

Richard Wei Vikram Adve Lane Schwartz
University of Illinois at Urbana-Champaign

Deep Learning Compiler Technologies

XLA

PyTorch JIT

Latte.jl

DLVM

NNVM / TVM

ONNX

Typing

Compute

Optimizations

Static Analysis

Intermediate Representation

Neural networks are programs

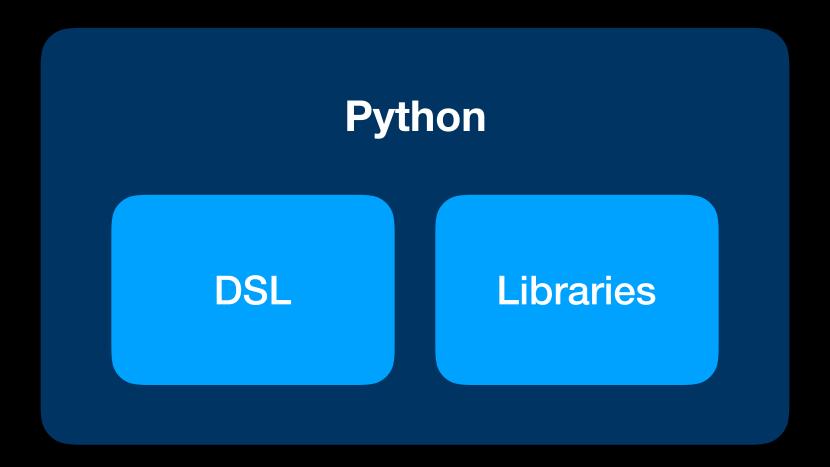
Control Flow

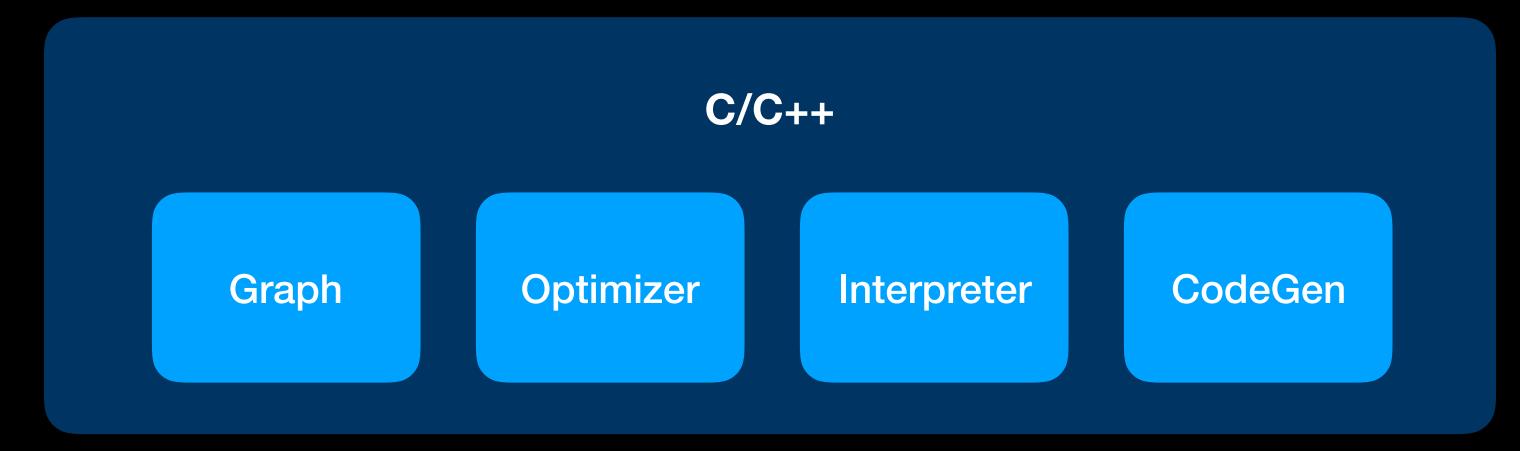
Automatic Differentiation

Auto Vectorization

A New Compiler Problem

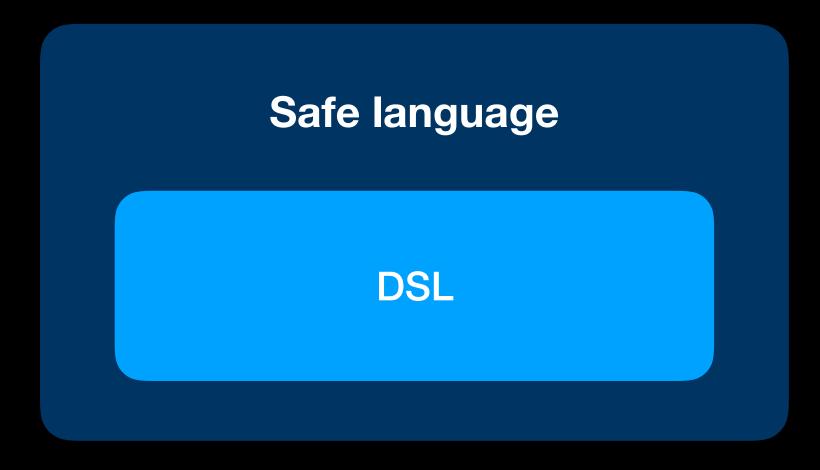
- Programs, not just a data flow graph
- Type safety
- Ahead-of-time AD
- Code generation
- Lightweight installation





Python

Safe language



- NN as a host language function
- Type safety
- Naturalness
 - Lightweight modular staging*
 - Compiler magic

Safe language

Libraries

DSL

- Trainer
- Layers
- Application API

Safe language

Libraries

DSL

Compiler Infrastructure

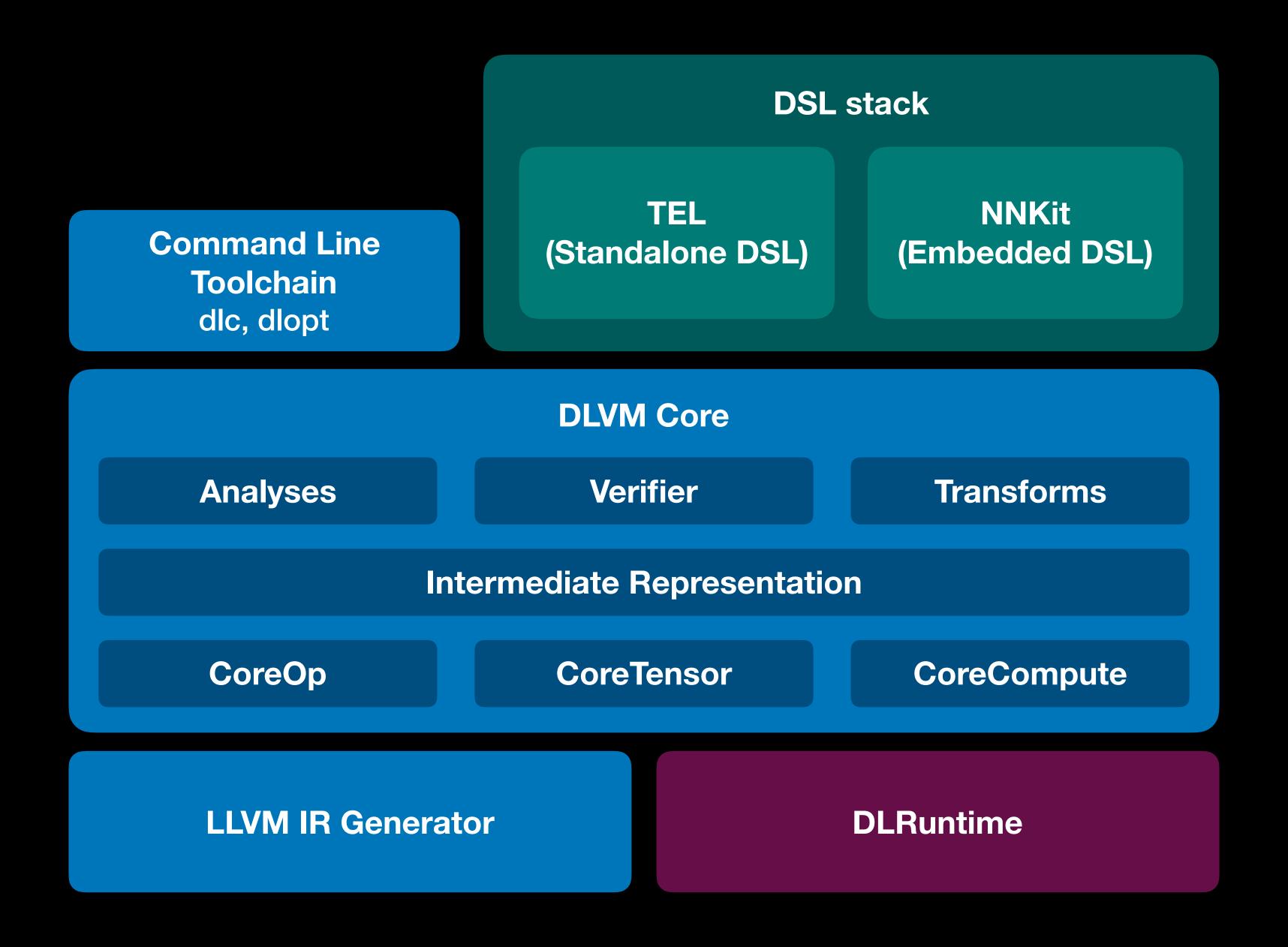
- Generic linear algebra IR
- Automatic differentiation
- Optimizations
- Code generation
- Runtime

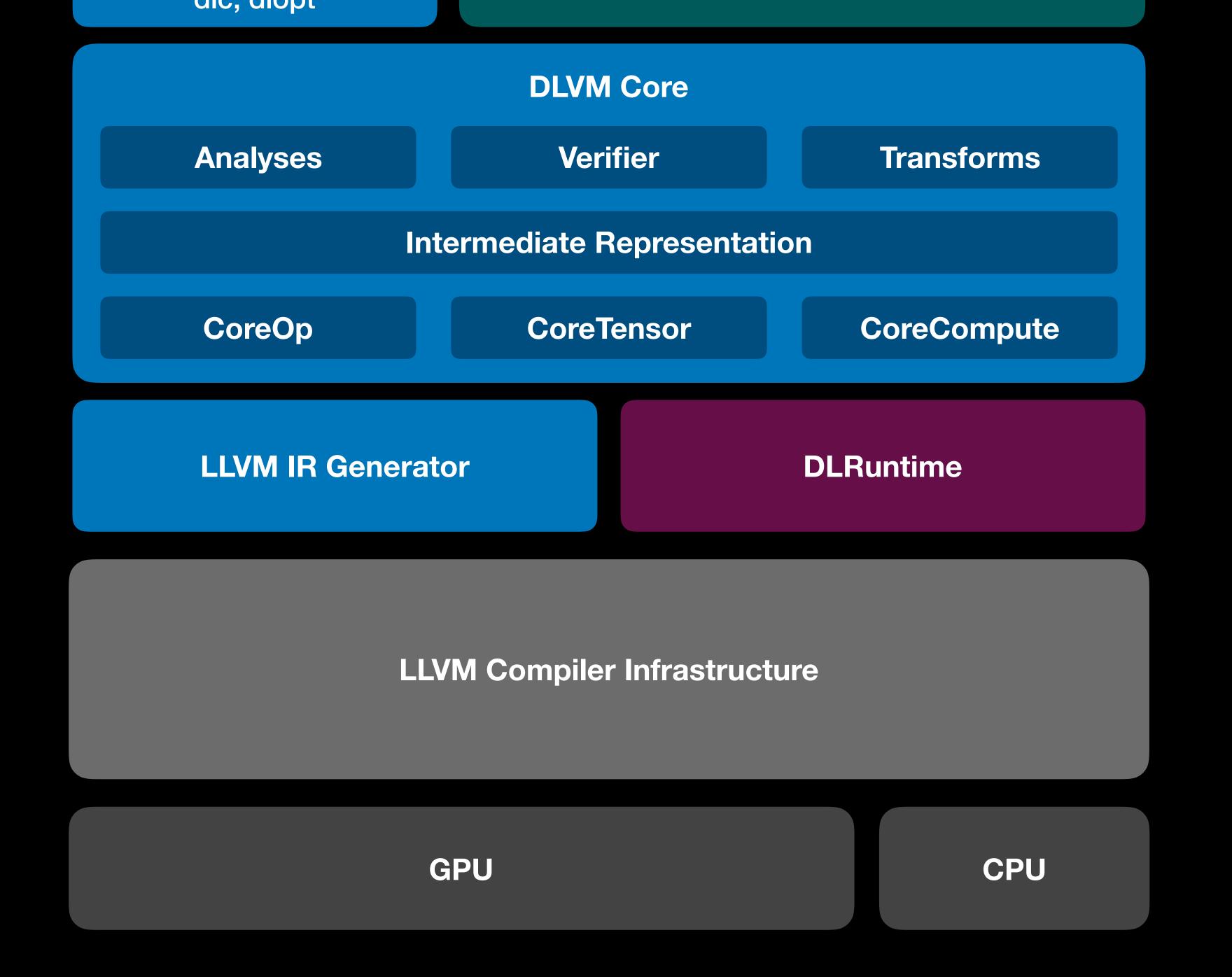
DSL

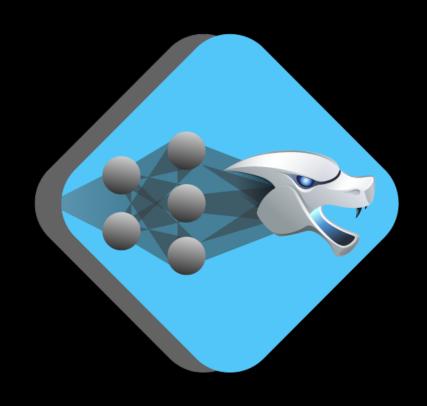
Compiler Infrastructure



- Linear algebra IR
- Framework for building DSLs
- Automatic backpropagator
- Multi-stage optimizer
- Static code generator based on LLVM







Core Language: DLVMIR

Tensor Jype

Rank	Notation	Descripton
0	i64	64-bit integer
	<100 x f32>	float vector of size 100
2	<100 x 300 x f64>	double matrix of size 100x300
	<100 x 300 x x bool>	rank-n tensor

First-class tensors

Domain-Specific Instructions

Kind	Example
Element-wise unary	tanh %a: <10 x f32>
Element-wise binary	power %a: <10 x f32>, %b: 2: f32
Dot	dot %a: <10 x 20 x f32>, %b: <20 x 2 x f32>
Concatenate	concatenate %a: <10 x f32>, %b: <20 x f32> along 0
Reduce	reduce %a: <10 x 30 x f32> by add along 1
Transpose	transpose %m: <2 x 3 x 4 x 5 x i32>
Convolution	convolve … kernel … strides … padding … dilation … groups …
Slice	slice %a: <10 x 20 x i32> from 1 upto 5
Random	random 768 x 10 from 0.0: f32 upto 1.0: f32
Select	select %x: <10 x f64>, %y: <10 x f64> by %flags: <10 x bool>
Compare	greaterThan %a: <10 x 20 x bool>, %b: <1 x 20 x bool>
Data type cast	dataTypeCast %x: <10 x i32> to f64

General-Purpose Instructions

Kind	Example
Function application	<pre>apply %foo(%x: f32, %y: f32): (f32, f32) -> <10 x 10 x f32></pre>
Branch	<pre>branch 'block_name(%a: i32, %b: i32)</pre>
Conditional (if-then-else)	<pre>conditional %cond: bool then 'then_block() else 'else_block()</pre>
Shape cast	shapeCast %a: <1 x 40 x f32> to 2 x 20
Extract	extract #x from %pt: \$Point
Insert	insert 10: f32 to %pt: \$Point at #x
Allocate stack	allocateStack
Allocate heap	allocateHeap \$MNIST count 1
Deallocate	deallocate %x: *<10 x f32>
Load	load %ptr: *<10 x i32>
Store	<pre>store %x: <10 x i32> to %ptr: *<10 x i32></pre>
Сору	<pre>copy from %src: *<10 x f16> to %dst: *<10 x f16> count 1: i64</pre>

Instruction Set

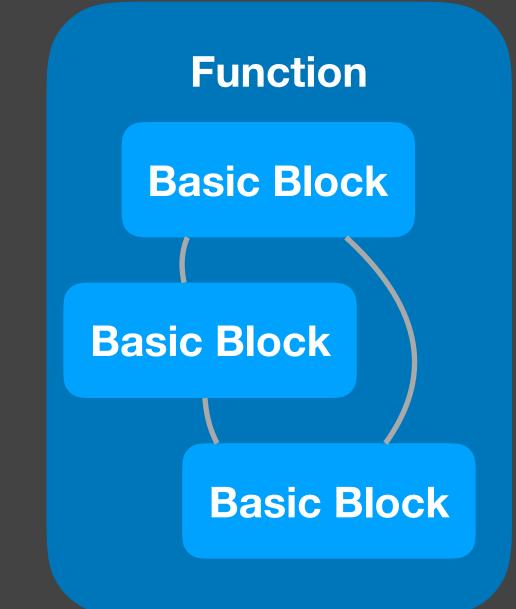
- Primitive math operators & general purpose operators
- No softmax, sigmoid
 - Composed by primitive math ops
- No min, max, relu
 - Composed by compare & select

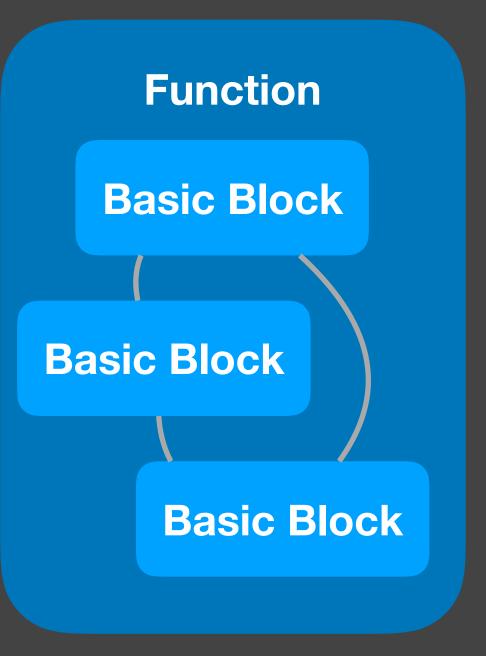
DLVMIR

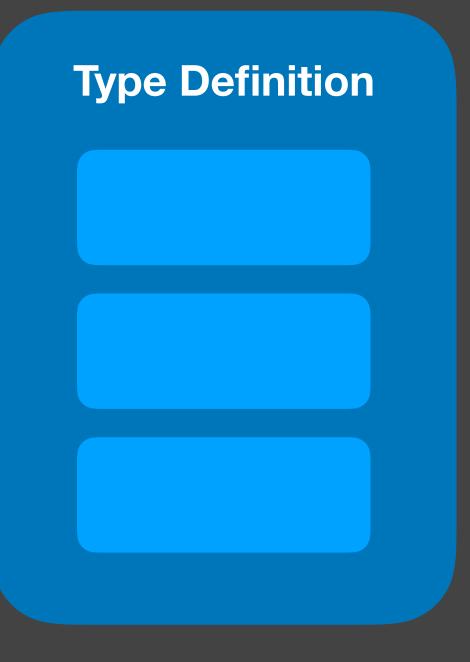
- Full static single assignment (SSA) form
 - Control flow graph (CFG) and basic blocks with arguments
- Custom type definitions
- Modular architecture (module function basic block instruction)
- Textual format & in-memory format
 - Built-in parser and verifier
 - Robust unit testing via LLVM Integrated Tester (lit) and FileCheck

DLVMIR

Module







```
module "my_module" // Module declaration
stage raw // Raw stage IR in the compilation phase
struct $Classifier {
    #w: <784 \times 10 \times f32>,
    #b: <1 \times 10 \times f32>,
type $MyClassifier = $Classifier
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
```

```
module "my_module" // Module declaration
stage raw // Raw stage IR in the compilation phase
struct $Classifier {
    #w: <784 \times 10 \times f32>,
    #b: <1 \times 10 \times f32>,
type $MyClassifier = $Classifier
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    0.1 = add \ 0.0: <1 \times 10 \times f32>, \ b: <1 \times 10 \times f32>
    conditional true: bool then 'b0() else 'b1()
'b0():
    return %0.1: <1 x 10 x f32>
'b1():
    return 0: <1 x 10 x f32>
```

Transformations: Differentiation & Optimizations

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
        %0.1 = add %0.0: <1 x 10 x f32>, %b: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}

[gradient @inference wrt 1, 2]
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
        -> (<784 x 10 x f32>, <1 x 10 x f32>)
```

Differentiation Pass

Canonicalizes every gradient function declaration in an IR module

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
                      -> (<784 x 10 x f32>, <1 x 10 x f32>) {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = dot %x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
        Generate adjoint code
```

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
                      -> (<784 x 10 x f32>, <1 x 10 x f32>) {
'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    %0.2 = transpose %x: <1 x 784 x f32>
    %0.3 = dot %0.2: <784 x 1 x f32>, 1: <1 x 10 x f32>
    \$0.4 = literal (\$0.3: <784 \times 10 \times f32>, 1: <1 \times 10 \times f32>): (<784 \times 10 \times f32>, <1 \times 10 \times f32>)
    return %0.4: (<784 x 10 x f32>, <1 x 10 x f32>)
```

Dead Code Elimination Pass

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
                       -> (<784 x 10 x f32>, <1 x 10 x f32>) {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = transpose %x: <1 x 784 x f32>
    %0.1 = dot %0.0: <784 \times 1 \times f32>, 1: <1 \times 10 \times f32>
    \$0.2 = literal (\$0.1: <784 \times 10 \times f32>, 1: <1 \times 10 \times f32>): (<784 \times 10 \times f32>, <1 \times 10 \times f32>)
    return %0.2: (<784 x 10 x f32>, <1 x 10 x f32>)
```

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
        %0.1 = add %0.0: <1 x 10 x f32>, %b: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}

[gradient @inference from 0]
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
        -> (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
```

from: selecting which output to differentiate in tuple return

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
        %0.1 = add %0.0: <1 x 10 x f32>, %b: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}

[gradient @inference from 0 wrt 1, 2]
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
        -> (<784 x 10 x f32>, <1 x 10 x f32>)
```

from: selecting which output to differentiate in tuple return wrt: with respect to arguments 1 & 2

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
        %0.1 = add %0.0: <1 x 10 x f32>, %b: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}

[gradient @inference from 0 wrt 1, 2 keeping 0]
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
        -> (<784 x 10 x f32>, <1 x 10 x f32>, <1 x 10 x f32>)
```

from: selecting which output to differentiate in tuple return wrt: with respect to arguments 1 & 2 keeping: keeping original output

```
func @inference: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
        %0.1 = add %0.0: <1 x 10 x f32>, %b: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}

[gradient @inference from 0 wrt 1, 2 keeping 0 seedable]
func @inference_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>, <1 x 10 x f32>)
        -> (<784 x 10 x f32>, <1 x 10 x f32>, <1 x 10 x f32>)
```

from: selecting which output to differentiate in tuple return

wrt: with respect to arguments 1 & 2

keeping: keeping original output

seedable: allow passing in back-propagated gradients as seed

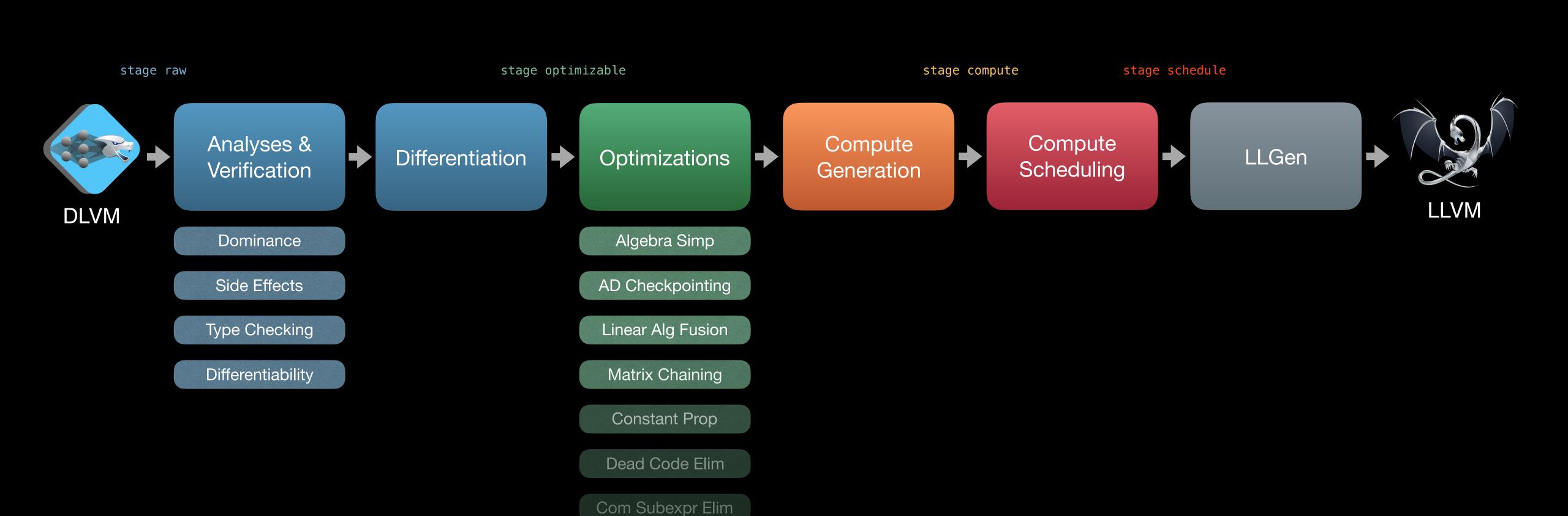
```
func @f: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
        %0.1 = add %0.0: <1 x 10 x f32>, %b: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}

func @g: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
   'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
        %0.0 = apply @f(%x, %w, %b): (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32>)
        %0.1 = tanh %0.0: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
        return %0.1: <1 x 10 x f32>
}
```

```
func @f: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 x 784 x f32>, %w: <784 x 10 x f32>, %b: <1 x 10 x f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
func @g: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    \$0.0 = apply @f(\$x, \$w, \$b): (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32>
    %0.1 = tanh %0.0: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
[gradient @g wrt 1, 2]
func @g_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> (<784 x 10 x f32>, <1 x 10 x f32>)
```

```
func @f: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = dot %x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
func @g: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    \$0.0 = apply @f(\$x, \$w, \$b): (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32>
    %0.1 = tanh %0.0: <1 x 10 x f32>
    return %0.1: <1 x 10 x f32>
[gradient @g wrt 1, 2]
func @g_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> (<784 x 10 x f32>, <1 x 10 x f32>)
                                                                                       Seed
[gradient @f wrt 1, 2 seedable]
func @f_grad: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>, <1 x 10 x f32>)
              -> (<784 x 10 x f32>, <1 x 10 x f32>)
```

Compilation Phases





DSL

DSL

DSL

- NN as program, not a graph
- Static analysis
- Type safety
- Naturalness
 - Lightweight modular staging
 - Compiler magic

NNKit: Staged DSL in Swift

NNKit

- It's a prototype!
- Tensor computation embedded in host language
- Type safety
- Generates DLVM IR on the fly

Language

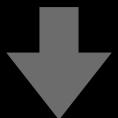
- Statically ranked tensors
 - T, Tensor1D<T>, Tensor2D<T>, Tensor3D<T>, Tensor4D<T>
- Type wrapper for staging Rep<Wrapped>
 - Rep<Float>, Rep<Tensor1D<Float>>, Rep<Tensor2D<T>>
- Operator overloading
 - func + <T: Numeric>(_: Rep<T>, _: Rep<T>) -> Rep<T>
 - func(_: Rep<Tensor2D<T>>, _: Rep<Tensor2D<T>>)

Language

- Lambda abstraction
 - func lambda<T, U>(_ f: (Rep<T>) -> Rep<U>) -> Rep<(T) -> U>
- Function application
 - subscript<T, U>(arg: Rep<T>) -> Rep<U> where Wrapped == (T) -> U
 - subscript<T, U>(arg: T) -> U where Wrapped == (T) -> U
 // JIT DLVM IR

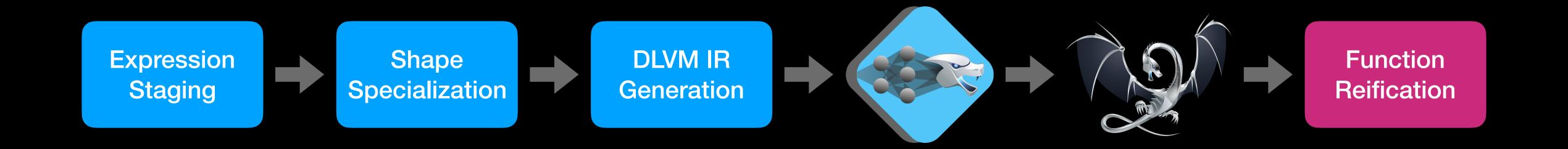
Staged Evaluation

Rep<(Float2D) -> Float2D>



(Float2D) -> Float2D

Staged Evaluation



Rep<(Float2D) -> Float2D>

(Float2D) -> Float2D

typealias Float2D = Tensor2D<Float>

```
typealias Float2D = Tensor2D<Float>
struct Parameters {
   var w: Float2D
   var b: Float2D
}
```

```
typealias Float2D = Tensor2D<Float>

struct Parameters {
    var w: Float2D
    var b: Float2D
}

let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
```

```
typealias Float2D = Tensor2D<Float>

struct Parameters {
    var w: Float2D
    var b: Float2D
}

let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }
}
```

```
typealias Float2D = Tensor2D<Float>

struct Parameters {
    var w: Float2D
    var b: Float2D
}

let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }

let params: Parameters = ...
```

```
typealias Float2D = Tensor2D<Float>
struct Parameters {
    var w: Float2D
    var b: Float2D
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x \cdot w + b
let params: Parameters = ...
let x: Float2D = [[0.0, 1.0]]
```

```
typealias Float2D = Tensor2D<Float>
struct Parameters {
    var w: Float2D
   var b: Float2D
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x \cdot w + b
let params: Parameters = ...
let x: Float2D = [[0.0, 1.0]]
f[x, params.w, params.b] // ==> result
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
         x \cdot w + b
f[x, w, b]
// x: 1x784, w: 784x10, b: 1x10
func @f: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>) -> <1 x 10 x f32> {
'entry(%x: <1 \times 784 \times f32>, %w: <784 \times 10 \times f32>, %b: <1 \times 10 \times f32>):
    %0.0 = dot %x: <1 x 784 x f32>, %w: <784 x 10 x f32>
    %0.1 = add %0.0: <1 \times 10 \times f32>, %b: <1 \times 10 \times f32>
    return %0.1: <1 x 10 x f32>
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
}
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }

let g = lambda { x, w, b in
    let linear = f[x, w, b]
    return tanh(linear)
}
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }

let g = lambda { x, w, b in
    let linear = f[x, w, b]
    return tanh(linear)
}

let ∇g = gradient(of: g, withRespectTo: (1, 2))
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }

let g = lambda { x, w, b in
    let linear = f[x, w, b]
    return tanh(linear)
}

let ∇g = gradient(of: g, withRespectTo: (1, 2))
// ∇g : Rep<(Float2D, Float2D, Float2D) -> (Float2D, Float2D)>
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
     lambda { x, w, b in
          x \cdot w + b
let g = lambda { x, w, b in
     let linear = f[x, w, b]
     return tanh(linear)
let \nabla g = gradient(of: g, withRespectTo: (1, 2))
// ∇g : Rep<(Float2D, Float2D, Float2D) -> (Float2D, Float2D)>
\nabla g f \approx \beta i \approx \beta t b \oplus f / \psi r = 1, (2 \partial g / \partial w, \partial g / \partial b)
func @g: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
           -> (<784 x 10 x f32>, <1 x 10 x f32>)
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
         x • w + b
let g = lambda { x, w, b in
    let linear = f[x, w, b]
    return tanh(linear)
let \nabla g = gradient(of: g, withRespectTo: (1, 2))
// ∇g : Rep<(Float2D, Float2D, Float2D) -> (Float2D, Float2D)>
\nabla g[x, w, b] // ==> (\partial g/\partial w, \partial g/\partial b)
[gradient @f wrt 1, 2]
func @g: (<1 x 784 x f32>, <784 x 10 x f32>, <1 x 10 x f32>)
         -> (<784 x 10 x f32>, <1 x 10 x f32>)
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }

let g = lambda { x, w, b in
    let linear = f[x, w, b]
    return tanh(linear)
}

let ∇g = gradient(of: g, withRespectTo: (1, 2), seedable: true)
// ∇g : Rep<(Float2D, Float2D, Float2D, Float2D) -> (Float2D, Float2D)>
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
    lambda { x, w, b in
        x • w + b
    }

let g = lambda { x, w, b in
    let linear = f[x, w, b]
    return tanh(linear)
}

let ∇g = gradient(of: g, withRespectTo: (1, 2), seedable: true, keeping: (0))
// ∇g : Rep<(Float2D, Float2D, Float2D, Float2D) -> (Float2D, Float2D, Float2D)>
```

```
let f: Rep<(Float2D, Float2D, Float2D) -> Float2D> =
     lambda { x, w, b in
         x \cdot w + b
let g = lambda { x, w, b in
     let linear = f[x, w, b]
     return tanh(linear)
let \nabla g = gradient(of: g, withRespectTo: (1, 2), seedable: true, keeping: (0))
// ∇g : Rep<(Float2D, Float2D, Float2D, Float2D) -> (Float2D, Float2D, Float2D)>
\nabla g[x, w, b, \partial h_{\partial g}] // ==> (\partial h/\partial w, \partial h/\partial b, g(x, w, b))
```



Libraries

DSL

Swift

Libraries

NNKit

DLVM



DLVM is written in Swift!

PL & Compilers + ML

- Programs, not just a data flow graph
- Type safety
- Ahead-of-time AD
- Code generation

dlvm.org

