

# Instruction level automatic differentiation on a reversible Turing machine

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This paper considers the instruction-level adjoint mode automatic differentiation (AD). Here, instruction-level means, given the backward rules of basic instructions like  $+$ ,  $-$ ,  $*$  and  $/$ , one can differentiate an arbitrary program efficiently. In this paper, we review why instruction-level AD is hard for traditional machine learning frameworks and propose a solution to these problems by back-propagating a reversible Turing machine. Instruction level AD is a powerful tool to generate backward rules. We demonstrate its power by differentiating over the reversible implementations of exp function, and linear algebra functions unitary matrix multiplication and QR decomposition. It is also a promising direction towards solving the notorious memory wall problem in machine learning. Also, we discuss the challenges that we face towards rigorous reversible programming from the instruction and hardware perspective.

## I. INTRODUCTION

There are two modes [LW: not only two, can be mixed. They are just to extremes.] of automatic differentiation (AD) [1], the tangent mode AD and the adjoint mode AD. Consider a multi-in multi-out function  $\vec{y} = f(\vec{x})$ , the tangent mode AD computes one column of its Jacobian  $\frac{\partial \vec{y}}{\partial x_i}$  efficiently, where  $x_i$  is one of the input variables, whereas the adjoint mode AD computes one row of Jacobian  $\frac{\partial y_i}{\partial \vec{x}}$  efficiently. Most popular automatic differentiation packages implement the adjoint mode AD because the adjoint mode is computational more efficient in variational applications, where the loss as output is always a scalar. However, implementing adjoint mode AD is harder than implementing its tangent mode counterpart. It requires a program's intermediate state for back-propagation, which includes

1. the computational graph,
2. and variables used in back propagation.

A computational graph is a directed acyclic graph (DAG) that records the relationship between data (edges) and functions (nodes). In Pytorch [2] and Flux [3], every variable has a tracker field that stores its parent information, i.e., the input data and function that generate this variable. TensorFlow [4] implements a static computational graph as a description of the program before actual computation happens. Source to source AD package Zygote [5, 6] uses an intermediate representation (IR) of a program, the static single assignment (SSA) form, as the computational graph in order to back-propagate a native Julia code. To cache intermediate states, it has to access the global storage.

Several limitations are observed in these AD implementations due to the recording and caching. First of all, these packages require a lot of primitive functions with programmer-defined backward rules. These backward rules are not necessary given the fact that, at the lowest level, these primitive functions are lowered to a finite set of instructions including

$+$ ,  $-$ ,  $*$ ,  $/$ , and conditional jump. By defining backward rules for these basic instructions, AD should work without extra effort. These machine learning packages can not use instructions as the computational graph for practical reasons. The cost of memorizing the computational graph and caching intermediate states is huge. It can decrease the performance for more than two orders when a program contains loops (as we will show later). Even more, the memory consumption for caching intermediate results increases linearly as time. In many deep learning models like recurrent neural network [7] and residual neural networks [8], the depth can reach several thousand. The memory is often the bottleneck of these programs, which is known as the memory wall problem. [9] Secondly, inplace functions are not handled properly in the diagram of computational graphs, because the notation of parent and child are not compatible with inplace operations. Even in Zygote that uses SSA as the computational graph, it is not trivial to handle inplace functions. On the other side, most functions in BLAS and LAPACK are implemented as inplace functions. All AD packages that use BLAS and LAPACK functions have to define their own backward rules for their non-inplace wrappers due to the lack of AD support to inplace functions. Thirdly, obtaining higher-order gradients are not efficient in these packages. For example, in most machine learning packages, people back-propagate the whole program of obtaining first-order gradients to obtain second-order gradients. The repeated use of back-propagation causes an exponential overhead concerning the order of gradients. A better approach is using Taylor propagation like in JAX [10]. However, Taylor propagation requires writing backward rules for all primitives[JG: true?].

Our solution to these issues is making a program reversible. It is not the same as the workarounds in the machine learning field that use information buffer [11] and reversible activation functions to reduce the memory allocations in recurrent neural networks [12] and residual neural networks [13]. Our approach is general. We develop an embedded domain-specific language (eDSL) in Julia language that implements a reversible Turing machine (RTM). [14, 15]. One can obtain the gradients of any program written in this eDSL at a comparable time with the forward computation. The AD implementation is similar to ForwardDiff [16] but runs backward. In history,

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there have been some prototypes of reversible languages like Janus [17], R (not the popular one) [18], Erlang [19] and object-oriented ROOPL [20]. These languages have reversible control flow that allows user to input an additional postcondition in control flows to help programs run backward. In the past, the primary motivation for making a program time-reversible is to support reversible devices. Reversible devices do not have a lower bound of energy consumption by Landauer principle [21]. However, people show less and less interest to reversible programming since 15 years ago since the energy efficiency of CMOS devices are still two orders [15] above this lower bound, this lower bound is not an urgent problem yet. The main contribution of our work is breaking the information barrier between the machine learning community and the reversible programming community, providing yet another strong motivation to develop reversible programming. Our eDSL borrows the design of reversible control flow in the Janus, meanwhile provides multiple-dispatch based abstraction. With these features, we implemented the AD engine with less than 100 lines of code. It generates native Julia code and is entirely compatible with Julia language.

In this paper, we first introduce the design of our eDSL in Sec. II. In Sec. III, we show how to back-propagation Jacobians and Hessians in a reversible programming language. We propose a self-consistent training strategy in Sec. IV that utilizes reversibility directly, which does require gradients. In Sec. V, we show several examples. We use eDSL to generate backward rules for exp function, unitary matrix multiplication and even QR decomposition. In Sec. VI, we discuss several important issues, how time-space tradeoff works, reversible instructions and hardware, and finally, an outlook to some open problems to be solved.

## II. LANGUAGE DESIGN

**[LW: you may separate general principle with specific implementation choices. First state clearly what are the key requirement, and difficulties. Then introduce the design which address them.]** We introduce NiLang, an eDSL in Julia that simulates RTM. Its grammar is shown in Appendix A. Its main feature is contained in a single macro @i. It interprets a NiLang function to a native Julia function. At the same time, it generates the inverse of this function. While the generated functions lower to reversible “instructions”, these instructions are closed under the inverse operation “ $\sim$ ”. Hence all functions defined in NiLang are also closed under “ $\sim$ ” operations.

In a modern programming language, functions are pushed to a global stack for scheduling. The memory layout of a function is consisted of input arguments, a function frame with information like the return address and saved memory segments, local variables, and working stack. After each call, the function clears the input arguments, function frame, local variables, and working stack, only stores the return value. In the reversible programming style, this kind of design pattern is no longer the best practice. One can not discard

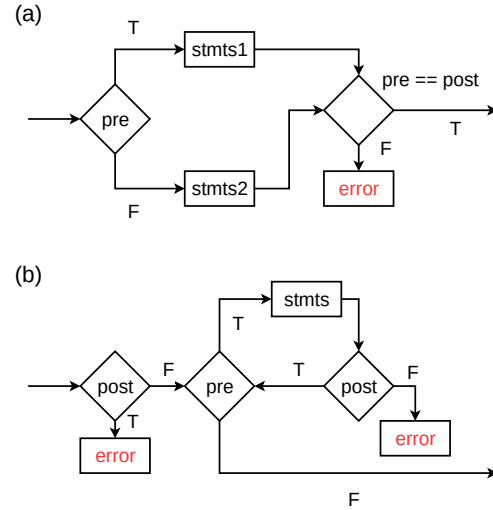


Figure 1. Flow chart for reversible (a) if statement and (b) while statement. “stmts”, “stmts1” and “stmts2” are statements, statements in true branch and statements in false branch respectively. “pre” and “post” are precondition and postconditions respectively. “error” refers to InvertibilityError.

input variables easily after a function call, since discarding information may ruin reversibility. Hence, a function or an instruction changes inputs “inplace” in NiLang. To design such an eDSL, we first introduce a reversible IR that plays a central role in NiLang.

### A. Reversible IR

In NiLang’s IR, a statement can be an instruction, a function call, a control flow, a macro call, or the inverse statement  $\sim$ . With the reversible IR, one can define the inverse of a statement easily, as shown in Table I.

The reversible control flow is different from the irreversible one that a conditional expression in a if or a while statements is a two-element tuple that consists of a precondition and a postcondition. This design allows users putting additional postcondition in control flows to help reverse the program. For the if statement as shown in Fig. 1 (a), the program enters the branch specified by precondition. After executing this branch, the program checks the consistency of precondition and postcondition to make sure they are the same. In the reverse pass, the program enters the branch specified by the postcondition. For the while statement as shown in Fig. 1 (b), before entering, the program check the postcondition to make sure it is false. After each iteration, the program asserts the postcondition to be true. The inverse function exchanges the precondition and postcondition. The definition of reversible for statement is similar to irreversible ones. Before entering the loop, the program stores variables start, step, and stop locally. After executing the loop, the program checks the values of these variables to make sure they are not changed. The reverse program exchanges start

statement	inverse
<code>&lt;f&gt;(&lt;args&gt;...)</code>	<code>(~&lt;f&gt;)(&lt;args&gt;...)</code>
<code>&lt;y!&gt; += &lt;f&gt;(&lt;args&gt;...)</code>	<code>&lt;y!&gt; -= &lt;f&gt;(&lt;args&gt;...)</code>
<code>&lt;y!&gt; .+= &lt;f&gt;(&lt;args&gt;...)</code>	<code>&lt;y!&gt; .-= &lt;f&gt;(&lt;args&gt;...)</code>
<code>&lt;y!&gt; ∇= &lt;f&gt;(&lt;args&gt;...)</code>	<code>&lt;y!&gt; ∇= &lt;f&gt;(&lt;args&gt;...)</code>
<code>&lt;y!&gt; .∇= &lt;f&gt;(&lt;args&gt;...)</code>	<code>&lt;y!&gt; .∇= &lt;f&gt;(&lt;args&gt;...)</code>
<code>@anc &lt;a&gt; = &lt;expr&gt;</code>	<code>@deanc &lt;a&gt; = &lt;expr&gt;</code>
<code>begin</code> <code>&lt;stmts&gt;</code> <code>end</code>	<code>begin</code> <code>~(&lt;stmts&gt;)</code> <code>end</code>
<code>if (&lt;pre&gt;, &lt;post&gt;)</code> <code>&lt;stmts1&gt;</code> <code>else</code> <code>&lt;stmts2&gt;</code> <code>end</code>	<code>if (&lt;post&gt;, &lt;pre&gt;)</code> <code>~(&lt;stmts1&gt;)</code> <code>else</code> <code>~(&lt;stmts2&gt;)</code> <code>end</code>
<code>while (&lt;pre&gt;, &lt;post&gt;)</code> <code>&lt;stmts&gt;</code> <code>end</code>	<code>while (&lt;post&gt;, &lt;pre&gt;)</code> <code>~(&lt;stmts&gt;)</code> <code>end</code>
<code>for &lt;i&gt;=&lt;m&gt;:&lt;s&gt;:&lt;n&gt;</code> <code>&lt;stmts&gt;</code> <code>end</code>	<code>for &lt;i&gt;=&lt;m&gt;:-&lt;s&gt;:&lt;n&gt;</code> <code>~(&lt;stmts&gt;)</code> <code>end</code>
<code>@safe &lt;expr&gt; x</code>	<code>@safe &lt;expr&gt;</code>

Table I. A collection of reversible statements.

and stop and inverse the sign of step.

There are no assign statements in a reversible language. A reversible replacement is the macro `@anc`. `@anc a = <expr>` binds variable `a` to an initial value specified by `<expr>`. Its inverse `@deanc a = <expr>` deallocates the variable `a`. Before deallocating the variable, the program checks that its value is the same as the value of `<expr>`, otherwise throws an `InvertibilityError`. `@anc` and `@deanc` must appear in pairs inside a function call, a `while` statement, or a `for` statement. `@deanc` will be added automatically. Similar designs in Janus and R are `local`/`delocal` statement and `let` statement. The additional check underlines the difference between the irreversible assign statement and reversible ancilla statement. The `@safe` macro allows users to use external statements that do not break reversibility. For example, one can use `@safe @show var` for debugging.

## B. Compiling

The interpretation of a reversible function consists three stages. The first stage preprocess human inputs to a reversible IR. The following example preprocess an `if` statement

```
julia> prettify(@code_preprocess if (pre, ~)
    z += x * y
end)
:(if (pre, pre)
    z += x * y
else
end)
```

The preprocessor expands the symbol `~` in the postcondition field of `if` statement to the precondition. In this stage, the preprocessor also adds missing `@deanc` to ensure `@anc` and `@deanc` statements appear in pairs and expands `@routine` macro. `@routine r <stmt>` records a statement to symbol `r`. In preprocessing stage, `~@routine r` will be replaced to `~<stmt>` for uncomputing. We will use macro extensively in the examples in Sec. V.

The second stage generates the reversed IR according to table Table I.

```
julia> prettify(@code_reverse if (pre, post)
    z += x * y
else
    z += x / y
end)
:(if (post, pre)
    z -= x * y
else
    z -= x / y
end)
```

The third stage is translating this IR and its inverse to native Julia code. The following example shows how to compile an `if` statement.

```
julia> prettify(@code_interpret if (pre, post)
    z += x * y
else
    z += x / y
end)
quote
    bat = pre
    if bat
        @assignback (PlusEq(*))(z, x, y)
    else
        @assignback (PlusEq(/))(z, x, y)
    end
    @invcheck post bat
end
```

The compiler translates the instruction according to Table II and adds `@assignback` before each instruction and function call statement. The macro `@assignback` assigns the output of a function to the argument list of a function, which will be explained in detail in the next subsection. It also adds `@invcheck post bat` statements to check the consistency between preconditions and postconditions to ensure

reversibility. This statement will throw an error if target variables `bat` and `post` are not “equal” to each other up to the rounding error. Finally, at the end of a function body, we attach a return statement that returns variables in the argument list. Now the function is ready to execute on the host language.

### C. Types and Dataviews

So far, the language design is not too different from a traditional reversible language. To the implementation of adjoint mode AD, we introduce types and dataviews. The constructor of a type is a reversible function. Its inverse is a “destructor” that does not deallocate memory directly but unpacks data. One can use `@iconstruct` to define a reversible constructor. The following example defines a type that can be used in a reversible context.

```
using NiLangCore, Test

struct DVar{T}
    x::T
    g::T
end

@iconstruct function DVar(xx, gg=zero(xx))
    gg += identity(xx)
end

@test (~DVar)(DVar(0.5)) == 0.5
```

The first parameter `xx` is the actual input of constructor, the assign statement in argument list `gg = zero(xx)` initialize a new memory. The body of the function is a reversible program that transforms `xx` and `gg` reversibly. Finally, the compiler appends a default constructor `DVar(xx, gg)` at the end to instantiate the new object. The destructor that coverts an object of type `DVar{T}` to type `T` can be defined by reversing the above statements.

A dataview of a data can be the data itself, a field of its view, an array element of its view, or a bijective mapping of its view. Before introducing dataviews, let us first consider the following example.

```
julia> using NiLangCore.ADCore

julia> arr = [GVar(3.0), GVar(1.0)]
2-element Array{GVar{Float64,Float64},1}:
 GVar(3.0, 0.0)
 GVar(1.0, 0.0)

julia> x, y = 1.0, 2.0
(1.0, 2.0)

julia> @instr -arr[2].g += x * y

julia> arr
2-element Array{GVar{Float64,Float64},1}:
 GVar(3.0, 0.0)
 GVar(1.0, -2.0)
```

In Julia, `-grad(arr[2]) += x * y` statement will raise a syntax error because a function call `(-)` can not be assigned, and `arr[3]` is an immutable type. In our eDSL, we wish it works because every memory cell should be modifiable. `@instr` translate the above statement to

```
1 res = (PlusEq{*})(-arr[2].g, x, y)
2 arr[2] = chfield(arr[2], Val{:g},
3   chfield(arr[2].g, -, res[1]))
4 x = res[2]
5 y = res[3]
```

`PlusEq{*})(-arr[2].g, x, y)` computes the output, which is a tuple of length 3. At lines 2-3, `chfield(x, Val{:g}, val)` modifies the `g` field of `x` and `chfield(x, -, res[1])` returns `-res[1]`. Here, modifying a field requires the default constructor of a type is not overwritten. The assignments at lines 4 and 5 are straight forward.

## III. AUTOMATIC DIFFERENTIATION

### A. First order gradient

Given a node  $\vec{y} = f(\vec{x})$  in a computational graph, the adjoint mode AD propagates the Jacobians in the reversed direction like

$$\begin{aligned} J_{O'}^O &= \delta_{O,O'}, \\ J_x^O &= J_y^O J_x^y, \end{aligned} \quad (1)$$

where  $O$  represents the outputs of the program,  $J_{x/y}^O$  is the adjoint to be propagated, and  $J_x^y$  is the local Jacobian matrix. The Einstein's notation is used here so that duplicated indices are summed over. This back-propagation rule can be rewritten in the language of tensor networks [22], as shown in Fig. 2.

In reversible programming with multiple-dispatch, we im-

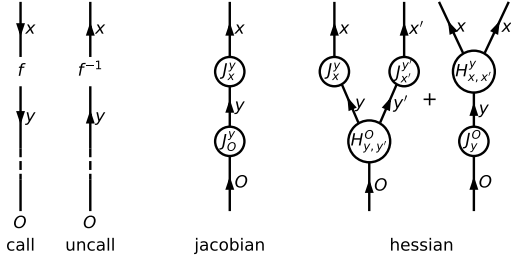


Figure 2. Adjoint rules for Jacobians and Hessians in tensor network language.

plement the adjoint mode AD as

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**Algorithm 1:** Reversible programming AD

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**Result:**  $\text{grad}(\vec{x}_g)$   
 let  $\text{iloss}$  be the index of loss variable in  $\vec{x}$   
 $\vec{y} = f(\vec{x})$   
 $\vec{y}_g = \text{GVar}(\vec{y})$   
 $\text{grad}(\vec{y}_g[\text{iloss}]) += 1.0$   
 $\vec{x}_g = f^{-1}(\vec{y}_g)$

---

Here, `GVar` is a reversible type. The constructor attaches a zero gradient field to a variable, which is similar to the dual number in tangent mode automatic differentiation [16]. If the input is an array, `GVar` will be broadcasted to each array element. One can access the gradient field of a `GVar` instance through the `grad` dataview. Its inverse `~GVar` deallocates the gradient field safely and returns its value field. Here, "safely" means before deallocation, the program will check the gradient field to make sure its value is restored to 0. When an instruction instruct meets a `GVar`, besides computing its value field  $\text{value}(\vec{y}) = \text{instruct}(\text{value}(\vec{x}))$ , it also updates the gradient field  $\text{grad}(\vec{y}) = [J_{\vec{x}}^{\vec{y}}]^{-1} \text{grad}(\vec{x})$ , where  $[J_{\vec{x}}^{\vec{y}}]^{-1}$  is the Jacobian of  $\text{instruct}^{-1}$ . One can define this gradient function on either `instruct` or `instruct-1`. If one defines the backward rule on `instruct`, the compiler will generate the backward rule for its inverse `instruct-1` as the inverse function. This is doable because the inverse and adjoint operation commutes [23]. In the following example, We bind the adjoint function of `ROT` to its reverse `IROT` by defining a new function that dispatch to `GVar`

```
@i function IROT(a!::GVar, b!::GVar, θ::GVar)
  IROT(value(a!), value(b!), value(θ))
  NEG(value(θ))
  value(θ) -= identity(π/2)
  ROT(grad(a!), grad(b!), value(θ))
  grad(θ) += value(a!) * grad(a!)
  grad(θ) += value(b!) * grad(b!)
  value(θ) += identity(π/2)
  NEG(value(θ))
  ROT(grad(a!), grad(b!), π/2)
end
```

The definition of `ROT` instruction could be found in Sec. B.

This backward rule has been included in `NiLang`, one can check the gradients by typing in a Julia REPL

```
julia> using NiLang, NiLang.AD

julia> x, y, θ = GVar(0.5), GVar(0.6), GVar(0.9)
              (GVar(0.5, 0.0), GVar(0.6, 0.0)), GVar(0.9, 0.0)

julia> @instr grad(x) += identity(1.0)

julia> @instr ROT(x, y, θ)

julia> x, y, θ
(GVar(-0.1591911616411577, 0.6216099682706646),
 GVar(0.7646294357761403, 0.7833269096274833),
 GVar(0.8999999999999999, 0.6))
```

The implementation of Algorithm 1 is so short that we present the function definition as follows.

```
@i function (g::Grad)(args...; kwargs...)
  @safe @assert count(x -> x isa Loss, args) == 1
  @anc iloss = 0
  @routine getiloss begin
    for i=1:length(args)
      if (tget(args,i) isa Loss, iloss==i)
        iloss += identity(i)
        (~Loss)(tget(args,i))
      end
    end
  end
  end

  g.f(args...; kwargs...)
  GVar(args)
  grad(tget(args,iloss)) += identity(1.0)
  (~g.f)(args...; kwargs...)

  ~@routine getiloss
end
```

Input variables must contain exactly one `Loss` instance. This program first checks the input parameters and locates the loss variable as `iloss`. Then `Loss` unwraps the loss variable. After computing the forward pass and backward pass, `@routine getiloss` uncomputes the ancilla `iloss` and returns the location information to the target variable. `tget(args, i)` returns the  $i$ -th element of a tuple. Here, in order to avoid confusion in supporting array indexing, we forbid tuple indexing deliberately.

The overhead of using `GVar` type is negligible thanks to Julia's multiple-dispatch and type inference. Let us consider a simple example that accumulates 1.0 to a target variable  $x$  for  $n$  times.

[JG: Grammarly here!]



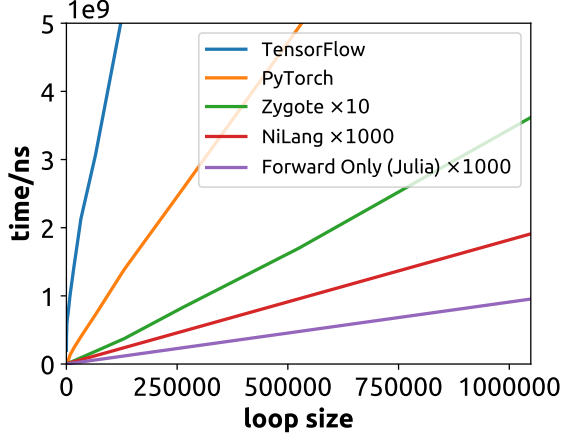


Figure 3. The time for obtaining gradient as function of loop size.  $\times n$  in legend represents a rescaling of time.

```
julia> using NiLang, NiLang.AD, BenchmarkTools

julia> @i function prog(x, one, n::Int)
    for i=1:n
        x += identity(one)
    end
end

julia> @benchmark prog'(Loss(0.0), 1.0, 10000)
BenchmarkTools.Trial:
  memory estimate:  1.05 KiB
  allocs estimate:  39
  -----
  minimum time:     35.838 μs (0.00% GC)
  median time:      36.055 μs (0.00% GC)
  mean time:        36.483 μs (0.00% GC)
  maximum time:     185.973 μs (0.00% GC)
  -----
  samples:          10000
  evals/sample:     1
```

We implement the same function with TensorFlow, PyTorch and Zygote for comparison. The code could be found in our paper’s github repository [24]. Benchmark results on CPU Intel(R) Xeon(R) CPU E5-2680 v4 @ 2.40GHz are shown in Fig. 3. One can see that the NiLang implementation is unreasonably fast, it is approximately two times the forward pass written in native Julia code. Reversible programming is not always as fast as its irreversible counterparts. In practical applications, a reversible program may have memory or computation overhead. We will discuss the details of time and space tradeoff in Sec. VIA.

## B. Second-order gradient

Second-order gradients can be obtained in two different approaches.

### 1. Back propagating first-order gradients

Back propagating the first-order gradients is the most widely used approach to obtain the second-order gradients. Suppose the function space is closed under gradient operation, one can obtain higher-order gradients by recursively differentiating lower order gradients without defining new backward rules.

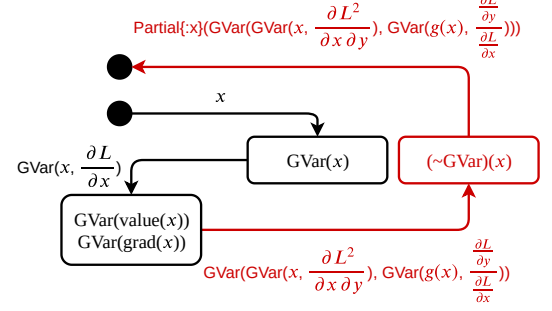


Figure 4. Obtaining the second-order gradient with the reverse differentiation approach. Black lines are computing gradients, red lines are back-propagating the process of obtaining the first-order gradients. Annotations on lines are data types and their fields used in the computation.

Fig. 4 show the four passes in computing Hessian. The first two passes (black lines) are obtaining gradients. Before entering the third pass, the program wraps each field in GVar with GVar. Then we pick a variable  $x_i$  and add 1 to  $\text{grad}(\text{grad}(x_i))$  to compute the  $i$ -th row of Hessian. At the final stage, the  $\sim\text{GVar}$  operation does not unwrap GVar directly because the second-order gradient fields may not be zero in this case. Instead, we use  $\text{Partial}\{x\}(\cdot)$  to safely compute  $\sim\text{GVar}$  on data type  $\text{GVar}\{<:\text{GVar}, <:\text{GVar}\}$ .  $\text{Partial}\{x\}$  takes the  $x$  field of an instance without deallocating memory. By repeating the above process for different  $x_i$ , one can obtain the Hessian matrix.

### 2. Taylor propagation

A probably more efficient approach is back-propagating Hessians directly [25] by

$$\begin{aligned} H_{O',O''}^O &= \mathbf{0}, \\ H_{x,x'}^O &= J_x^y H_{y,y'}^O J_{x'}^{y'} + J_y^O H_{x,x'}^y. \end{aligned} \quad (2)$$

Here, the Hessian tensor  $H_{x,x'}^O$  is rank three, where the top index is often taken as a scalar and omitted. In tensor network language, the above equation can be represented as in Fig. 2. Hessian propagation is a special case of Taylor propagation. With respect to the order of gradients, Taylor propagation is exponentially more efficient in obtaining higher-order gradients than differentiating lower order gradients recursively. However, the exhausted support to Taylor propagation [10] requires much more effort than Jacobian propagation, this is why most AD packages choose the recursive approach.

Instruction level automatic differentiation has the advantage of having very limited primitives. It is more flexible in obtaining higher-order gradients like Hessian. An example is provided in Sec. VB.

### C. Gradient on ancilla problem

An ancilla can also carry gradient during computation. As a result, even if an ancilla can be uncomputed regoriously in the original program, its GVar version can not be safely uncomputed. In these case, we simply “drop” the gradient field instead of raising an error. In this subsection, we prove the following theorem

**Theorem 1.** *Dropping the gradient field of an ancilla at deallocation stage does not harm the reversibility of a gradient function.*

*Proof.* Consider a reversible function  $\vec{y}, b = f(\vec{x}, a)$ , where  $a$  and  $b$  are the input and output values of an ancilla. The reversibility requires  $b = a$  for any  $\vec{x}$ . So that

$$\frac{\partial b}{\partial \vec{x}} = \vec{0}. \quad (3)$$

In the backward pass, we discarded the gradient field of  $b$ . The gradient fields are derived from the values of variables, they should not have any effect to the value fields. The rest is to show changing the value of  $\text{grad}(b)$  does not result in a different  $\text{grad}(\cdot(\vec{x}))$  in the backward pass. It can be seen from the expression the back-propagation rule

$$\frac{\partial O}{\partial \vec{x}} = \frac{\partial O}{\partial \vec{y}} \frac{\partial \vec{y}}{\partial \vec{x}} + \frac{\partial O}{\partial b} \frac{\partial b}{\partial \vec{x}}, \quad (4)$$

where the second term with  $\frac{\partial O}{\partial b}$  vanishes naturally. Hence one can assume any value in the gradient field of an ancilla when entering a function, it does not have to be the discarded value.  $\square$

This theorem is very important to the reversibility of gradient functions, without it, the recursive differentiation scheme to obtain second-order gradients can not work. On the other side, we emphasis that although the initial value of the gradient field of an ancilla can be randomly chosen, not having a gradient field at the begining is a different story.

## IV. LEARN BY CONSISTENCY

Consider a training task that with input  $\vec{x}^*$  and output  $\vec{y}^*$ , find a set of parameters  $\vec{p}_x$  that satisfy  $\vec{y}^* = f(\vec{x}^*, \vec{p}_x)$ . In traditional machine learning, we define a loss  $\mathcal{L} = \text{dist}(\vec{y}^*, f(\vec{x}^*, \vec{p}_x))$  and minimize it with gradient  $\frac{\partial \mathcal{L}}{\partial \vec{p}_x}$ . This works only when the target function is locally differentiable.

Here we provide an alternative by making use of reversibility. We construct a reversible program  $\vec{y}, \vec{p}_y = f_r(\vec{x}, \vec{p}_x)$ , where  $\vec{p}_x$  and  $\vec{p}_y$  are “garbage” spaces which include trainable

parameters and auxillary parameters. The algorithm can be summarized as

---

### Algorithm 2: Learn by consistency

---

**Result:**  $\vec{p}_x$   
Initialize  $\vec{x}$  to  $\vec{x}^*$ , garbage space  $\vec{p}_x$  to random.  
**if**  $\vec{p}_y$  is null **then**  
     $\vec{x}, \vec{p}_x = f_r^{-1}(\vec{y}^*)$   
**else**  
     $\vec{y}, \vec{p}_y = f_r(\vec{x}, \vec{p}_x)$   
    **while**  $\vec{y} \neq \vec{y}^*$  **do**  
         $\vec{y} = \vec{y}^*$   
         $\vec{x}, \vec{p}_x = f_r^{-1}(\vec{y}, \vec{p}_y)$   
         $\vec{x} = \vec{x}^*$   
         $\vec{y}, \vec{p}_y = f_r(\vec{x}, \vec{p}_x)$

---

Here,  $\text{garbage}(\cdot)$  is a function for taking the garbage space. This algorithm utilizes the self-consistency relation

$$\vec{p}_x^* = \text{garbage}(f_r^{-1}(\vec{y}^*, \text{garbage}(f_r(\vec{x}^*, \vec{p}_x^*)))), \quad (5)$$

Similar idea of training by consistency is used in self-consistent meanfield theory [26] in physics. The difficult part of self-consistent training is to find a self-consistency relation, here the reversibility provides a natural self-consistency relation. Learn by consistency can be used to handle discrete optimization. However, it is not a silver bullet, and should be used with caution. Let’s consider the following example

```
@i function f1(y!, x, p!)
    p! += identity(x)
    y! -= exp(x)
    y! += exp(p!)
end

@i function f2(y!, x!, p!)
    p! += identity(x!)
    y! -= exp(x!)
    x! -= log(-y!)
    y! += exp(p!)
end

function train(f)
    loss = Float64[]
    p = 1.6
    for i=1:100
        y!, x = 0.0, 0.3
        @instr f(y!, x, p)
        push!(loss, y!)
        y! = 1.0
        @instr (~f)(y!, x, p)
    end
    loss
end
```

Functions `f1` and `f2` computes  $f(x, p) = e^{(p+x)} - e^x$  and stores the output in a new memory `y!`. The only difference is `f2` “uncompute”  $x$  arithmetically. The task of training is to find a  $p$  that make the output value equal to target value

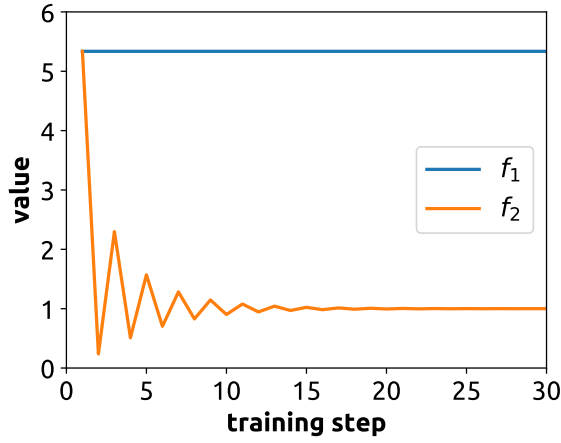


Figure 5. The value of  $x$  as a function of self-consistent training step.

1. After 100 steps,  $f_2$  runs into the fixed point with  $x$  equal to 1 upto machine precision. However,  $f_1$  does not do any training. The training of  $f_2$  fails because this function actually computes  $f_1(y, x, p) = y + e^{(p+x)} - e^x, x, x + p$ , where the training parameter  $p$  is completely determined by the garbage space on the output side  $x \cup x + p$ . As a result, shifting  $y$  directly is the only approach to satisfy the consistency relation. On the other side,  $f_2(y, x, p) = y + e^{(p+x)} - e^x, \tilde{0}, x + p$ , the garbage space can not uniquely determine the input garbage space  $p$  and  $y$ . Here we use  $\tilde{0}$  to denote the zero with rounding error.

By viewing  $\vec{x}$  and parameters in  $\vec{p}_x$  as variables, we can study the trainability from the information perspective.

**Theorem 2.** Only if the conditional entropy  $S(\vec{y}|\vec{p}_y)$  is nonzero, algorithm 2 is trainable.

*Proof.* The above example reveals a fact that the training can not work when the output  $\vec{p}_y$  completely determines  $\vec{p}_x$ , that is

$$\begin{aligned}
 S(\vec{p}_x|\vec{p}_y) &= S(\vec{p}_x \cup \vec{p}_y) - S(\vec{p}_y) \\
 &\leq S((\vec{p}_x \cup \vec{x}) \cup \vec{p}_y) - S(\vec{p}_y), \\
 &\leq S((\vec{p}_y \cup \vec{y}) \cup \vec{p}_y) - S(\vec{p}_y), \\
 &\leq S(\vec{y}|\vec{p}_y).
 \end{aligned} \tag{6}$$

The third line uses the bijectivity  $S(\vec{x} \cup \vec{p}_x) = S(\vec{y} \cup \vec{p}_y)$ .  $\square$

This inequality shows that when the garbage space on the output side satisfies  $S(\vec{y}|\vec{p}_y) = 0$ , i.e. contains all information to determine the output field, the input parameters are also completely determined by this garbage space. In the above examples, it corresponds to the case  $S(e^{(x+y)-e^x}|x \cup x + y) = 0$  in  $f_1$ . One should remove the redundancy of information by uncomputing to make training by consistency work properly.

## V. EXAMPLES

### A. Computing Fibonacci Numbers

An example that everyone likes

```
@i function rfib(out, n::T) where T
  @anc n1 = zero(T)
  @anc n2 = zero(T)
  @routine init begin
    n1 += identity(n)
    n1 -= identity(1.0)
    n2 += identity(n)
    n2 -= identity(2.0)
  end
  if (value(n) <= 2, ~)
    out += identity(1.0)
  else
    rfib(out, n1)
    rfib(out, n2)
  end
  ~@routine init
end
```

The following example shows how to construct a reversible while statement. It computes the first Fibonacci number that greater or equal to  $x$

```
@i function rfib100(n, x)
  @safe @assert n == 0
  while (fib(n) < x, n != 0)
    n += identity(1)
  end
end
```

In this example, the postcondition  $n \neq 0$  is false before entering the loop, and becomes true in later iterations. In the reverse program, the while statement stops at  $n == 0$ .

### B. exp function

An exp function can be computed using Taylor expansion

$$y+ = \sum_n \frac{x^n}{\text{factorial}(n)} \tag{7}$$

There is a recursive algorithm to compute this expression. The recursion relation is written as  $s_n = \frac{x s_{n-1}}{n}$ , where  $s_n \equiv \frac{x^n}{\text{factorial}(n)}$  is the term to be accumulated to  $y$ . This algorithm mimics the famous pebble game [14]. However, there is no known constant memory and polynomial time solution to pebble game. Here the case is different. Notice  $*$  and  $/$  are arithmetically reversible to each other, we can “uncompute” previous state  $s_{n-1}$  by  $s_{n-1} = \frac{n s_n}{x}$  approximately to deallocate the memory. The implementation is



```

using NiLang, NiLang.AD

@i function iexp(y!, x::T; atol::Float64=1e-14)
    where T
        @anc anc1 = zero(T)
        @anc anc2 = zero(T)
        @anc anc3 = zero(T)
        @anc iplus = 0
        @anc expout = zero(T)

        y! += identity(1.0)
        @routine r1 begin
            anc1 += identity(1.0)
            while (value(anc1) > atol, iplus != 0)
                iplus += identity(1)
                anc2 += anc1 * x
                anc3 += anc2 / iplus
                expout += identity(anc3)
                # arithmetic uncompute
                anc1 -= anc2 / x
                anc2 -= anc3 * iplus
                SWAP(anc1, anc3)
            end
        end

        y! += identity(expout)

    ~@routine r1
end

```

Here, the definition of SWAP instruction can be found in Appendix B. The two lines below the comment “# arithmetic uncompute” uncompute variables anc1 and anc2 approximately, which is only arithmetically true. As a result, the final output is not exact due to the rounding error. On the other side, the reversibility is not affected since the inverse call at the last line of function uncomputes all ancilla bits rigorously. The while statement takes two conditions, the precondition and postcondition. Precondition  $\text{val}(\text{anc1}) > \text{atol}$  indicates when to break the forward pass and post condition  $\text{iplus} \neq 0$  indicates when to break the backward pass.

To obtain gradients, one can wrap the variable  $y!$  with Loss type and feed it into  $\text{iexp}'$

```

julia> y!, x = 0.0, 1.6
(0.0, 1.6)

julia> @instr iexp'(Loss(y!), x)

julia> grad(x)
4.9530324244260555

```

$\text{iexp}'$  is a callable instance of type  $\text{Grad}\{\text{typeof}(\text{iexp})\}$ , which wraps input variables with updates gradient fields as outputs. It is reversible and differentiable, hence one can use back-propagates this function to obtain Hessians as introduced in Sec. III B 1. It is implemented in NiLang as `simple_hessian`.

```

julia> y!, x = 0.0, 1.6
(0.0, 1.6)

julia> simple_hessian(iexp, (Loss(y!), x))
2×2 Array{Float64,2}:
 0.0  0.0
 0.0  4.95303

```

A more efficient Taylor propagation approach introduced in Sec. III B 2 can be accessed by feeding variables into  $\text{iexp}'$

```

julia> y!, x = 0.0, 1.6
(0.0, 1.6)

julia> @instr iexp'(Loss(y!), x)

julia> collect_hessian()
2×2 Array{Float64,2}:
 0.0  0.0
 0.0  4.95303

```

$\text{iexp}'$  computes the second-order gradients by wrapping variables with type `BeijingRing` [27]. Whenever an  $n$ -th variable or ancilla is created, we push a ring of size  $2n - 1$  to a global tape. Whenever an ancilla is deallocated, we pop a ring from the top. The  $n$ -th ring stores  $H_{i \leq n, n}$  and  $H_{n, i < n}$ . We didn't use the symmetry relation  $H_{i, j} = H_{j, i}$  to save memory here in order to simplify the implementation of backward rules described in the right most panel of Fig. 2. The final result can be collected by calling `collect_hessian`, it will read out the Hessian stored in the global tape.

### C. QR decomposition

Let's consider a slightly non-trivial function, the QR decomposition

```

@i function iqr(Q, R, A::AbstractMatrix{T}) where T
    @anc anc_norm = zero(T)
    @anc anc_dot = zeros(T, size(A,2))
    @anc ri = zeros(T, size(A,1))
    for col = 1:size(A, 1)
        ri .+= identity.(A[:,col])
        for precol = 1:col-1
            idot(anc_dot[precol], Q[:,precol], ri)
            R[precol,col] +=
                identity(anc_dot[precol])
            for row = 1:size(Q,1)
                ri[row] -= anc_dot[precol] *
                    Q[row, precol]
            end
        end
        inorm2(anc_norm, ri)

        R[col, col] += anc_norm^0.5
        for row = 1:size(Q,1)
            Q[row,col] += ri[row] / R[col, col]
        end

        ~(ri .+= identity.(A[:,col]));
        for precol = 1:col-1
            idot(anc_dot[precol], Q[:,precol], ri)
            for row = 1:size(Q,1)
                ri[row] -= anc_dot[precol] *
                    Q[row, precol]
            end
        end
        inorm2(anc_norm, ri)
    end
end

```

```

@i function idot(out, v1::AbstractVector{T}, v2)
    where T
        @anc anc1 = zero(T)
        for i = 1:length(v1)
            anc1 += identity(v1[i])
            CONJ(anc1)
            out += v1[i]*v2[i]
            CONJ(anc1)
            anc1 -= identity(v1[i])
        end
    end

@i function inorm2(out, vec::AbstractVector{T})
    where T
        @anc anc1 = zero(T)
        for i = 1:length(vec)
            anc1 += identity(vec[i])
            CONJ(anc1)
            out += anc1*vec[i]
            CONJ(anc1)
            anc1 -= identity(vec[i])
        end
    end
end

```

One can easily check the correctness of the gradient function

```

using Test
A = randn(4,4)
q = zero(A)
r = zero(A)

@i function test1(out, q, r, A)
    iqr(q, r, A)
    out += identity(q[1,2])
end

@i function test2(out, q, r, A)
    iqr(q, r, A)
    out += identity(r[1,2])
end

@test check_grad(test1, (Loss(0.0), q, r, A);
    atol=0.05, verbose=true)
@test check_grad(test2, (Loss(0.0), q, r, A);
    atol=0.05, verbose=true)

```

Here, the `check_grad` function is a gradient checker function defined in module `NiLangCore.ADCore`.

#### D. Unitary Matrices

This implementatin of QR decomposition is very naive that does not consider reorthogonalization. `idot` and `inorm2` are functions to compute dot product and vector norm. They are implemented as

Unitary matrices can be used to ease the gradient exploding and vanishing problem in recurrent networks [28–30]. One of the simplest way to parametrize a unitary matrix is representing a unitary matrix as a product of two-level unitary operations [30]. A real unitary matrix of size  $N$  can be parametrized

compactly by  $N(N - 1)/2$  rotation operations [31]

$$\text{ROT}(a!, b!, \theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} a! \\ b! \end{bmatrix}, \quad (8)$$

where  $\theta$  is the rotation angle,  $a!$  and  $b!$  are target registers.

```
@i function umm!(x, θ)
  @anc k = 0
  @anc Nin = size(x, 2)
  @anc Nout = size(x, 1)
  for j=1:Nout
    for i=Nin-1:-1:j
      k += identity(1)
      ROT(x[i], x[i+1], θ[k])
    end
  end

  # uncompute k
  for j=1:Nout
    for i=Nin-1:-1:j
      k -= identity(1)
    end
  end
end
```

## VI. DISCUSSION AND OUTLOOK

In this paper, we introduce a Julia eDSL NiLang that simulates a reversible Turing machine (RTM). We developed an instruction-level automatic differentiation tool on this eDSL for differential programming. It can differentiate over any program to any order reliably and efficiently without sophisticated designs to memorize computational graph and intermediate states. Also, we introduce a new training strategy that does not rely on gradients, learn by consistency.

In the following, we discussed some practical issues reversible programming, and several future directions to go.

### A. Time Space Tradeoff

In history, there has been many other designs of reversible languages and instruction sets. One of the main reason why RTM is not so popular is it may have either a space overhead propotional to computing time  $T$  or a computational overhead that sometimes can be exponential. In the simplest g-segment trade off scheme [32, 33],

$$\text{Time}(T) = \frac{T^{1+\epsilon}}{S^\epsilon} \quad (9)$$

$$\text{Space}(T) = \epsilon 2^{1/\epsilon} (S + S \log \frac{T}{S}) \quad (10)$$

with  $T$  and  $S$  the time and space usage on a irreversible Turing machine,  $\epsilon$  is the control parameter. It is related to the g-segment trade off parameters by  $g = k^n$ ,  $\epsilon = \log_k(2k - 1)$  with  $n \geq 1$  and  $k \geq 1$ . This section, we try to convince the readers

that the overhead of reversible computing is not as terrible as people thought.

First, at  $\epsilon \rightarrow 0$ , the resource used by a RTM is same as the caching strategy used in a traditional machine learning package that memorizing every inputs of primitives. Memorizing inputs always make a program reversible since it does not discard any information. For deep neural networks, people used checkpointing trick to trade time with space [34], which is also a widely used trick in reversible programming [14]. RTM just provides more alternatives to trade time and space.

Second, some computational overhead of running recursive algorithms with limited space resources can be mitigated by "pseudo uncomputing" without sacrificing reversibility like in the `iexp` example. With reversible floating point `*` and `/` operations [35], many primitives can be implemented with pure reversible functions, which may significant decrease the computation time and memory usage. We will review this point in Sec. VIB.

Third, making reversible programming an eDSL rather than a independant language allows flexible choices between reversibility and computational overhead. For example, in order to deallocate the gradient memory in a reversible language one has to uncompute the whole process of obtaining this gradient. As a reversible eDSL, we have the flexibility to deallocate the memory irreversibly, i.e. trade energy with time. To quantify the overhead of uncomputing, we introducing the concept

**Definition 1** (program granularity). The logarithm of the ratio between the execution time of a reversible program and its irreversible counter part.

$$\log_2 \frac{\text{Time}(T)}{T} \quad (11)$$

Whenever the program uncomputes the memory, the program granularity increases by approximately one. In instruction design, defining primitive functions like `iexp`, and deallocating gradients used for training, we need uncomputing ancilla bits and increase the granularity. The overhead increase exponentially as the granuality increase. The granularity can be decreased by cleverer compilation of a program, since the uncomputing of ancillas can be executed at any level of abstraction.

### B. Instructions and Hardwares

So far, our eDSL is not really compiled to instructions, instead, it runs on a irreversible host Julia. In the future, it can be compiled to low level instructions and is execute on a reversible devices. For example, the control flow defined in this NiLang can be compiled to reversible instructions like conditioned `goto` instruction. The reversibility requires the target instruction a `comefrom` instruction that specifying the postcondition. [36]

Arithmetic instructions should be redesigned to support better reversible programs. The major obstacle to exact reversibility programming is current floating point adders used in our computing devices are not exactly reversible.

There are proposals of reversible floating point adders and multipliers [35, 37–39] that introduces garbage bits to ensure reversibility. With these infrastructure, a reversible program can be executed without suffering from the irreversibility from rounding error and reduce the computational and memory overhead significantly. Notably, in machine learning field, information buffer is used to make multiplication operations [11] reversible and reduce memory cost.

Reversible programming is not necessarily related to reversible hardware. Reversible programs are a subset of irreversible programs, hence can be simulated efficiently on CMOS devices [36]. By using reversible hardware [], the computation may cost zero energy by Landauer’s principle [21]. Reversible hardware are not necessarily related to reversible gates such as Toffoli gate and Fredkin gate. Devices with the ability of recovering signal energy is able to save energy, which is known as generalized reversible computing. [40, 41] In the following, we comment briefly on a special type of reversible device Quantum computer.

### 1. Quantum Computers

One of the fundamental difficulty of building a quantum computer is, unlike a classical state, an unknown quantum state can not be copied. Quantum random access memory [42] is very hard to design and implement, which is known to have many caveats [43]. A quantum state in an environment will decoherence and can not be recovered, this underlines the simulation nature of quantum devices. Reversible computing does not enjoy the quantum advantage, nor the quantum disadvantages of non-cloning and decoherence. The reversibility of quantum computing comes from the fact that microscopic processes are unitary. On the other side, the irreversibility is rare, it can come from interacting with classical devices. Irreversible processes include decaying, qubit state resetting, measurements and classical feedbacks to quantum devices. These are typically harder to implement on a quantum device.

Given the fundamental limitations of quantum decoherence and non-cloning and the reversible nature of microscopic world. It is reasonable to have a reversible computing device to bridge the gap between classical and universal quantum computing. By introducing entanglement little by little, we can accelerate some basic components. For example, quantum Fourier transformation provides an interesting alternative to the adders and multipliers by introducing one additional CPHASE gate even though it is a classical-in classical-out algorithm. [44] The compiling theory developed for reversible programming will have profounding effect to quantum computing.

### C. Outlook

NiLang can be used in solving many existing problems. First of all, it can be used to generate AD rules for existing machine learning packages. For example, in Zygote, a user sometimes need to define new primitives. If this primitive

is written in NiLang, then the backward rules can be generated automatically. Second, we can built reversible BLAS and LAPACK, from matrix multiplication, tensor contraction to singular value decomposition (SVD) and eigenvalue decomposition (ED). These operations are extensively used in physics [45, 46]. However, for long time, many linear algebra AD rules suffer from the gradient exploding problem [47–49]. Third, control problem in robotics [50] also needs gradients. The control parameters are often floating point numbers rather than tensors. Writing a control program reversibly should boost the training performance a lot. Fourth, NiLang is a strong candidate towards breaking the memory wall problem in machine learning. Unlike the tradeoff schemes in traditional machine learning that use checkpointing and reversible primitives. NiLang provides a more systematic and elegant time-space tradeoff scheme. It prefers inplace and memory efficient implementations. The implementation of unitary matrix costs zero extra memory, Differentiating over reversible integrators [51, 52] without intermediate state caching is also possible. Besides, the time-space tradeoff can potentially be optimized at compiling stage as discussed above.

To solve the above problems better, NiLang can be improved from multiple perspectives. We call for better compiling that decreases granularity and hence reduces overhead, rigorous reversible floating point arithmetics to let the reversibility free from rounding error. It is also interesting to see how it can be combined with a high performance quantum simulator like Yao [53]. It can provide control flow to Yao’s quantum block intermediate representation, while Yao can provide the quantum features for NiLang. Notice by introducing quantum rotation gates  $R_y(\theta)$  and  $R_z(\theta)$  in the reversible programming, we can make NiLang a path integral based universal quantum simulator. Reversible programming is known to have advantage in parallel computing in handle asynchronous computing [54] and debugging with bidirectional move [55]. It is interesting to see how NiLang combines with other parts of Julia ecosystem like CUDAnative [56] and Debugger.

**[LW: you need much better ending. Talk about broader perspective rather than technique details.]**

## VII. ACKNOWLEDGMENTS

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## Appendix A: NiLang Grammar

### Terminologies

- *ident*, symbols

- *num*, numbers

- $\epsilon$ , empty statement

- *JuliaExpr*, native Julia expression

- $[ ]$ , zero or one repetitions.

$\langle \text{Stmts} \rangle ::= \epsilon$   
 $\quad | \langle \text{Stmt} \rangle$   
 $\quad | \langle \text{Stmts} \rangle \langle \text{Stmt} \rangle$   
 $\langle \text{Stmt} \rangle ::= \langle \text{BlockStmt} \rangle$   
 $\quad | \langle \text{IfStmt} \rangle$   
 $\quad | \langle \text{WhileStmt} \rangle$   
 $\quad | \langle \text{ForStmt} \rangle$   
 $\quad | \langle \text{InstrStmt} \rangle$   
 $\quad | \langle \text{RevStmt} \rangle$   
 $\quad | \langle @\text{anc} \rangle \langle \text{Stmt} \rangle$   
 $\quad | \langle @\text{routine} \rangle \langle \text{Stmt} \rangle$   
 $\quad | \langle @\text{safe} \rangle \text{JuliaExpr}$   
 $\quad | \langle \text{CallStmt} \rangle$   
 $\langle \text{BlockStmt} \rangle ::= \text{begin} \langle \text{Stmts} \rangle \text{end}$   
 $\langle \text{RevCond} \rangle ::= ( \text{JuliaExpr} , \text{JuliaExpr} )$   
 $\langle \text{IfStmt} \rangle ::= \text{if} \langle \text{RevCond} \rangle \langle \text{Stmts} \rangle [\text{else} \langle \text{Stmts} \rangle] \text{end}$   
 $\langle \text{WhileStmt} \rangle ::= \text{while} \langle \text{RevCond} \rangle \langle \text{Stmts} \rangle \text{end}$   
 $\langle \text{Range} \rangle ::= \text{JuliaExpr} : \text{JuliaExpr} [ : \text{JuliaExpr} ]$   
 $\langle \text{ForStmt} \rangle ::= \text{for ident} = \langle \text{Range} \rangle \langle \text{Stmts} \rangle \text{end}$   
 $\langle \text{KwArg} \rangle ::= \text{ident} = \text{JuliaExpr}$   
 $\langle \text{KwArgs} \rangle ::= [\langle \text{KwArgs} \rangle , ] \langle \text{KwArg} \rangle$   
 $\langle \text{CallStmt} \rangle ::= \text{JuliaExpr} ( [\langle \text{DataViews} \rangle] [ : \langle \text{KwArgs} \rangle] )$   
 $\langle \text{Constant} \rangle ::= \text{num} \mid \pi$   
 $\langle \text{InstrBinOp} \rangle ::= += \mid -= \mid \forall=$   
 $\langle \text{InstrTrailer} \rangle ::= [.] ( [\langle \text{DataViews} \rangle] )$   
 $\langle \text{InstrStmt} \rangle ::= \langle \text{DataView} \rangle \langle \text{InstrBinOp} \rangle \text{ident} [\langle \text{InstrTrailer} \rangle]$   
 $\langle \text{RevStmt} \rangle ::= \sim \langle \text{Stmt} \rangle$   
 $\langle @\text{routine} \rangle ::= @\text{routine ident} \langle \text{Stmt} \rangle$   
 $\langle \text{AncArg} \rangle ::= \text{ident} = \text{JuliaExpr}$   
 $\langle @\text{anc} \rangle ::= @\text{anc} \langle \text{AncArg} \rangle$   
 $\quad | @\text{deanc} \langle \text{AncArg} \rangle$   
 $\langle @\text{safe} \rangle ::= @\text{safe} \text{JuliaExpr}$   
 $\langle \text{DataViews} \rangle ::= \epsilon$   
 $\quad | \langle \text{DataView} \rangle$   
 $\quad | \langle \text{DataViews} \rangle , \langle \text{DataView} \rangle$   
 $\langle \text{DataView} \rangle ::= \langle \text{DataView} \rangle [ \text{JuliaExpr} ]$   
 $\quad | \langle \text{DataView} \rangle . \text{ident}$   
 $\quad | \text{JuliaExpr} ( \langle \text{DataView} \rangle )$   
 $\quad | \langle \text{DataView} \rangle '$   
 $\quad | - \langle \text{DataView} \rangle$   
 $\quad | \langle \text{Constant} \rangle$   
 $\quad | \text{ident}$   
 $\quad | \text{ident} \dots$

One can use `@i function`  $\langle \text{Stmts} \rangle$  `end` to define a function and its inverse. All *JuliaExpr* should be pure, otherwise the reversibility is not guaranteed.

Dataview is a bijective mapping of an object or a field (or item) of an object. When modifying the dataview of an object, it changes the object directly with the `chfield` method.

## Appendix B: Instruction Table

The translation of instructions to Julia functions

instruction	translated	symbol
$y += f(\text{args} \dots)$	<code>PlusEq(f)(args...)</code>	$\oplus$
$y -= f(\text{args} \dots)$	<code>MinusEq(f)(args...)</code>	$\ominus$
$y \forall= f(\text{args} \dots)$	<code>XorEq(f)(args...)</code>	$\odot$

Table II. Instructions and their interpretation in NiLang.

The list of instructions implemented in NiLang

instruction	output
<code>SWAP(a, b)</code>	$b, a$
<code>ROT(a, b, <math>\theta</math>)</code>	$a \cos \theta - b \sin \theta, b \cos \theta + a \sin \theta, \theta$
<code>IROT(a, b, <math>\theta</math>)</code>	$a \cos \theta + b \sin \theta, b \cos \theta - a \sin \theta, \theta$
$y += a^b$	$y + a^b, a, b$
$y += \exp(x)$	$y + e^x, x$
$y += \log(x)$	$y + \log x, x$
$y += \sin(x)$	$y + \sin x, x$
$y += \cos(x)$	$y + \cos x, x$
$y += \text{abs}(x)$	$y +  x , x$
<code>NEG(y)</code>	$-y$
<code>CONJ(y)</code>	$y'$

Table III. A collection of reversible instructions, “.” is the broadcast operations in Julia.