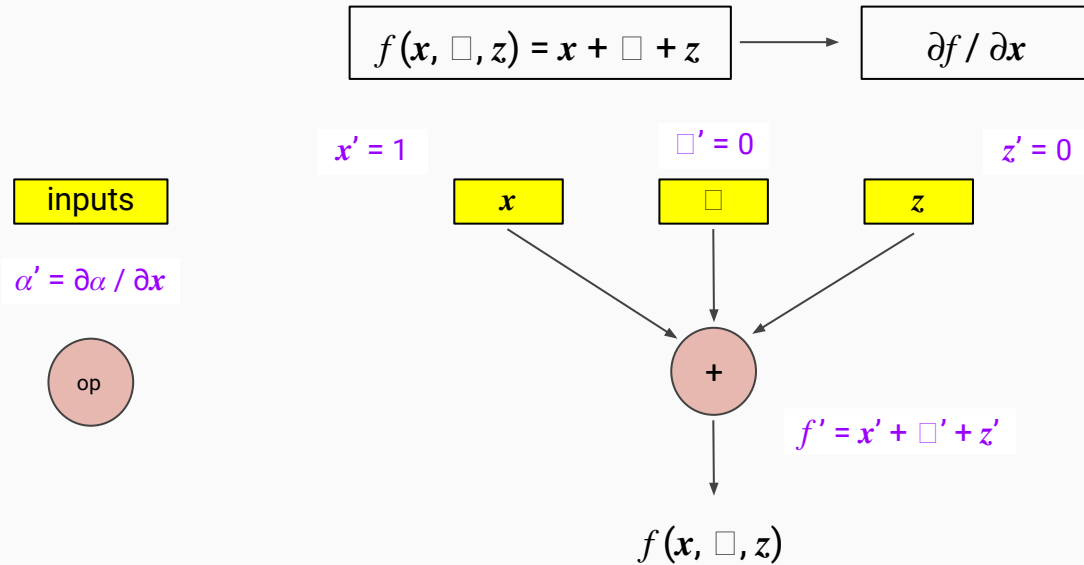# Vectorized forward mode AD in clad
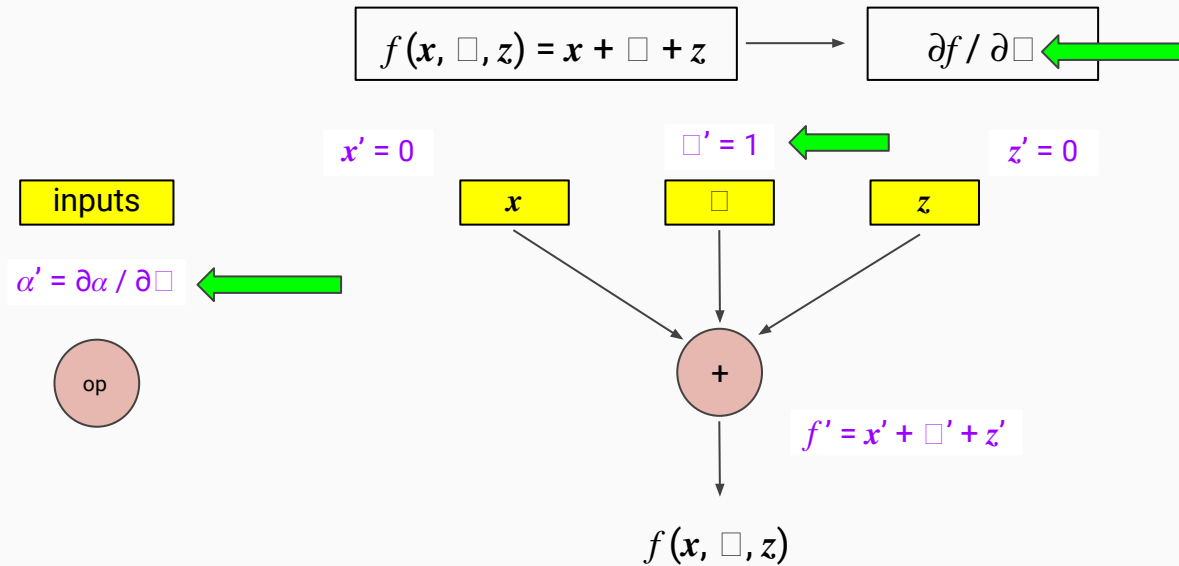
By Vaibhav Thakkar
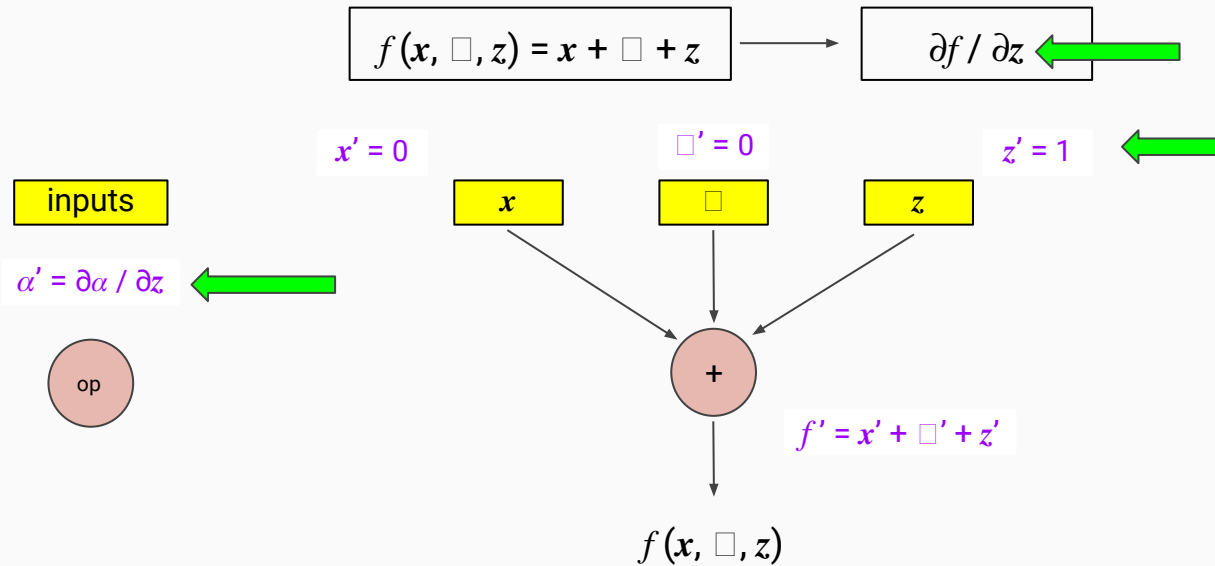
Forward mode AD

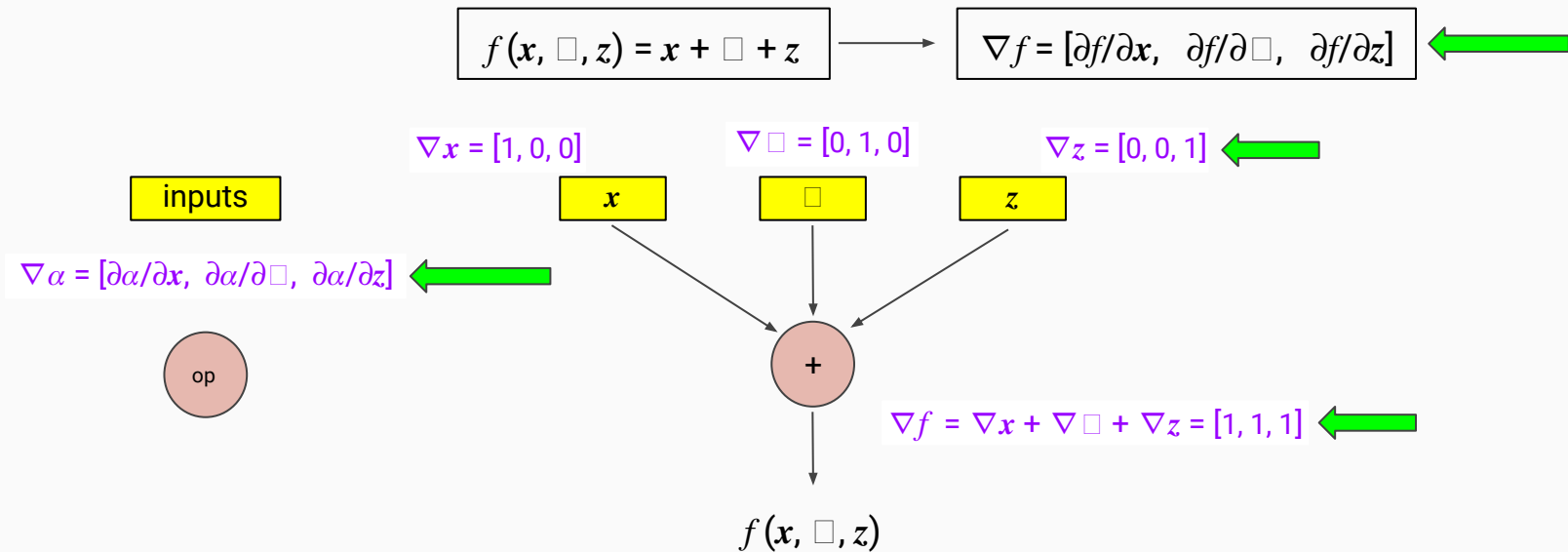$$f(x, \square, z) = x + \square + z$$

$$\partial f / \partial x$$

$x' = 1$

$\square' = 0$

$z' = 0$

inputs

x

$\square$

z

$\alpha' = \partial \alpha / \partial x$

op

+

$f' = x' + \square' + z'$

$f(x, \square, z)$

Forward mode AD

$f(\boldsymbol{x}, \square, \boldsymbol{z}) = \boldsymbol{x} + \square + \boldsymbol{z}$ $\longrightarrow$ $\partial f / \partial \square$ ⬅

$x' = 0$ $\square' = 1$ ⬅ $z' = 0$

inputs

| $\boldsymbol{x}$ | | $\square$ | | $\boldsymbol{z}$ |

$\alpha' = \partial \alpha / \partial \square$ ⬅

(op)

(+)

$f' = x' + \square' + z'$

$f(\boldsymbol{x}, \square, \boldsymbol{z})$

Forward mode AD

$$f(\boldsymbol{x}, \square, z) = \boldsymbol{x} + \square + z \longrightarrow \partial f / \partial z$$

$x' = 0$ $\square' = 0$ $z' = 1$

inputs $\boldsymbol{x}$ $\square$ z

$\alpha' = \partial\alpha / \partial z$

op

$f' = \boldsymbol{x}' + \square' + z'$

$f(\boldsymbol{x}, \square, z)$

Vectorized Forward mode AD

$f(\boldsymbol{x}, \square, z) = \boldsymbol{x} + \square + z$ → $\nabla f = [\partial f/\partial \boldsymbol{x}, \quad \partial f/\partial \square, \quad \partial f/\partial z]$

$\nabla \boldsymbol{x} = [1, 0, 0]$ $\nabla \square = [0, 1, 0]$ $\nabla z = [0, 0, 1]$

inputs $\boldsymbol{x}$ $\square$ z

$\nabla \alpha = [\partial \alpha/\partial \boldsymbol{x}, \; \partial \alpha/\partial \square, \; \partial \alpha/\partial z]$

op   +

$\nabla f = \nabla \boldsymbol{x} + \nabla \square + \nabla z = [1, 1, 1]$

$f(\boldsymbol{x}, \square, z)$

Vectorized Forward Mode AD

Problem

For computing gradient of a function with n-dimensional input - forward mode requires n forward passes, 1 for each input.

Can we instead compute the complete gradient in one pass?
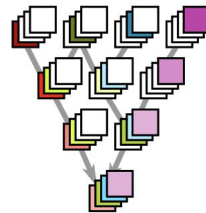

Proposed Solution

Instead of accumulating a single scalar value of derivative with respect to a particular node - maintain a gradient vector at each node.

Initialised by a 1-hot vector for each input node

Progress till now

Updated clad interface

```cpp
double f(double x, double y, double z) {
  return 1.0*x + 2.0*y + 3.0*z;
}


int main() {
  // Call clad to generate the derivative of f wrt x and z.
  auto f_dx = clad::differentiate<clad::opts::vector_mode>(f, "x,z");

  // Execute the generated derivative function.
  double dx = 0, dy = 0, dz = 0;
  f_dx.execute(/*x=*/ 3, /*y=*/ 4, /*z=*/ 5, &dx, &dz);
}
```

```cpp
void f_dvec_0_2(double x, double y, double z, double *_d_x, double *_d_z) {
    clad::array<double> _d_vec_x = {1., 0.};
    clad::array<double> _d_vec_y = {0., 0.};
    clad::array<double> _d_vec_z = {0., 1.};
    {
        clad::array<double> _d_vec_ret = 1. * _d_vec_x + 2. * _d_vec_y + 3. * _d_vec_z;
        *_d_x = _d_vec_return[0];
        *_d_z = _d_vec_return[1];
        return;
    }
}
```

Differentiating array parameters

```
// A function for weighted mean of array elements.
double weighted_mean(double* arr, double* weights, int n) {
  double res = 0;
  for (int i = 0; i < n; ++i) {
    res += weights[i] * arr[i];
  }
  return res;
}
```

- Each arr[i] is a separate independent variable which needs to maintain a vector - this means we need a matrix to store **_d_vector_arr**.

- Can be multiple array parameters, so multiple matrix instances.

```
void weighted_sum_dvec_0_1(double *arr, double *weights, int n, clad::array_ref<double> _d_arr, clad::array_ref<double> _d_weights) {
  unsigned long indepVarCount = _d_arr.size() + _d_weights.size();
  clad::matrix<double> _d_vector_arr = clad::identity_matrix(_d_arr.size(), indepVarCount, 0UL);
  clad::matrix<double> _d_vector_weights = clad::identity_matrix(_d_weights.size(), indepVarCount, _d_arr.size());
  ...
  ...
}
```

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Major Features added

- Support for vectorized forward mode for functions containing any of the following:
    - Arithmetic operations
    - Variable assignments
    - Control flow (if statements / loops)

- Restructured ForwardModeVisitor classes to separate out the logic from basic forward mode AD.

- Improved the interface of *clad::differentiate* to take bit-masked options and allowing user to specify multiple input params for differentiation.

- Fixed all LLVM assertions errors when using vector mode
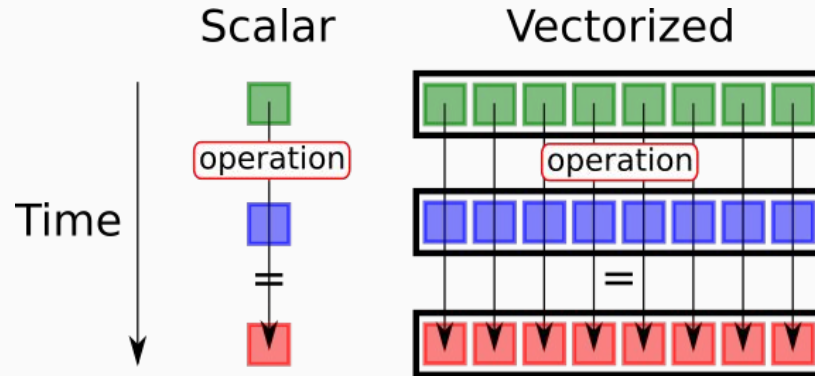   - Required generating an overload function

Major Features added

- Adding support for differentiation array parameters
  - Required adding a clad::matrix class along with benchmarks.

- Documentation and demo examples for vector mode.

- Some utilities like adding clang-format and clang-tidy in GitHub checks to ensure code quality.

Next Goal

Improving efficiency

- Current implementation is for vectorization at algorithmic level.

  - To achieve performance speedups - we need to perform operations in parallel at hardware level by instructing the compiler that it is safe to vectorize these operations.

Future Goals

Missing features

- Adding support for differentiating function with call expressions.
    - *std::exp, std::sin, … custom_defined_fn (x, y, z)*

- Object oriented feature support - differentiating methods and functors.

- Improving compute and memory efficiency by activity analysis (enzyme also does this).

- Reverse vector mode.
    - *General* reverse mode AD - traverse from single output to all inputs.
    - *Vectorized* reverse mode AD - traverse from multiple output to all inputs.

Questions ?