The Calysto Scheme Project

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Calysto Scheme is written in Scheme in Continuation-Passing Style, and converted through a series of correctness-preserving program transformations into Python. It has support for standard Scheme functionality, including call/cc, as well as syntactic extensions, a nondeterministic operator for automatic backtracking, and many extensions to allow Python interoperation. Because of its Python foundation, it can take advantage of modern Python libraries, including those for machine learning and other pedagogical contexts. Although Calysto Scheme was developed with educational purposes in mind, it has proven to be generally useful due to its simplicity and ease of installation. It has been integrated into the Jupyter Notebook ecosystem and used in the classroom to teach introductory Programming Languages with some interesting and unique twists.

CCS Concepts: • **Software and its engineering** → **General programming languages**; **Functional languages**; **Integrated and visual development environments**.

Additional Key Words and Phrases: Scheme, Python, Jupyter, Computer Science education

1 INTRODUCTION

This paper describes the development of Calysto Scheme, a full-featured implementation of the Scheme programming language written in Scheme, which can be automatically translated into other languages, such as Python and C# [Project 2023]. Although our path through the development of this system was circuitous, the completed project ended up being far more interesting (and useful) than we could have imagined.

The initial motivation for Calysto Scheme grew out of an earlier open-source project called Calico that was designed to be a multi-programming-language framework and learning environment for computing education [Blank et al. 2012]. The basic premise of this earlier project was to create a common architecture, user interface, and set of libraries for a variety of programming languages (see Figure 1).

Many engaging "pedagogical contexts" for learning about computer science have been developed, including media computation [Guzdial 2003], gaming, AI and robotics [Summet et al. 2009], visualization, music, and art. However, these contexts often depend on a set of libraries developed for a specific programming language, which may constrain the choice of language if an instructor wishes to have students explore a particular learning context. Having a common framework separates the details of a specific language from other pedagogical goals.

One of the interesting aspects of Calico was that instead of having students learn a different IDE for each language under study, such as IDLE for Python, or DrRacket for Scheme, students could remain in the same IDE, but simply switch the programming language. This is similar in spirit to the way that one can switch languages in DrRacket [Flatt 2012]. However, in Calico, supported

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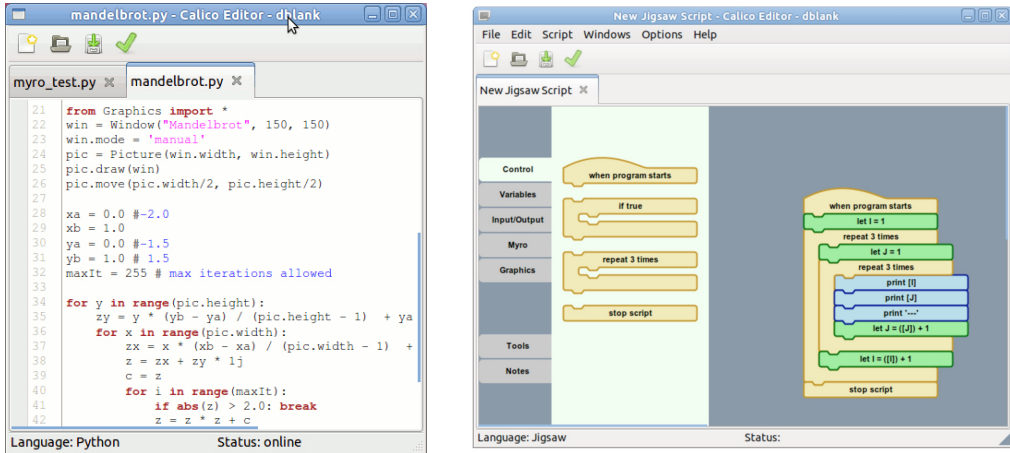
Fig. 1. The Calico interface, running Python (left), and Jigsaw, a visual block-based language (right).

languages can easily interoperate through shared libraries and data structures, even if the languages have little else in common with each other.

At the time (2007), Microsoft had embarked on a related goal. They were actively developing what they called the Dynamic Language Runtime (DLR) as part of the .NET framework. The DLR abstraction layer created a common API and allowed one to create languages, such as IronPython and IronRuby [Project 2011], without having to rewrite the common parts for each language. Our earlier project adopted the DLR as its foundation, and used these Iron languages. In addition, the Calico team developed other languages to augment these, including a visual block-based language.

However, there was a gap in the languages available: there was no Scheme implementation that could work in this environment. Although the development of both IronLisp and IronScheme [Pritchard 2022] had been attempted by other groups, they both ultimately failed for various reasons, including lack of support for tail-call optimization (TCO) in the DLR.[1]

Of course, Scheme can be implemented in languages without TCO. So we set out to fill this void by developing a Scheme without using the DLR for internal function calls, but still allowing integration with the DLR for interoperation with other functionality, such as calling libraries.

But why focus on Scheme? After all, creating a full implementation from scratch was not a small undertaking, especially since we were not actively involved in programming languages research. The answer is simple: Scheme is a wonderful language that captures many sophisticated ideas in a simple syntax. We believed that students needed to be exposed to these ideas, and we wanted to use a Scheme that contained all of the features of a modern implementation. We both studied Computer Science at Indiana University, Bloomington, and were exposed to the beautiful ideas taught in the Programming Languages courses there, and felt compelled to do our part in passing the ideas on to the next generation of students. Thus, we began the development of what would become Calysto Scheme.

Once the core Scheme language was written in Scheme, we converted it to a low-level implementation written in C#, which could take advantage of the DLR. The final conversion step to C# was relatively straightforward. At this point, we were able to add Scheme to our list of supported languages, including Python, F#, and Ruby. The code snippets in Figure 2 show demo scripts written

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[1]IronScheme eventually did include at least some support for first-class continuations. However, it was incrementally added beginning in late 2008 [Pritchard 2008] after we had begun building Calysto Scheme.

in these four languages, all of which call functions from the same underlying Python graphics library. Each script creates a graphics window titled "Hello", and draws a line between points (0, 0) and (100, 100). The calls to library functions in each language differ merely in their syntax, but there are many deeper differences between the languages in terms of semantics.

```
# Python Graphics Example
import Graphics
win = Graphics.Window("Hello")
line = Line((0,0), (100,100))
line.draw(win)


;; Scheme Graphics Example
(using "Graphics")
(define win (Graphics.Window "Hello"))
(define line (Graphics.Line (Graphics.Point 0 0) (Graphics.Point 100 100)))
(line.draw win)


// F# Graphics Example
module MyModule
let win = Graphics.Window("Hello")
let line = new Graphics.Line(new Graphics.Point(0,0), new Graphics.Point(100,100))
line.draw(win)


# Ruby Graphics Example
win = Graphics::WindowClass.new("Hello")
line = Graphics::Line.new(Graphics::Point.new(0,0), Graphics::Point.new(100,100))
line.draw(win)
```

Fig. 2. Calling the same graphics library functions from four different languages in Calico.

Although we initially targeted C# as the implementation language, we eventually decided to replace C# with Python (see below). The core Calysto Scheme architecture remained the same, only the final transformation step needed to be changed to target Python rather than C#. The transformation to Python also included changing calls to C#'s DLR to calls to standard Python functions. The following section outlines the overall Calysto Scheme design pipeline.

2   CALYSTO SCHEME DESIGN

Calysto Scheme ensures full support for call/cc and tail-call optimization, with no limit placed on the depth of the call stack. Unfortunately, languages such as C# and Python impose a maximum depth on their recursion stack and do not support tail-call optimization. Therefore, our approach was to implement the Calysto Scheme interpreter in Scheme, and then automatically convert it, via a series of correctness-preserving program transformations, into low-level register machine code that does not rely on the recursion stack, which can then be directly transformed into Python (or C#) as the final step. The high-level Scheme version of the interpreter is written in Continuation-Passing Style (CPS), with continuations initially represented as anonymous lambda functions. The continuations are then converted to a data structure representation (as lists), and from there passing information to functions via arguments is replaced by passing information via a set of global registers, which removes the reliance on the call stack. At this stage, the computation is driven by

a single "trampoline" loop, essentially equivalent to a while loop [Friedman and Wand 2008; Ganz et al. 1999].

As an example of the transformation process, consider a simple recursive function that adds up the first *n* positive integers. We start with a version of this function written in CPS, using functional continuations, as shown below. For example, calling the top-level function (sum 100) returns 5050.

```
(define sum-cps
  (lambda (n k)
    (if (= n 0)
        (k 0)
        (sum-cps (- n 1)
          (lambda (value)
            (k (+ n value)))))))

;; top-level function
(define sum
  (lambda (n)
    (sum-cps n (lambda (value) value))))
```

We wrote a program that takes any Scheme program written in CPS, such as the above, and transforms the code into an equivalent register machine, with continuations represented as lists. The resulting register machine for sum is shown in Figure 3. Calling (sum 100) still returns 5050, as before.

At this stage, all functions other than the trampoline simply execute if-statements or update registers via assignment statements, without ever calling another function directly (except for low-level built-in primitives like car or +). This avoids building up chains of function calls. This code can then be converted into Python in a straightforward way (see Figure 4). Since the Python version of sum is no longer constrained by the depth of the recursion stack, it can be called with arbitrarily large values of *n*.

In a similar fashion, we transform our Calysto Scheme interpreter from a high-level recursive CPS program written in Scheme into an equivalent low-level register machine written in Python, which does not grow Python's call stack. After the build process completes, the output is a single Python file with no dependencies, which can be easily installed and used.

There is an interesting aspect to creating a language in this manner: the implementation can be tested at each stage of the transformation process to ensure correctness. That is, the same suite of Scheme test programs can be run independently with the CPS, Data Structures, Register Machine, and Python implementations. In essence, the initial CPS definition serves as both a high-level language specification and an executable implementation of the language, from which the other three implementations are subsequently derived. This allows us to test each stage separately to catch bugs in the CPS specification and the transformation process itself.

The current version of Calysto Scheme requires an existing Scheme implementation to carry out the transformations from CPS to Data Structures, and from Data Structures to Register Machine. The final transformation step from Scheme to Python is carried out by a Python program. We used Petite Chez Scheme in early development, and switched to Chez Scheme when it was made open source. In principle, it would be possible to make Calysto Scheme be self-hosting (*i.e.*, Calysto Scheme could carry out the transformations itself). However, our transformation program currently relies on Chez Scheme's syntax-rules macro definition facility, which differs somewhat from the version of define-syntax implemented in Calysto Scheme.

```scheme
;; global registers
(define n_reg 'undefined)
(define k_reg 'undefined)
(define value_reg 'undefined)
(define fields_reg 'undefined)
(define pc 'undefined)
(define final_reg 'undefined)

(define trampoline
  (lambda ()
    (if pc
        (begin
          (pc)
          (trampoline))
        final_reg)))

(define make-cont
  (lambda args
    (cons 'continuation args)))

(define apply-cont
  (lambda ()
    (let ((label (cadr k_reg))
          (fields (cddr k_reg)))
      (set! fields_reg fields)
      (set! pc label))))

(define <cont-1>
  (lambda ()
    (set! final_reg value_reg)
    (set! pc #f)))

(define <cont-2>
  (lambda ()
    (let ((n (car fields_reg))
          (k (cadr fields_reg)))
      (set! k_reg k)
      (set! value_reg (+ n value_reg))
      (set! pc apply-cont))))

(define sum-cps
  (lambda ()
    (if (= n_reg 0)
        (begin
          (set! value_reg 0)
          (set! pc apply-cont))
        (begin
         (set! k_reg (make-cont <cont-2> n_reg k_reg))
         (set! n_reg (- n_reg 1))
         (set! pc sum-cps)))))

;; top-level function
(define sum
  (lambda (n)
    (set! k_reg (make-cont <cont-1>))
    (set! n_reg n)
    (set! pc sum-cps)
    (trampoline)))
```

Fig. 3. Scheme register machine code

```python
# global registers
n_reg = None
k_reg = None
value_reg = None
fields_reg = None
pc = None
final_reg = None

def trampoline():
    while pc:
        pc()
    return final_reg

def car(lst):
    return lst[0]

def cdr(lst):
    return lst[1:]

def cadr(lst):
    return car(cdr(lst))

def cddr(lst):
    return cdr(cdr(lst))

def make_cont(*args):
    return ("continuation",) + args

def apply_cont():
    global fields_reg, pc
    label = cadr(k_reg)
    fields = cddr(k_reg)
    fields_reg = fields
    pc = label

def cont_1():
    global final_reg, pc
    final_reg = value_reg
    pc = False

def cont_2():
    global k_reg, value_reg, pc
    n = car(fields_reg)
    k = cadr(fields_reg)
    k_reg = k
    value_reg = n + value_reg
    pc = apply_cont

def sum_cps():
    global value_reg, pc, k_reg, n_reg
    if n_reg == 0:
        value_reg = 0
        pc = apply_cont
    else:
        k_reg = make_cont(cont_2, n_reg, k_reg)
        n_reg = n_reg - 1
        pc = sum_cps

# top-level function
def sum(n):
    global k_reg, n_reg, pc
    k_reg = make_cont(cont_1)
    n_reg = n
    pc = sum_cps
    return trampoline()
```

Fig. 4. Python register machine code

3 SYNTACTIC EXTENSION

Calysto Scheme supports syntactic extension through its own version of define-syntax, which can define simple macros using standard list notation in conjunction with unification pattern matching variables beginning with the ? character. For example, consider the following macro expansion rules for the logical expressions and and or:

(and *exp*) → *exp*
(and *exp*$_1$ *exp*$_2$ *exp*$_3$ ...) → (if *exp*$_1$ (and *exp*$_2$ *exp*$_3$ ...) #f)

(or *exp*) → *exp*
(or *exp*$_1$ *exp*$_2$ *exp*$_3$ ...) → (if *exp*$_1$ #t (or *exp*$_2$ *exp*$_3$ ...))

Although and and or are already available as special forms in Calysto Scheme, in principle they could be implemented with the following recursive macro definitions:

```
(define-syntax and
  [(and ?exp) ?exp]
  [(and ?first-exp . ?other-exps) (if ?first-exp (and . ?other-exps) #f)])

(define-syntax or
  [(or ?exp) ?exp]
  [(or ?first-exp . ?other-exps) (if ?first-exp #t (or . ?other-exps))])
```

For example, the input expression (or a b c d) would match the pattern of the second clause above, with the variable ?first-exp bound to a and the variable ?other-exps bound to the list (b c d). The corresponding template subexpression (or . ?other-exps) would then get instantiated as (or b c d), and recursively expanded further. This type of pattern matching facility is similar to Chez Scheme's syntax-rules form, except that instead of using ellipses to match sequences of zero or more expressions, Calysto Scheme's define-syntax uses improper lists.

Compared to syntax-rules, however, this approach has some limitations and cannot capture certain transforms that can be expressed using ellipses. For example, to transform the expression (let ((i e) ...) b) into ((lambda (i ...) b) e ...), the ellipses are used to separate the let-bindings into their constituent identifiers and value expressions, but this cannot be done using Calysto Scheme's unification pattern matching mechanism.

Although Calysto's define-syntax form is not as powerful or general as syntax-case or syntax-rules, it does provide the ability to easily define a fairly wide range of syntactic transforms via pattern matching, as shown in the previous examples. Including a fully-general syntactic extension system, like that provided in Chez Scheme, was not a central goal of the Calysto project, but we nevertheless felt that it was important to provide at least basic support for easy-to-use, user-defined macros in Calysto Scheme.

4 EXAMPLE: NONDETERMINISTIC BACKTRACKING

In their classic text *Structure and Interpretation of Computer Programs* (SICP) [Abelson and with Julie Sussman 1996], Abelson and Sussman introduce the nondeterministic "amb" operator for automatic backtracking. We have incorporated this operator into Calysto Scheme as the special form (choose *arg*$_1$ *arg*$_2$ ... *arg*$_n$), which nondeterministically chooses one of its arguments to evaluate and returns the resulting value. From there, the computation proceeds normally, unless (choose) is subsequently invoked with no arguments, at which point the computation "fails"

and immediately jumps back to the previous choose expression, whereby a different argument is chosen to evaluate next, and the computation restarts from that point with the new value. Many constraint-satisfaction problems can be elegantly solved using choose.

As an extended example illustrating both choose and define-syntax, suppose we wish to write a program to determine how to color a map of (a portion of) Western Europe using four distinct colors. We first define a function to nondeterministically return one of four possible colors:

```
(define choose-color
  (lambda ()
    (choose 'red 'yellow 'blue 'white)))
```

The color-europe program begins by nondeterministically assigning a color to each country on the map:

```
(define color-europe
  (lambda ()
    (let ([portugal (choose-color)]
          [spain (choose-color)]
          [france (choose-color)]
          [belgium (choose-color)]
          [germany (choose-color)]
          [luxembourg (choose-color)]
          [italy (choose-color)]
          [switzerland (choose-color)])
       ...)))
```

Next, we must apply the following constraint to each country: its chosen color must be different from that of all of its adjacent neighbors. For example, since Luxembourg is bordered by France, Belgium, and Germany, we could express its color constraint as follows:

```
(require (not (member luxembourg (list france belgium germany))))
```

The require function is a built-in Calysto Scheme primitive similar to an assertion statement, which takes a boolean value as input and invokes (choose) if the input is false in order to force the program to backtrack to the most recent choice point, instead of raising an exception. However, a more elegant approach might be to define a new syntactic form called color that expands to the above code but expresses the constraint in a more readable way:

```
(color luxembourg different from france belgium germany)
```

The Calysto Scheme macro definition for color is given below, along with the complete program to determine a consistent map-coloring:

```
(define-syntax color
  [(color ?country different from . ?neighbors)
   (require (not (member ?country (list . ?neighbors))))])
```

```
(define color-europe
  (lambda ()
    (let ([portugal (choose-color)]
          [spain (choose-color)]
          [france (choose-color)]
          [belgium (choose-color)]
          [germany (choose-color)]
          [luxembourg (choose-color)]
          [italy (choose-color)]
          [switzerland (choose-color)])
      ;; apply the constraints
      (color portugal different from spain)
      (color spain different from france portugal)
      (color france different from spain italy switzerland belgium germany luxembourg)
      (color belgium different from france luxembourg germany)
      (color germany different from france switzerland belgium luxembourg)
      (color luxembourg different from france belgium germany)
      (color italy different from france switzerland)
      (color switzerland different from france italy germany)
      ;; return a coloring that satisfies the constraints
      (list (list 'portugal portugal)
            (list 'spain spain)
            (list 'france france)
            (list 'belgium belgium)
            (list 'germany germany)
            (list 'luxembourg luxembourg)
            (list 'italy italy)
            (list 'switzerland switzerland)))))
```

Calling (color-europe) returns the solution ((portugal red) (spain yellow) (france red)
(belgium yellow) (germany blue) (luxembourg white) (italy yellow) (switzerland
white)). However, this is not the only valid solution; many other color combinations will work.
We can force the program to backtrack to find another combination that satisfies the constraints,
simply by calling (choose) as many times as we like, until all valid choices have been returned:

```
==> (choose)
((portugal red) (spain yellow) (france red) (belgium yellow) (germany blue)
 (luxembourg white) (italy blue) (switzerland yellow))
==> (choose)
((portugal red) (spain yellow) (france red) (belgium yellow) (germany blue)
 (luxembourg white) (italy blue) (switzerland white))
```

and so on. Eventually, after all possible combinations of choices satisfying the constraints have
been returned, any subsequent calls to (choose) will return the string "no more choices", until a
new choose expression is executed.

5 PYTHON / SCHEME INTEROPERATION

There are a number of ways that Calysto Scheme and Python can interoperate. For example,
Python code can be directly evaluated from within Scheme. Scheme functions can be defined in an
environment shared with Python, and then called by Python programs. And Python functions and
libraries can be imported directly into Scheme and called from within Scheme programs.

Whereas in Scheme the function eval can be used to evaluate all types of expressions, Python
makes a distinction between evaluating expressions and executing statements. Thus in Calysto

Scheme, the function `python-eval` is used to evaluate strings representing Python expressions, and `python-exec` is used to execute Python statements.

```
(python-eval "1 + 2")
→ 3
(python-exec
"
def multiply(a, b):
    return a * b
")
(python-eval "multiply(2, 3)")
→ 6
```

The special form `func` turns a Scheme procedure into a Python function, and `define!` puts it into the shared environment with Python:

```
(define! square (func (lambda (n) (* n n))))
(python-eval "square(3)")
→ 9
```

As a simple illustration of Calysto Scheme's ability to leverage the power of Python libraries, consider the following example, in which the elements of a nested Scheme list are summed by converting it to a NumPy array and then applying the NumPy sum function, instead of first flattening the list or recursively summing the sublists:

```
(import "numpy")
(let ([matrix3d '(((10 20 30) (40 50 60))
                  ((70 80 90) (100 110 120))
                  ((130 140 150) (160 170 180))
                  ((190 200 210) (220 230 240)))])
  (numpy.sum (numpy.array matrix3d)))
→ 3000
```

Plotting data with Python's Matplotlib library is likewise a simple matter in Calysto Scheme:

```
(import-as "matplotlib.pyplot" "plt")
(plt.plot '(1 2 3 4 5) '(1 4 9 16 25))
(plt.show)
```

Python dictionaries can also be created and manipulated from within Calysto Scheme using a special syntax, as shown in the example interaction below:

```
==> (define d (dict '((apple : red) (banana : yellow) (lime : green))))
==> d
{'apple': red, 'banana': yellow, 'lime': green}
==> (get-item d 'apple)
red
==> (set-item! d 'apple 77)
==> d
{'apple': 77, 'banana': yellow, 'lime': green}
```

A more complex example that shows the power of combining these features is shown in Figure 5. This Scheme code sets up a series of machine learning experiments using the NumPy and TensorFlow libraries imported from Python, along with a third-party library called comet_ml that provides tools for managing experiments. The choose operator is used to select a particular combination of "hyperparameters" for an experiment, and a neural network is then defined using TensorFlow functions. Many TensorFlow functions are configured via keyword parameters in Python, which here we provide as Calysto Scheme dictionaries. After an experiment using a particular set of hyperparameters has run to completion, we can simply invoke (choose) to pick a new combination of hyperparameters and rerun the experiment.

```
(import-as "tensorflow" "tf")
(import-as "numpy" "np")
(import "comet_ml")

;; load the MNIST dataset using the Keras load_data function
(define dataset (tf.keras.datasets.mnist.load_data))

;; prepare the dataset
(define x_train (/ (get-item (get-item dataset 0) 0) 255.0))
(define y_train (get-item (get-item dataset 0) 1))
(define x_test (/ (get-item (get-item dataset 1) 0) 255.0))
(define y_test (get-item (get-item dataset 1) 1))

(define loss_fn (tf.keras.losses.SparseCategoricalCrossentropy (dict '((from_logits : #t)))))

(let* ([optimizer (choose "adam" "rmsprop" "sgd")]
       [dropout_rate (choose 0.0 0.1 0.2 0.4)]
       [activation (choose "relu" "sigmoid")]
       [hidden_layer_size (choose 10 20 30)]
       [options (dict `((optimizer : ,optimizer)
                        (loss : ,loss_fn)
                        (metrics : ,(vector "accuracy"))))]
       [epochs 5]
       [experiment (comet_ml.Experiment (dict '((project_name : "calysto-scheme"))))]
       [model (tf.keras.models.Sequential
                (vector
                 (tf.keras.layers.Flatten (dict '((input_shape : (28 28)))))
                (tf.keras.layers.Dense hidden_layer_size (dict `((activation : ,activation))))
                 (tf.keras.layers.Dropout dropout_rate)
                 (tf.keras.layers.Dense 10)))])
  (print experiment.url)
  (model.compile options)
  (model.summary)
  (experiment.log_parameters (dict `((optimizer : ,optimizer)
                                     (dropout_rate : ,dropout_rate)
                                     (activation : ,activation)
                                     (hidden_layer_size : ,hidden_layer_size)
                                     (epochs : ,epochs)))
                             (dict))
  (experiment.set_model_graph model)
  (let ([history (model.fit x_train y_train (dict `((epochs : ,epochs))))]
        [step 0])
    (map (lambda (key)
           (set! step 0)
           (map (lambda (v)
                  (experiment.log_metric key v step)
                  (set! step (+ step 1)))
                (get-item history.history key)))
         history.history))
  (experiment.end))
```

Fig. 5. Calysto Scheme code for running TensorFlow experiments.

6 CALYSTO SCHEME IN JUPYTER

The Jupyter Project is a language-independent client-server system for running code using a web browser as the IDE [Kluyver et al. 2016]. Initially, Jupyter was limited to Python (and was originally called IPython [Pérez and Granger 2007]). However, the developers realized that their system could be used for any language, and the Jupyter Project was born. Today, Jupyter is one of the most-used tools in data science. Jupyter Notebooks allow the mixing of code, text, mathematics, and visualizations within a single executable document.

In many ways, the goals of Jupyter were similar to the original goals of our Calico project: language independence with a common UI. In fact, when Jupyter was announced, we realized that this made more sense than our C#-based system, and we began migration of our project to the Jupyter framework. Calysto Scheme, in fact, gets its name from Callisto, the second largest moon of the planet Jupiter.

Running Calysto Scheme in a Jupyter environment (such as notebook, jupyterlab, console, or qtconsole) provides the following additional features:

- TAB completions of Scheme functions and variable names
- Ability to directly display rich media such as images
- Access to so-called magics (% meta-commands)
- Ability to easily run shell commands using the "! command" format
- LaTeX-style equations and variables

For example, in Calysto Scheme running in Jupyter, one can create a lambda function with the Greek symbol λ in place of the lambda keyword by typing **\lambda** and pressing [TAB] (see Figure 6). Building on top of the Jupyter system makes Calysto Scheme easy to use, and brings it into a modern language environment.

Fig. 6. Calysto Scheme running in a Jupyter Notebook.

Fig. 7. Example of a traceback in Calysto Scheme.

Many Jupyter language kernels (including IPython's) also support a set of meta-commands called "magics". These meta-commands allow the user to easily perform a variety of functions such as running operating system commands, creating files, timing execution, and many more.

We wanted the Calysto Scheme Jupyter kernel also to have easy-to-use meta-commands. However, rather than building those directly into the Calysto Scheme kernel, we decided to put them in a separate abstraction layer. Thus, we collaborated with others to create a project called "Metakernel" [Silvester 2015]. Metakernel supports many meta-commands, including many designed for educational use, and does so in a language-independent manner. Metakernel's GitHub page currently lists over 700 different projects that have incorporated it in one way or another. In fact, Metakernel may be the most widely used contribution of the Calysto Scheme Project to date.

The full list of Metakernel's magics can be found in [Blank 2015a]. All of these extend Calysto Scheme to make it more useful in Jupyter environments. However, one meta-command that deserves special mention in this context is the `%parallel` magic. If a parallel computing cluster is available, this magic turns Calysto Scheme into a parallelized interpreter. For example, the following command initializes the cluster for running Calysto Scheme:

```
%parallel calysto_scheme CalystoScheme
```

After initializing the cluster, individual Scheme expressions or entire code cells can be run in parallel using the `%px` command. Figure 8 shows an excerpt of Calysto Scheme code for computing the Mandelbrot set in parallel. A full example of parallel execution can be found in [Blank 2015b].

```
In [15]:    %%time
            %%px --set_variable results

            (define portion (int (/ n cluster_size)))

            (for col in (range n) do
                (for row in (range (* cluster_rank portion)
                                   (* (+ cluster_rank 1) portion)) do
                    (let* ((x0 (+ (- xc (/ size 2)) (* size (/ col n))))
                           (y0 (+ (- yc (/ size 2)) (* size (/ row n))))
                           (z0 (complex x0 y0))
                           (gray (- MAX (mandelbrot z0 MAX))))
                        (mset! matrix col row (ascii gray))
                        (printf ".")))
                (printf "\n"))

            matrix

        Time: 19.94576096534729 seconds.
```

Fig. 8. Parallel processing code for generating the Mandelbrot set in Calysto Scheme.

It should be noted that many computer science educators find the use of Jupyter Notebooks to be problematic. The main objection is that it is easy for a student to create hidden state that may lead to unexpected and non-intuitive results. For example, one can edit cells that have already been executed, creating dependencies that are difficult to reproduce. On the other hand, we have also heard educators lament that "Jupyter is *too* convenient" for the student.

In spite of these warnings, Jupyter Notebooks are popular with data scientists and others who tell stories with code, visualizations, and text. This can make an excellent environment for teaching and learning. One of us (Blank) taught all of his classes for four years using nothing but Jupyter. That included courses on Data Structures (Java), Cognitive Science (Python), Assembly Language, Introduction to Computer Science (Processing), Programming Languages (Scheme), and Creative Writing (English). This was accomplished by hosting a local JupyterHub instance[2] at Bryn Mawr College, so that students did not need to install anything and could perform all of their work via the web browser. For more on these ideas, see [O'Hara et al. 2015].

Judging from the Calysto Scheme issues reported on GitHub, most people discover Calysto Scheme through the Jupyter Project's "Try Jupyter" page [Maintainers 2023], where Calysto Scheme is featured along with kernels for C++, Julia, GNU Octave, R, and Ruby. See Figure 9. Many people apparently also use Calysto Scheme for working through SICP exercises.

7 STACK-LIKE TRACEBACKS FOR DEBUGGING

In Calysto Scheme, tracebacks are available to help with debugging. For example, in Figure 7 the definition of the factorial function contains a typo, with q instead of 1 for the base case, which generates an unbound variable error. The traceback shows the sequence of recursive calls that were made before the error occurred. In many Scheme implementations, since control is not

---

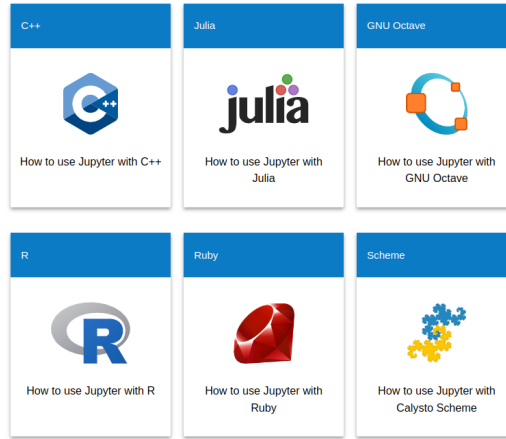[2]Incidentally, this was the very first publicly-hosted JupyterHub instance.

Fig. 9. Calysto Scheme is available online via the Jupyter Project's "Try Jupyter" page.

managed with a stack, it is not possible to generate such a stack trace. However, in Calysto Scheme stack tracing can be enabled or disabled via the parameter use-stack-trace. For example, calling (use-stack-trace #f) turns off stack tracing.

8 SCHEME IN PYTHON, PYTHON IN SCHEME

An approach commonly taken in teaching a course on Programming Languages is to implement an interpreter for a subset of Scheme in another language, such as Python. This is a relatively straightforward process, which is considerably simplified by Scheme's easy-to-parse syntax. For example, the following code shows part of an interpreter written in Python with the functions `evaluator` and `apply_operator` for evaluating Scheme expressions and applying Scheme functions, respectively:

```
# Scheme-in-Python interpreter

# define parser, reader, tokenizer, and utilities (Map, car, cdr, etc.)

def evaluator(expr):
    if car(expr) == "literal":
        return cadr(expr)
    elif car(expr) == "application":
        return apply_operator(evaluator(cadr(expr)),
                              Map(evaluator, caddr(expr)))
    else:
        raise Exception("Invalid AST: %s" % expr)

def apply_operator(op, operands):
    if op == "+":
        return sum(operands)
    else:
        raise Exception("Unknown operator: %s" % op)

evaluator(parser(reader(tokenizer("(+ 1 2)"))))
→ 3
```

Conversely, one could also teach programming language principles by implementing Python in Scheme. However, this would be much more challenging to attempt in a single semester course, due to the complexity of Python's syntax. However, if it were possible to outsource the parsing of Python syntax into Abstract Syntax Tree (AST) structures, then one could commence with building a Python interpreter written in Scheme that operates directly on Python ASTs. Because Calysto Scheme can call Python libraries, this becomes a simple task, as the ast Python library has the ability to take strings of Python code and turn them into ASTs [Blank 2016].

Mirroring the above Python functions for interpreting Scheme code, one can easily construct similar functions written in Scheme for interpreting Python ASTs:

```
;; Python-in-Scheme interpreter

(import "ast")

(define evaluator
  (lambda (ast_expr)
   (cond
     [(isinstance ast_expr ast.Module)
      (evaluator (get-item ast_expr.body 0))]
     [(isinstance ast_expr ast.Num)
      ast_expr.n]
     [(isinstance ast_expr ast.Expr)
      (evaluator ast_expr.value)]
     [(isinstance ast_expr ast.BinOp)
      (apply-operator ast_expr.op
         (evaluator ast_expr.left)
         (evaluator ast_expr.right))]
     [else (error 'evaluator (format "Unknown ast: ~s" ast_expr))])))

(define apply-operator
  (lambda (op v1 v2)
    (cond
      [(isinstance op ast.Add) (+ v1 v2)]
      [else (error 'apply-operator (format "Invalid operator: ~s" op))])))

(evaluator (ast.parse "1 + 2"))
  → 3
```

The main differences between the Scheme interpreter in Python, and the Python interpreter in Scheme arise from the different ways in which they represent abstract syntax. For example, the Scheme expression (+ 1 2) is treated as a function application AST by the Scheme-in-Python interpreter, whereas the Python expression "1 + 2" is treated as a binary operator AST by the Python-in-Scheme interpreter. One could easily change the Scheme abstract syntax structures to more closely mimic the Python AST structures if desired, in order to make the two interpreters more symmetric.

9   SUMMARY

In this paper we have presented Calysto Scheme, a full-featured implementation of the Scheme language written in Scheme and transpiled into Python, with support for easy interoperation with many Python libraries, as well as Jupyter Notebooks. This system was originally designed primarily with CS education in mind, and has found many novel uses, including as an effective platform for teaching programming-language concepts through the hands-on development of Scheme interpreters in Python, and, in parallel, Python interpreters in Scheme. Although our focus has been mainly on pedagogy, we are gratified that others have found Calysto Scheme to be useful in more general contexts as well.

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