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MindIR: the intermediate representation of MindSpore

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COMPUTATIONAL ABSTRACTIONS FOR PROBABILISTIC AND DIFFERENTIABLE PROGRAMMING WORKSHOP

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MindSpore: Open Source All-Scenario AI Framework

Mar 2020 — MindSpore Went open source

Sep 2020 — MindSpore 1.0 Commercial use

[M]s 昇思 MindSpore — **MindSpore 1.8**

2022 — MindSpore 2.0

Develop once Deploy on device, edge, and cloud

All-scenario applications

5,000+ applications online

All-scenario deployment

Free from cross-platform model conversion

Large-scale model training native support, accelerating innovation

200-billion-parameter model

Auto parallel

80% ↓

Parallel code

Auto tuning

60% ↓

Tuning time

MindSpore for science, accelerating AI for Science

MindSporeElec

Electromagnetic simulation kit

10x ↑

Mobile phone EM simulation performance

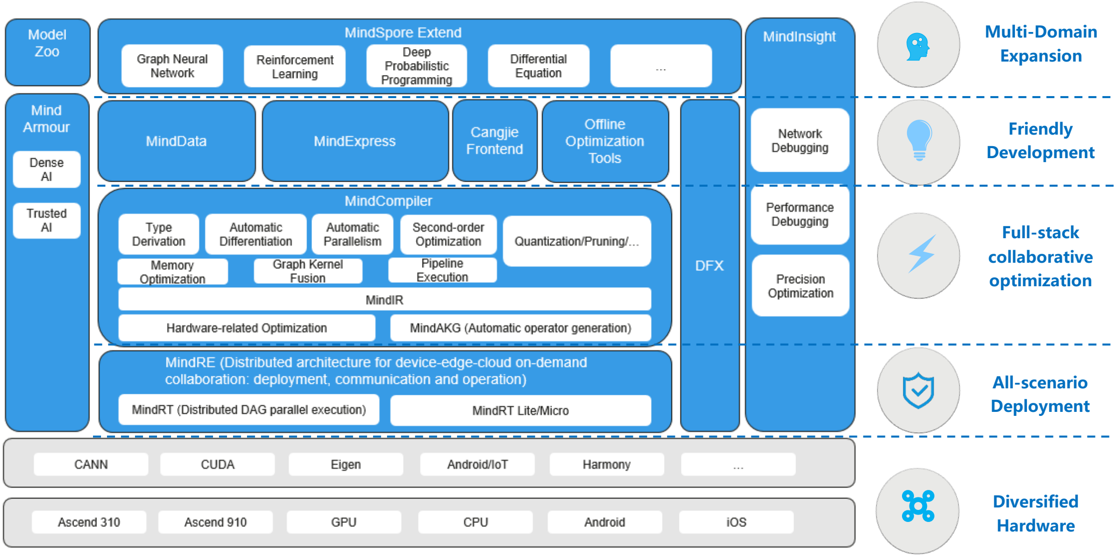
MindSpore SPONGE

Molecular simulation kit

50% ↑

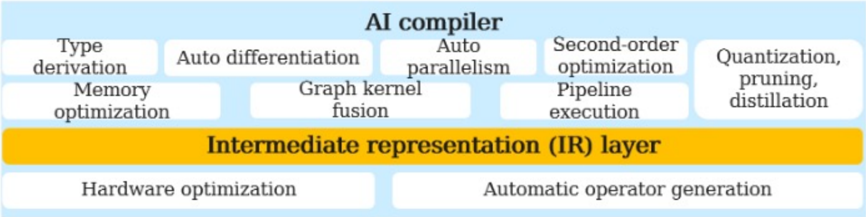
Biopharmaceutical compound computing efficiency

MindSpore: Open Source All-Scenario AI Framework



MindCompiler: the graph compiler of MindSpore

- In the AI software stack, the graph compiler optimizes the processing of a forward, or backward pass over the computation graphs that describe deep learning models.
- MindCompiler is the graph compiler of MindSpore to achieve three major kinds of optimizations, including
  - hardware-independent optimization (type inference, automatic differentiation, expression simplification, etc.);
  - hardware-related optimization (automatic parallelism, memory optimization, graph kernel fusion, pipeline execution, etc.);
  - deployment and inference-related optimizations (quantization, pruning, etc.).
- MindCompiler based on the unified device-cloud MindIR.



MindIR: A bit of motivation

- Compared other “general purpose” IRs, the IR of the graph compiler of AI framework has some special requirements and challenges:
    - Tensor representation;
    - Automatic differentiation;
    - JIT;
    - Implicit parallelism.
- Some hints from previous studies:
    - Sea of nodes: to construct graphs via use-def chains. The graph form is a single tiered structure instead of a two-tiered Control-Flow Graph (CFG) containing basic blocks (tier 1) of instructions (tier 2). control and data dependencies have the same form and implementation.
    - Thorin: a functional graph-based IR that abandons explicit scope nesting in favor of a dependency graph. The relationship between free variables and subgraphs is obtained via data dependency on the graph.
    - A-Normal form: partition expressions into two forms, atomic expressions and complex expression. All complex expression must be let-bound, or else appear in tail position.

```
<aexp> ::= NUMBER | STRING | VAR | BOOLEAN | PRIMOP
         |  (lambda (VAR …) <exp>)
<cexp> ::= (<aexp> <aexp> …)
         |  (if <aexp> <exp> <exp>)
<exp> ::= (let ([VAR <cexp>]) <exp>) | <cexp> | <aexp>
```

MindIR: a function-style graph-based IR

- MindSpore IR (MindIR) is a function-style IR based on graph representation.
  - Function-style IR makes automatic differentiation and implicit parallelism analysis more convenient;
  - Graph-based IR with a single tiered structure is suitable for JIT optimizations;
  - A-Normal form gets rid of scope and is easy to read and check.
- BNF: An variant A-Normal form used in MindIR with ‘if’ being treated as a prim operation
  - ➢ <Anode> ::= Scalar | Named | Tensor | Var | Prim | MetaFunc | Func | Type | Shape| Param
  - ➢ <CNode> ::= (<Anode> …)
  - ➢ <AnfNode> ::= <CNode> | <ANode>
- ANode in a MindIR corresponds to the atomic expression of ANF.
  - ValueNode refers to a constant node, which can carry a constant value (such as a scalar, symbol, tensor, type, and dimension), a primitive function (Primitive), or a common function (FuncGraph).
  - ParameterNode refers to a parameter node, which indicates the formal parameter of a function.
- CNode in a MindIR corresponds to the compound expression of ANF, indicating a function call.

[M]^S 昇思 MindSpore

MindIR: An example

Python Code

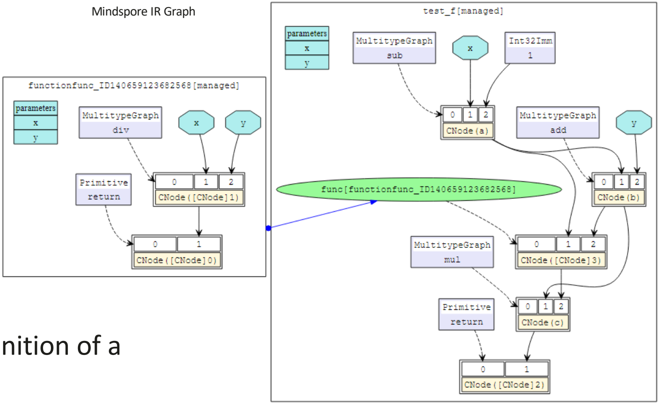
```python
def func(x, y):
    return x / y

def test_f(x, y):
    a = x - 1
    b = a + y
    c = b * func(a, b)
    return c
```

ANF

```
lambda (x, y)
    let a = x - 1 in
    let b = a + y in
    let func = lambda (x, y)
        let ret = x / y in
        ret end in
    let %1 = func(a, b) in
    let c = b * %1 in
    c end
```

Mindspore IR Graph



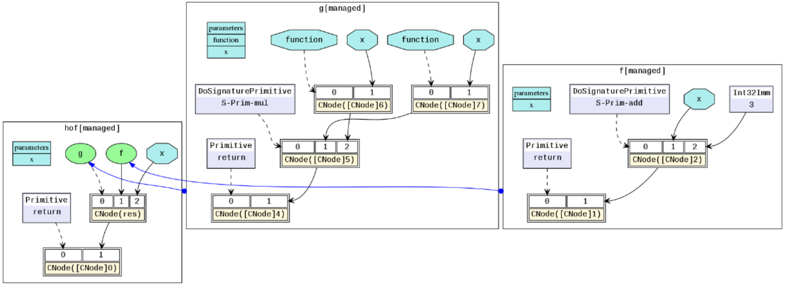
- In a MindIR, a function graph indicates the definition of a common function.
- Each expression is bound as a node, and the dependency is represented by using the directed edges between nodes.

MindIR: Higher-Order Functions

Python Code

```python
@ms_function
def hof(x):
    def f(x):
        return x + 3
    def g(function, x):
        return function(x) * function(x)
    res = g(f, x)
    return res
```

Mindspore IR Graph



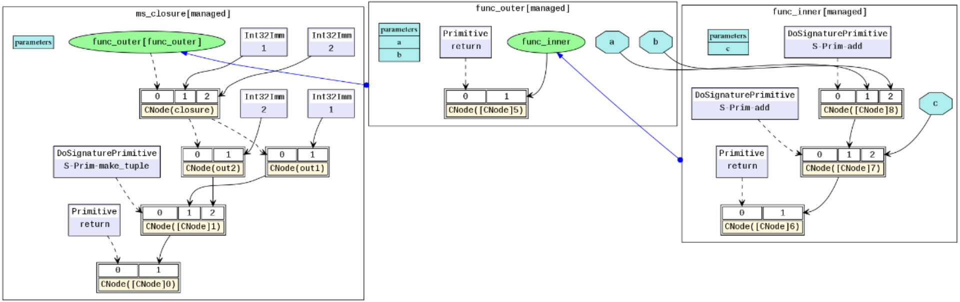
- In functional programming, the function definition itself is a value.
- In a MindIR, a function, defined by a subgraph, can be transferred as the input or output of other higher-order functions.
- Higher-order semantics greatly improve the flexibility and simplicity of MindSpore representations.

MindIR: Free Variables and Closures

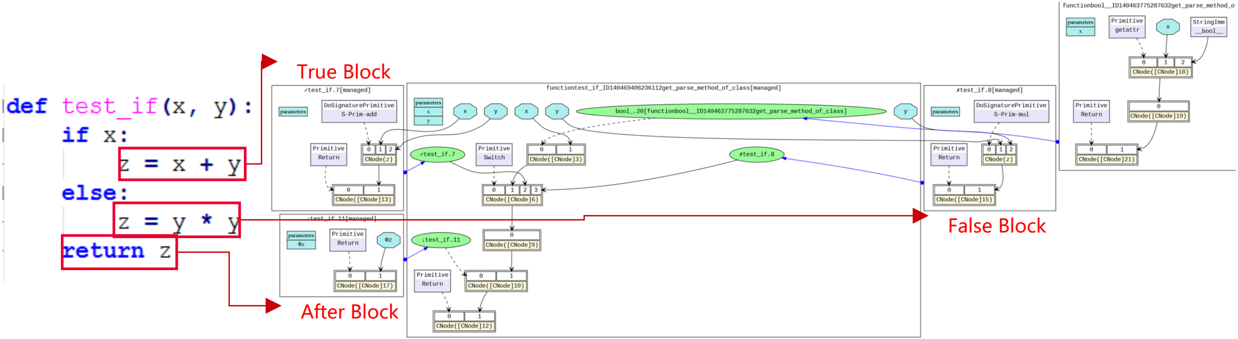
- In a MindIR, a code block is represented as a function graph.
- The scope environment can be considered as the context where the function is called.
- The capture method of free variables is value copy instead of reference.

```python
@ms_function
def func_outer(a, b):
    def func_inner(c):
        return a + b + c
    return func_inner

@ms_function
def ms_closure():
    closure = func_outer(1, 2)
    out1 = closure(1)
    out2 = closure(2)
    return out1, out2
```



MindIR: Control Flows



- In a MindIR, control flows are expressed in the form of high-order function selection and calling.
- This form transforms a control flow into a data flow of higher-order functions, making automatic differentiation of control flows possible.

MindIR: Autodiff

- MindIR implements automatic differentiation based source transformation.
- Each function call is transformed to return an additional value, which is a closure called the 'backpropagator'.
  - The backpropagator computes the derivative with respect to the inputs given the derivatives with respect to the outputs;
  - The backpropagators of primitives are known;
  - The backpropagators of user-defined functions is constructed by calling the backpropagators of the function calls in the body in reverse order by the chain rule.
- The design of MindIR help the automatic differential algorithm works in the case of control flows such as conditional jumps, loops, and recursion.

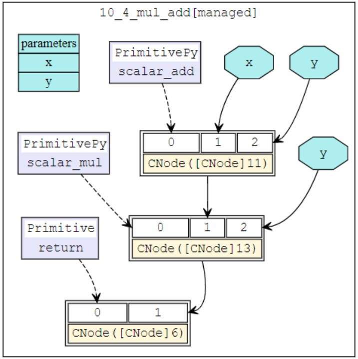
```
def f(x, y):
    a = pow(x, 3)
    b = pow(y, 4)
    c = mul(a, b)
    return c
```

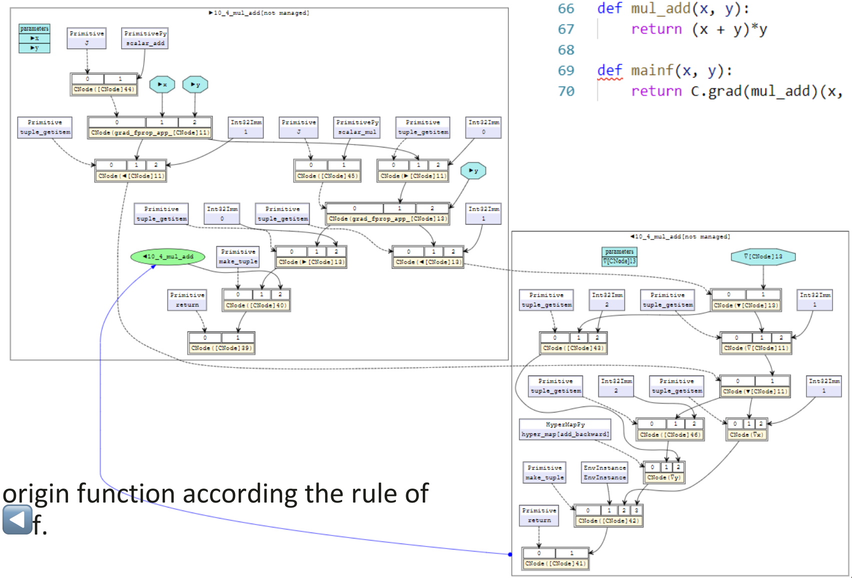
```
def ▶f(▶x, ▶y):
    ▶a, ◀a = ▶pow(▶x, ▶3)
    ▶b, ◀b = ▶pow(▶y, ▶4)
    ▶c, ◀c = ▶mul(▶a, ▶b)
    def ◀f(∇c):
        ∇x, ∇y, ∇a, ∇b, ∇c = 0...
        ∇mul_fv, ∇a, ∇b += ◀c(∇c)
        ∇pow_fv, ∇y, ∇exp_4 += ◀b(∇b)
        ∇pow_fv, ∇x, ∇exp_3 += ◀a(∇a)
        return {}, ∇x, ∇y
    return ▶c, ◀f
```

```
dfdx = ◀f(1.0)[1] = ▶f(x, y)[1](1.0)[1]
```

Reverse-Mode AD in a Functional Framework: Lambda the Ultimate Propagator by B. A. Pearlmutter and J. M. Siskind 2008

MindIR: Autodiff





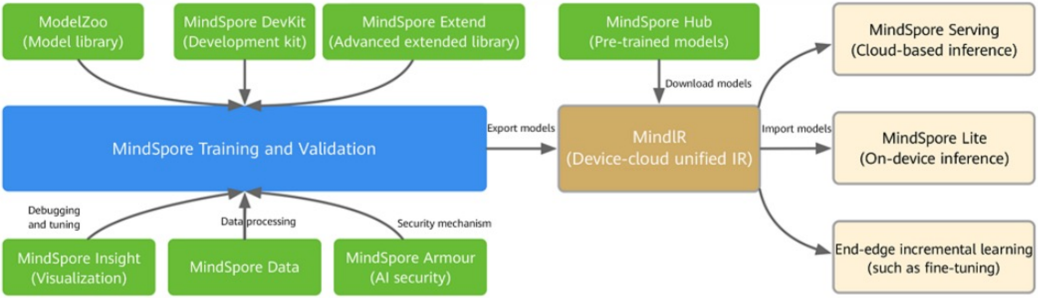
```python
def mul_add(x, y):
    return (x + y)*y

def mainf(x, y):
    return C.grad(mul_add)(x, y)
```

Perform auto diff transform on origin function according the rule of Generating ▶️f and Generating ◀️f.

MindIR: Execution Process

- As the unified model file of MindSpore, MindIR stores network structures and weight parameter values. In addition, it can be deployed on the on-cloud Serving and the on-device Lite platforms to execute inference tasks.
- A MindIR file supports the deployment of multiple hardware forms.
  - On-cloud deployment and inference on Serving: After MindSpore trains and generates a MindIR model file, the file can be directly sent to MindSpore Serving for loading and inference.
  - On-device inference and deployment on Lite: MindIR can be directly used for Lite deployment.




thank you
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