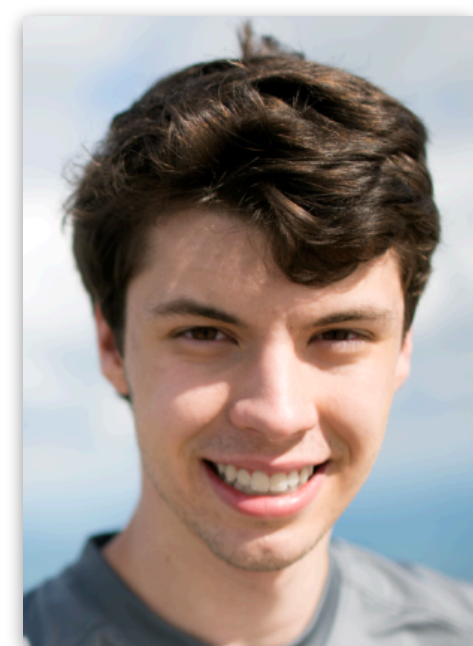
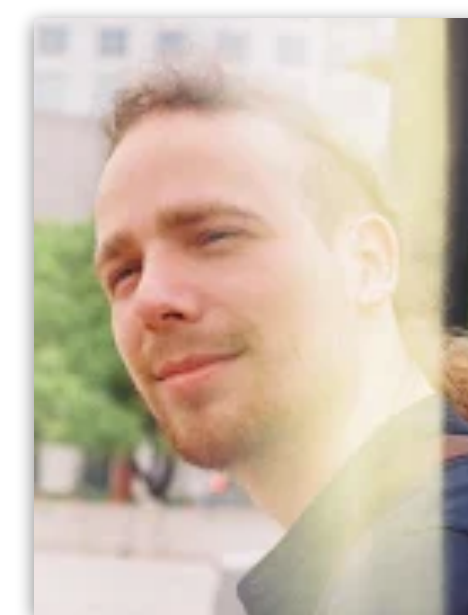




Instead of Rewriting Foreign Code for Machine Learning, Automatically Synthesize Fast Gradients



William S. Moses



Valentin Churavy



wmoses@mit.edu
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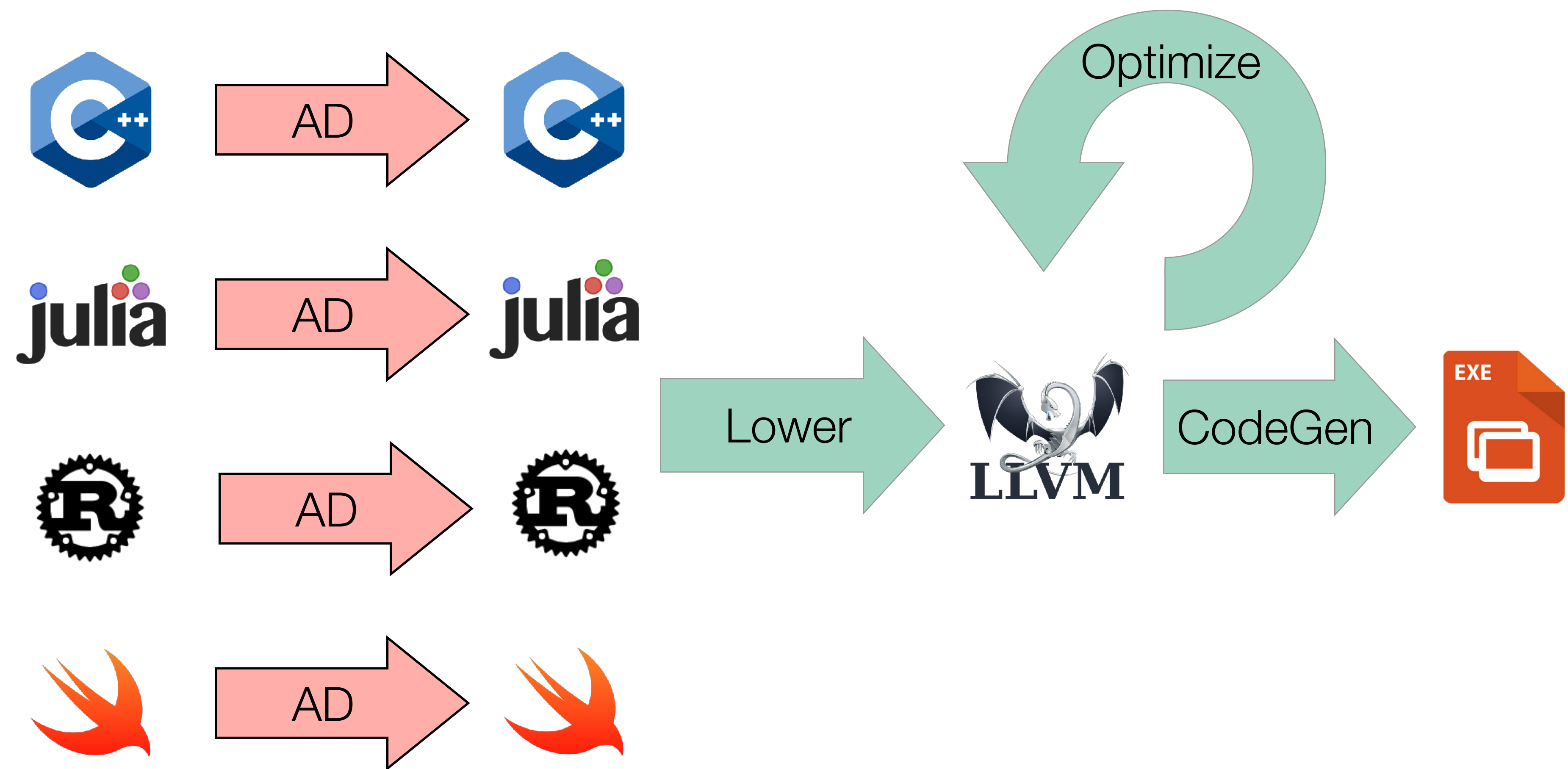


Differentiation & Machine Learning

- Computing derivatives is key to many machine learning algorithms
- Existing approaches:
 - Rewrite all code in a differentiable DSL (PyTorch, TensorFlow, Taichi, etc)
 - Manually writing gradient functions
- Hinders application of ML to new domains
- Automatic differentiation (AD) aims to close this gap



Existing Automatic Differentiation Pipelines



Optimization & Automatic Differentiation

Differentiating before optimizing can create *asymptotically slower* gradients.

$O(n^2)$

```
for i=0..n {  
  out[i] /= mag(in)  
}
```

Optimize

$O(n)$

```
res = mag(in)  
for i=0..n {  
  out[i] /= res  
}
```

AD

$O(n)$

```
d_res = 0.0  
for i=n..0 {  
  d_res += d_out[i]...  
}  
d_mag(d_in, d_res)
```

$O(n^2)$

```
for i=0..n {  
  out[i] /= mag(in)  
}
```

AD

$O(n^2)$

```
for i=n..0 {  
  d_res = d_out[i]...  
  d_mag(d_in, d_res)  
}
```

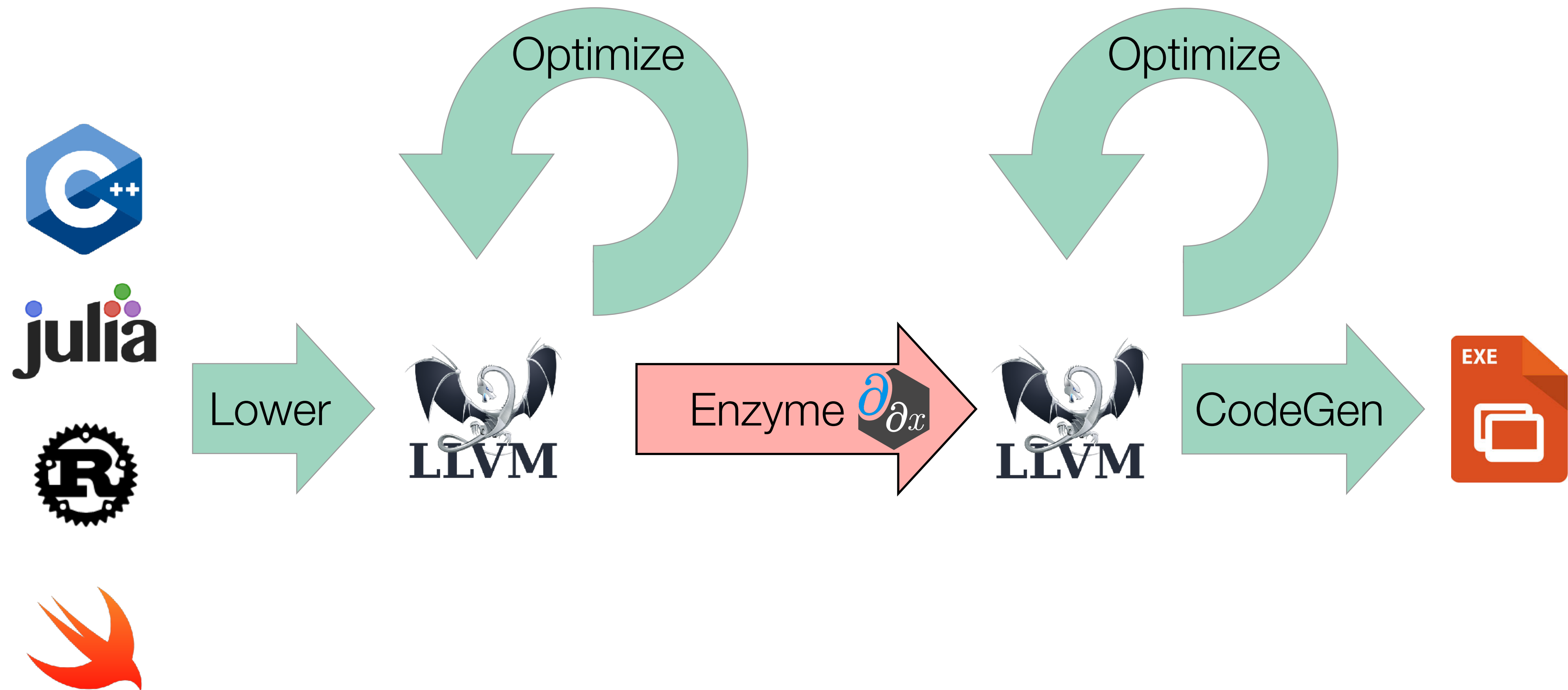
Optimize

$O(n^2)$

```
for i=n..0 {  
  d_res = d_out[i]...  
  d_mag(d_in, d_res)  
}
```

Enzyme Approach

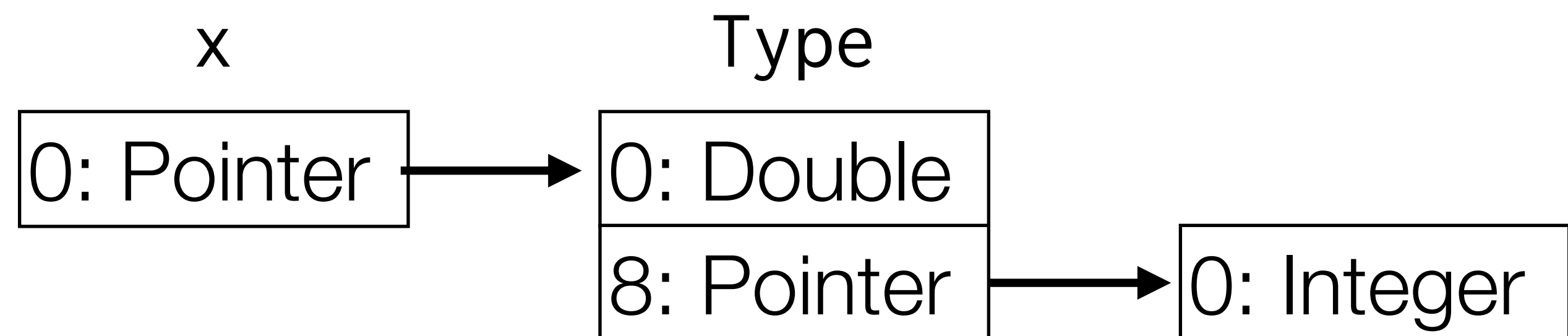
Perform AD on ***optimized, language-independent*** representation!



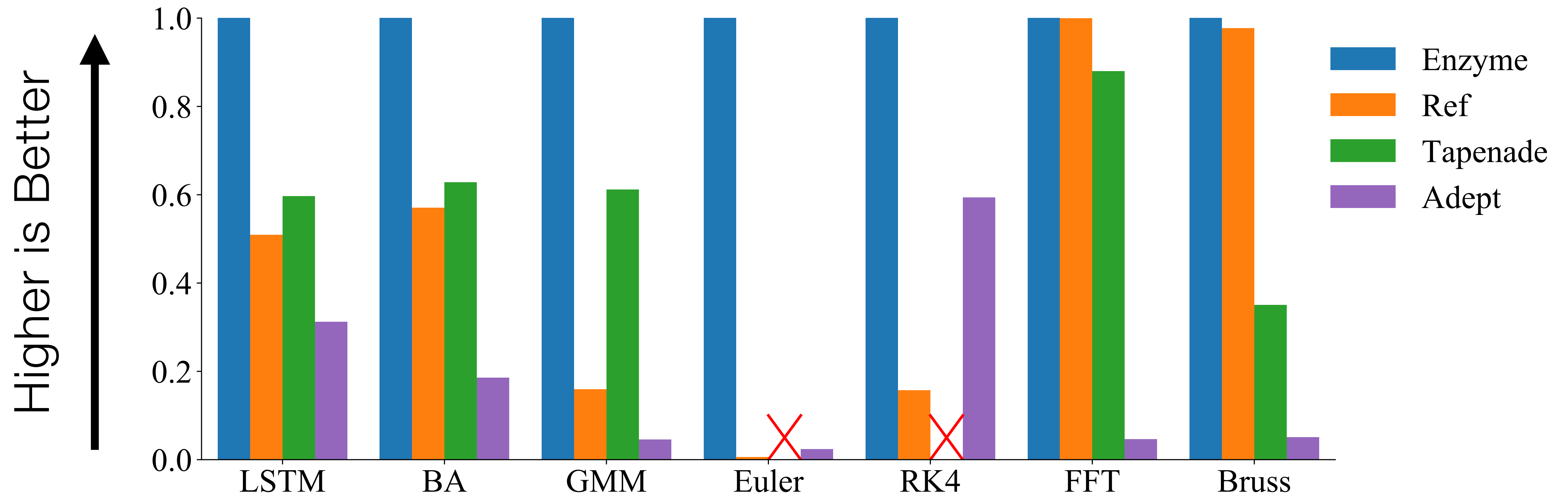
Challenges of Low-Level AD

- “AD is more effective in high-level compiled languages (e.g. Julia, Swift, Rust, Nim) than traditional ones such as C/C++, Fortran and LLVM IR [...]” – Innes
- Low-level code lacks information necessary to compute adjoints
- Created new interprocedural analyses to derive information and optimize

```
struct Type {  
    double;  
    int*;  
}  
  
x = Type*;
```



Speedup of Enzyme



Enzyme is ***4.2x faster*** than Reference!



PyTorch-Enzyme & TensorFlow-Enzyme

```
import torch
from torch_enzyme import enzyme

# Create some initial tensor
inp = ...

# Apply foreign function to tensor
out = enzyme("test.c", "f").apply(inp)

# Derive gradient
out.backward()
print(inp.grad)
```

```
import tensorflow as tf
from tf_enzyme import enzyme

inp = tf.Variable(...)
# Use external C code as a regular TF op

out = enzyme(inp, filename="test.c",
              function="f")

# Results is a TF tensor
out = tf.sigmoid(out)
```

```
// Input tensor + size, and output tensor
void f(float* inp, size_t n, float* out);

// diffe_dupnoneed specifies not recomputing the output
void diffef(float* inp, float* d_inp, size_t n, float* d_out) {
    __enzyme_autodiff(f, diffe_dup, inp, d_inp, n, diffe_dupnoneed, (float*)0, d_out);
}
```





- Tool for performing reverse-mode AD of statically analyzable LLVM IR
- Differentiates code in a variety of languages (C, C++, Fortran, Julia, Rust, Swift, etc)
- 4.2x speedup over AD before optimization
- State-of-the art performance with existing tools
- PyTorch-Enzyme & TensorFlow-Enzyme lets researchers use foreign code in ML workflow
- Open source (enzyme.mit.edu & join our mailing list)
- For more information come to our poster & spotlight presentation!

END

