MLC LLM: Universal Large-language Model Deployment with ML Compilation

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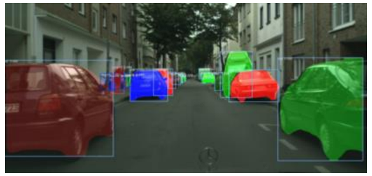
History of Machine Learning Revolutions

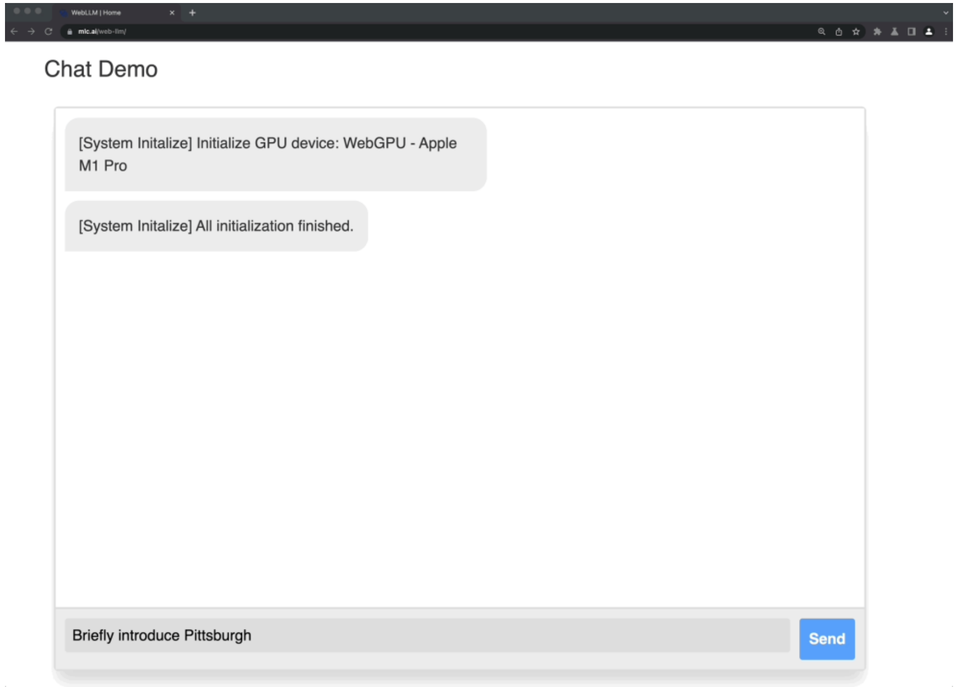
	Big Data	Deep Learning	Generative AI
			Bard Llama 2
Key Capabilities	**Recommendation** **Data analytics**	**Strong pattern recognition capabilities**	**Open ended conversations** **Generalist models**
ML Systems	dmlc XGBoost Apache Spark GraphLab	TensorFlow tvm	**MLSys plays an even more central role**

2010 **2013** **2023**

Systems for Generative AI: Challenges and Opportunities

Generative AI

Open ended conversations
Generalist models



Memory Llama-70B would consume 320GB VRAM to just to store parameters in fp32

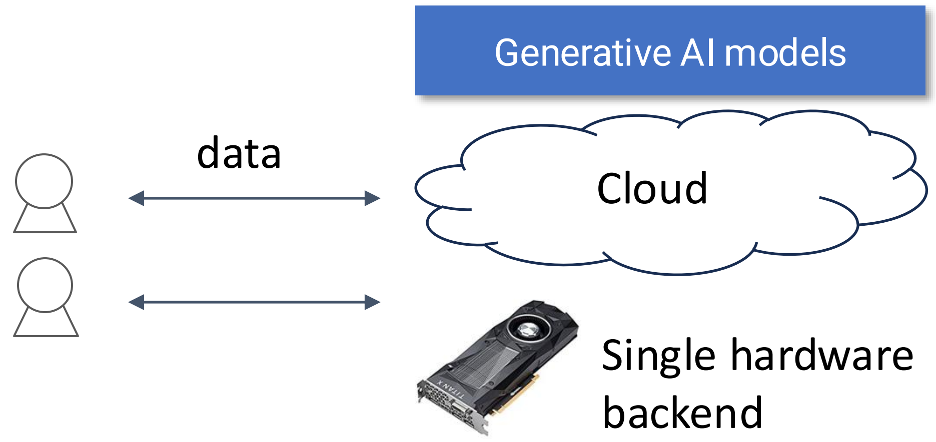
Compute The post-Moore era brings great demand for diverse specialized compute, system support becomes bottleneck

Integration Goes beyond single chat model, modern AI applications can see, talk, compose music. Need to coordinate multiple models and system components.

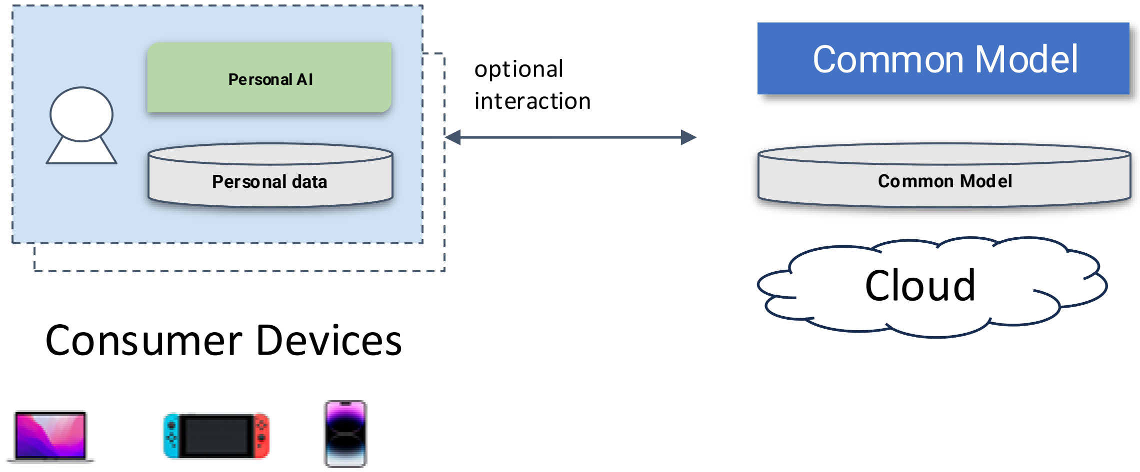
Evolutions and co-design Keep up with new demands, new modeling approaches, hardware variants, and co-design

The Case for Bringing Generative AI Everywhere

Generative AI Paradigm Today



Just like personal computers
can we get our own personal AI?



Machine Learning Systems: Typical Engineering Approach

ML Models

Llama 2, Whisper, CLIP, SAM, …

- Specialized libraries and systems for each backend (labor intensive)
- Non-automatic optimizations

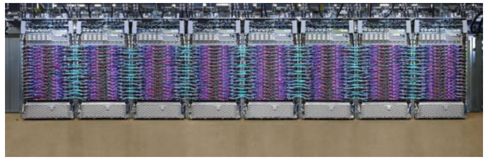
Nvidia Stack

AMD Stack

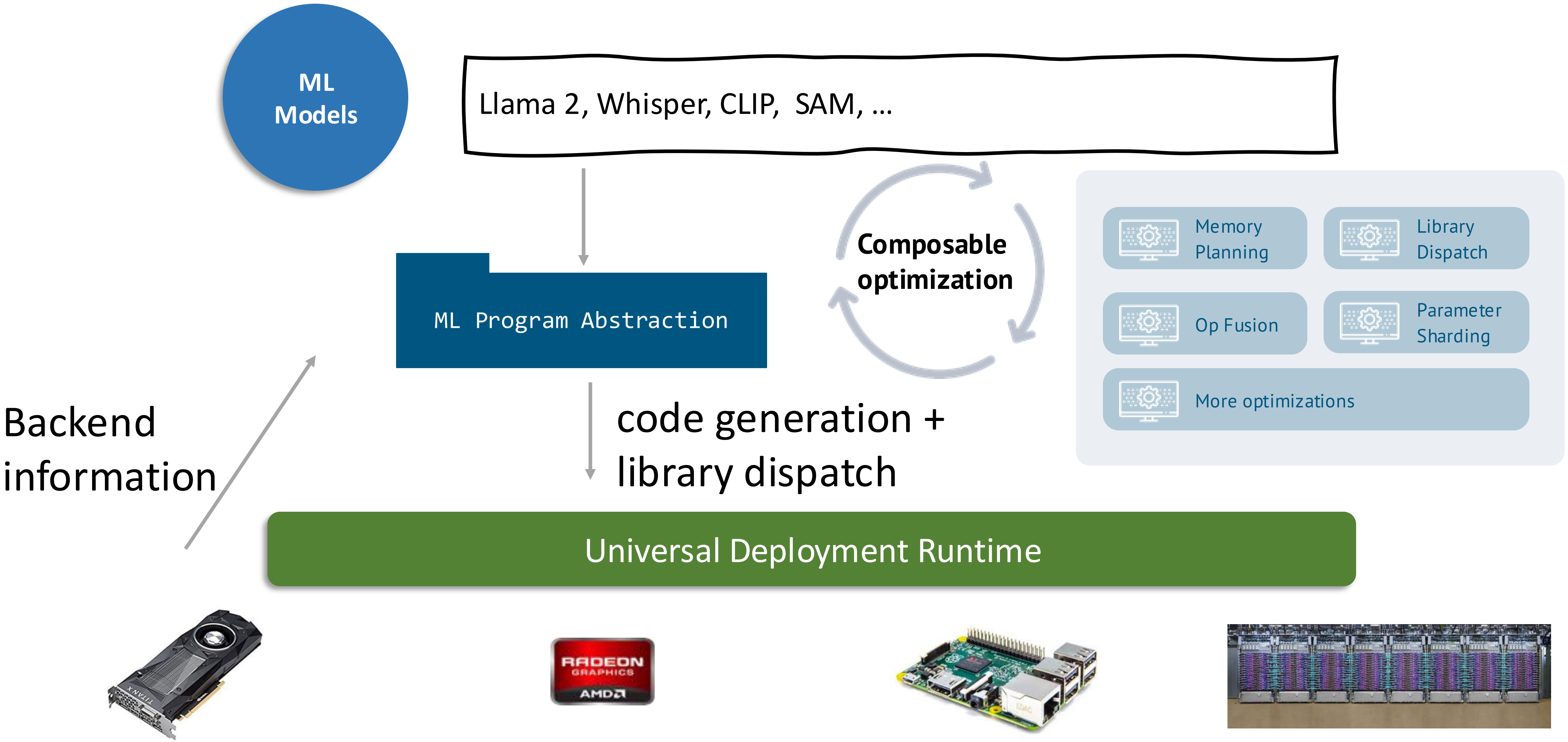
RADEON GRAPHICS AMD

ARM-Compute

TPU Stack



ML Compilation



Abstractions for ML Compilation

There are four different categories of abstractions we use to accelerate machine learning today

Computational Graphs

Computational graph and its extensions enable high level program rewriting and optimization.

Tensor Programs

Tensor program abstractions focus on loop and layout transformation for fused operators.

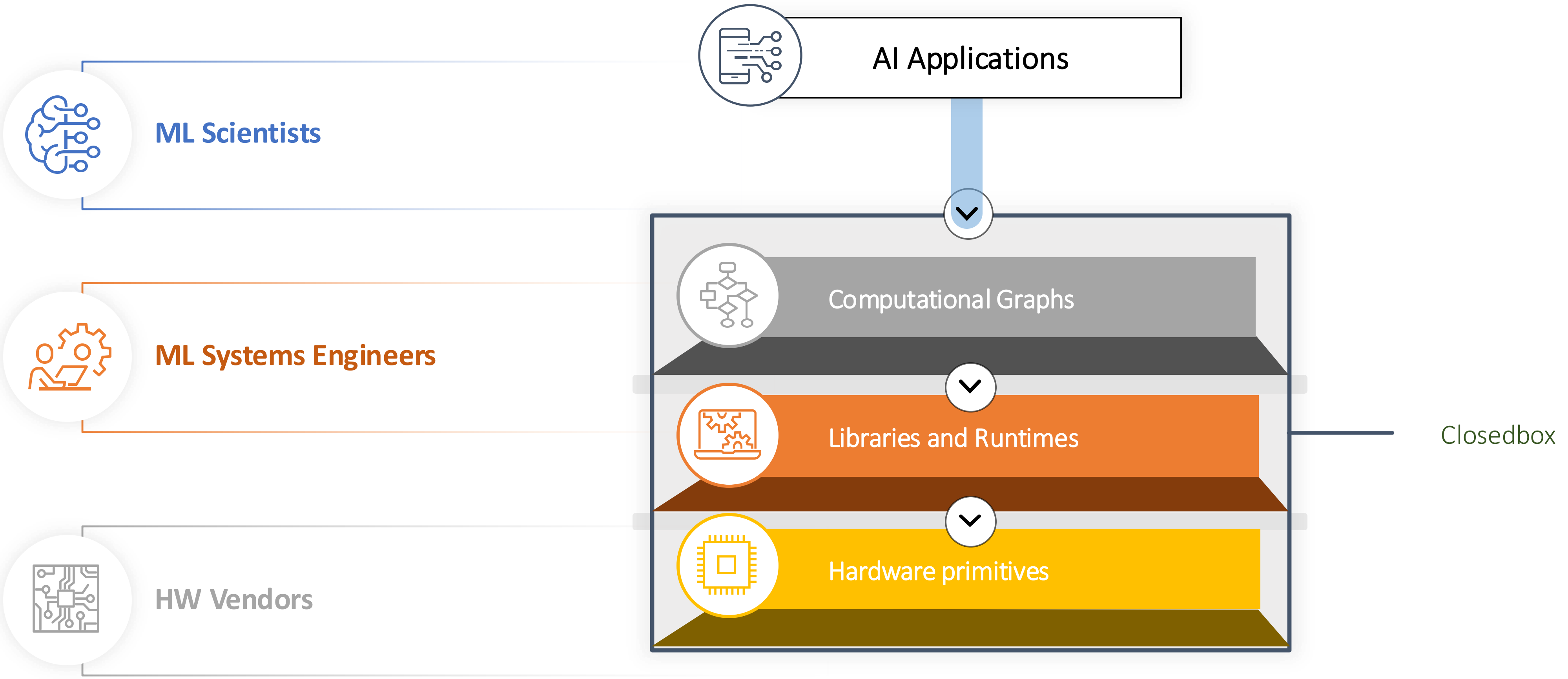
Libraries and Runtimes

Optimizing libraries are built by vendors and engineers to accelerate key operators of interest.

Hardware Primitives

The hardware builders exposes novel primitives to provide native hardware acceleration.

Current Frameworks and Challenges



What is the Biggest Challenge?

ML modeling

- Language Models
- Diffusion
- MultiQuery Attention
- RoPE

ML Engineering

- Memory Planning
- Library Dispatch
- Sparse Weights
- Paged Attention
- Op Fusion
- Parameter Sharding
- Quantized Kernels
- Layout Optimization

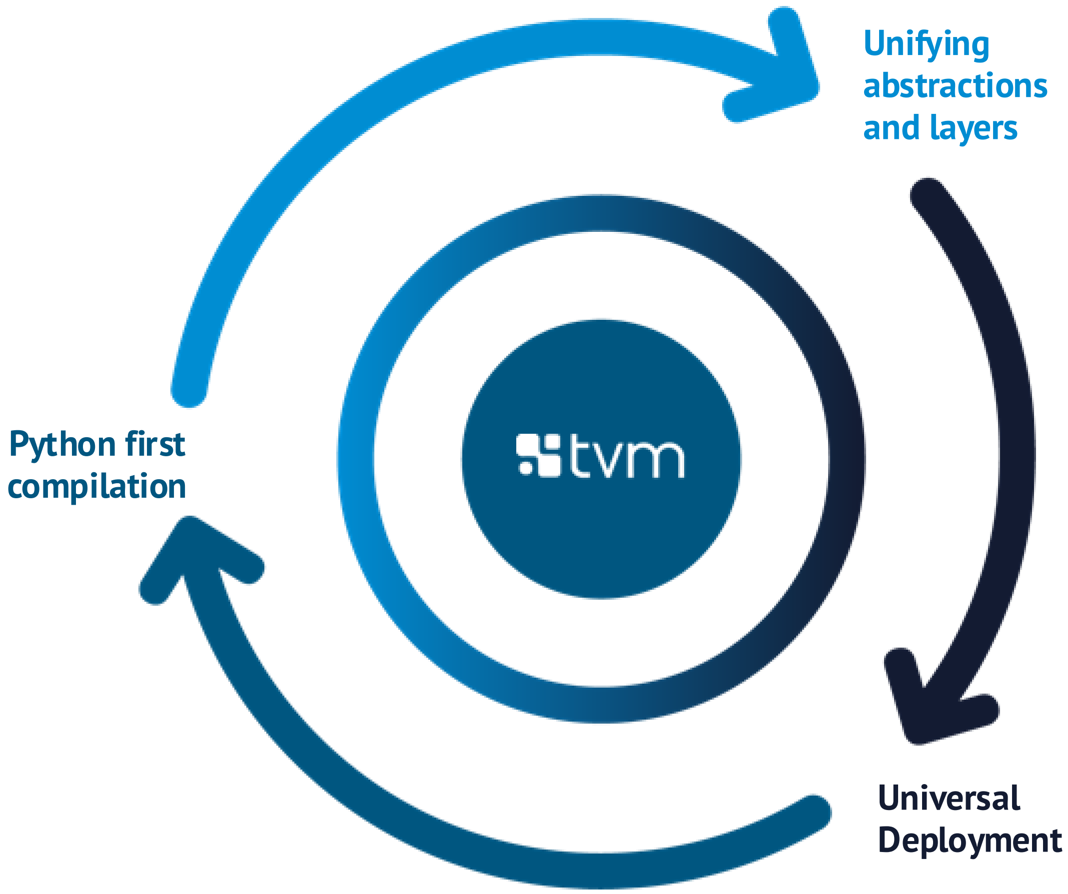
ML engineering now becomes critical and go hand in hand with ML modeling
It is not about build silver bullet once but **continuous improvement and innovations**

TVM Unity

Mission

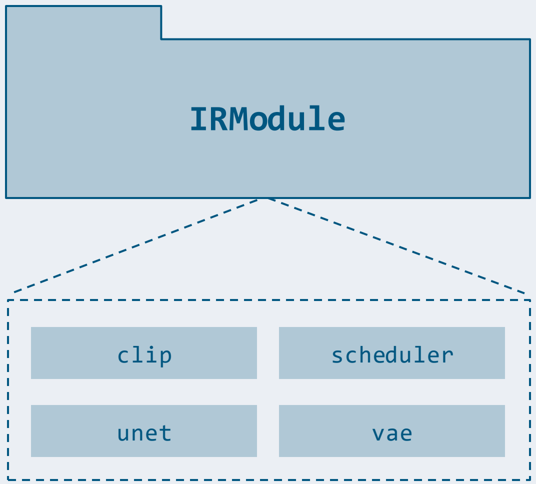
Empower community members to optimize any machine learning models and run them on any hardware backend.

This is not a single step journey.



IRModule as the Central Abstraction

Centers around one key construct



A collection of (tensor) functions that correspond to model components.

Accessible in python through TVMScript

```
>>> mod.show()
```

```python
import tvm.script
from tvm.script import tir as T, relax as R

@tvm.script.ir_module
class Module:
    @R.function
    def vae(
        data: R.Tensor(("n", 4, 64, 64), "float32"),
        params: R.Tuple(R.Tensor((4, 4, 1, 1), "float32"),
                        R.Tensor((1, 4, 1, 1), "float32"),
                        ...)
    ) -> R.Tensor(("n", 512, 512, 3),"float32"):
        n = T.int64()
        with R.dataflow():
            w0: R.Tensor((4, 4, 1, 1), "float32") = params[0]
            lv0: R.Tensor((n, 4, 64, 64), "float32") = R.nn.conv2d(
                data, w0, strides=[1, 1]
            )
            b0: R.Tensor((1, 4, 1, 1), "float32") = params[1]
            lv1: R.Tensor((n, 4, 64, 64), "float32") = R.add(lv0, b0)
            ...
```

Unifying abstractions by encapsulation computational graph, tensor program, library, hardware primitives, and their interactions in the same module

Python First Development

Import

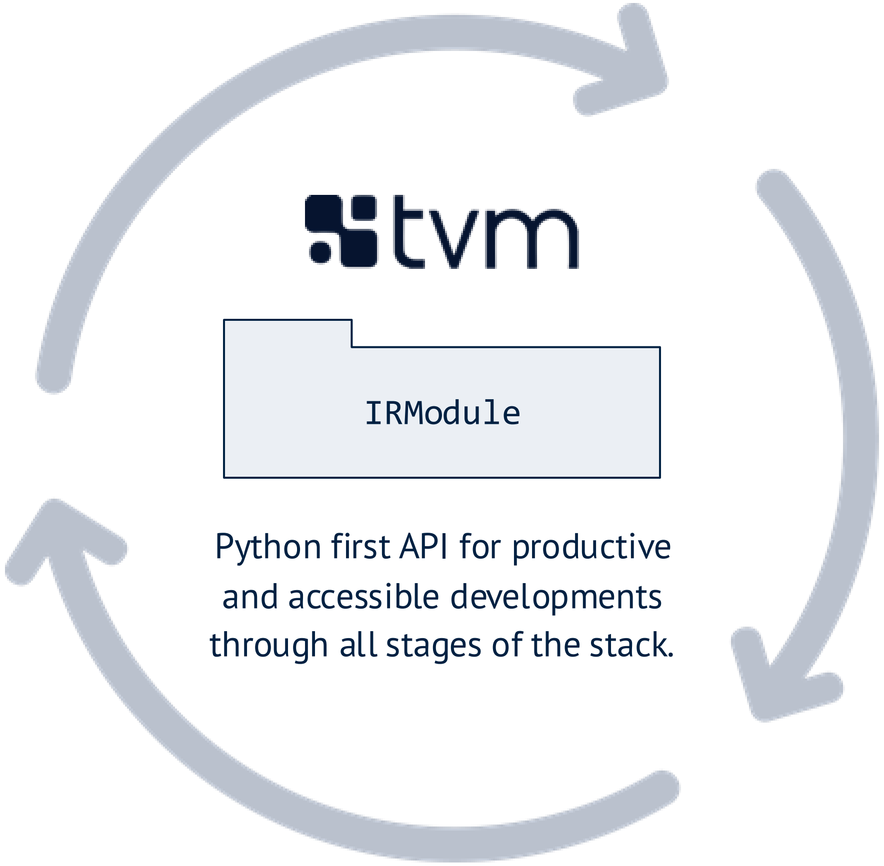
```
mod = frontend.from_fx(torch_graph)
```

Inspect and interact

```
mod = my_script_module.Module

sch = tvm.tir.Schedule(mod)
sch.work_on("add")
add_block = sch.get_block("T_add")
(i,) = sch.get_loops(add_block)
i0, i1 = sch.split(i, [None, 128])
sch.bind(i0, "blockIdx.x")
sch.bind(i1, "threadIdx.x")
mod = sch.mod

mod.show()
```



Python first API for productive and accessible developments through all stages of the stack.

Transform and optimize

```
seq = transform.Sequential([
    transform.FuseOps(),
    transform.FuseTIR()
])
mod = seq(mod)
```

Deploy

```
ex = relax.build(mod, target)
ex.export_library("model.so")
```

Universal Deployment

IRModule

```python
@tvm.script.ir_module
class Module:
    @R.function
    def vae(
        data: R.Tensor(("n", 4, 64, 64), "float32"),
        params: R.Tuple(R.Tensor((4, 4, 1, 1), "float32"),
                        R.Tensor((1, 4, 1, 1), "float32"),
                        ...)
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            lv0: R.Tensor((n, 4, 64, 64), "float32") = R.nn.conv2d(
                data, w0, strides=[1, 1]
            )
            b0: R.Tensor((1, 4, 1, 1), "float32") = params[1]
            lv1: R.Tensor((n, 4, 64, 64), "float32") = R.add(lv0, b0)
            ...
```

```python
>>> ex = relax.build(mod, target)
```

Every tensor function (e.g. vae) becomes a native runnable function on the target platform after build.

Runs everywhere

Python

```python
data = tvm.nd.from_dlpack(other_array)
vm = relax.VirtualMachine(ex, tvm.cuda())
out = vm["vae"](data, params)
```

torch.compile integration

```python
vae = torch.compile(
    vae, backend=relax.frontend.relax_dynamo())
out = vae(data, params)
```

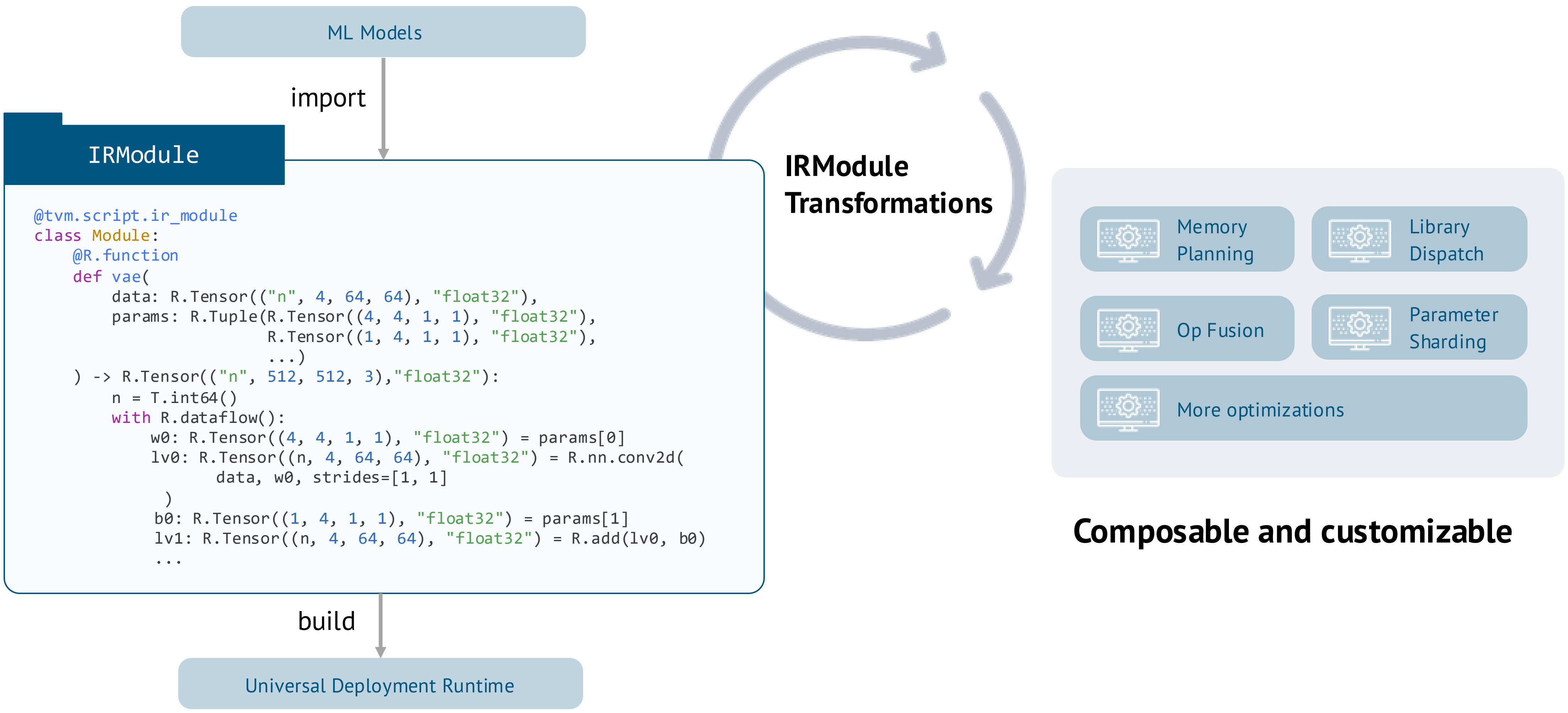
c++

```cpp
runtime::Module vm = ex.GetFunction("load_executable")()
vm.GetFunction("init")(...)
NDArray out = vm.GetFunction("vae")(data, params)
```

Javascript (web)

```javascript
tvm = await tvmjs.instantiate(wasmSource, new EmccWASI())
vm = tvm.createVirtualMachine(tvm.webgpu())
out = vm.getFunction("vae")(data, params)
```

Productive Framework for ML Compilation



Continuous Improvement Process

ML Compilation Out of Box

Model

↓

ML Compilation

↓

Optimized Model

Continuous ML Compilation Evolution Process

- New hardware backends
- New settings
  (e.g. dyn shape, distributed)
- New libraries
- New joint optimizations

This is not a one shot game, but continuous ML compilation evolution process for every new model, backend features, new improvements. We can enable more people to do it, together :)

Elements of TVM Unity

Abstraction Elements of TVM Unity

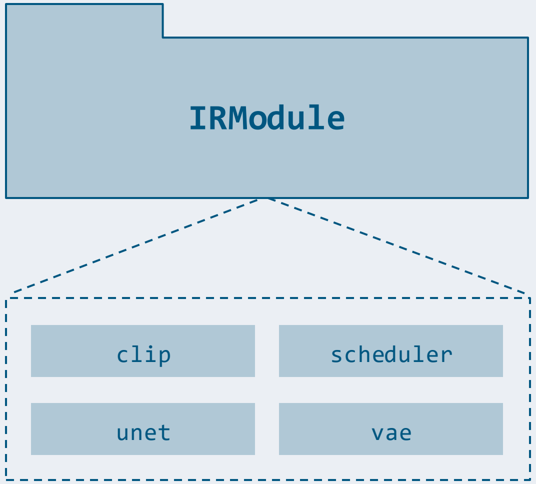
First-class symbolic shape support

Composable Tensor Program Optimization

Unifying Libraries and Compilation

First class Symbolic Shape

Centers around one key construct



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            lv0: R.Tensor((n, 4, 64, 64), "float32") = R.nn.conv2d(
                data, w0, strides=[1, 1]
            )
            b0: R.Tensor((1, 4, 1, 1), "float32") = params[1]
            lv1: R.Tensor((n, 4, 64, 64), "float32") = R.add(lv0, b0)
            ...
```

First-class symbolic shape support to enable dynamic shape compilation.

Symbolic Shape vs Any Shape

Symbolic Shape

```
@R.function
def symbolic_shape_fn(x: R.Tensor(("n", 2, 2), "float32")):
    n, m = T.int64(), T.int64()
    with R.dataflow():
        lv0: R.Tensor((n, 4), "float32")) = R.reshape(x, R.shape(n, 4))
        lv1: R.Tensor((n * 4,), "float32")) = R.flatten(lv0)
        lv2: R.Tensor(ndim=1, dtype="float32") = R.unique(lv1)
        lv3 = R.match_cast(lv2, R.Tensor((m,), "float32"))
        gv0: R.Tensor((m,), "float32") = R.exp(lv3)
        R.output(gv0)
    return gv0
```

- Tracks the shape values (n, n * 4)
- More optimizations
- Flexible fallback for unknown and rematch
- Shape is part of computation

Any Shape Dimension

```
@R.function
def any_shape_fn(x: R.Tensor((?, 2, 2), "float32")):
    n = R.get_shape_value(x, axis=0)
    with R.dataflow():
        lv0: R.Tensor((?, 4), "float32")) = R.reshape(x, R.shape(n, 4))
        lv1: R.Tensor((?,), "float32")) = R.flatten(lv0)
        lv2: R.Tensor(?, "float32") = R.unique(lv1)

        gv0: R.Tensor((?,), "float32") = R.exp(lv3)
        R.output(gv0)
    return gv0
```

- Most approaches so far
- ? denotes any shape value
- No relation information: cannot prove shape equivalence by only looking at any dimensions

Optimizations Enabled by Symbolic Shape

Static memory planning for dynamic shape

Dynamic shape aware operator fusion

Layout rewriting and padding

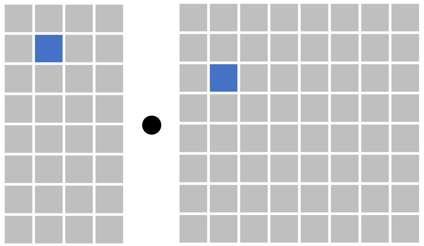
Abstraction Elements of TVM Unity

First-class symbolic shape support

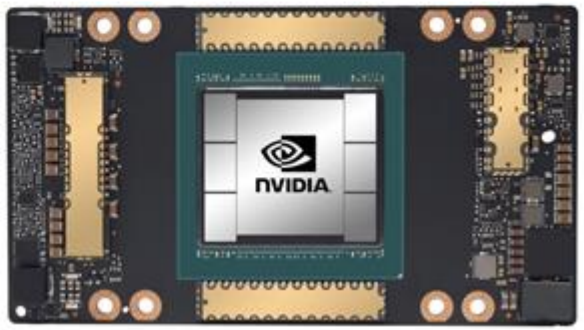
Composable Tensor Program Optimization

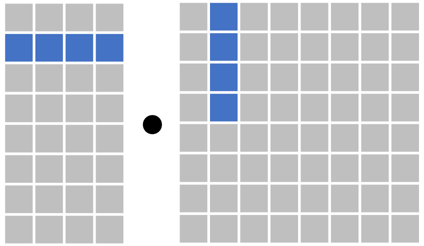
Unifying Libraries and Compilation

Hardware Trend

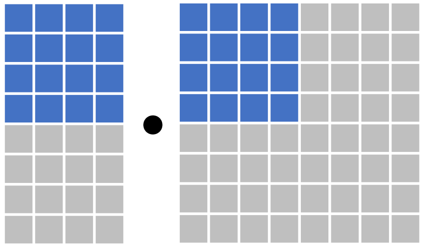


Scalar Computing





Vector Computing



Tensor Computing

- Google TPU
- Nvidia Tensor Core
- AMD Matrix Core
- Intel Matrix Engine
- Apple Neural Engine
- Arm Ethos-N
- T-Head Hanguang
- ……

Elements of a Tensorized Program

```
for ic.outer, kh, ic.inner, kw in grid(...):

  for ax0 in range(...):
    load_matrix_sync(A.wmma.matrix_a, 16, 16, 16, ...)


  for ax0 in range(...):
    load_matrix_sync(W.wmma.matrix_b, 16, 16, 16, ...)


  for n.c, o.c in grid(...):
    wmma_sync(Conv.wmma.accumulator,
              A.wmma.matrix_a,
              W.wmma.matrix_b,
              ...)


for n.inner, o.inner in grid(...):
  store_matrix_sync(Conv.wmma.accumulator, 16, 16, 16)
```

Example Snippet: Conv2D on Tensor Core

Optimized loop nests with thread binding

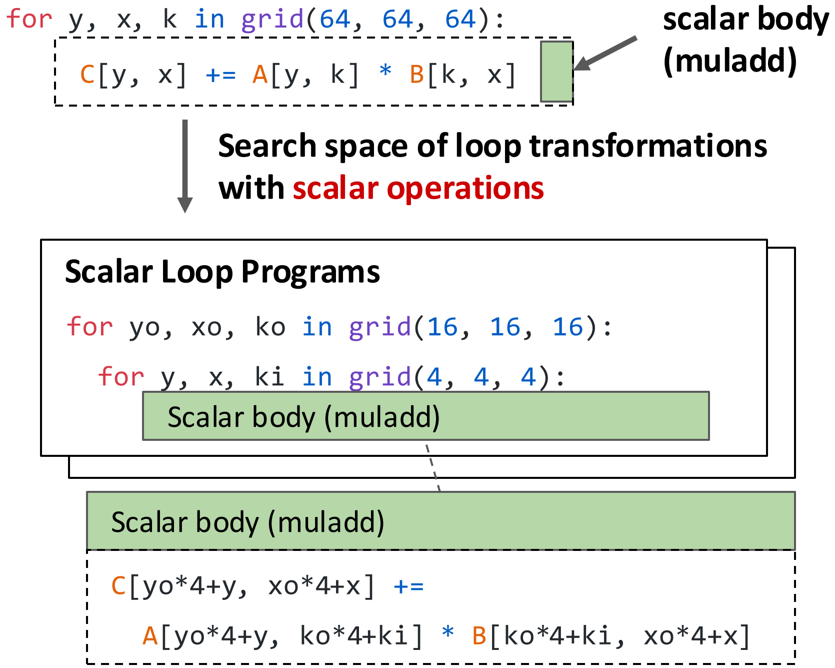
Multi-dimensional data load into specialized hardware storage

Opaque tensorized computation body
16x16 matrix multiplication

Multi-dimensional data store

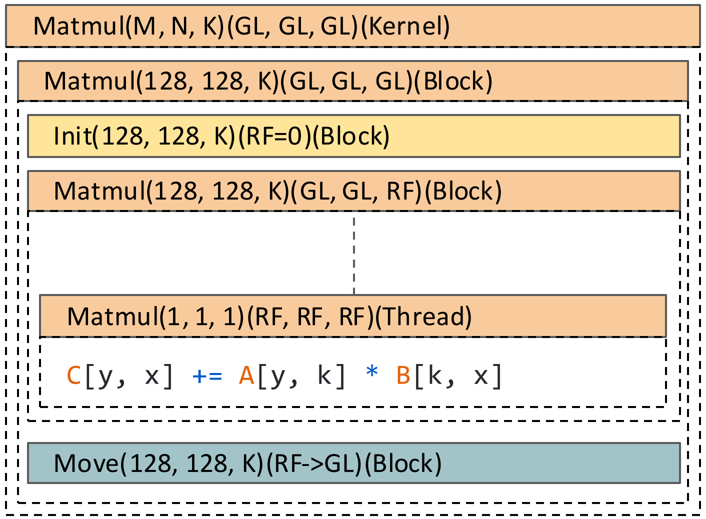
Existing Abstractions

Bottom up: Transform and optimize multi-dimensional loop nests with scalar body (Halide, TVM/TE, Affine)



Harder to represent tensorized computation body

Top Down: Recursive decomposition of tasks into smaller ones (Fireiron, Stripe)



Less obvious for loop nest transformation optimizations

TensorIR Abstraction: Divide and Solve(Conquer)

```
for y, x, k in grid(64, 64, 64):
  C[y, x] += A[y, k] * B[k, x]
```

Introduce a key abstraction called **block** to **divide** and isolate the problem space into outer loop nests and **tensorized** body

```
for yo, xo, ko in grid(16, 16, 16):
  block (by=yo, bx=xo, bk=ko)
    for y, x, k in grid(4, 4, 4):
      C[by*16+y, bx*16+x] +=
        A[by*16+y, bk*16+k] * B[bk*16+k, bx*16+x]
```

Tensorized body (matmul4x4) isolated from the outer loop nests

Key Ideas

- Divide problem into sub-tensor computation blocks
- Generalize loop optimization for tensorized computation
- Combination of the above approaches in any order

Search space of loops transformations with **tensorized operations**

Tensorized Programs

```
for yo, xo, k in grid(4, 4, 16):
  for yi, xi in grid(4, 4):
    block (by, bx, bk=...)
    Tensorized body (matmul4x4)
```

Map tensorized body based on instructions provided by the backend.

Option 0: Tensorized body (matmul4x4)

```
accel.matmul_add4x4(
  C[by*16:by*16+4, bx*16:bx*16+4],
  A[by*16:by*16+4, bk*16:bk*16+4],
  B[bk*16:bk*16+4, bx*16:bx*16+4])
```

Option 1: Tensorized body (matmul4x4)

```
for y, x, k in grid(4, 4, 4):
  C[by*16+y, bx*16+x] +=
    A[by*16+y, bk*16+k] * B[bk*16+k, bx*16+x]
```

Elements of TensorIR: Block

```
for yo, xo, ko in grid(16, 16, 16):
  with block(domain=(16, 16, reduce_axis(16)),
           other_signatures) as vy, vx, vk:

    vy = var_bind(yo)
    vx = var_bind(xo)
    vk = var_bind(ko)


    for yi, xi, ki in grid(4, 4, 4):
      C[vy*4 + yi, vx*4 + xi] +=
        A[vy*4 + yi, vk*4 + ki] * B[vk*4 + ki, vx*4 + xi]
```

outer loop

signature

iterator binding

body

Block Signature

Iterator domain and constraints:

```
vy: data_parallel_axis(length=16)
vx: data_parallel_axis(length=16)
vk: reduce_axis(length=16)
```

Producer consumer dependency relations

```
read A[vy*4:vy*4+4, vk*4:vk*4+4]
read B[vk*4:vk*4+4, vx*4:vx*4+4]
reduce_update C[vy*4:vy*4+4, vx*4:vx*4+4]
```

Isolate the internal computation tensorized computation from external loops

Imperative Schedule Transformation

```
for i, j in  grid(64, 64):
    produceA
    A [i, j] = …
for yo, xo, k in grid(4, 4, 16):
    for yi, xi in grid(4, 4):
        blockB
        vy = var_bind(yo*4 + yi)
        vx = var_bind(xo*4 + xi)
        vk = var_bind(ko)
        body
```

```
s = tvm.tir.Schedule(myfunc)
prodA = s.get_block("produceA")
k = s.get_loop("k")

s.compute_at(prodA, k)
```

blockB signature

Iterator domain and constraints:

```
vy: data_parallel_axis(length=16)
vk: data_parallel_axis(length=16)
vk: reduce_axis(length=16)
```

Producer consumer dependency relations

```
read A[vy*4:vy*4+4, vk*4:vk*4+4]
read B[vk*4:vk*4+4, vx*4:vx*4+4]
reduce_update C[vy*4:vy*4+4, vx*4:vx*4+4]
```

Block signature dependency information used during transformation

Imperative Schedule Transformation

```
for yo, xo, k in grid(4, 4, 16):
    for i, j in  grid(16, 4):
        produceA
        A [yo*16 + i, k*4 + j] = ...
    for yi, xi in grid(4, 4):
        blockB
        vy = var_bind(yo*4 + yi)
        vx = var_bind(xo*4 + xi)
        vk = var_bind(ko)
        body
```

```
s = tvm.tir.Schedule(myfunc)
prodA = s.get_block("produceA")
k = s.get_loop("k")

s.compute_at(prodA, k)
```

- **Interactive**: Schedule as imperative transformations of the IR.
- **Modularize**: Analysis only depend on the block signature
- **Extensible**: No schedule tree, easy to add new schedule primitives

Isolating Tensorized Computations

```
for i, j, ko in grid(64, 64, 16):
    for ki in range(4):
        block (vi = i, vj = j, reduce vk = ko*4 + ki)
        C[vi, vj] += A[vi, vk] * B[vk, vj]
```

```
s = tvm.tir.Schedule(myfunc)
ki = s.get_loop("ki")

s.blockize(ki)
```

Isolating Tensorized Computations

```
for i, j, ko in grid(64, 64, 16):
    block
    for ki in range(4):
        block (vi = i, vj = j, reduce vk = ko*4 + ki)
            C[vi, vj] += A[vi, vk] * B[vk, vj]
```

```
s = tvm.tir.Schedule(myfunc)
ki = s.get_loop("ki")

s.blockize(ki)
```

Tensorization

```
for y, x, k in grid(64, 64, 64):
    C[y, x] += A[y, k] * B[k, x]
```

Step 1. Original workload

```
for yo, xo, ko in grid(16, 16, 16):
  block (by=yo, bx=xo, bk=ko)
  for y, x, k in grid(4, 4, 4):
    C[by*16+y, bx*16+x] +=
      A[by*16+y, bk*16+k] * B[bk*16+k, bx*16+x]
```

Step 2.
Split + Reorder + Blockize
Getting the 4x4x4 matrix multiplication to be tensorized

Step 3. Substitute the inner block with equivalent computation block

Tensorized Programs

```
for yo, xo, ko in grid(16, 16, 16):
  block (by=yo, bx=xo, bk=ko)
  Tensorized body (matmul4x4)
```

Map tensorized body based on instructions provided by the backend.

Option 1: Utilize accelerator tensor instruction	Option 2: Scalar Computing

`accel.matmul_add4x4(`
`  C[by*16:by*16+4, bx*16:bx*16+4],`
`  A[by*16:by*16+4, bk*16:bk*16+4],`
`  B[bk*16:bk*16+4, bx*16:bx*16+4])`
	`for y, x, k in grid(4, 4, 4):`
	`  C[by*16+y, bx*16+x] +=`
	`    A[by*16+y, bk*16+k] *`
	`    B[bk*16+k, bx*16+x]`

Bringing TensorIR into TVM Unity

IRModule

```
import tvm.script
from tvm.script import tir as T, relax as R

@tvm.script.ir_module
class IRModule:
    @T.prim_func
    def mm(
        X: T.Buffer(("n", 128), "float32"),
        W: T.Buffer((128, 64), "float32"),
        Y: T.Buffer(("n", 64), "float32")
    ):
        n = T.int64()
        for i, j, k in T.grid(n, 64, 128):
            Y[i, j] += X[i, k] * W[k, j]

    @R.function
    def main(
        X: R.Tensor(("n", 128), "float32"),
        W: R.Tensor((128, 64), "float32")
    ):
        n = T.int64()
        with R.dataflow():

            lv0 = R.call_tir(mm, (X, W), R.Tensor((n, 64), "float32"))

            gv0 = R.relu(lv0)
            R.output(gv0)
        return gv0
```

TensorIR functions
Loops, thread blocks

Call into TensorIR function via destination passing

Analysis based Program Optimization

IRModule

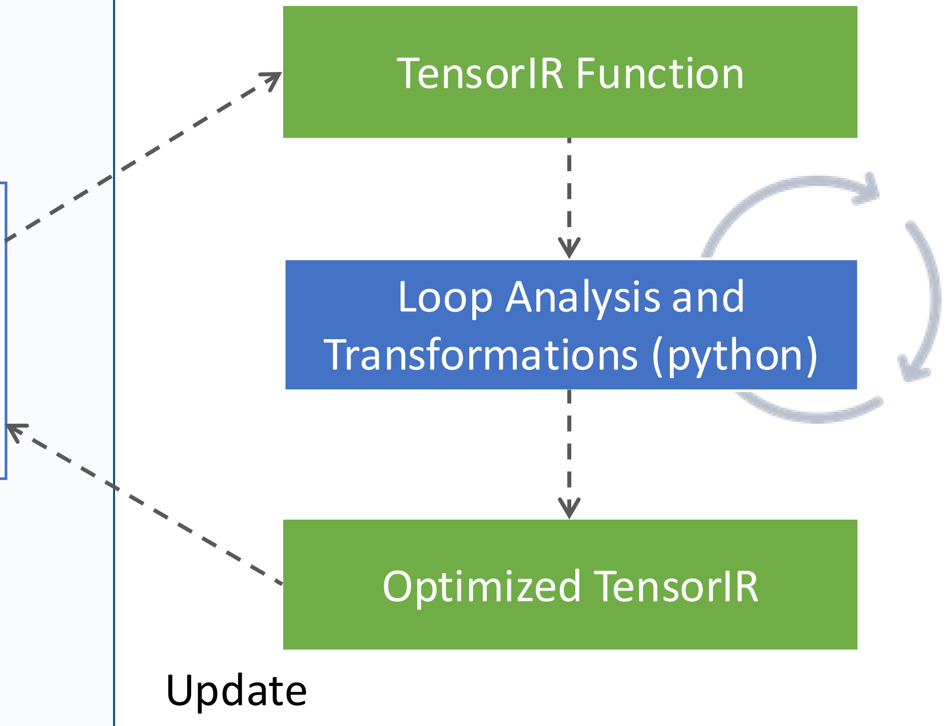
```
import tvm.script
from tvm.script import tir as T, relax as R

@tvm.script.ir_module
class IRModule:
    @T.prim_func
    def mm(
        X: T.Buffer(("n", 128), "float32"),
        W: T.Buffer((128, 64), "float32"),
        Y: T.Buffer(("n", 64), "float32")
    ):
        n = T.int64()
        for i, j, k in T.grid(n, 64, 128):
            Y[i, j] += X[i, k] * W[k, j]


    @R.function
    def main(
        X: R.Tensor(("n", 128), "float32"),
        W: R.Tensor((128, 64), "float32")
    ):
        n = T.int64()
        with R.dataflow():

            lv0 = R.call_tir(mm, (X, W), R.Tensor((n, 64), "float32"))

            gv0 = R.relu(lv0)
            R.output(gv0)
        return gv0
```



Abstraction Elements of TVM Unity

First-class symbolic shape support

Composable Tensor Program Optimization

Unifying Libraries and Compilation

Bringing Compilation and Libraries Together

AI Applications

Computational Graphs

Libraries and Runtimes

Hardware Primitives

Horizontal boundaries between
two kinds of approaches

Sweet spot moves as the field evolves, but it is usually hard to do smooth transitions

AI Applications

Computational Graphs

Tensor Programs

Hardware Primitives

Library Driven

Performance for standard models

Engineering intensive

Leverages domain expertise

Compilation Driven

Performance for all models

Challenging to apply domain expertise

Abstraction to Unify Libraries and Compilation

IRModule

```python
import tvm.script
from tvm.script import tir as T, relax as R

@tvm.script.ir_module
class Module:
    @R.function
    def vae(
        data: R.Tensor(("n", 4, 64, 64), "float32"),
        params: R.Tuple(R.Tensor((4, 4, 1, 1), "float32"),
                        R.Tensor((1, 4, 1, 1), "float32"),
                        ...)
    ) -> R.Tensor(("n", 512, 512, 3),"float32"):
        n = T.int64()
        with R.dataflow():
            w0: R.Tensor((4, 4, 1, 1), "float32") = params[0]

            lv0: R.Tensor((n, 4, 64, 64), "float32") = R.call_dps_packed(
                "cutlass_conv2d", w0, R.Tensor((n, 4, 64), "float32")
            )

            lv1: R.Tensor((n, 4, 64, 64), "float32") = R.add(lv0, b0)
            ...
```

Library Embedded via DLPack

```cpp
void CutlassConv2D(
   DLTensor* input,
   DLTensor*output
) {
   ...
}

TVM_REGISTER_GLOBAL("cutlass_conv2d")
.set_body(CutlassConv2D);
```

Call into runtime library function registered via TVM FFI

Unify Libraries and Compilation

The fused conv_add operator is defined with Relax-BYOC offloading to TensorRT, a library with optimized kernels for Nvidia GPUs.

```
@tvm.script.ir_module
class MyMod:
    @R.function
    def conv_add(x: R.Tensor(("n", 4, 64, 64)),
                 w: R.Tensor((4, 4, 1, 1)),
                 b0: R.Tensor((1, 4, 1, 1))):
        R.func_attrs({"codegen": "tensorrt"})
        gv0 = op.conv2d(x, w, padding=(1,1))
        gv1 = op.add(gv0, b0)
        return gv1

    @R.function
    def vae(data: R.Tensor(("n", 4, 64, 64), "float32"),
            params: R.Tuple(...)
    ) -> R.Tensor(("n", 512, 512, 3), "float32"):
        n = T.int64()
        with R.dataflow():
            lv1: R.Tensor((n, 4, 64, 64), "float32") =
                conv_add(data, params[0], params[1])
```

Offloading Pass →

Relax-BYOC replaces all instances of conv_add with direct calls to TensorRT, while retaining the overall structure of the module.

```
@tvm.script.ir_module
class MyMod:
    @R.function
    def vae(data: R.Tensor(("n", 4, 64, 64), "float32"),
            params: R.Tuple(...)
    ) -> R.Tensor(("n", 512, 512, 3), "float32"):
        n = T.int64()
        with R.dataflow():
            lv1: R.Tensor((n, 4, 64, 64), "float32") =
                call_dps_packed("conv_relu_tensorrt",
                                data, params[0],
                                params[1], R.Tensor(
                                (n, 4, 64, 64), "float32"))
```

Unify Libraires and Compilation

Bringing **library-based offloading** and **native compilation** together

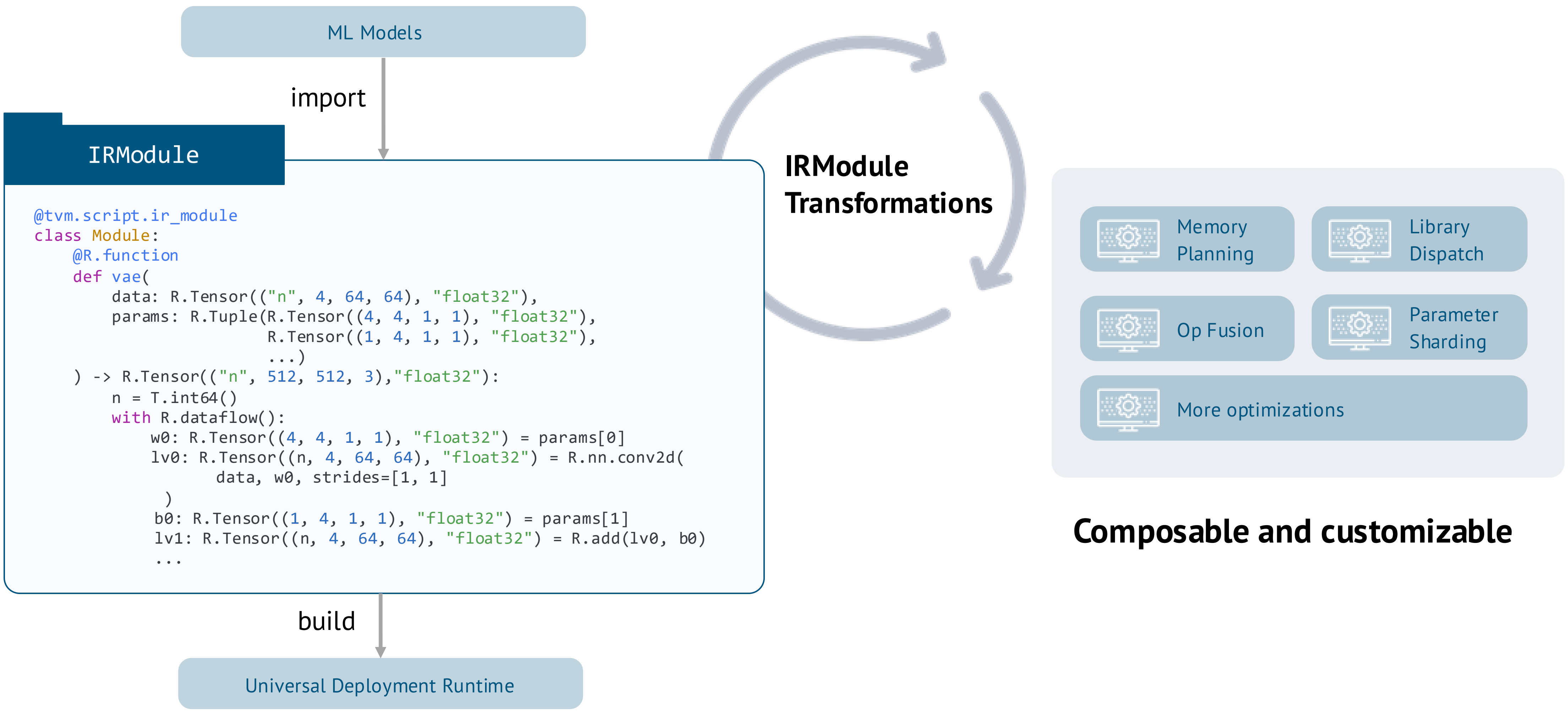
```
import tvm.script
from tvm.script import tir as T, relax as R

@tvm.script.ir_module
class MyMod:
    @R.function
    def vae(data: R.Tensor(("n", 4, 64, 64), "float32"),
            params: R.Tuple(...)
    ) -> R.Tensor(("n", 512, 512, 3), "float32"):
        n = T.int64()
        with R.dataflow():
            lv1: R.Tensor((n, 4, 64, 64), "float32") =
                call_dps_packed("conv_relu_cutlass",,
                                data, params[0], params[1],
                                R.Tensor((n, 4, 64, 64), "float32"))
            w1: R.Tensor((512, 4, 3, 3), "float32") = params[2]
            lv2: R.Tensor((n, 512, 64, 64), "float32") = R.nn.conv2d(
                     lv1, w1, strides=[1, 1]
                 )
```

Library Offloading

Native Compilation

ML Compilation in Action

Productive Framework for ML Compilation



Enabling Incremental Developments

New model or backend

```
mod = frontend.from_fx(model)
mod = relax.get_pipeline()(mod)
```

- **Part of the model accelerated**
- **Find room for improvements**

Composable customizations

Mix your own library and compilation

```
mod = DispatchToLibary("attention")(mod)
mod = DefaultTIRLegalization(mod)
```

Try out new fusion patterns

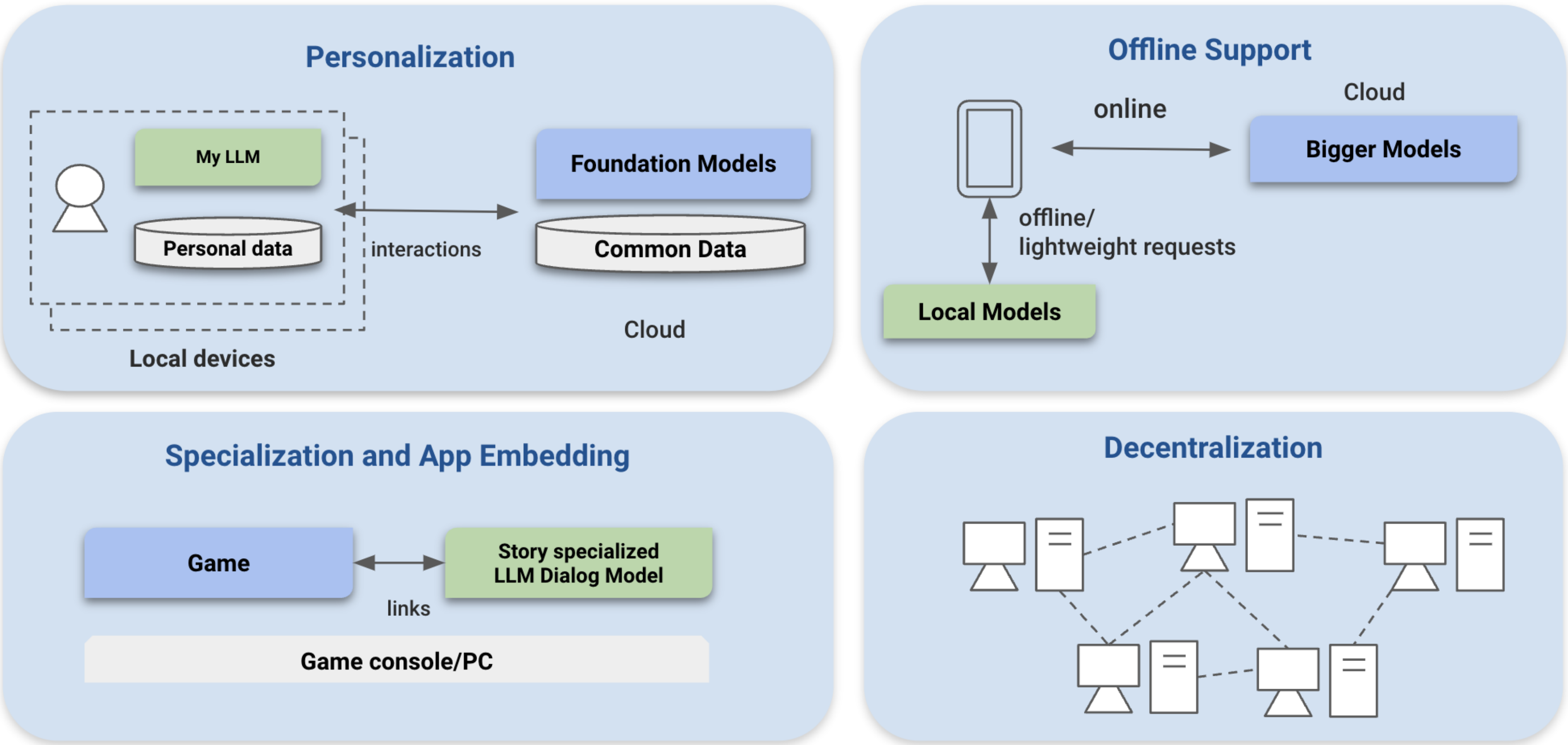
```
mod = CustomizeFusion()(mod)
mod = transform.Sequential([
    transform.FuseOps(),
    transform.FuseTIR()
])(mod)
```

Milestones and Feedbacks

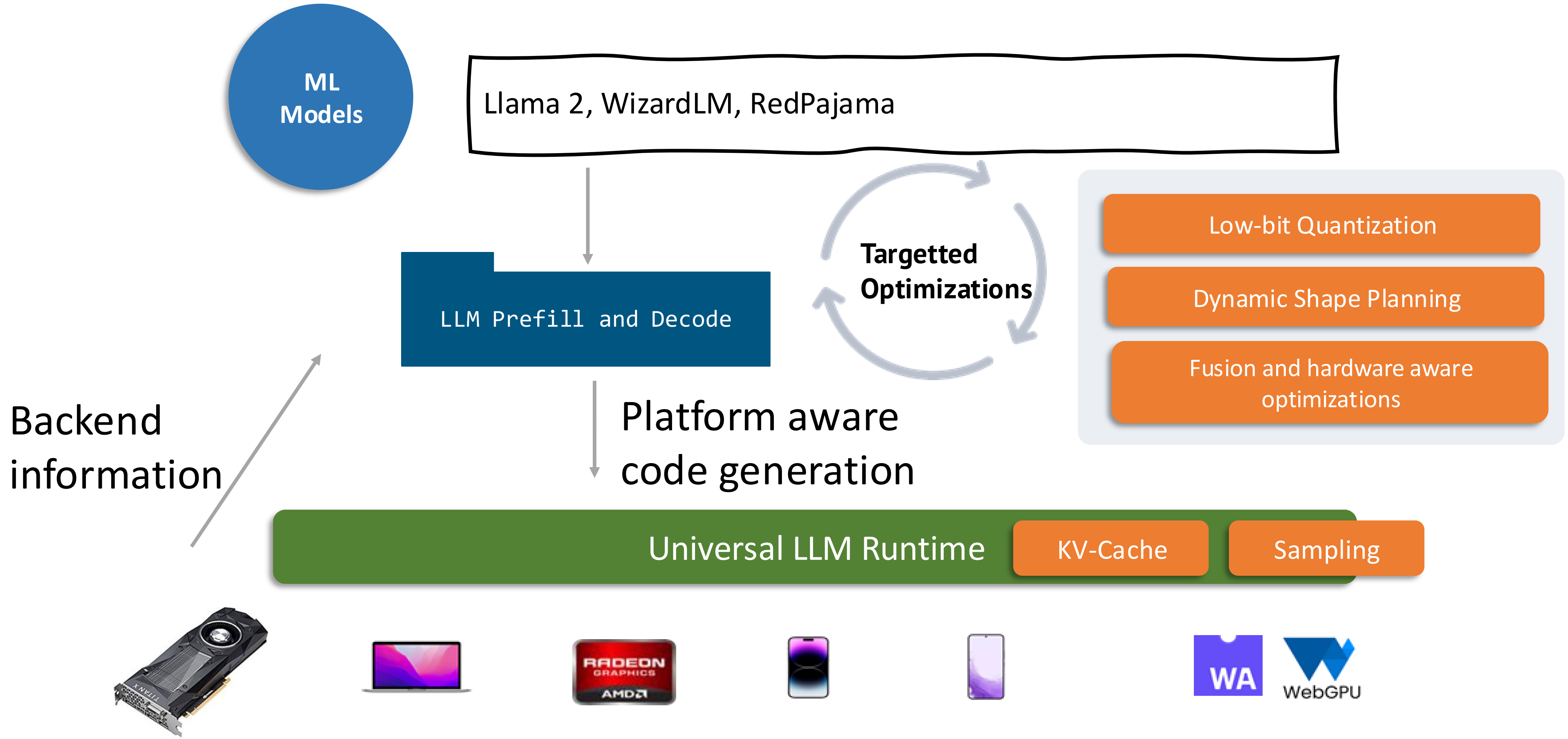
- **Feedback to out of box pipelines**
- **Full model accelerated and offloaded to target env**
- **Deploy ML compilation improvements to prod.**

This is not a one shot game, but continuous process for every new model, backend features, new improvements in machine learning compilation.

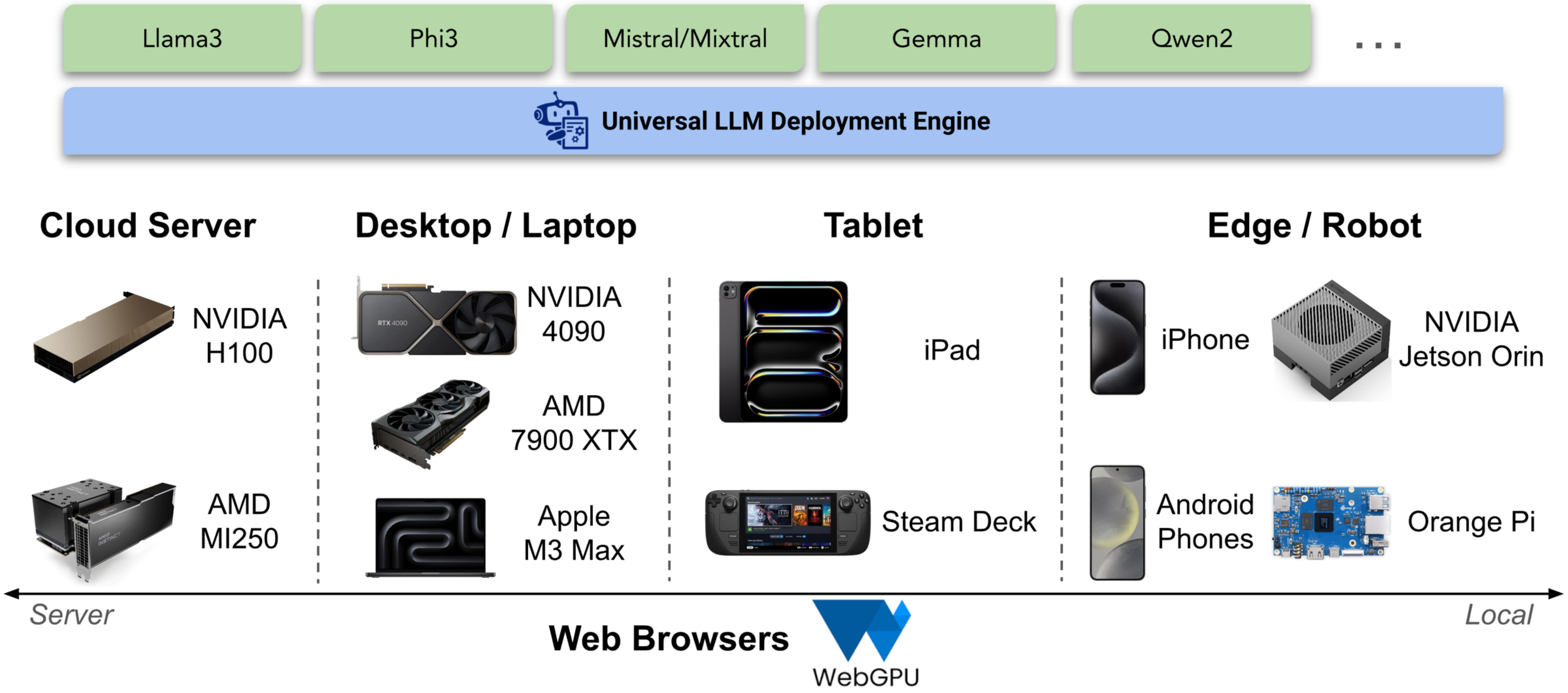
Bringing foundational models to consumer devices



ML Compilation can help



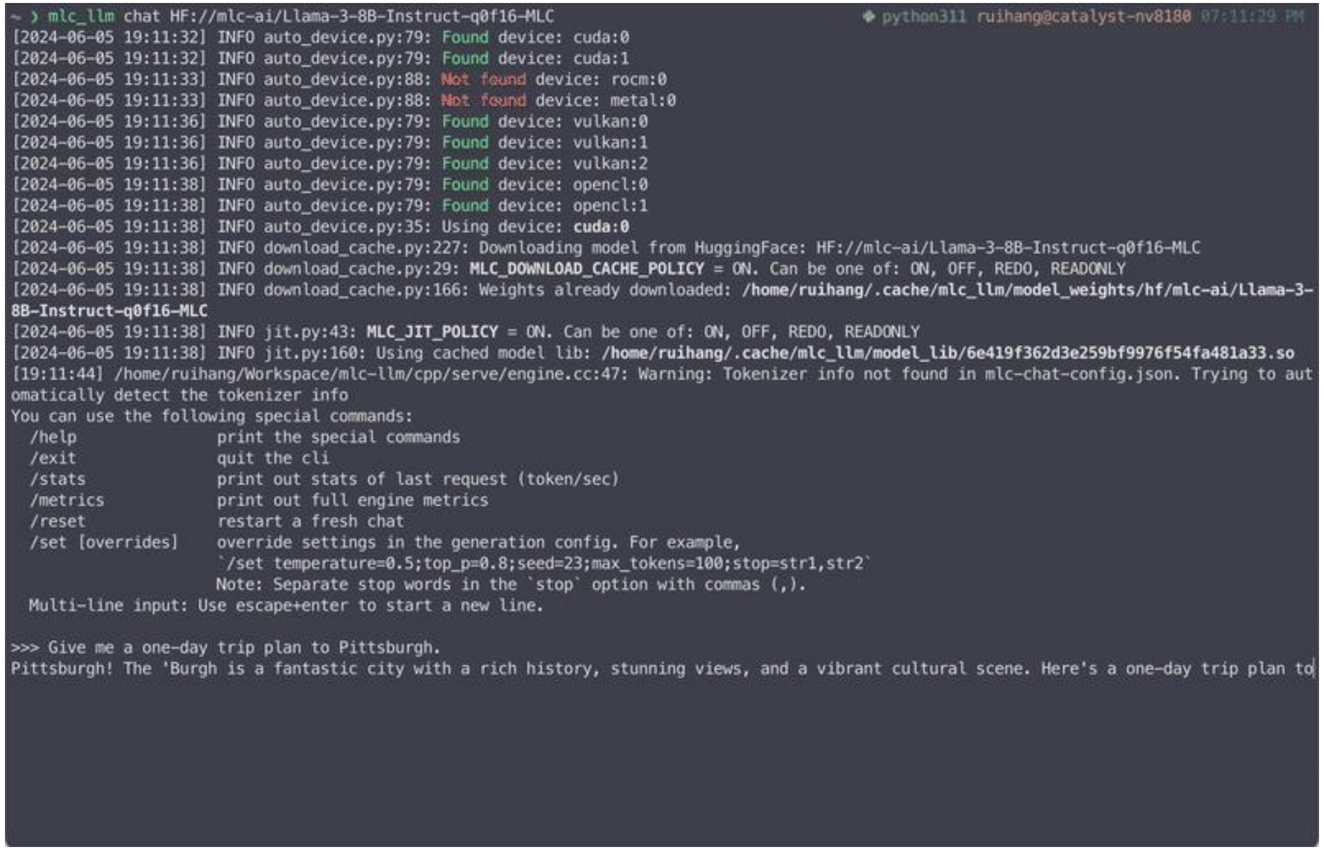
MLCEngine: Universal LLM Deployment



MLCEngine: Windows Linux Mac

```
>> mlc_llm chat HF://mlc-ai/Llama-3-8B-Instruct-q4f16_1-MLC
```

Running across platforms

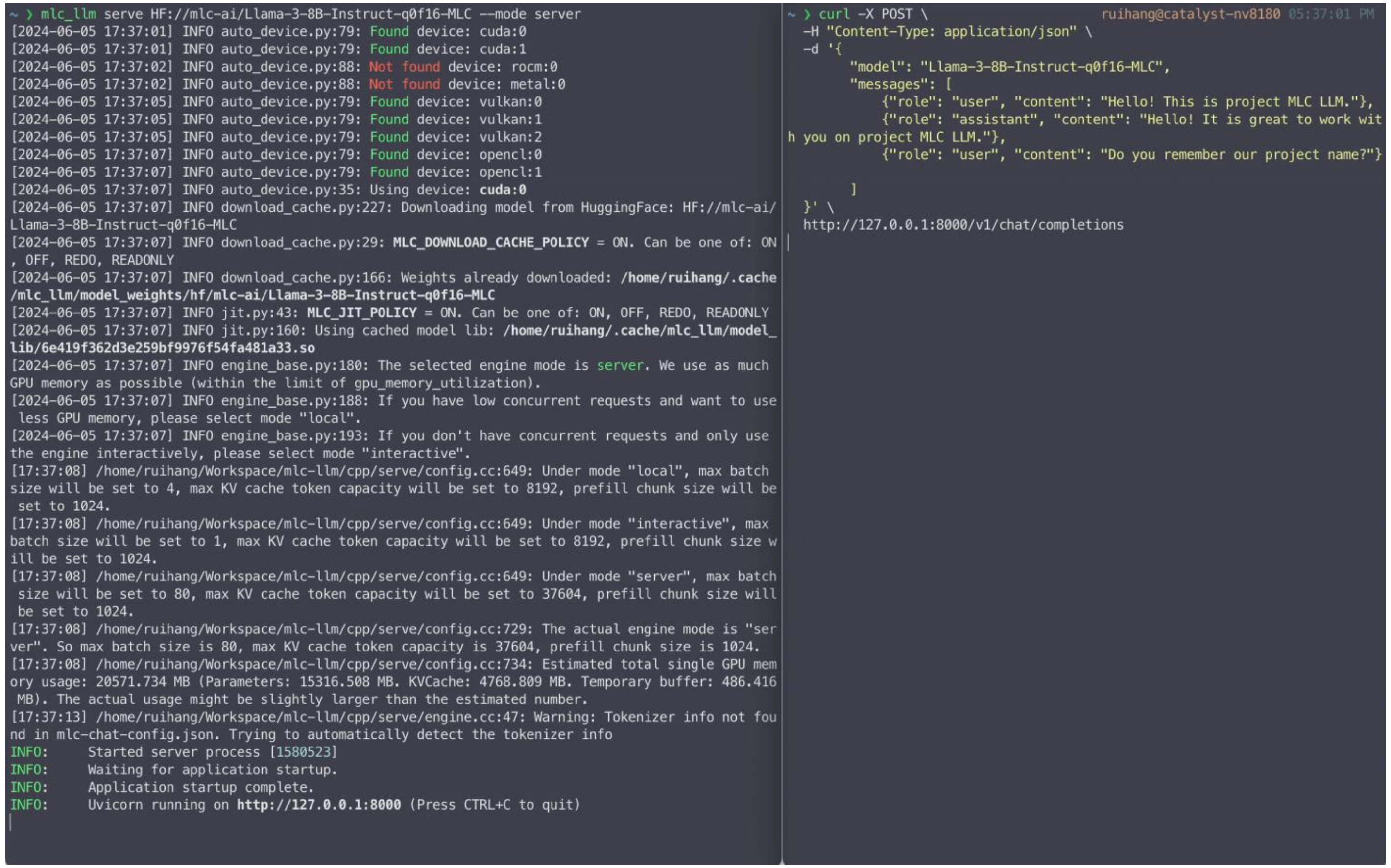


```
~ ❯ mlc_llm chat HF://mlc-ai/Llama-3-8B-Instruct-q0f16-MLC          python311 ruihang@catalyst-nv8180 07:11:29 PM
[2024-06-05 19:11:32] INFO auto_device.py:79: Found device: cuda:0
[2024-06-05 19:11:32] INFO auto_device.py:79: Found device: cuda:1
[2024-06-05 19:11:33] INFO auto_device.py:88: Not found device: rocm:0
[2024-06-05 19:11:33] INFO auto_device.py:88: Not found device: metal:0
[2024-06-05 19:11:36] INFO auto_device.py:79: Found device: vulkan:0
[2024-06-05 19:11:36] INFO auto_device.py:79: Found device: vulkan:1
[2024-06-05 19:11:36] INFO auto_device.py:79: Found device: vulkan:2
[2024-06-05 19:11:38] INFO auto_device.py:79: Found device: opencl:0
[2024-06-05 19:11:38] INFO auto_device.py:79: Found device: opencl:1
[2024-06-05 19:11:38] INFO auto_device.py:35: Using device: cuda:0
[2024-06-05 19:11:38] INFO download_cache.py:227: Downloading model from HuggingFace: HF://mlc-ai/Llama-3-8B-Instruct-q0f16-MLC
[2024-06-05 19:11:38] INFO download_cache.py:29: MLC_DOWNLOAD_CACHE_POLICY = ON. Can be one of: ON, OFF, REDO, READONLY
[2024-06-05 19:11:38] INFO download_cache.py:166: Weights already downloaded: /home/ruihang/.cache/mlc_llm/model_weights/hf/mlc-ai/Llama-3-
8B-Instruct-q0f16-MLC
[2024-06-05 19:11:38] INFO jit.py:43: MLC_JIT_POLICY = ON. Can be one of: ON, OFF, REDO, READONLY
[2024-06-05 19:11:38] INFO jit.py:160: Using cached model lib: /home/ruihang/.cache/mlc_llm/model_lib/6e419f362d3e259bf9976f54fa481a33.so
[19:11:44] /home/ruihang/Workspace/mlc-llm/cpp/serve/engine.cc:47: Warning: Tokenizer info not found in mlc-chat-config.json. Trying to aut
omatically detect the tokenizer info
You can use the following special commands:
  /help               print the special commands
  /exit               quit the cli
  /stats              print out stats of last request (token/sec)
  /metrics            print out full engine metrics
  /reset              restart a fresh chat
  /set [overrides]    override settings in the generation config. For example,
                      `/set temperature=0.5;top_p=0.8;seed=23;max_tokens=100;stop=str1,str2`
                      Note: Separate stop words in the `stop` option with commas (,).
  Multi-line input: Use escape+enter to start a new line.

>>> Give me a one-day trip plan to Pittsburgh.
Pittsburgh! The 'Burgh is a fantastic city with a rich history, stunning views, and a vibrant cultural scene. Here's a one-day trip plan to
```

MLCEngine: OpenAI-Compatible Server

```
>> mlc_llm serve HF://mlc-ai/Llama-3-8B-Instruct-q4f16_1-MLC
```

Full OpenAI support



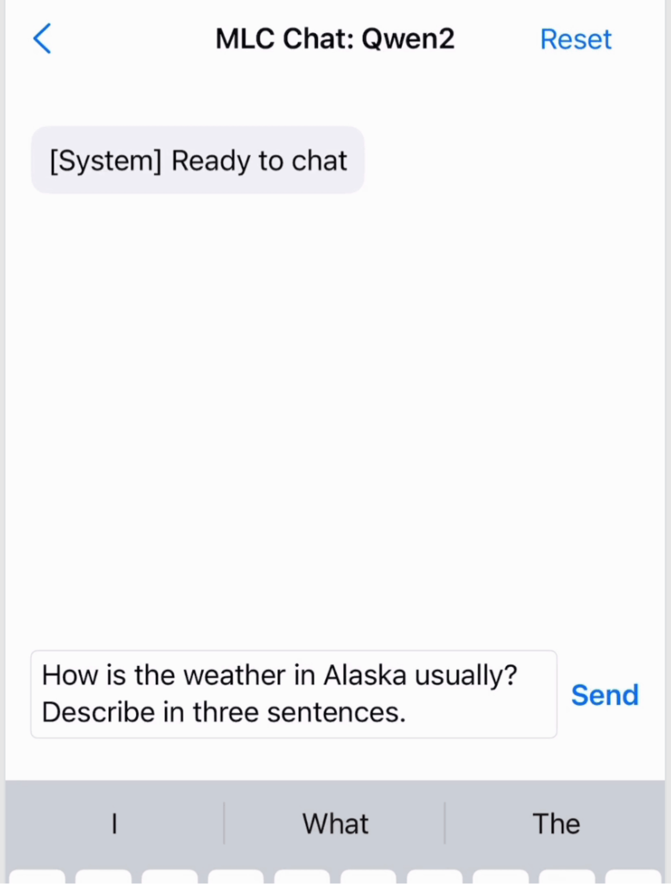
iOS SDK

OpenAI-style swift API

Demo on AppStore

Search for MLC Chat

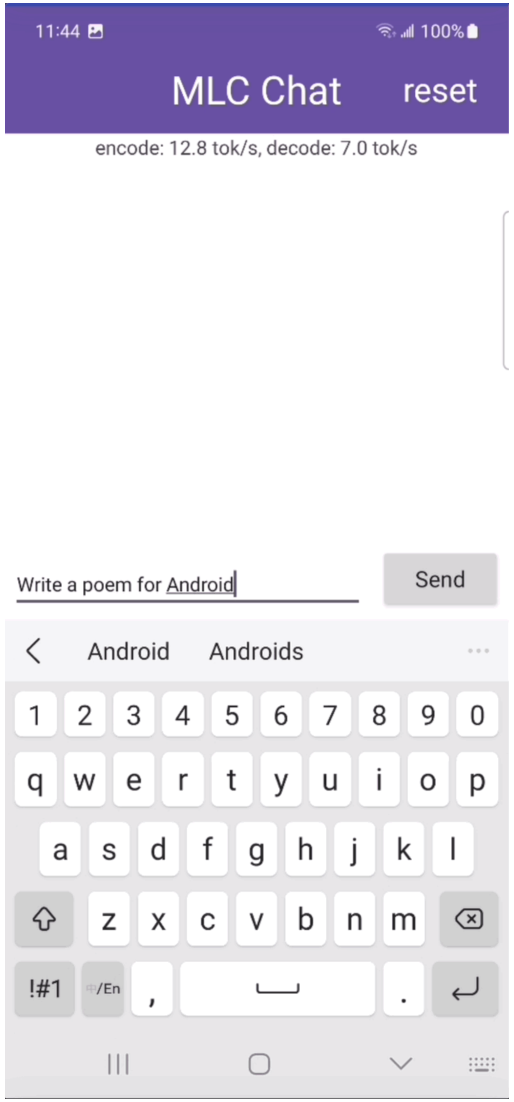
```swift
func requestGenerate(prompt: String) {
    appendMessage(role: .user, message: prompt)
    appendMessage(role: .assistant, message: "")

    Task {
        self.historyMessages.append(
            ChatCompletionMessage(role: .user, content: prompt)
        )

        var finishReasonLength = false
        for await res in await engine.chat.completions.create(
            messages: self.historyMessages,
            stream_options: StreamOptions(include_usage: true)
        ) {
            for choice in res.choices {
                if let content = choice.delta.content {
                    self.streamingText += content.asText()
                }
                if let finish_reason = choice.finish_reason {
                    if finish_reason == "length" {
                        finishReasonLength = true
                    }
                }
            }
        }
    }
}
```



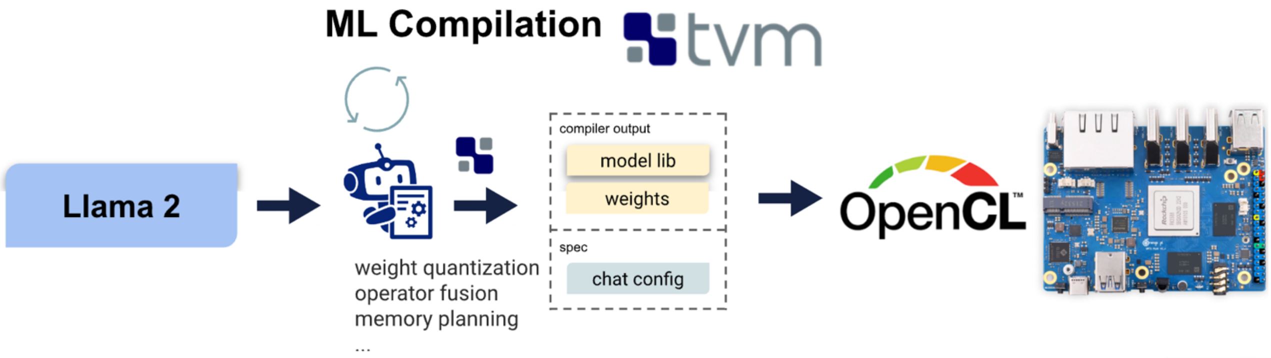
MLC LLM: Android

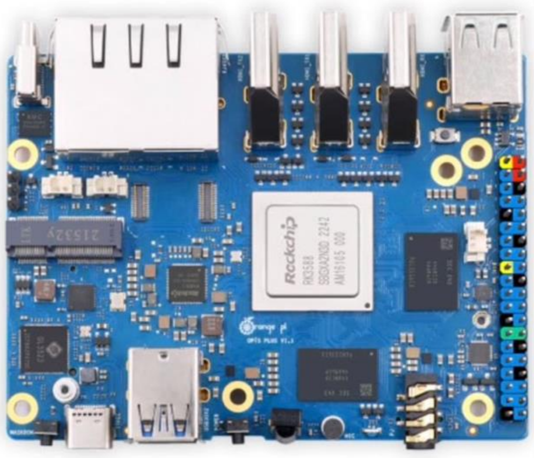
Snapdragon Gen2

Enables larger models than iPhone



Bringing LLMs to 100$ Orange Pi



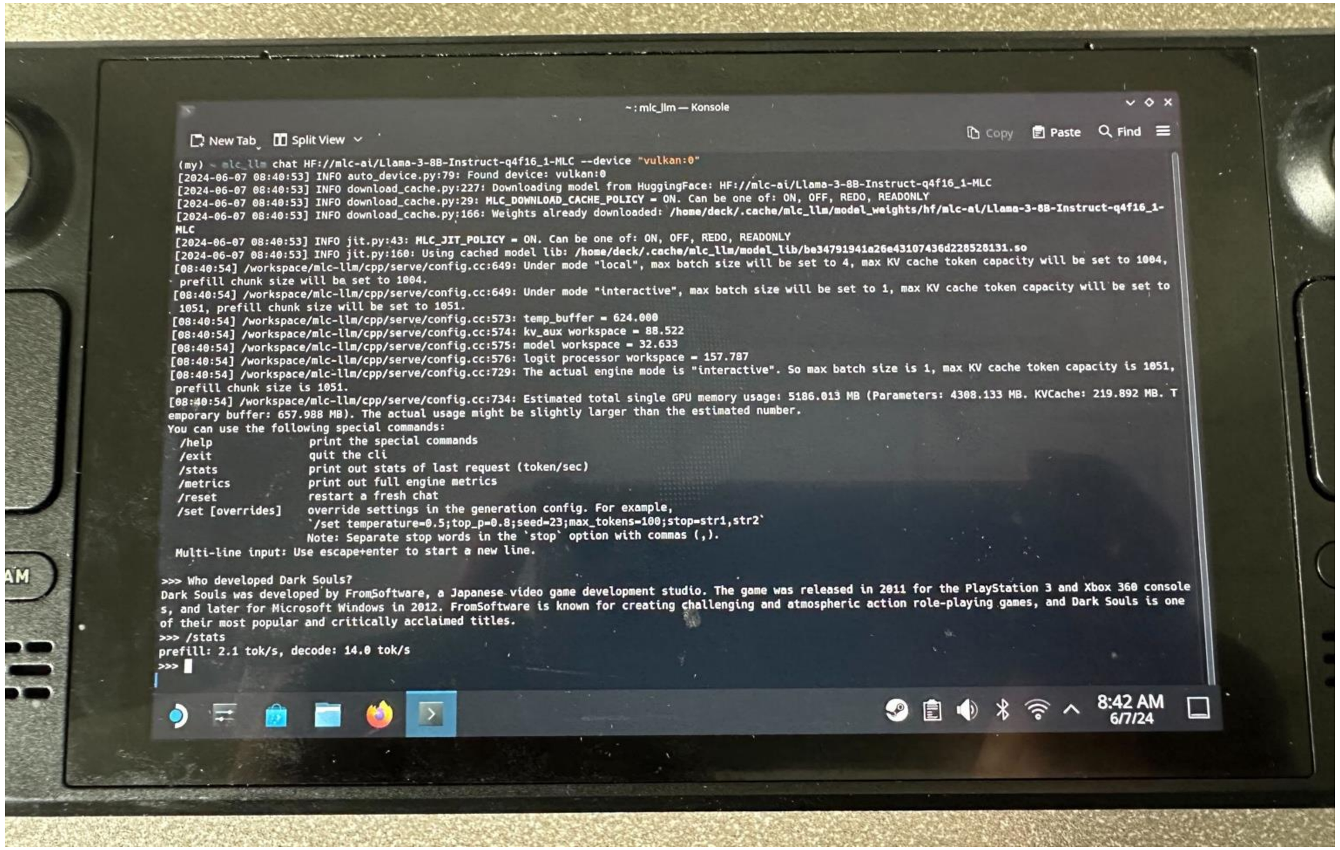


```
chris@chris-rk3588: ~/Documents/mlc_chat_cli

(GPT) chris@chris-rk3588:~/Documents/mlc_chat_cli$ mlc_chat_cli --local-id mlc-chat-Llama-2-7b-chat-hf-q4f16_1
Use MLC config: "/home/chris/Documents/mlc_chat_cli/dist/prebuilt/mlc-chat-Llama-2-7b-chat-hf-q4f16_1/mlc-chat-config.json"
Use model weights: "/home/chris/Documents/mlc_chat_cli/dist/prebuilt/mlc-chat-Llama-2-7b-chat-hf-q4f16_1/ndarray-cache.json"
Use model library: "/home/chris/Documents/mlc_chat_cli/dist/prebuilt/lib/Llama-2-7b-chat-hf-q4f16_1-opencl.so"
You can use the following special commands:
  /help               print the special commands
  /exit               quit the cli
  /stats              print out the latest stats (token/sec)
  /reset              restart a fresh chat
  /reload [local_id]  reload model `local_id` from disk, or reload the current model if `local_id` is not specified

Loading model...
arm_release_ver: g13p0-01eac0, rk_so_ver: 3
arm_release_ver of this libmali is 'g6p0-01eac0', rk_so_ver is '7'.
Loading finished
Running system prompts...
System prompts finished
[INST]: write a three line poem about llama
[/INST]: Of course, I'd be happy to help! Here's a three-line poem about llamas:
Fluffy and gentle, with eyes so bright,
Llamas roam the Andes, with grace in sight,
Their woolly coats shine, in the sun's warm light.
[INST]: /stats
prefill: 4.9 tok/s, decode: 2.6 tok/s
[INST]:
```

LLM on SteamDeck

Leverages vulkan backend

Out of box support



Efficient Structured Generation

Built-in support

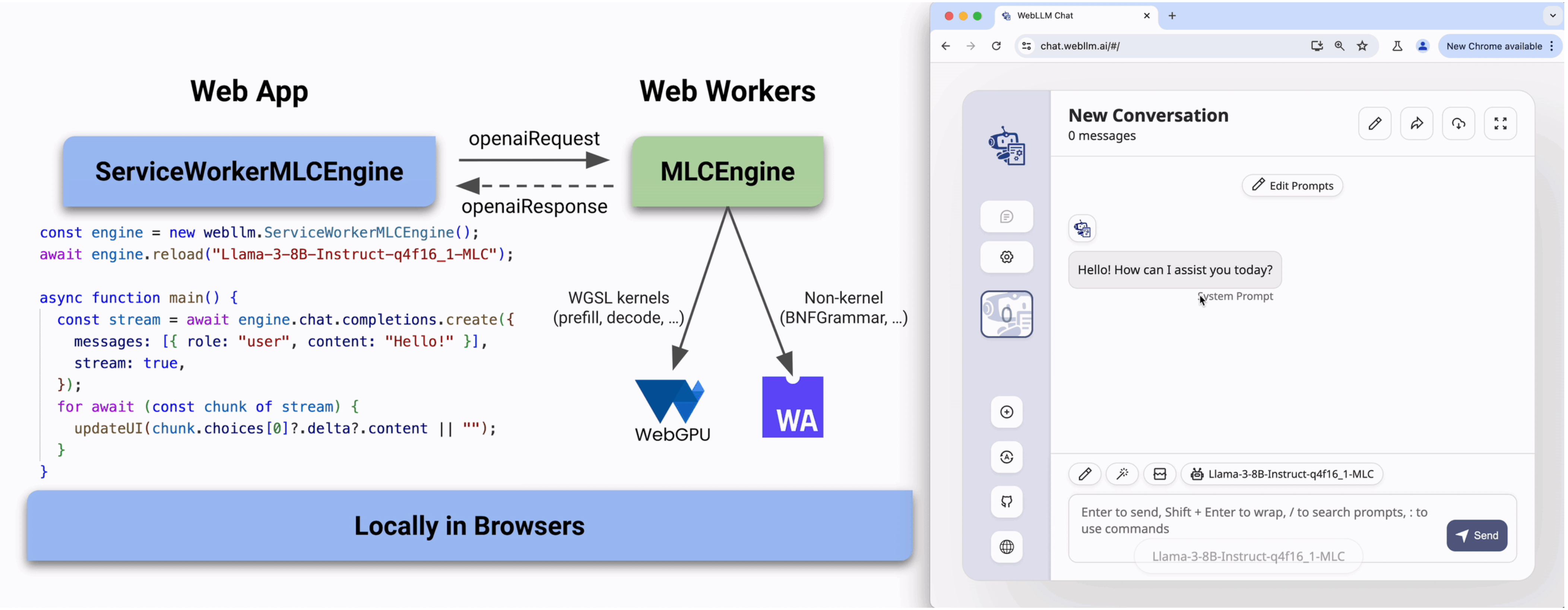
Near zero overhead

Important for agent use cases

```
In [6]: class Country(pydantic.BaseModel):
   ...:     name: str
   ...:     capital: str
   ...:

In [7]: class Countries(pydantic.BaseModel):
   ...:     country: List[Country]
   ...:

In [8]: prompt = "Randomly list three countries and their capitals in JSON."

In [9]: schema = json.dumps(Countries.model_json_schema())

In [10]: response = engine.chat.completions.create(
    ...:     messages=[{"role": "user", "content": prompt}],
    ...:     response_format={"type": "json_object", "schema": schema},
    ...: )

In [11]: print(response.choices[0].message.content)
{"country": [{"name": "Japan", "capital": "Tokyo"}, {"name": "Brazil", "capital": "Brasilia"},
 {"name": "India", "capital": "New Delhi"}]}

In [12]:
```

Try it out via WebLLM: https://huggingface.co/spaces/mlc-ai/WebLLM-JSON-Playground

WebLLM



Runs directly in browser client https://webllm.mlc.ai/

Open Source Project

MLC LLM is an open source community under active development

We welcome collaborations and contributions

MACHINE LEARNING COMPILATION llm.mlc.ai