notional machine is
 571 depicted in Figure 12.



582 Fig. 11. Instantiation of the commutative diagram in Figure 3 for a notional machine focused on type-checking
 583 programs in *TYPEDARITH*. The notional machine exposes the inner workings of the typing algorithm.
 584

585 Interestingly, given an expression e , once we label all nodes in the ExpressionTutor diagram of e
 586 with their types, the depiction of the resulting diagram is similar to the typing derivation tree of e .
 587

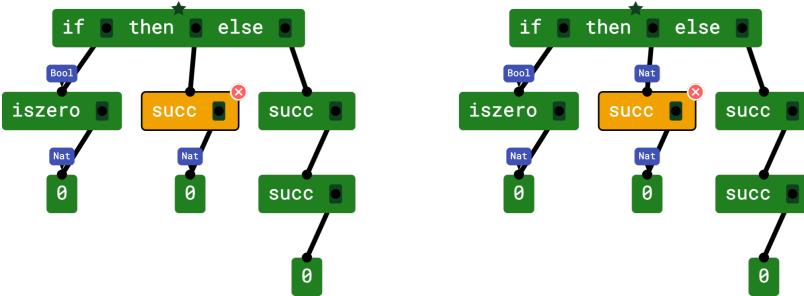


Fig. 12. One step in the notional machine `TYPEDExPTUTORDIAGRAM` as it types the term if `iszzero 0` then `succ 0` else `succ succ 0` in the language `TYPEDARITH`.

Section	Notional Machine	Programming Language	Focus
3.1	ALLIGATOR	UNTYPEDLAMBDA	Evaluation
3.2	LISTASSTACK	-	Data Structure (List)
3.3	ARRAYASPARKINGSPOTS	JAVA	Evaluation (Arrays)

Table 2. Notional machines, programming languages, and aspects of focus used in Section 3.

Note that types are themselves trees but here we're representing them in a simplified form as textual labels because the primary goal of ExpressionTutor is to represent the structure of terms, not the structure of types.

3 ANALYZING EXISTING NOTIONAL MACHINES

So far we have seen how we can design sound notional machines by constructing f_{NM} using f_{PL} and functions that convert between A_{PL} and A_{NM} . Now we will analyze existing notional machines, using their informal description to construct all components of the commutative diagram. In particular, here, we have a description of f_{NM} entirely in terms of A_{NM} . We then use property-based testing, using the soundness condition as a property, to uncover unsoundnesses and suggest improvements that eliminate them. Table 2 shows the notional machines we use in this section as well as the corresponding programming language and aspect of the semantics of the programming language that the notional machine focuses on.

3.1 Debugging a Notional Machine: The Case of Alligator Eggs

Alligator Eggs⁹ is a game conceived by Bret Victor to introduce the lambda-calculus in a playful way. It is essentially a notional machine for the untyped lambda-calculus. The game has three kinds of pieces and is guided by three rules.

Pieces. The pieces are *hungry alligators*, *old alligators*, and *eggs*. Old alligators are white, while hungry alligators and eggs are colored with colors other than white. The pieces are placed in a plane and their relative position with respect to each other determines their relationship. All pieces placed under an alligator are said to be guarded by that alligator. An alligator together with the pieces that may be guarded by it form a family. Families placed to the right of another family may be eaten by the guardian of the family on the left, depending on the applicability of the gameplay rules.

⁹<http://worrydream.com/AlligatorEggs/>

687 correspond to the rules that guide the evolution of alligator families. First, we look more precisely
 688 at the game pieces and their relationship with $\text{Term}_{U\lambda}$ to model A_{NM} .

689 **Eggs** An egg corresponds to a variable use and its color corresponds to the variable name.

690 **Hungry alligators** A hungry alligator somewhat corresponds to a lambda abstraction with its
 691 color corresponding to the name of the variable introduced by the lambda (a variable definition)
 692 and the pieces guarded by the hungry alligator corresponding to the body of the lambda
 693 abstraction. But differently from a lambda abstraction, a hungry alligator doesn't have to be
 694 guarding any pieces, which has no direct correspondence with the lambda calculus because a
 695 lambda abstraction cannot have an empty body.

696 **Old alligators** An old alligator somewhat corresponds to parentheses but not exactly. The lambda
 697 abstraction in the term $(\lambda t. \lambda f. t) a b$ requires parentheses because conventionally the
 698 body of a lambda abstraction extends as far to the right as possible, so without the parentheses
 699 its body would be $t a b$ instead of t . However the corresponding alligator families shown in
 700 Figure 13 don't require an old alligator. On the other hand, if we want to represent the term
 701 $a (b c)$, then we need an old alligator. Figure 14 shows an example of a term that requires
 702 an old alligator.

703 Now let's look at the terms of the untyped lambda-calculus. If hungry alligators are lambda
 704 abstractions and eggs are variables then what is an application? Applications are formed by the
 705 placement of pieces on the game board. When an alligator family or egg (corresponding to a term
 706 t_1) is placed to the left of another family or egg (corresponding to a term t_2), then this corresponds
 707 to the term t_1 applied to t_2 (in lambda calculus represented as $t_1 t_2$).

708 Notice that because every egg must be guarded by a hungry
 709 alligator with the same color, strictly speaking, an egg cannot
 710 appear all by itself. That corresponds to the fact that in the
 711 untyped lambda-calculus only lambda terms are values, so a
 712 term cannot have unbounds variables. Textbooks, of course,
 713 often use examples with unbound variables but these are ac-
 714 tually metavariables that stand for an arbitrary term. So, for
 715 convenience, we will consider that an egg by itself also forms
 716 a family.

717 We can then model an alligator family as the type
 718 *AlligatorFamily*, and a game board as simply a list of alliga-
 719 tor families. The result is the commutative diagram shown in
 720 Figure 15.

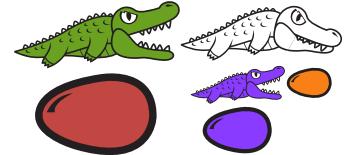


Fig. 14. Old alligator in
 $(\lambda a. y) ((\lambda b. b) c)$

721 **data AlligatorFamily = HungryAlligator Color [AlligatorFamily]**
 722 | **OldAlligator [AlligatorFamily]**
 723 | **Egg Color**

724 The abstraction function α relies on some function $\text{nameToColor} :: \text{Name} \rightarrow \text{Color}$.

$\alpha :: \text{Term}_{U\lambda}$	$\rightarrow [\text{AlligatorFamily}]$
$\alpha (\text{Var name})$	$= [\text{Egg } (\text{nameToColor name})]$
$\alpha (\text{Lambda name } e)$	$= [\text{HungryAlligator } (\text{nameToColor name}) (\alpha e)]$
$\alpha (\text{App } e1 e2 @ (\text{App } -))$	$= \alpha e1 + [\text{OldAlligator } (\alpha e2)]$
$\alpha (\text{App } e1 e2)$	$= \alpha e1 + \alpha e2$

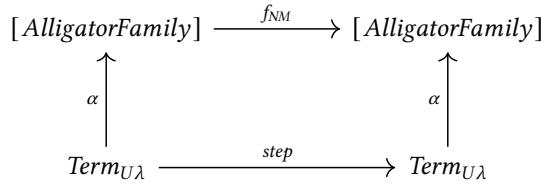


Fig. 15. First attempt at instantiating the commutative diagram in Figure 3 for the notional machine ALLIGATOR.

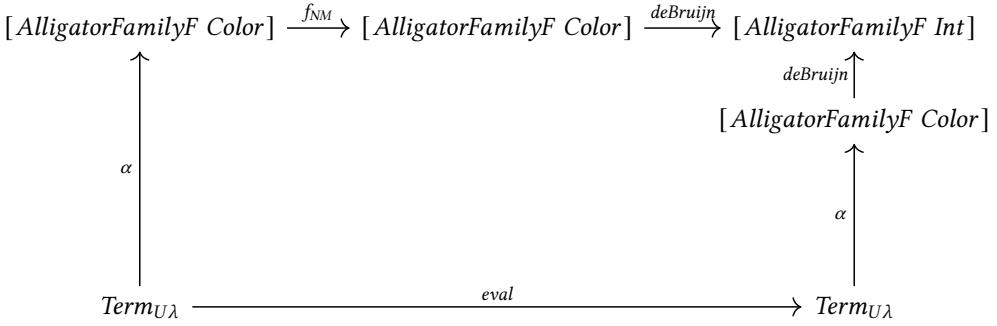
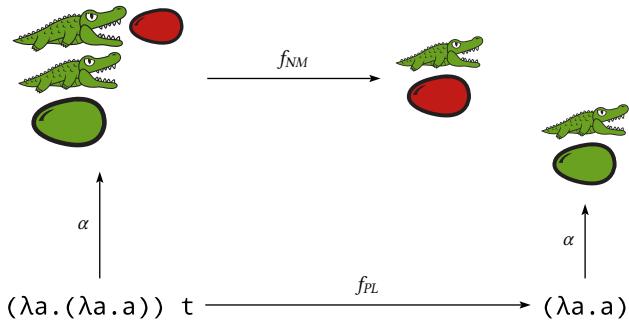


Fig. 16. Second attempt at instantiating the commutative diagram in Figure 3 for the notional machine ALLIGATOR.

From Proof to Property-Based Testing. The commutativity of the diagrams presented in Chapter 2 was demonstrated using equational reasoning. Here instead, we implement the elements that constitute the commutative diagram and use property-based testing to test if the diagram commutes. This approach is less formal and it doesn't prove the notional machine correct, but it is lightweight and potentially more attractive to users that are not familiar with equational reasoning or mechanised proofs. We will see here that, despite its limitations, this approach can go a long way in revealing issues with a notional machine. The idea is that a generator generates terms $t_i :: Term_{U\lambda}$ and checks that $(f_{NM} \circ \alpha) t_i \equiv (\alpha \circ step) t_i$.

de Bruijn Alligators. The first challenge is that we need to compare values of type $[AlligatorFamily]$ that were produced using f_{NM} with values produced using $step$. As we have seen, the colors in $AlligatorFamily$ correspond to variable names but the way $step$ generates fresh names (which then are turned into colors) may be different from the way f_{NM} will generate fresh colors. In fact, the original description of ALLIGATOR anticipates the challenge of comparing alligator families. In the description of possible gameplays, they clarify that to compare alligator families we need to take into account that families with the same "color pattern" are equivalent. This can be achieved by using a *de Bruijn representation* [Bruijn 1972] of Alligators. We turn $AlligatorFamily$ into $AlligatorFamilyF Color$ and before comparing families we transform them into $AlligatorFamilyF Int$ following the de Bruijn indexing scheme. The commutative diagram we are moving towards is shown in Figure 16.

Evaluation Strategy. With this setup in place, the next step is to implement f_{NM} in terms of the game rules. The eating rule (together with the color rule) somewhat corresponds to beta-reduction but under what evaluation strategy? The choice of evaluation strategy turns out to affect not

Fig. 17. Unsoundness: *bound* occurrences of a variable should not be substituted.

only the eating rule but also the old age rule. According to the original description, any hungry alligator that has something to eat can eat and one of the original examples shows a hungry alligator eating an egg even when they are under another hungry alligator. That would correspond to a *full beta-reduction* evaluation strategy but we will stick to a call-by-value lambda-calculus interpreter so we will adapt the rules accordingly. The old age rule has to be augmented to trigger the evolution of an old alligator family that follows a topmost leftmost hungry alligator and families under a topmost leftmost old alligator. The eating rule should be triggered only for the topmost leftmost hungry alligator, unless it is followed by an old alligator (in which case the augmented old age rule applies). The color rule plays an important role in the correct behavior of the eating rule as a correspondence to beta-reduction. That's because indeed "the color rule corresponds to (over-cautious) alpha-conversion", so it is responsible for avoiding variable capture.

With all the rules implemented, we can define a function *evolve* that applies them in sequence. We will then use *evolve* in the definition of f_{NM} . One application of *evolve* corresponds to one step in the notional machine layer but that step doesn't correspond to a step in the programming language layer. For example, The main action of the old age rule (to remove old alligators) doesn't have a correspondence in the reduction of terms in UNTYPEDLAMBDA. In terms of simulation theory, in this case the simulation of the programming language by the notional machine is not lock-step. To adapt our property-based testing approach, instead of making f_{PL} equal to *step*, we will simply reduce the term all the way to a value (leading to the use of *eval* as f_{PL} in Figure 16) and correspondingly define f_{NM} to be the successive applications of *evolve* until we reach a fixpoint.

3.1.3 Problem: Substitution of Bound Variables. Now we have all the building blocks of the commutative diagram. We can put them together by running the property-based tests to try to uncover issues in the diagram and indeed we do. According to the eating rule, after eating, a hungry alligator dies and if it was guarding any eggs of the same color, each of those eggs hatches into what was eaten. So the family corresponding to $(\lambda a. (\lambda a. a)) t$, for example, would evolve to the family corresponding to $\lambda a. t$ instead of $\lambda a. a$, as shown in Figure 17. This issue corresponds to a well-known pitfall in substitution: we cannot substitute *bound* occurrences of a variable, only the ones that are *free*.

The issue can be solved in one of the following ways:

- (1) Refining the description of the eating rule, changing "if she was guarding any eggs of the same color, each of those eggs hatches into what she ate" into "if she was guarding any eggs of the same color **that are not guarded by a closer alligator with the same color**, each of those eggs hatches into what she ate";

- 834 (2) Restricting all colors of hungry alligators in a family to be distinct;
 835 (3) Defining colors to correspond to de Bruijn indices instead of names. This means that not
 836 only colors wouldn't be repeated in the same family but also that every family would use the
 837 same "color scheme" for structurally equivalent terms.
 838

839 3.2 Notional Machines for Data Structures

840 Although most notional machines focus on the semantics of programming language constructs,
 841 some notional machines instead focus on data structures. One such notional machine, which we
 842 model in this section, is the "List as Stack of Boxes" (Figure 18), described by Du Boulay and O'Shea
 843 [1976] and included in the dataset of notional machines analyzed by Fincher et al. [2020].
 844

845 For notional machines focussing on the dy-
 846 namic semantics of a language (EXPTREE, EX-
 847 PTREE, TAPLMEMORYDIAGRAM), the type A_{PL}
 848 represents a program in the language under
 849 focus (and in the case of TAPLMEMORYDIA-
 850 GRAM, additional information needed to eval-
 851 uate the program) and the function f_{PL} performs
 852 an evaluation step. In the case of TYPEDEXPTU-
 853 TORDIAGRAM, which focusses on type-checking
 854 (the static semantics of TYPEDARITH), A_{PL} also
 855 represents a program in that language and f_{PL}
 856 performed type-checking. Now we will model a
 857 notional machine focussing on a data structure,
 858 so A_{PL} represents that data structure and there
 859 are several f_{PL} functions, one for each opera-
 860 tion supported by that data structure. The type
 861 A_{NM} can be seen as an abstraction of A_{PL} and it
 862 should provide corresponding operations. The
 863 commutation of the diagram demonstrates the correctness of this abstraction.

Modelling "List as Stack of Boxes" requires some adaptations to the original description:

- 864 (1) To avoid partiality of the operations typically used to access the head and tail of a list (FIRST
 865 and REST in the original description), we define a list using three operations: *Empty* and *Cons*
 866 to construct a list and *uncons* :: $List\ a \rightarrow Maybe\ (a, List\ a)$ to deconstruct it. That change also
 867 has a convenient representation in the notional machine.
- 868 (2) In the stack of boxes, each value is shown as a *String* in a box, which means we can only
 869 represent lists of values for which we can create a *String* representation.
- 870 (3) The original description wasn't explicit about the representation of an empty list. We need a
 871 corresponding empty stack of boxes that can be treated as a stack and not just the absence of
 872 boxes. For that we will use a pallet (used to hold boxes in storage). The original description
 873 mentions a pallet in two contexts:
 - 874 (a) "boxes are stacked on a pallet so that they can be picked up as one stack". That's an
 875 important part of the notional machine's behavior but we also need to be able to pick up a
 876 box from the top of the stack;
 - 877 (b) "The beginning of a list, the top of the stack, is marked with [and the end of the list, the
 878 pallet is marked with]". Here there's an asymmetry between the end of the list, represented
 879 with a pallet, and the beginning of the list, which has no representation in the notional
 880 machine. Our denotation of pallet is different: it is the representation of an empty list.

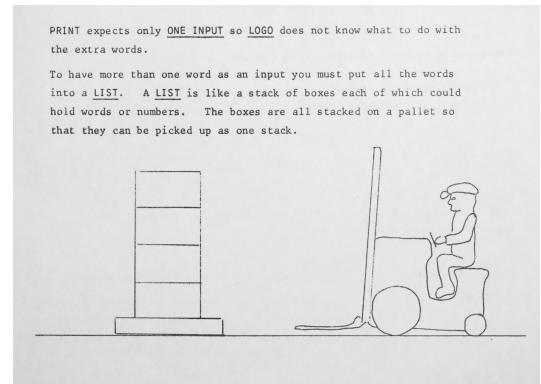


Fig. 18. The "List as Stack of Boxes" notional machine as described by Du Boulay and O'Shea [1976].

The result is that we can construct lists either with a pallet or by stacking a box on top of a stack, which must have eventually a pallet at the end. To deconstruct it, we can pick up a box from the top of the stack ($\text{pickUp} :: \text{Stack} \rightarrow \text{Maybe}(\text{Box}, \text{Stack})$). When trying to pick up a box, either there is only the pallet, in which case we get nothing, or there is a box on top of a stack, in which case we are left with the box and the rest of the stack.

3.3 A Notional Machines for Arrays

With the techniques we have developed so far, we can turn again to the notional machine "Array as Row of Parking Spaces is Parking Lot", which we presented in the Section 1.1. There we considered Java as the underlying programming language and already identified the first issue, caused by the difference between the representation of arrays of primitive types and arrays of reference types. Here, we will make the notional machine more precise and in the process resolve two problems.

One way to approach the problem would be to model the subset of Java needed for the notional machine to work but Java is a fairly complex language so instead can approach this problem in a way similar to the one taken in the last section: modeling the PL layer simply as an idealized array and the operations it supports. An array supports three operations: *allocating* an array of a given type and a given length, *reading* an element at a given index, and *writing* an element to a given index.

3.3.1 Problem: reference types versus primitive types. One of the appeals of the notional machine is that because a newly allocated array of objects doesn't contain "valid" values (their slots contain `null`) we would represent it as an empty parking lot. We want to keep this appeal so the first issue is immediately revealed because arrays of primitive types are really different in that, when newly allocated, their slots already contain valid values. These arrays would be represented as fully booked parking lots with slots that can never be empty! Here, instead of changing the design of the notional machine, we can use this distinction (this misfit in the metaphor), as a learning opportunity and explicitly discuss it with the students. There is still a decision to be made about how exactly the values in the array are going to be represented. We could represent a value as a car with the string representation of the value drawn on its roof, but representing both the unboxed and boxed versions of an integer with the same string could be confusing. Instead, we could opt for representing values of reference types as cars of a different color, for example. Of course an array can also contain other arrays, which are themselves objects, and that complicates the picture.

3.3.2 Problem: representing multiple arrays. To represent multiple arrays, and the relationship between them, we can't model the PL layer simply as an idealized array¹⁰. Instead, the programming language here is LAMBDAREF augmented with arrays. We first used this language in Section 2.3, where the TAPLMEMORYDIAGRAM notional machine represented all constructs of the language as well as the program's state as it ran (its memory): the store and name environment. Here instead, we want to represent only arrays and values so the notional machine layer contains, besides the parking lot, essentially a sequence of statements equivalent to the occurrences of all terms in the program that manipulate arrays (an array allocation, array access, and assignment of a value to an array slot) as they happen when the program runs. This way we can ignore all other terms in the language and aspects of the program's memory as it runs. Besides the information present in the array-manipulating terms themselves, we need one more thing: to be able to uniquely identify each array (e.g. with its location, or address). We annotate each parking lot with the corresponding

¹⁰ Indeed the representation of lists shown in Section 3.2 is not suitable to represent lists that contain lists.

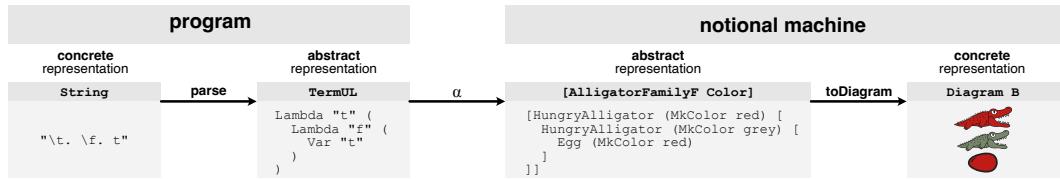


Fig. 20. Both program and notional machine have abstract and concrete representations.

location (for example using an @ and the location identifier) which we use to identify the parking lot when we write or read from the corresponding array slot.

We can then represent values of reference type using their locations. We could instead use arrows, like we've done in TAPLMEMORYDIAGRAM, but that wouldn't work for ref's because here we are only representing arrays.

4 ABSTRACT VS. CONCRETE SYNTAX OF NOTIONAL MACHINES

When reasoning about a notional machine, it's important to distinguish between the data types that represents the notional machine (the information present in A_{NM} and B_{NM}) and how the notional machine is visualized. This difference is akin to the distinction between the concrete syntax and the abstract syntax of a language. Like a programming language, a notional machine has a concrete and an abstract syntax as well. We also refer to those as concrete and abstract representations of a notional machine. Notice that the concrete representation of a notional machine may not only be a diagram or image that can be depicted on paper but it could also be made of physical objects or enacted with students. In fact, many notional machines are ludic in nature or are built around a metaphor, so the concrete representation of a notional machine is very important.

Figure 20 shows the different layers at play here. On the programming language side, the *parse* function converts from the concrete to the abstract syntax of the language. The function α maps from language constructs to notional machine constructs. On the notional machine side, the function *toDiagram* maps from the abstract representation of the notional machine to its concrete representation, e.g., in the form of an actual diagram. In the case of ALLIGATOR, we use the *diagrams* library [Yates and Yorgey 2015; Yorgey 2012] to construct the concrete representation so *toDiagram* produces a value of type *Diagram B*, where the type parameter *B* (for Backend) determines the output format of the diagram (e.g. SVG).

By decoupling the abstract from the concrete representation, a notional machine can have multiple concrete representations. Alligator Eggs, for example, also describes another concrete syntax that it calls "Schematic Form". This concrete representation is suitable for working with the notional machine using pencil and paper. Figure 19 shows the Church numeral two (the term $\lambda f. \lambda x. f (f x)$), represented using both concrete representations. In the schematic representation, colors are presented with variable names. An alligator is drawn as a line ending with a < for a mouth, and is preceded by a variable name corresponding to its color. An old alligator is drawn with a line without a mouth. An egg is drawn just with the variable name corresponding to its color.

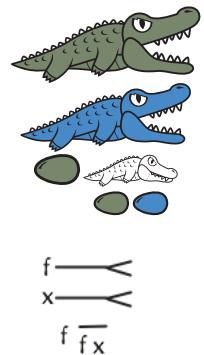


Fig. 19. Multiple concrete representations.

981 5 EVALUATION

982 The notional machines we presented so far not only exemplify how to use our framework to reason
 983 about notional machines but also were chosen to be representative of the design space of notional
 984 machines used in practice. To characterize this design space we analyzed the notional machines in
 985 the dataset collected by Fincher et al. [2020] and classified them according to three dimensions:
 986 form, focus, and language construct. For each dimension, we present the categories of the dimension
 987 and for each category we show the number of notional machines in that category, the percentage
 988 that number represents of the total, and the sections of the paper containing notional machines
 989 that fall into that category. The notional machines are often not precisely described so we often had
 990 to make assumptions about their characteristics, how they relate to an underlying programming
 991 language, and how they are used to teach programming concepts.

992 The form (Table 3) of a notional machine can
 993 be metaphorical (primarily inspired by and repre-
 994 sented with real world objects) or diagram-
 995 matic (represented with diagrams). The distinc-
 996 tion between the two is not always clear-cut,
 997 given that a notional machine may mix both
 998 forms and some real world objects can be rep-
 999 resented diagrammatically. Nevertheless, this
 1000 distinction is useful because metaphorical no-
 1001 tional machines may be more difficult to be
 1002 made sound, given the existing degrees of free-
 1003 dom and constraints of the real world objects they are inspired by.

Form	Num	Perc.	Covered
Metaphorical	22	56.41%	3.2 3.3 3.1
Diagrammatic	16	41.03%	2.1 2.2 2.3 2.4
Both	1	2.56%	-
Total	37	100.00%	-

Table 3. Notional machines in the dataset published by Fincher et al. [2020] classified according to their form.

1004 Most notional machines in the dataset focus (Table 4) on the runtime semantics (Evaluation)
 1005 of a programming language construct (or set of conceptually related constructs) so we further
 1006 break down these notional machines into the constructs (or set of constructs) they are primarily
 1007 focused on (Table 5). Here the classification is also not clear-cut, not only because a notional
 1008 machine may focus on multiple constructs but also because some constructs are related to others.
 1009 For example, notional machines that focus on functions often (although not always) represent
 1010 variables as well but only the ones that solely (or primarily) focus on variables are classified as
 1011 such. The category control flow encompasses constructs like loops and conditional statements,
 1012 which primarily affect control flow. The category Misc includes five notional machines each of
 1013 which focuses on a different construct: string literal, Procedure (side-effecting functions), objects,
 1014 instructions (lower level operations), and one that is not clear from the description.

1016 5.1 Expressing Complex Language Semantics

1017 Although the notional machines presented here as well as in the dataset by Fincher et al. [2020]
 1018 focus on aspects of program semantics that one may consider simple, the framework we presented
 1019 can be used to reason about more complex aspects of program semantics. An example is the
 1020 conceptual models to reason about Ownership Types in Rust by Crichton et al. [2023]. The authors
 1021 present two models: a dynamic and a static. In our framework, each model can be seen as a notional
 1022 machine. The authors divide each model into a formal model (about which formal statements can
 1023 be made), which would correspond to the abstract representation of the notional machine, and an
 1024 informal model, which would correspond to the concrete representation of the notional machine.
 1025 In the dynamic model, our PL layer would be the Rust language and our NM layer would be Miri.
 1026 In the static model, our PL layer would be the Polonius model of borrow checking and our NM
 1027 layer would be the *permissions model* of borrow checking (introduced by the authors).

Focus	Num	Perc.	Covered
Evaluation	32	82.05%	2.1 2.2 2.3 3.3 3.1
Type-checking	2	5.13%	2.4
Parsing	2	5.13%	no
Data Structure	2	5.13%	3.2
Logic Gates	1	2.56%	no
Total	37	100.00%	-

Table 4. Notional machines in the dataset published by Fincher et al. [2020] classified according to their broad focus.

Construct	Num	Perc.	Covered
References	8	20.51%	2.3
Functions	5	12.82%	2.1 2.2
Variables	4	10.26%	2.1 2.2 2.3
Arrays	4	10.26%	3.3
Methods	3	7.69%	no
Control Flow	2	5.13%	no
Expressions	1	2.56%	2.1 2.2
Misc	5	12.82%	no
Total	32	82.05%	-

Table 5. Notional machines in the dataset published by Fincher et al. [2020] classified according to their narrow focus.

6 RELATED WORK

The term notional machine was coined by Du Boulay [1986] to refer to “the idealised model of the computer implied by the constructs of the programming language”. Therefore it restricts the use of notional machines as means to help understand the runtime behavior of a program or the dynamic semantics of a language. Fincher et al. [2020], a working group that included du Boulay, has a thorough literature review and discussion of the term notional machine and established a broader definition as “pedagogic devices to assist the understanding of some aspect of programs or programming”, which includes uses of notional machines as means to help understand the static semantics of a language. The “Expressions as Trees” notional machine, for example, is used for both. We adopt here this broader view of notional machine.

Another related and important term is conceptual model. Fincher et al. [2020] states that a “notional machine is effectively a special kind of conceptual model.” That’s important because conceptual models, such as the Substitution Model and the Environment Model used in the SICP book (Structure and Interpretation of Computer Programs) [Abelson et al. 1996], and SICPJS [Abelson and Sussman 2022], for example, are well understood to be essential for reasoning about programs. Notional machines that are sound are indeed conceptual models. The concrete representation of the notional machine can be thought of as embodying the visualization of this conceptual model.

The idea of simulating or representing a program by means of another program is an old one, and was first studied in detail in the 1970s by Milner [1971] and Hoare [1972]. Many of our notional machines illustrate a reduction, stepping, or evaluation ‘aspect’ of a programming language. Wadler et al. [2020] descriptions of how to relate such reduction systems with simulation, lock-step simulation, and bisimulation. The commutative diagram describing the desired property of a notional machine appears in many places in the literature, and is a basic concept in Category Theory. Closer to our application is its use as ‘promotion condition’ [Bird 1984; Wang et al. 2013].

Where computing education researchers capture program behavior through notional machines, programming language researchers instead use semantics [Krishnamurthi and Fisler 2019]. Our work can be seen as a rather standard approach to show the correctness of one kind of semantics of (part of) a programming language, most often the operational semantics, with respect to another semantics, often a reduction semantics. An example of such an approach has been described by Clements et al. [2001], whose Elaboration Theorem describes a property that is very similar to our soundness requirement. The lack of a formal approach to showing the soundness of notional

machines is also noted by Pollock et al. [2019], who develop a formal approach to specifying correct program state visualization tools, based on an executable semantics of the programming language formulated in the K framework [Rosu and Ţerbanuță 2010]. In this paper we study a broader collection of notional machines than just program state visualization tools, and we apply our approach to study the soundness of notional machines.

Computing educators practitioners use a diverse set of notional machines [Fincher et al. 2020]. Some notional machines form the basis of automated tools. The BlueJ IDE, which features prominently in an introductory programming textbook [Kölling and Barnes 2017], includes a graphical user interface to visualize objects, invoke methods, and inspect object state. PythonTutor [Guo 2013], an embeddable web-based program visualization system, is used by hundreds of thousands of users to visualize the execution of code written in Python, Java, JavaScript, and other programming languages. UUHistle [Sorva and Sirkia 2010], a “visual program simulation” system, takes a different approach: instead of visualizing program executions, it requires students to perform the execution steps in a constrained interactive environment. When developing such widely used tools, starting from a sound notional machine is essential.

Dickson et al. [2022] discuss the issues around developing and using a notional machine in class. They note, amongst others, “that a notional machine must by definition be correct, but a student’s mental model of the notional machine often is not”, and that “specifying a notional machine was more difficult than we thought it would be”. Our work can help in developing a notional machine, and pointing out flaws in it.

7 CONCLUSIONS

A notional machine are popular in computer science education, commonly used both by instructors in their teaching practice as well as by researchers. Despite their popularity, there has been no precise formal characterization of what should be the relationship between a notional machine and the aspect under its focus that would allow one to evaluate whether or not they are consistent with each other. We, therefore, introduced a definition of soundness for notional machines. The definition is based on simulation, a well-established notion widely used in many areas of computer science. Demonstrating soundness essentially amounts to constructing a commutative diagram relating the notional machine with the object of its focus.

Using this definition, we showed how we can (1) systematically design notional machines that are sound by construction, and (2) analyze existing notional machines to uncover inconsistencies and suggest improvements.

An important insight in the process is to distinguish between the concrete representation of the notional machine (typically visual) and its abstract representation, about which we can make formal statements. This distinction is akin to the distinction between the concrete and the abstract syntaxes of a programming language.

This work intends more generally to establish a framework to reason about notional machines, placing the research on notional machines on firmer ground. As such, it can be used to address challenges such as the design, analysis, and evaluation of notional machines, and the construction of automated tools based on notional machines.

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1226 **A PROGRAMMING LANGUAGE DEFINITIONS**

1227 The programming languages used throughout the paper mostly follows the presentation in the
 1228 book Types and Programming Languages by Pierce [2002] with minor changes. In particular, italics
 1229 are used for metavariables and the axioms in the reduction (evaluation) rules and typing rules are
 1230 shown with explicitly empty premises.
 1231

1232 **A.1 UntypedLambda**

1233 Figure 21 shows the syntax and evaluation rules for the untyped lambda calculus by Church [1936,
 1234 1941], that we have referred to as UNTYPEDLAMBDA. This language is used in Sections 2.1, 2.2,
 1235 and 3.1 .
 1236

1237 Syntax	1238	1239 Evaluation
		$\frac{}{(x.t_1)v_2 \longrightarrow [x \mapsto v_2]t_1} E\text{-APPABS}$
$t ::=$ x variable $\lambda x.t$ abstraction $t t$ application		$\frac{t_1 \longrightarrow t'_1}{t_1 t_2 \longrightarrow t'_1 t_2} E\text{-APP1}$ $\frac{t_2 \longrightarrow t'_2}{v_1 t_2 \longrightarrow v_1 t'_2} E\text{-APP2}$
$v ::=$ $\lambda x.t$		

1247 Fig. 21. The untyped lambda calculus (UNTYPEDLAMBDA).

1248 **A.2 TypedArith**

1249 We define here the language TYPEDARITH, used in Section 2.4. Figure 22 shows its syntax and
 1250 evaluation (reduction) rules and Figure 23 shows its typing rules. The appeal of using this language
 1251 to present a notional machine focused on the types is its simplicity. Terms don't require type
 1252 annotations and the typing rules don't require a type environment. In fact, Pierce uses it as the
 1253 simplest example of a typed language when introducing type safety.
 1254

1255 **A.3 TypedLambdaRef**

1256 In Section 2.3, we showed the language TYPEDLAMBDAREF, used to design a notional machine
 1257 that focuses on references. This language is composed of the simply-typed lambda calculus, the
 1258 TYPEDARITH language, tuples, the *Unit* type, sequencing, and references. Our goal is again simplicity
 1259 and this is the simplest language we need for the examples in the book that use the diagram. Figure 24
 1260 shows its syntax and evaluation (reduction) rules. We show only the reduction rules for sequencing,
 1261 references, and tuples because the rules for the rest of the language are similar to what we showed
 1262 before, except for the store then needs to be threaded through all the rules. Although that is a typed
 1263 language, we don't present its typing rules because the notional machine in Section 2.3 is focused
 1264 only on its runtime behavior and not its types.
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1275	Syntax	Evaluation
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1279		$\frac{}{\text{if true then } t_2 \text{ else } t_3 \longrightarrow t_2} \text{E-IFTRUE}$
1280		
1281		$\frac{}{\text{if false then } t_2 \text{ else } t_3 \longrightarrow t_3} \text{E-IFFALSE}$
1282	$t ::=$ terms:	$\frac{t_1 \longrightarrow t'_1}{\text{if } t_1 \text{ then } t_2 \text{ else } t_3 \longrightarrow \text{if } t'_1 \text{ then } t_2 \text{ else } t_3} \text{E-IF}$
1283	true constant true	
1284	false constant false	
1285	if t then t else t conditional	
1286	0 constant zero	
1287	succ t successor	
1288	pred t predecessor	
	iszero t zero test	
1289	$v ::=$ values:	
1290	true	$\frac{}{\text{succ } t_1 \longrightarrow \text{succ } t'_1} \text{E-SUCC}$
1291	false	
1292	nv	
1293	$nv ::=$ numeric values:	
1294	0	$\frac{}{\text{pred } 0 \longrightarrow 0} \text{E-PREDZERO}$
1295	succ nv	
1296		$\frac{}{\text{pred } (\text{succ } nv_1) \longrightarrow nv_1} \text{E-PREDSUCC}$
1297		
1298		$\frac{t_1 \longrightarrow t'_1}{\text{pred } t_1 \longrightarrow \text{pred } t'_1} \text{E-PRED}$
1299		
1300		$\frac{}{\text{iszero } 0 \longrightarrow \text{true}} \text{E-ISZEROZERO}$
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1302	Fig. 22. Syntax and reduction rules of the TYPEDARITH language.	
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1324	Syntax	Typing rules
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1326		$\frac{}{\text{true} : \text{Bool}}$ T-TRUE
1327		$\frac{}{\text{false} : \text{Bool}}$ T-FALSE
1328		$\frac{t_1 : \text{Bool} \quad t_2 : T \quad t_3 : T}{\text{if } t_1 \text{ then } t_2 \text{ else } t_3 : T}$ T-IF
1329		
1330		
1331		
1332	$T ::=$ types: Bool type of booleans Nat type of natural numbers	$\frac{}{0 : \text{Nat}}$ T-ZERO
1333		$\frac{t_1 : \text{Nat}}{\text{succ } t_1 : \text{Nat}}$ T-SUCC
1334		$\frac{t_1 : \text{Nat}}{\text{pred } t_1 : \text{Nat}}$ T-PRED
1335		
1336		
1337		
1338		
1339		$\frac{t_1 : \text{Nat}}{\text{iszero } t_1 : \text{Bool}}$ T-ISZERO
1340		
1341		
1342	Fig. 23. Syntax of types and typing rules of the TYPEDARITH language.	
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Sound Notional Machines

1373	Syntax	Evaluation
1374	$t ::=$ terms:	
1375	x variable	
1376	$\lambda x : T. t$ abstraction	
1377	$t t$ application	
1378	$\mid \text{true}$ boolean true	
1379	$\mid \text{false}$ boolean false	
1380	$\mid 0$ zero	
1381	$\mid \text{succ } t$ successor	
1382	$\mid \text{pred } t$ predecessor	
1383	$\mid \text{iszero } t$ zero test	
1384	$\mid \text{unit}$ unit constant	
1385	$\mid t; t$ sequence	
1386	$\mid \text{ref } t$ reference creation	
1387	$\mid !t$ dereference	
1388	$\mid t := t$ assignment	
1389	$\mid l$ location	
1390	$\mid \{t_i\}_{i \in 1..n}$ tuple	
1391	$\mid t.i$ projection	
1392	$v ::=$ values:	
1393	$\lambda x : T. t$	
1394	$\mid \text{true}$	
1395	$\mid \text{false}$	
1396	$\mid 0$	
1397	$\mid \text{succ } v$	
1398	$\mid \text{unit}$	
1399	$\mid l$	
1400	$\mid \{v_i\}_{i \in 1..n}$	
1401	$T ::=$ types:	
1402	$T \rightarrow T$ function type	
1403	$\mid \text{Bool}$ boolean type	
1404	$\mid \text{Nat}$ natural number type	
1405	$\mid \text{Unit}$ unit type	
1406	$\mid \text{Ref } T$ reference type	
1407	$\mid \{T_i\}_{i \in 1..n}$ tuple type	
1408	$\mu ::=$ store:	
1409	\emptyset empty store	
1410	$\mid \mu, l \mapsto v$ location binding	
1411		
1412		Fig. 24. TYPEDLAMBDAREF : Syntax and Evaluation
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