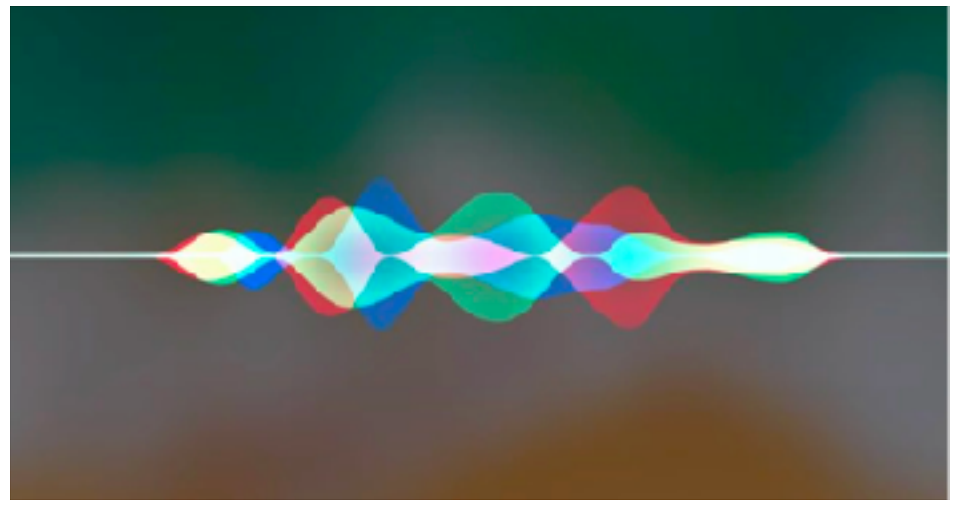
TVM: Learning-based Learning Systems

Tianqi Chen

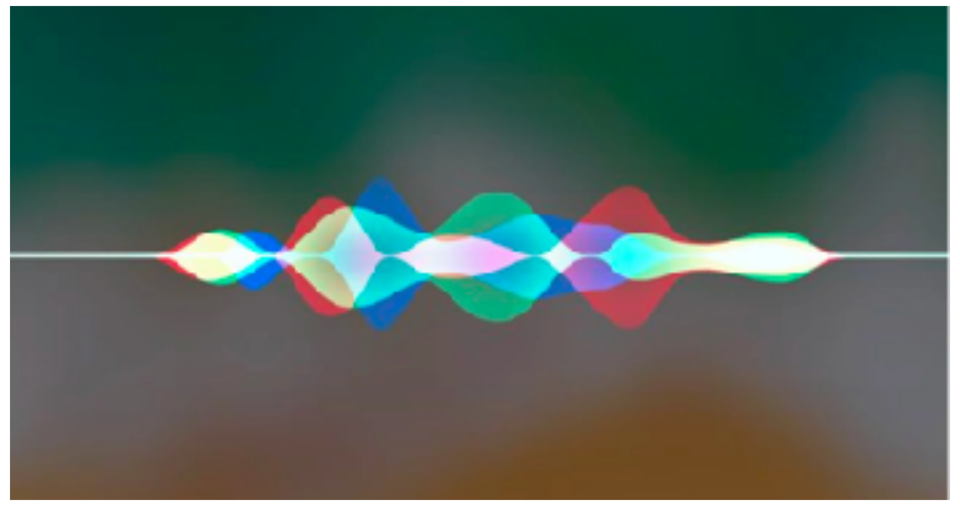
Paul G. Allen School of Computer Science & Engineering
University of Washington

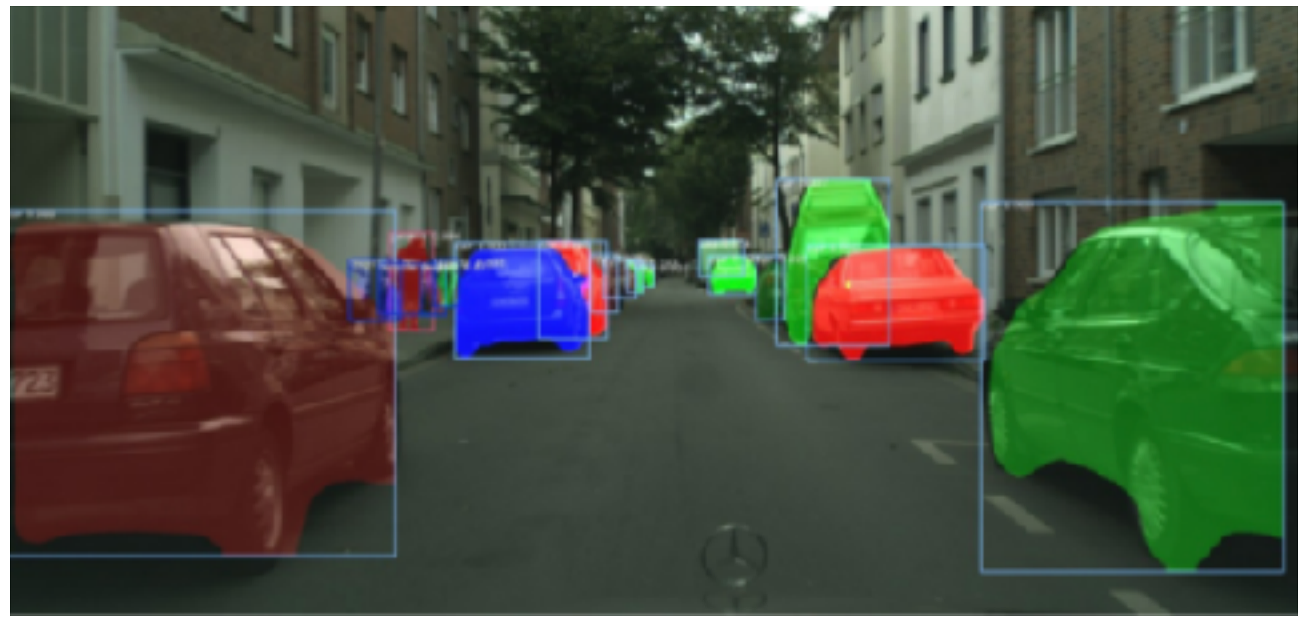
Machine Learning is Everywhere

Machine Learning is Everywhere

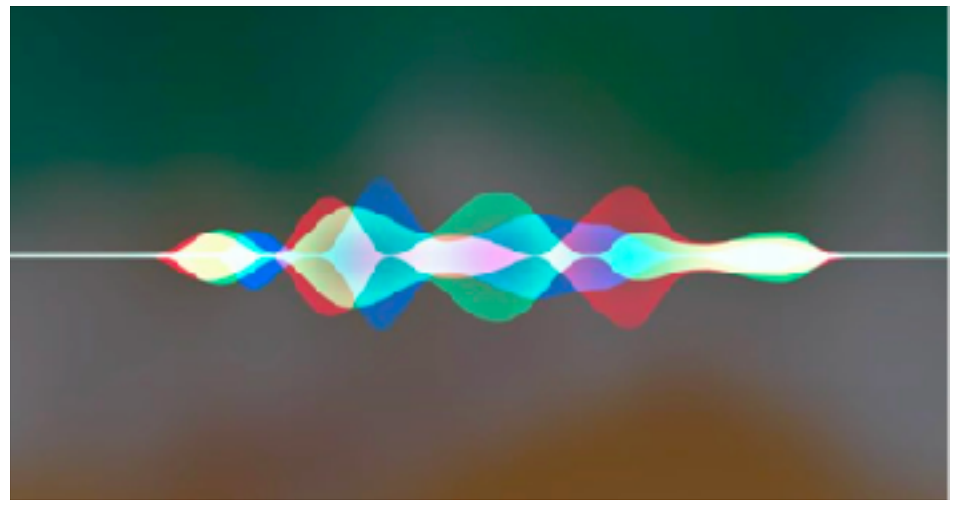


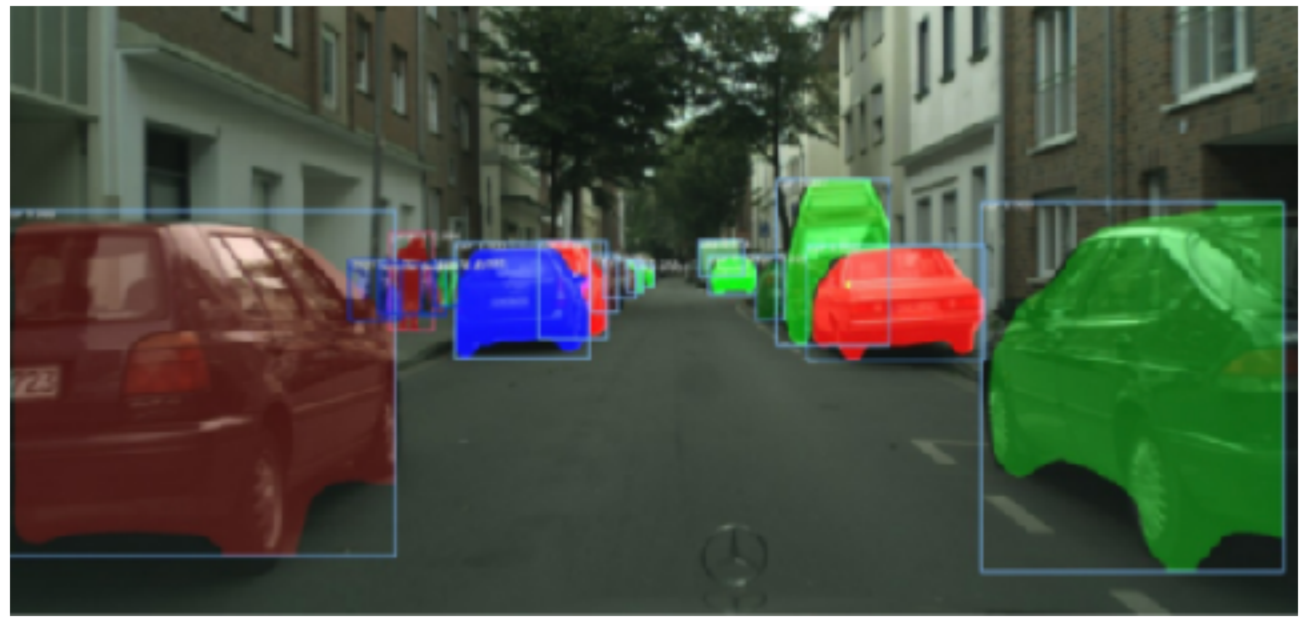
Machine Learning is Everywhere

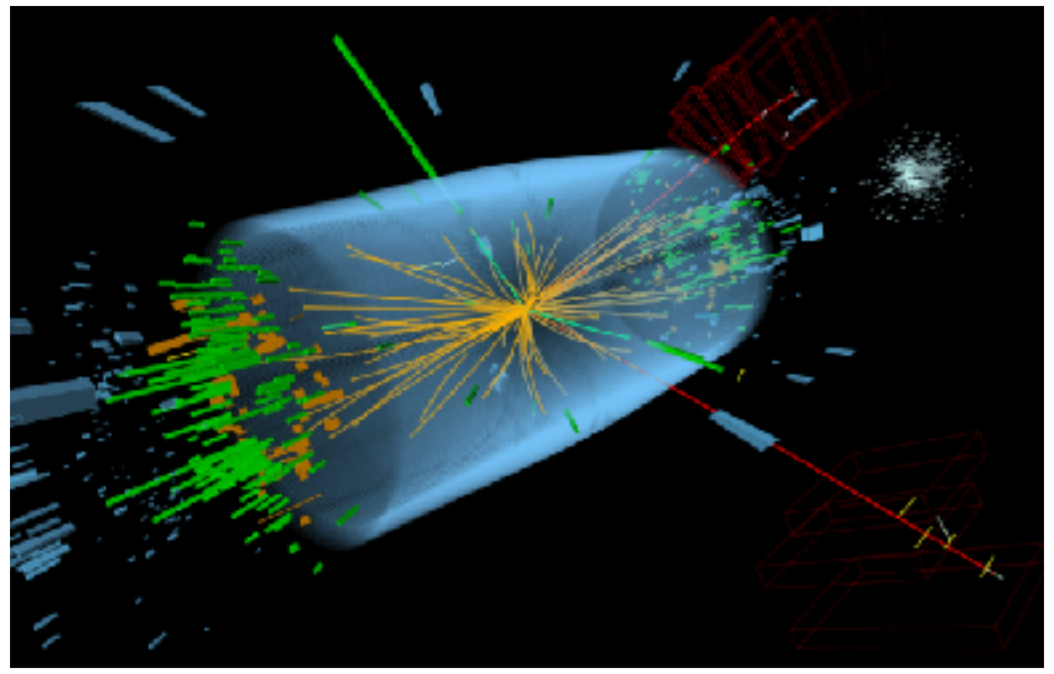




Machine Learning is Everywhere







Higgs challenge

Abbreviated History of Machine Learning

Based on personal view

Abbreviated History of Machine Learning

1960

Based on personal view

Abbreviated History of Machine Learning

Research

1960

Based on personal view

Abbreviated History of Machine Learning

SVM
ConvNet

LSTM
GBM

Research

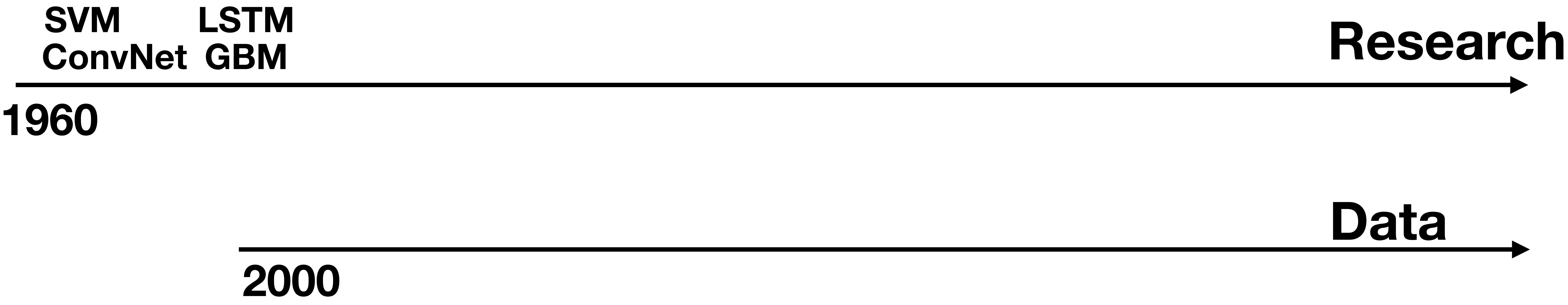
1960

Based on personal view

Abbreviated History of Machine Learning

Based on personal view

Abbreviated History of Machine Learning



Based on personal view

Abbreviated History of Machine Learning

SVM LSTM

ConvNet GBM

Research

1960

flickr

Google

WIKIPEDIA
The Free Encyclopedia

Data

2000 MTurk

Based on personal view

Abbreviated History of Machine Learning

SVM LSTM
ConvNet GBM

Research

1960

Data

2000

MTurk

Based on personal view

Abbreviated History of Machine Learning

SVM **LSTM**

ConvNet **GBM**

Research

1960

flickr

Google

WIKIPEDIA
The Free Encyclopedia

kaggle

Data

2000 **MTurk**

IMAGENET

Based on personal view

Abbreviated History of Machine Learning

SVM LSTM
ConvNet GBM

Research

1960

flickr
Google
Wikipedia
The Free Encyclopedia

kaggle

Data

2000 MTurk IMAGENET

2006

Based on personal view

Abbreviated History of Machine Learning

SVM **LSTM**
ConvNet **GBM**

Research

1960

flickr
Google
Wikipedia
The Free Encyclopedia

kaggle



Data

2000 **MTurk** IMAGENET

Hardware

2006

Based on personal view

Abbreviated History of Machine Learning

SVM **LSTM**
ConvNet **GBM**

Research

1960

flickr Google WIKIPEDIA The Free Encyclopedia

kaggle

Data

2000 **MTurk** IMAGENET

Public Cloud

Hardware

2006

Based on personal view

Abbreviated History of Machine Learning

SVM LSTM
ConvNet GBM

Research

1960

flickr
Google
Wikipedia
The Free Encyclopedia

kaggle

Data

2000

MTurk

IMAGENET

Public
Cloud

NVIDIA
CUDA

Hardware

2006

Based on personal view

Abbreviated History of Machine Learning

SVM **LSTM**
ConvNet **GBM**

Research

1960

flickr
Google
Wikipedia
The Free Encyclopedia

kaggle

Data

2000

MTurk

IMAGENET

Public Cloud

NVIDIA CUDA

Hardware

2006

Based on personal view

Abbreviated History of Machine Learning

SVM LSTM

ConvNet GBM

Research

1960

flickr

Google

Wikipedia
The Free Encyclopedia

kaggle

Data

2000

MTurk

IMAGENET

Public
Cloud

NVIDIA
CUDA

Hardware

2006

2010

Based on personal view

Abbreviated History of Machine Learning

SVM **LSTM**
ConvNet **GBM**

Research

1960

flickr
Google
Wikipedia
The Free Encyclopedia

kaggle

Data

2000 **MTurk** IMAGENET

Public Cloud

NVIDIA CUDA

Hardware

2006

ML Systems

2010

Based on personal view

Abbreviated History of Machine Learning

SVM **LSTM**
ConvNet **GBM**

Research

1960

flickr
Google
WIKIPEDIA
The Free Encyclopedia

kaggle

Data

2000

MTurk

IMAGENET

Public Cloud

NVIDIA CUDA

Hardware

2006

ML Systems

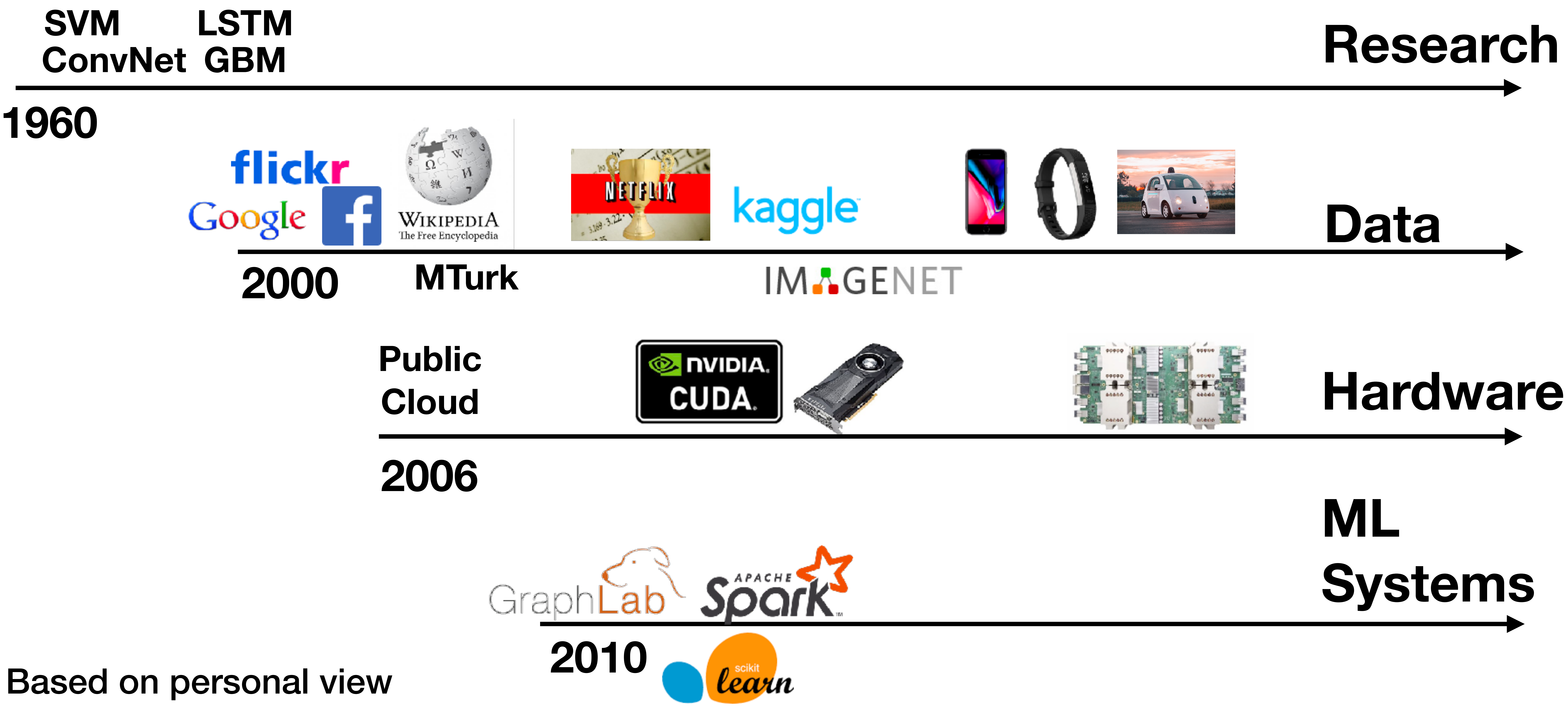
GraphLab

APACHE Spark

2010

Based on personal view

Abbreviated History of Machine Learning



Based on personal view

Abbreviated History of Machine Learning

SVM LSTM
ConvNet GBM

Research

1960

flickr
Google
Wikipedia The Free Encyclopedia

kaggle

Data

2000 MTurk IMAGENET

Public Cloud

NVIDIA CUDA

Hardware

2006

ML Systems

GraphLab
Apache Spark

2010
scikit learn
Caffe

Based on personal view

Abbreviated History of Machine Learning

Research

SVM LSTM
ConvNet GBM

1960

Data

flickr
Google
Wikipedia The Free Encyclopedia

kaggle

2000 MTurk IMAGENET

Hardware

Public
Cloud

NVIDIA CUDA

2006

ML Systems

GraphLab APACHE Spark dmlc XGBoost

2010 scikit learn Caffe

Based on personal view

Abbreviated History of Machine Learning

Research

SVM LSTM
ConvNet GBM

1960

Data

flickr
Google
Wikipedia
The Free Encyclopedia

kaggle

2000 MTurk IMAGENET

Hardware

Public Cloud

NVIDIA CUDA

2006

ML Systems

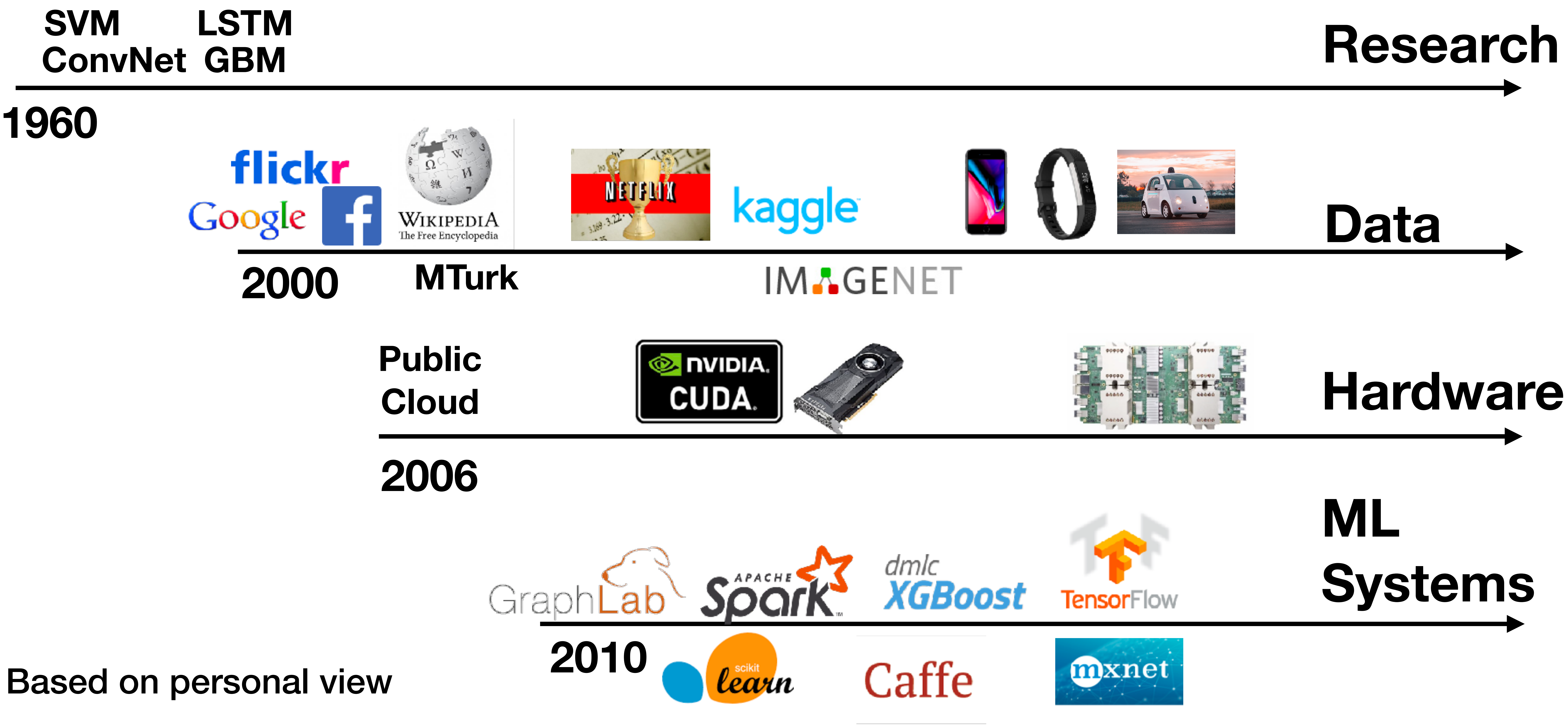
GraphLab
APACHE Spark
dmlc XGBoost

2010

scikit learn
Caffe
mxnet

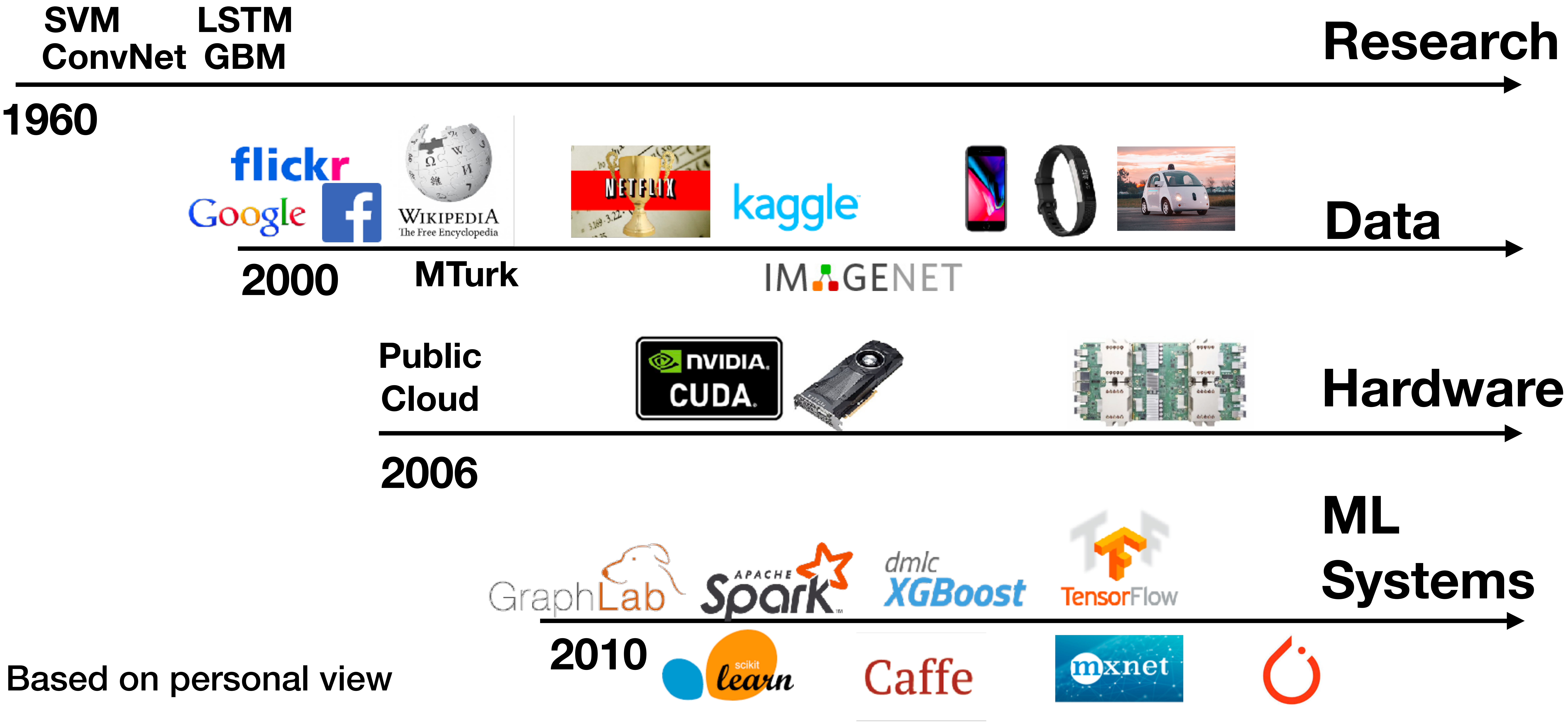
Based on personal view

Abbreviated History of Machine Learning



Based on personal view

Abbreviated History of Machine Learning



Based on personal view

Learning Systems

dmlc XGBoost	mxnet	tvm
Data science for everyone	Scale up deep learning	Deploy AI everywhere

Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

Scale up
deep learning

tvm

Deploy AI
everywhere

Accessible and **scalable** learning systems

Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

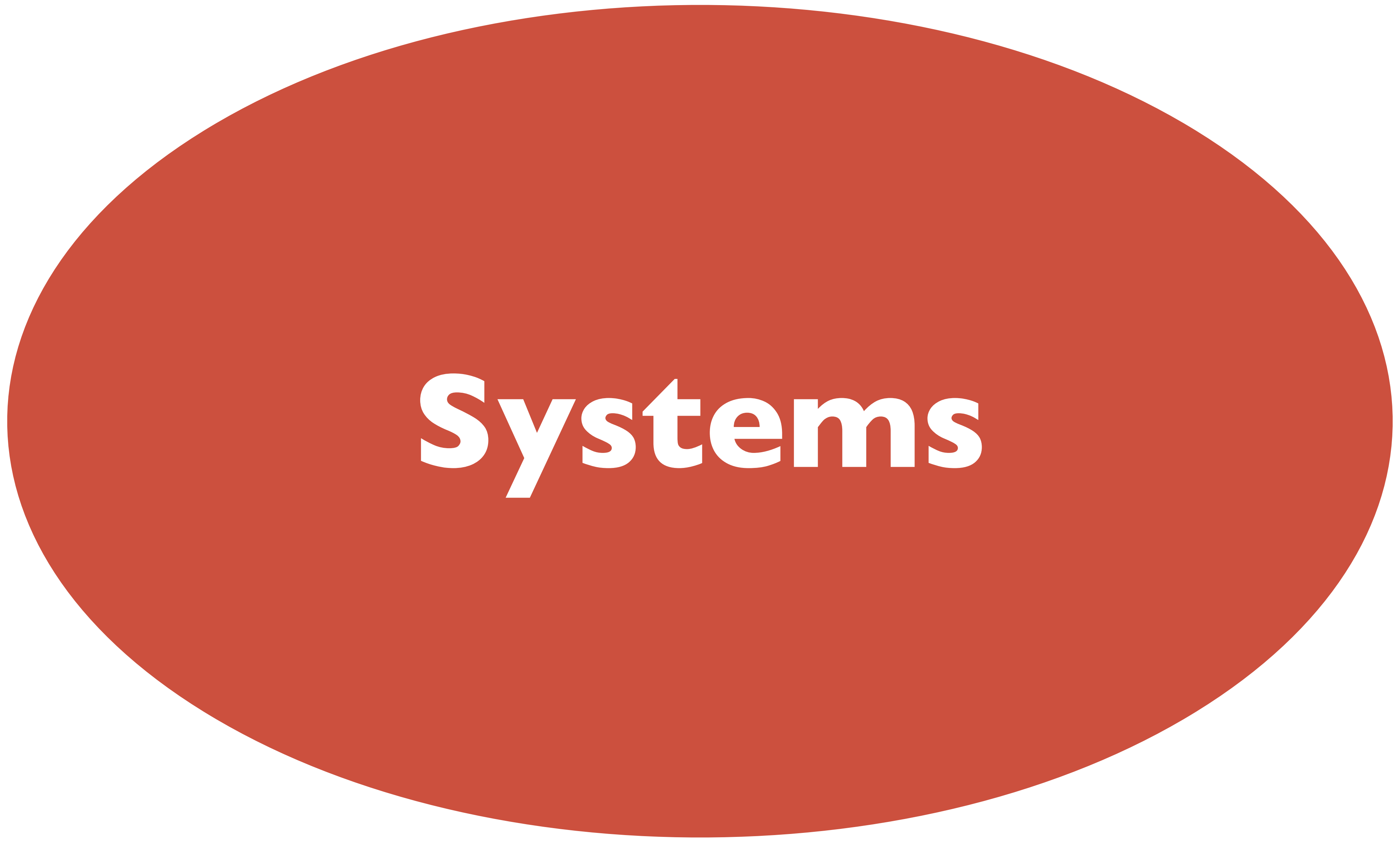
Scale up
deep learning

tvm

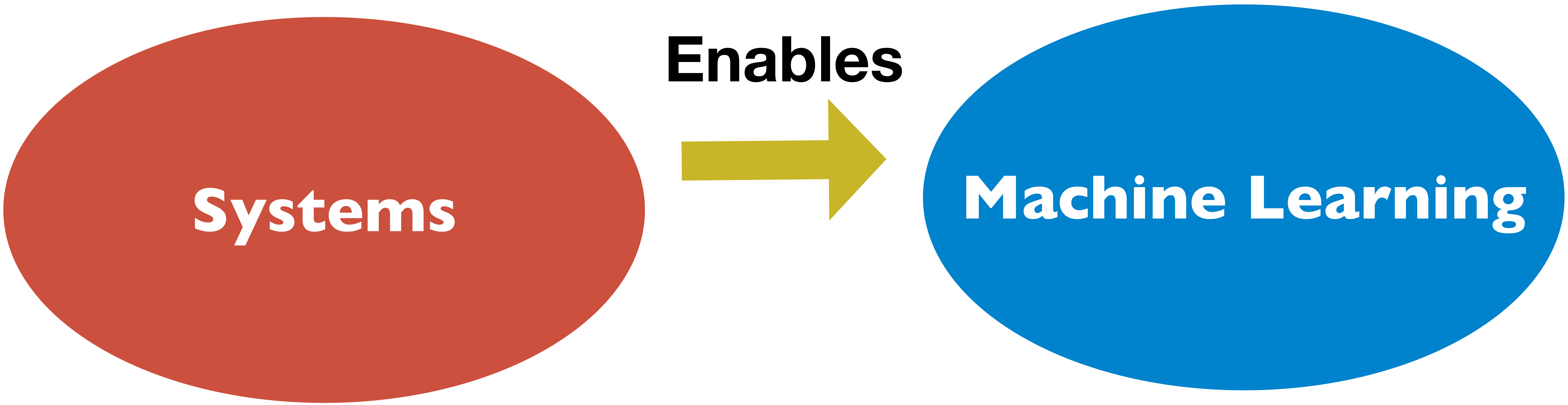
Deploy AI
everywhere

Accessible and **scalable** learning systems

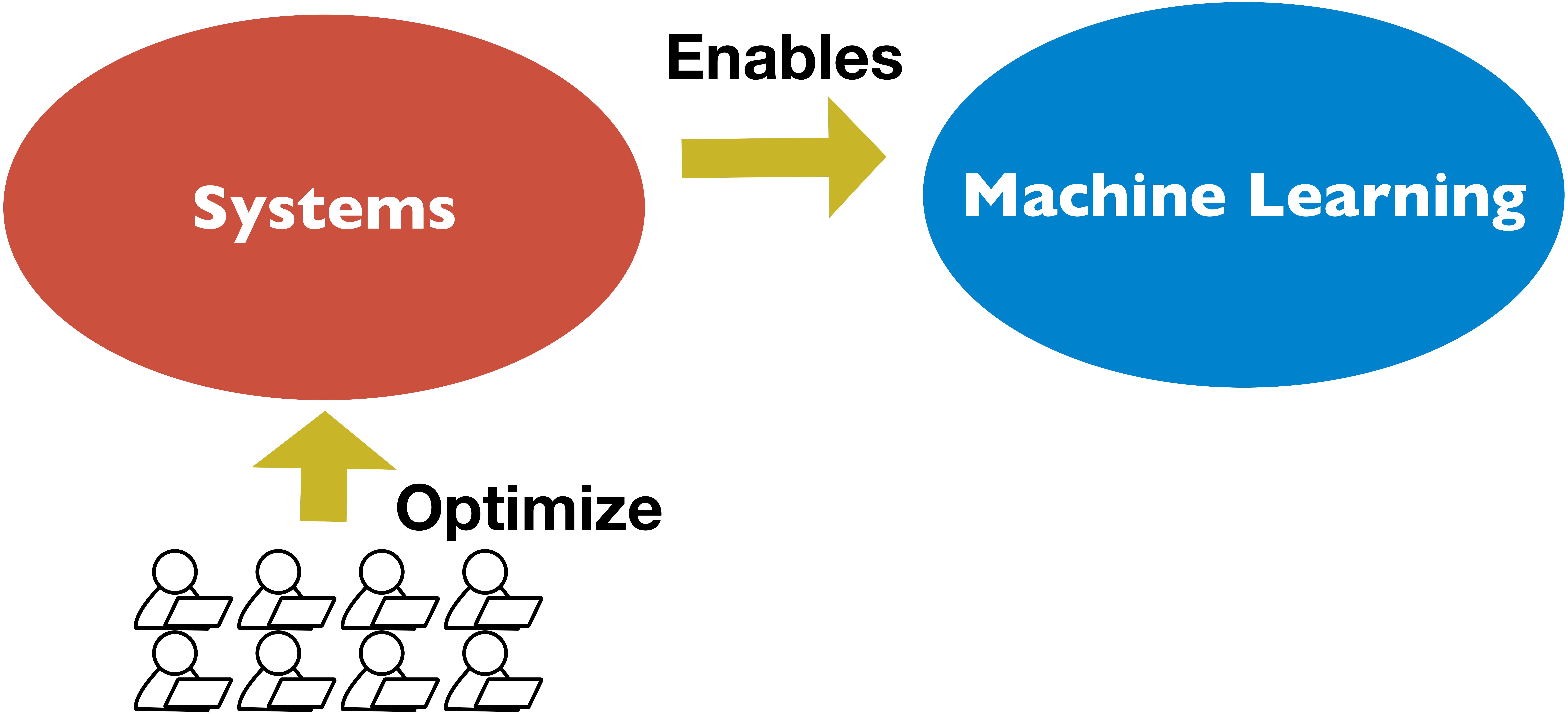
Current Learning Systems



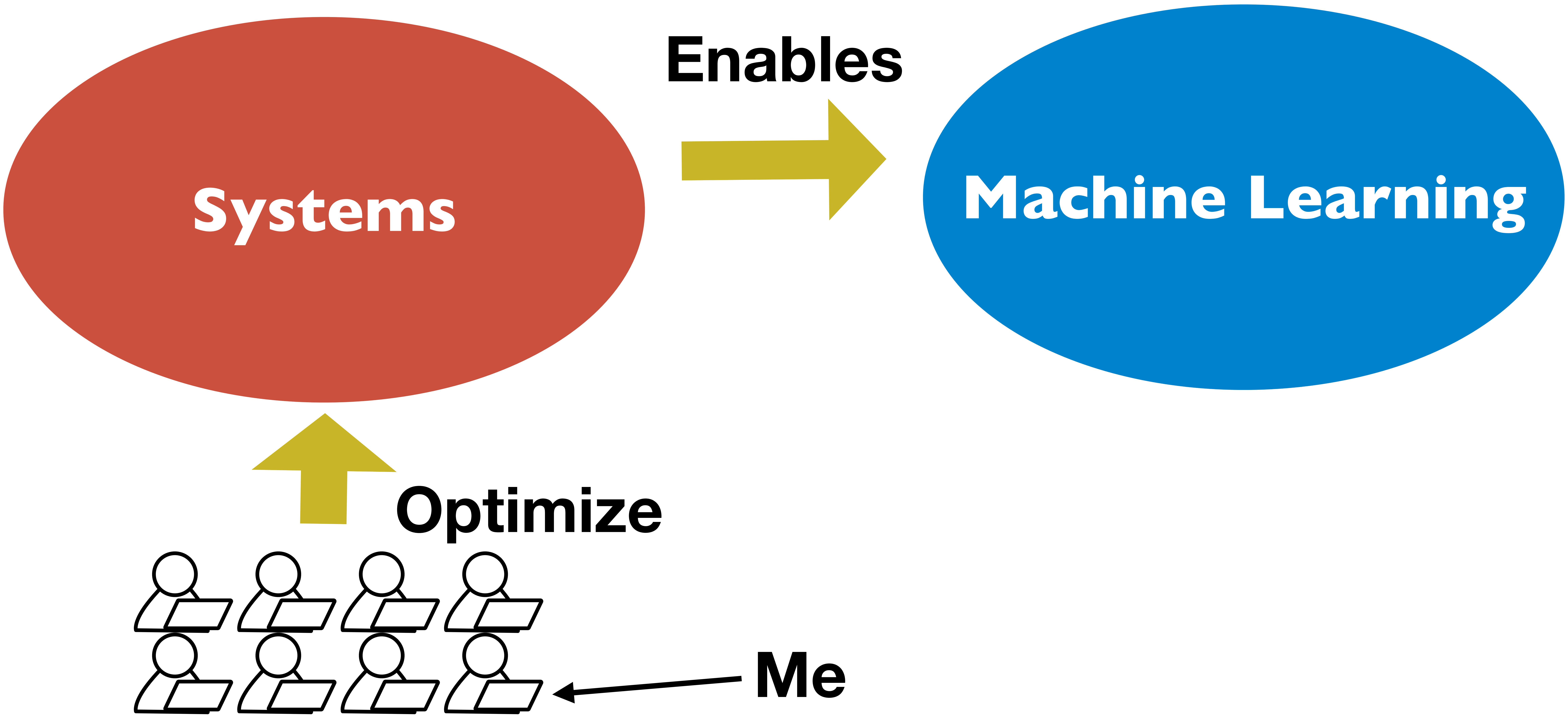
Current Learning Systems



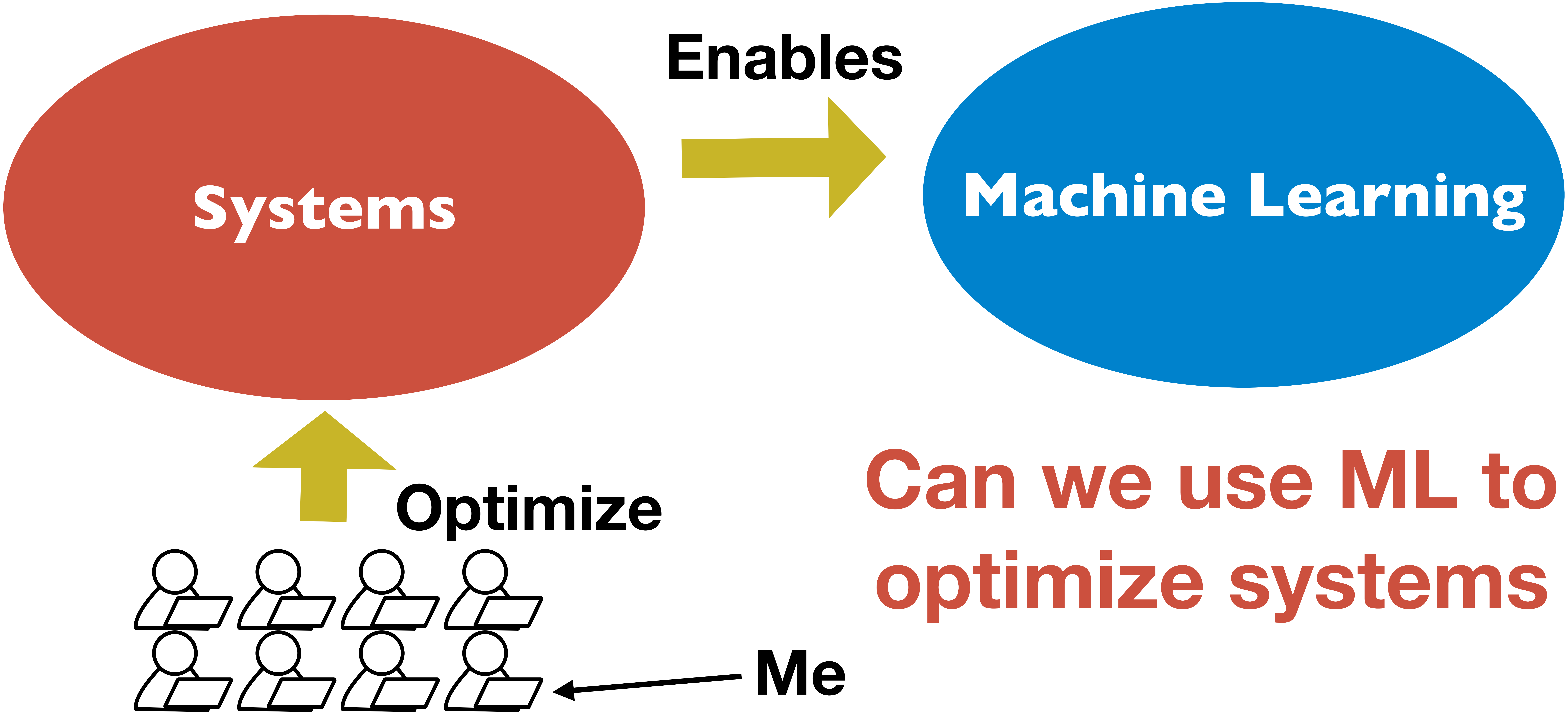
Current Learning Systems



Current Learning Systems

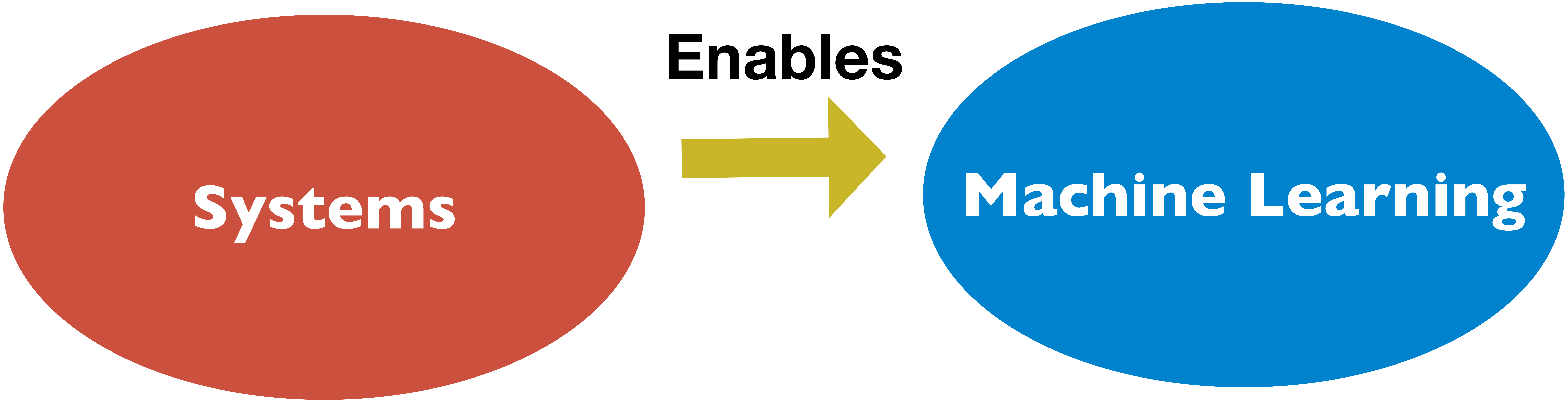


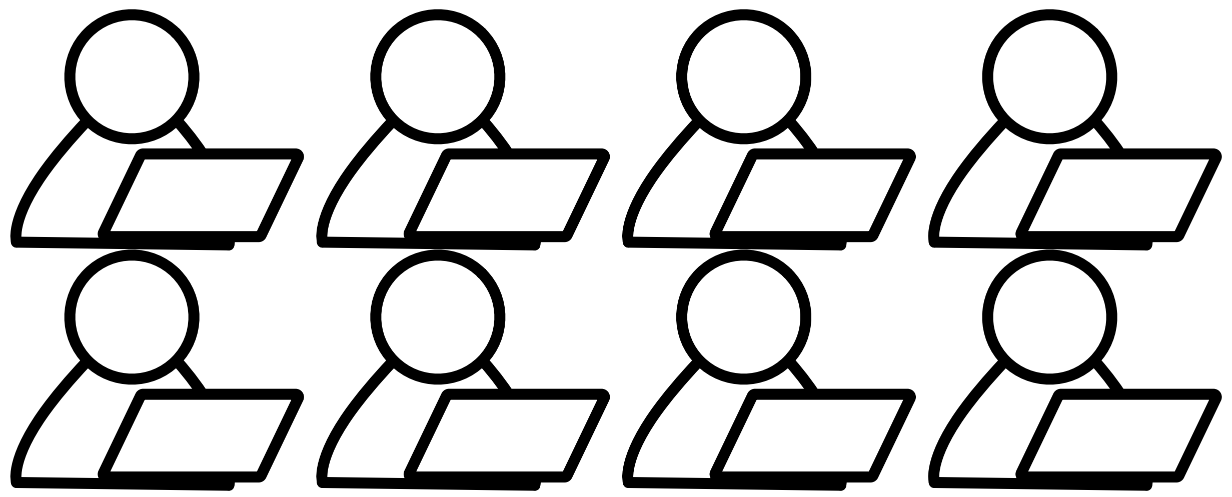
Current Learning Systems



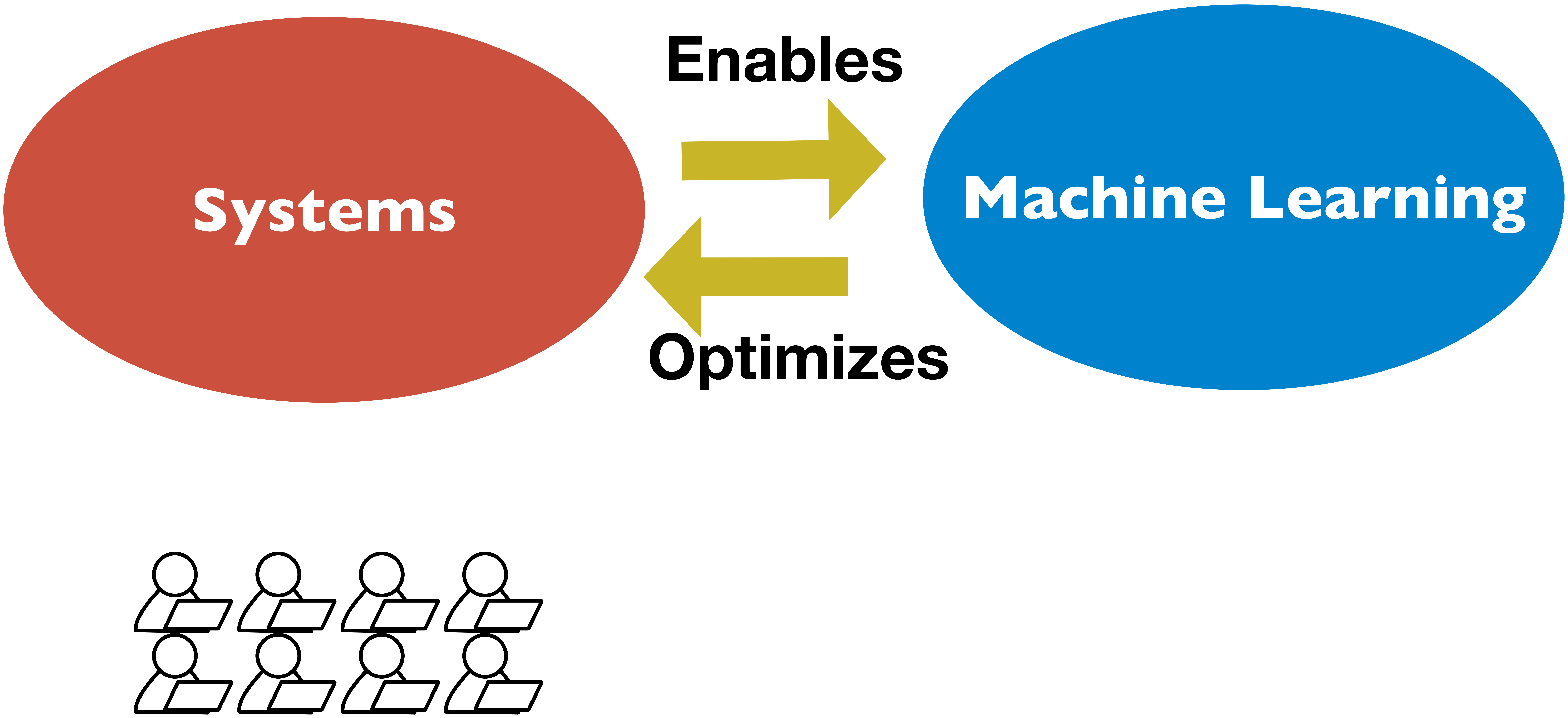
Can we use ML to optimize systems

Learning-based Learning Systems

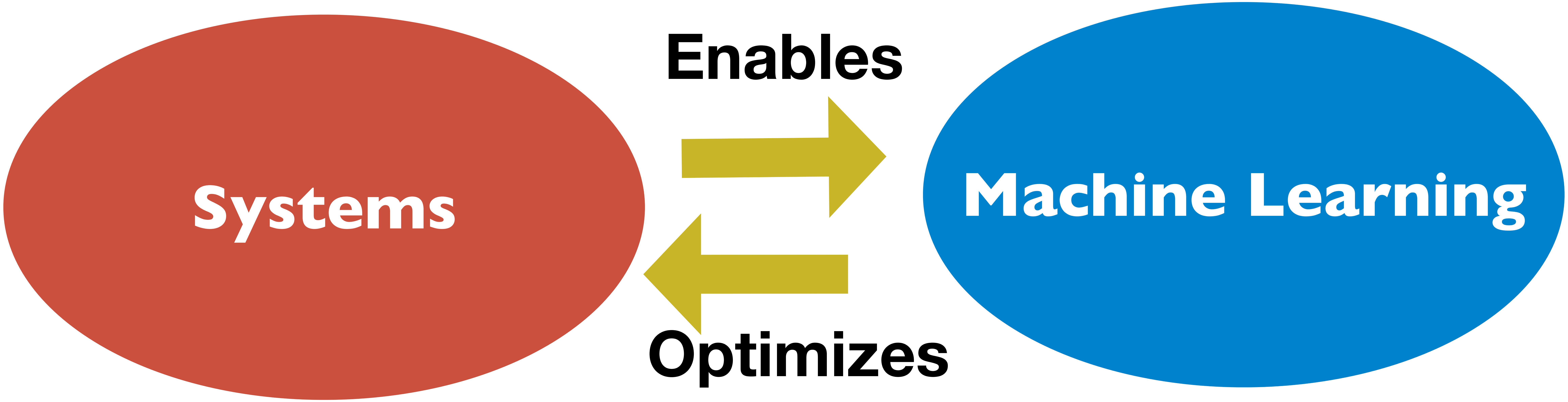


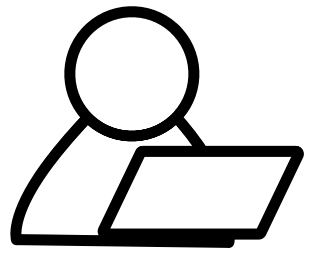


Learning-based Learning Systems



Learning-based Learning Systems





My Research

dmlc XGBoost

Data science for everyone

mxnet

Scale up deep learning

tvm

Deploy AI everywhere

TVM: An Automated End-to-End Optimizing Compiler for Deep Learning. **Chen et al. OSDI 18**

Learning to Optimize Tensor Programs. **Chen et al. NeurIPS 18**

My Research

dmlc XGBoost

Data science for everyone

mxnet

Scale up deep learning

tvm

Deploy AI everywhere

TVM: An Automated End-to-End Optimizing Compiler for Deep Learning. **Chen et al. OSDI 18**

Learning to Optimize Tensor Programs. **Chen et al. NeurIPS 18**

TVM: Learning-based Learning System

Why do we need machine learning for systems

How to build intelligent systems with learning

End to end learning-based learning system stack

TVM: Learning-based Learning System

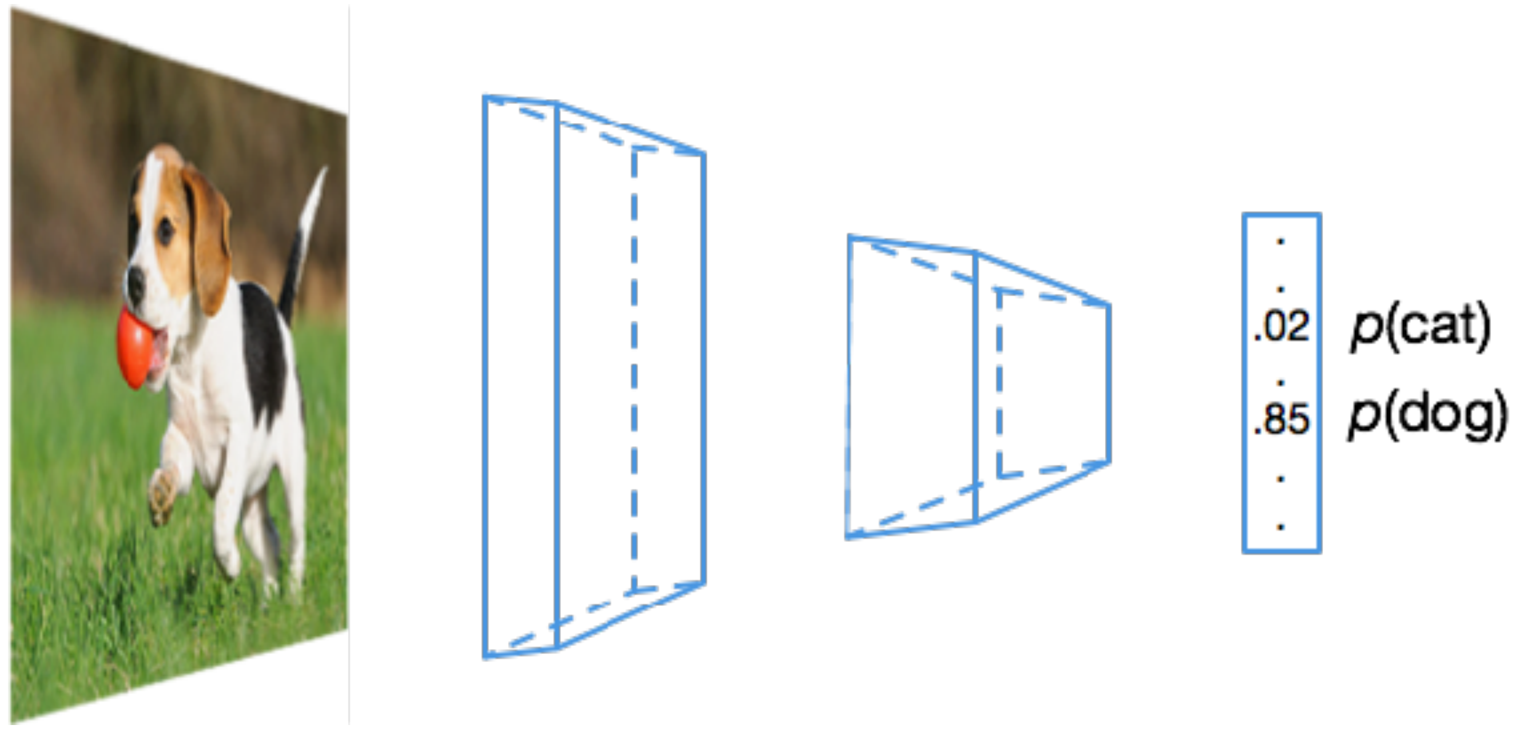
Why do we need machine learning for systems

How to build intelligent systems with learning

End to end learning-based learning system stack

Problem: Deep Learning Deployment

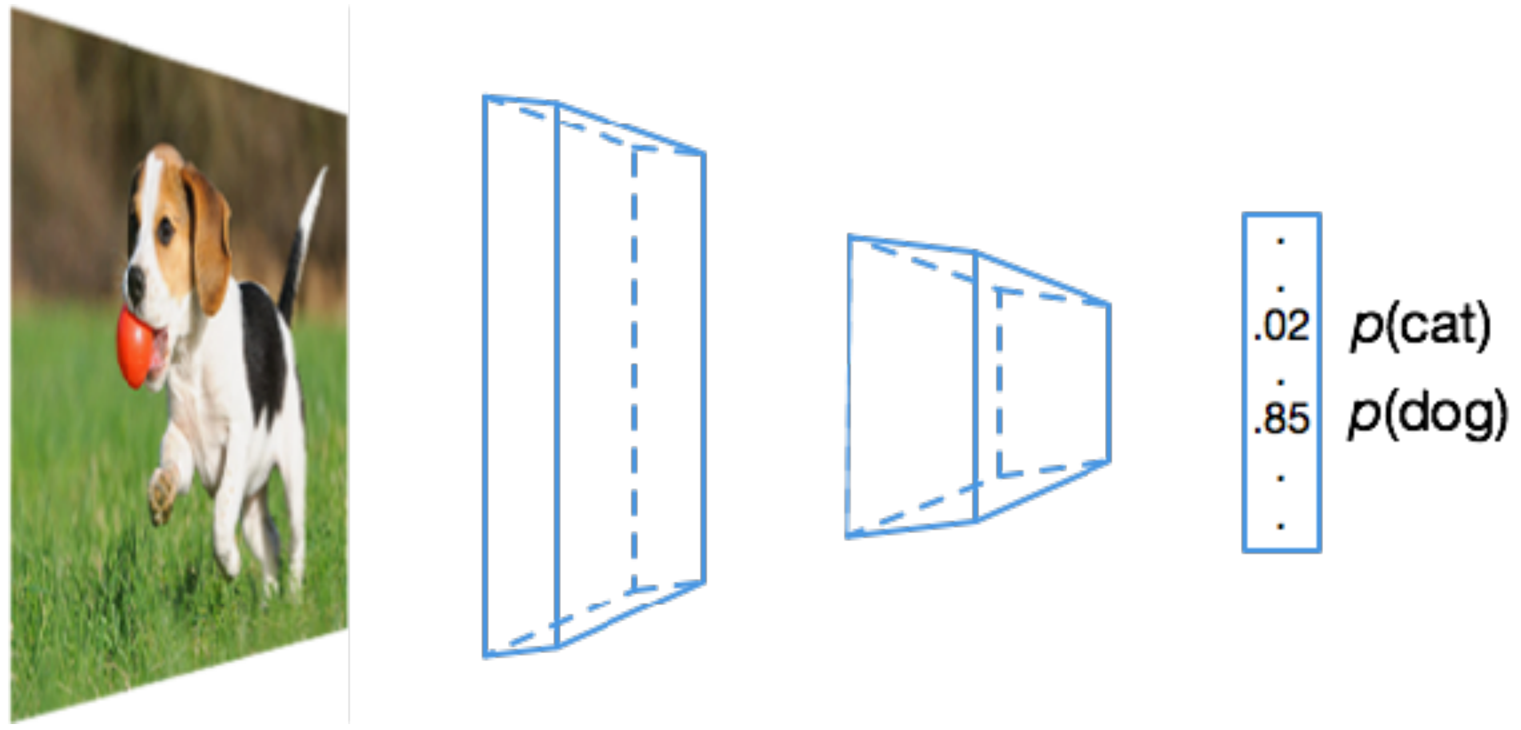
Model



Hardware Backends

Problem: Deep Learning Deployment

Model

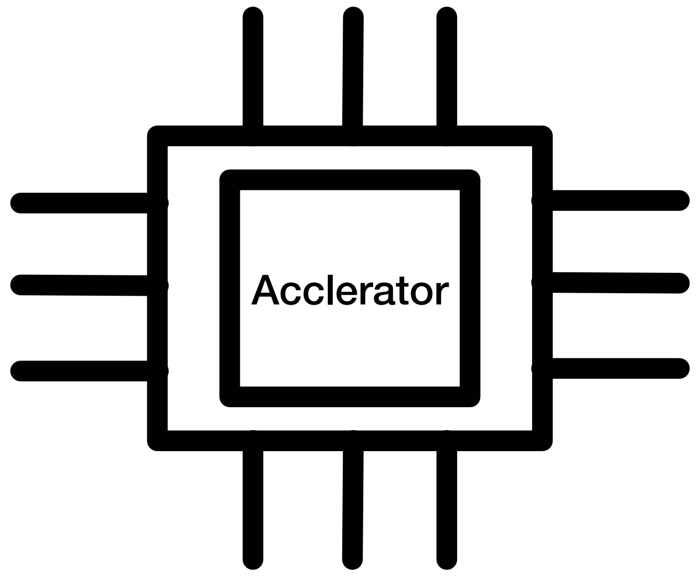


Deploy

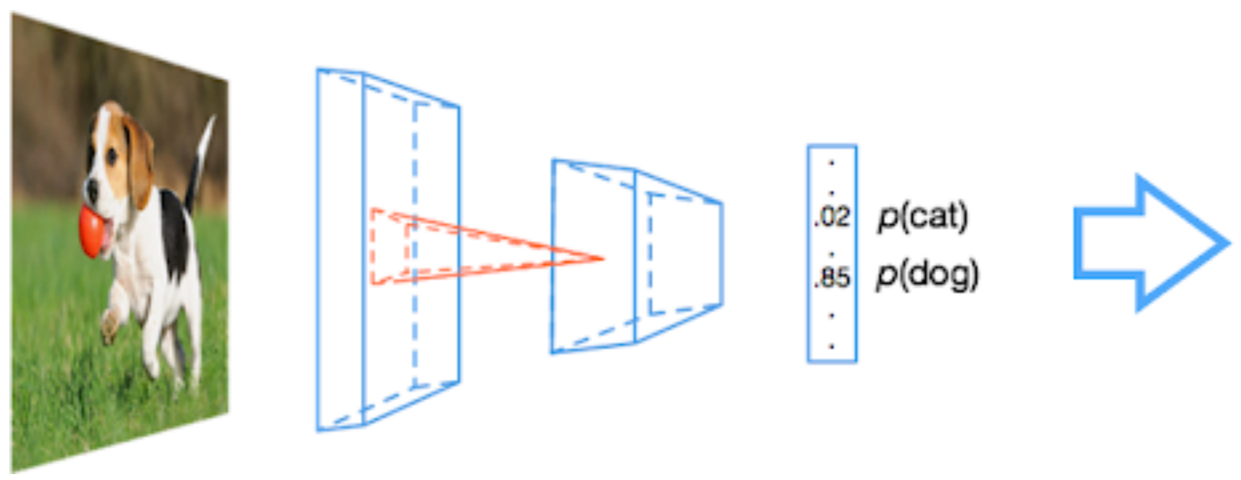
Hardware Backends

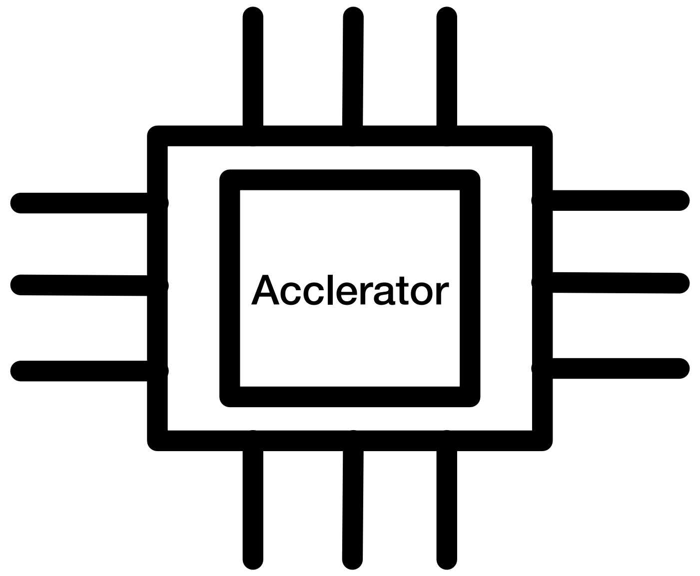
How did I Start to Work on This Problem?

How did I Start to Work on This Problem?

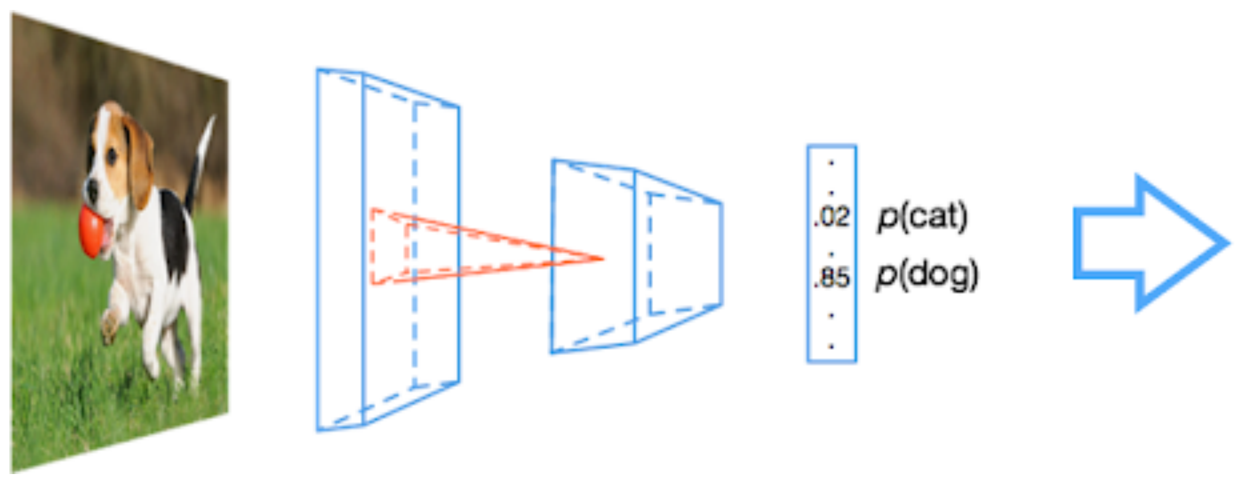


How did I Start to Work on This Problem?

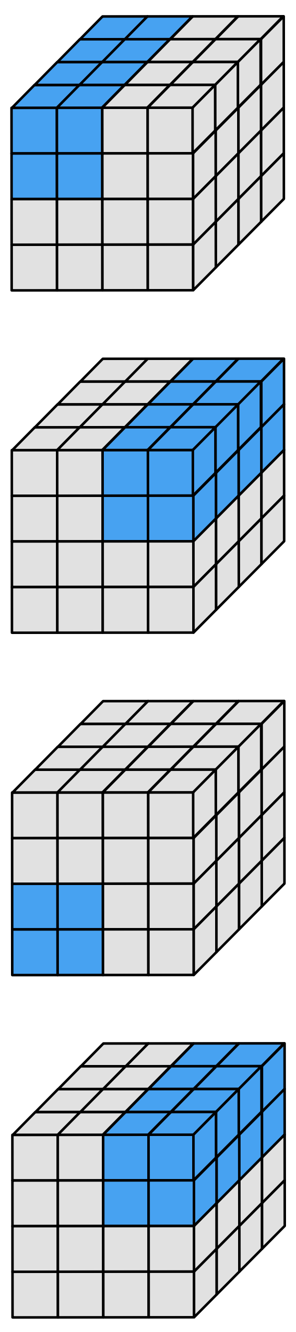




How did I Start to Work on This Problem?



```
// Pseudo-code for convolution program for the VIA accelerator
// Virtual Thread 0
0x00: LOAD(PARAM[ 0-71])                                          // LD@TID0
0x01: LOAD(ACTIV[ 0-24])                                          // LD@TID0
0x02: LOAD(LDBUF[ 0-31])                                          // LD@TID0
0x03: PUSH(LD->EX)                                                // LD@TID0
0x04: POP (LD->EX)                                                // EX@TID0
0x05: EXE (ACTIV[ 0-24],PARAM[ 0-71],LDBUF[ 0-31],STBUF[ 0- 7])   // EX@TID0
0x06: PUSH(EX->LD)                                                // EX@TID0
0x07: PUSH(EX->ST)                                                // EX@TID0
0x08: POP (EX->ST)                                                // ST@TID0
0x09: STOR(STBUF[ 0- 7])                                          // ST@TID0
0x0A: PUSH(ST->EX)                                                // ST@TID0
// Virtual Thread 1
0x0B: LOAD(ACTIV[25-50])                                          // LD@TID1
0x0C: LOAD(LDBUF[32-63])                                          // LD@TID1
0x0D: PUSH(LD->EX)                                                // LD@TID1
0x0E: POP (LD->EX)                                                // EX@TID1
0x0F: EXE (ACTIV[25-50],PARAM[ 0-71],LDBUF[32-63],STBUF[32-39])   // EX@TID1
0x10: PUSH(EX->LD)                                                // EX@TID1
0x11: PUSH(EX->ST)                                                // EX@TID1
0x12: POP (EX->ST)                                                // ST@TID1
0x13: STOR(STBUF[32-39])                                          // ST@TID1
0x14: PUSH(ST->EX)                                                // ST@TID1
// Virtual Thread 2
0x15: POP (EX->LD)                                                // LD@TID2
0x16: LOAD(PARAM[ 0-71])                                          // LD@TID2
0x17: LOAD(ACTIV[ 0-24])                                          // LD@TID2
0x18: LOAD(LDBUF[ 0-31])                                          // LD@TID2
0x19: PUSH(LD->EX)                                                // LD@TID2
0x1A: POP (LD->EX)                                                // EX@TID2
0x1B: POP (ST->EX)                                                // EX@TID2
0x1C: EXE (ACTIV[ 0-24],PARAM[ 0-71],LDBUF[ 0-31],STBUF[ 0- 7])   // EX@TID2
0x1D: PUSH(EX->ST)                                                // EX@TID2
0x1E: POP (EX->ST)                                                // ST@TID2
0x1F: STOR(STBUF[ 0- 7])                                          // ST@TID2
// Virtual Thread 3
0x20: POP (EX->LD)                                                // LD@TID3
0x21: LOAD(ACTIV[25-50])                                          // LD@TID3
0x22: LOAD(LDBUF[32-63])                                          // LD@TID3
0x23: PUSH(LD->EX)                                                // LD@TID3
0x24: POP (LD->EX)                                                // EX@TID3
0x25: POP (ST->EX)                                                // EX@TID2
0x26: EXE (ACTIV[25-50],PARAM[ 0-71],LDBUF[32-63],STBUF[32-39])   // EX@TID3
0x27: PUSH(EX->ST)                                                // EX@TID3
0x28: POP (EX->ST)                                                // ST@TID3
0x29: STOR(STBUF[32-39])                                          // ST@TID3
```



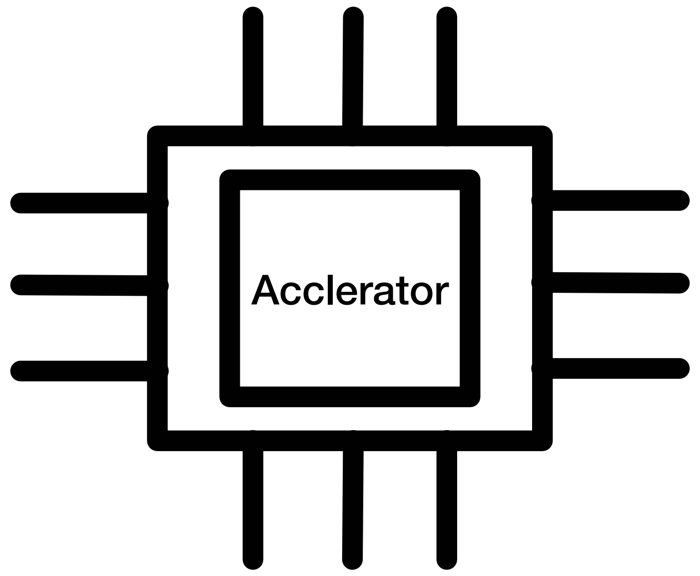
(a) Blocked convolution program with multiple thread contexts

```
// Convolution access pattern dictated by micro-coded program.
// Each register index is derived as a 2-D affine function.
// e.g. idx_rf = a_rf y+b_rf x+c_rf^0, where c_rf^0 is specified by
//      micro op 0 fields.
for y in [0…i)
  for x in [0…j)
    rf[idx_rf^0] += GEVM(act[idx_act^0], par[idx_par^0])
    rf[idx_rf^1] += GEVM(act[idx_act^1], par[idx_par^1])
    …
    rf[idx_rf^n] += GEVM(act[idx_act^n], par[idx_par^n])
```

(b) Convolution micro-coded program

```
// Max-pool, batch normalization and activation function
// access pattern dictated by micro-coded program.
// Each register index is derived as a 2D affine function.
// e.g. idx_dst = a_dst y+b_dst x+c_dst^0, where c_dst^0 is specified by
//      micro op 0 fields.
for y in [0…i)
  for x in [0…j)
    // max pooling
    rf[idx_dst^0] = MAX(rf[idx_dst^0], rf[idx_src^0])
    rf[idx_dst^1] = MAX(rf[idx_dst^1], rf[idx_src^1])
    …
    // batch norm
    rf[idx_dst^m] = MUL(rf[idx_dst^m], rf[idx_src^m])
    rf[idx_dst^m+1] = ADD(rf[idx_dst^m+1], rf[idx_src^m+1])
    rf[idx_dst^m+2] = MUL(rf[idx_dst^m+2], rf[idx_src^m+2])
    rf[idx_dst^m+3] = ADD(rf[idx_dst^m+3], rf[idx_src^m+3])
    …
    // activation
    rf[idx_dst^n-1] = RELU(rf[idx_dst^n-1], rf[idx_src^n-1])
    rf[idx_dst^n] = RELU(rf[idx_dst^n], rf[idx_src^n])
```

(c) Max pool, batch norm and activation micro-coded program



Deploy Deep Learning Everywhere

Frameworks

Hardware

Deploy Deep Learning Everywhere

Frameworks

Hardware

Deploy Deep Learning Everywhere

Frameworks

Hardware

Deploy Deep Learning Everywhere

Frameworks

Hardware

Deploy Deep Learning Everywhere

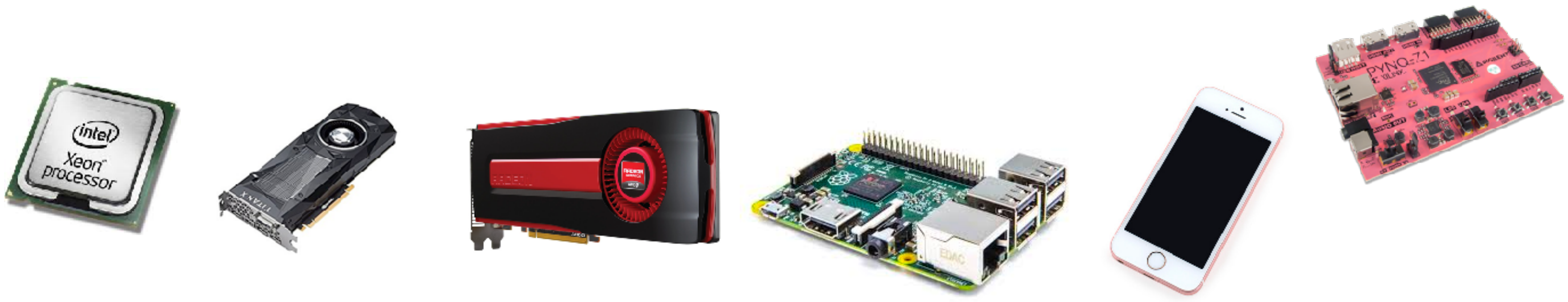
Frameworks

Hardware

Deploy Deep Learning Everywhere

Frameworks

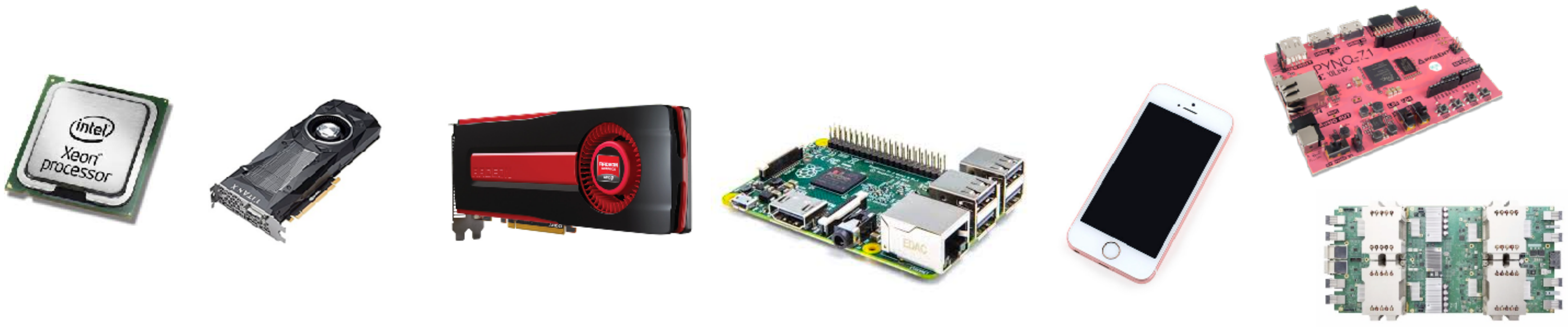
Hardware



Deploy Deep Learning Everywhere

Frameworks

Hardware

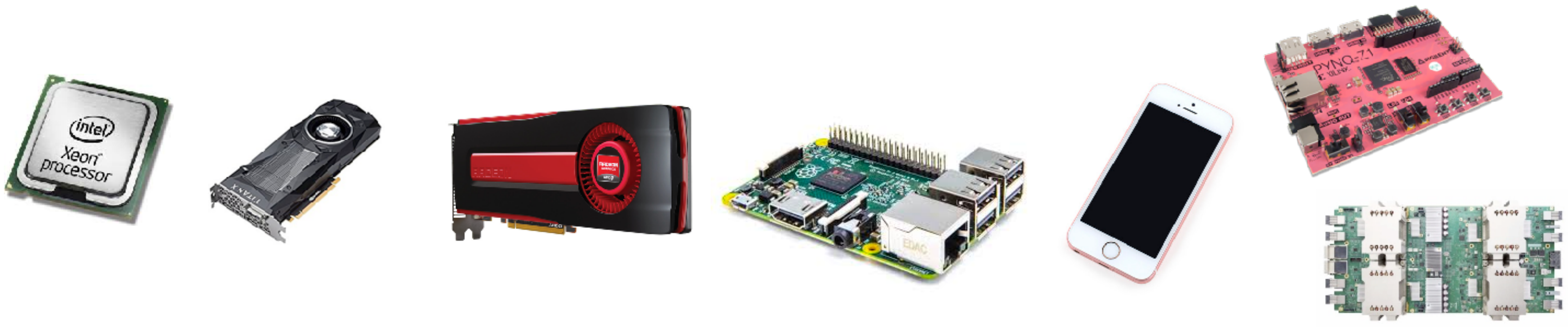


Deploy Deep Learning Everywhere

Frameworks

Huge gap between model/frameworks and hardware backends

Hardware



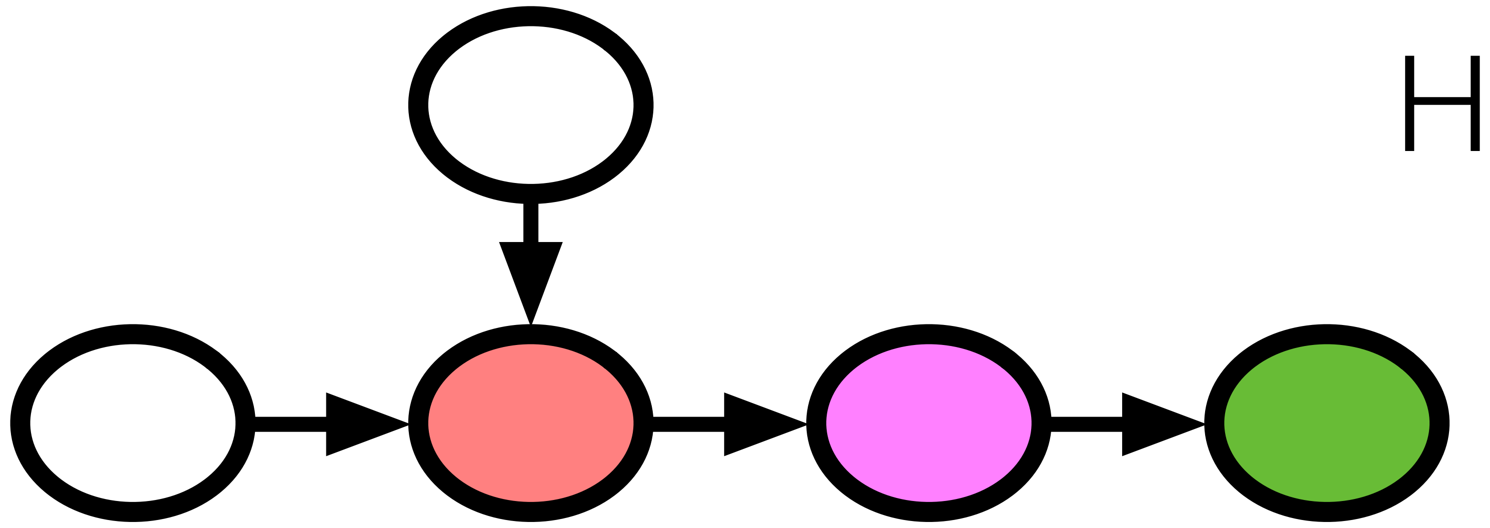
Existing Deep Learning Frameworks

Frameworks

Hardware

Existing Deep Learning Frameworks

Frameworks

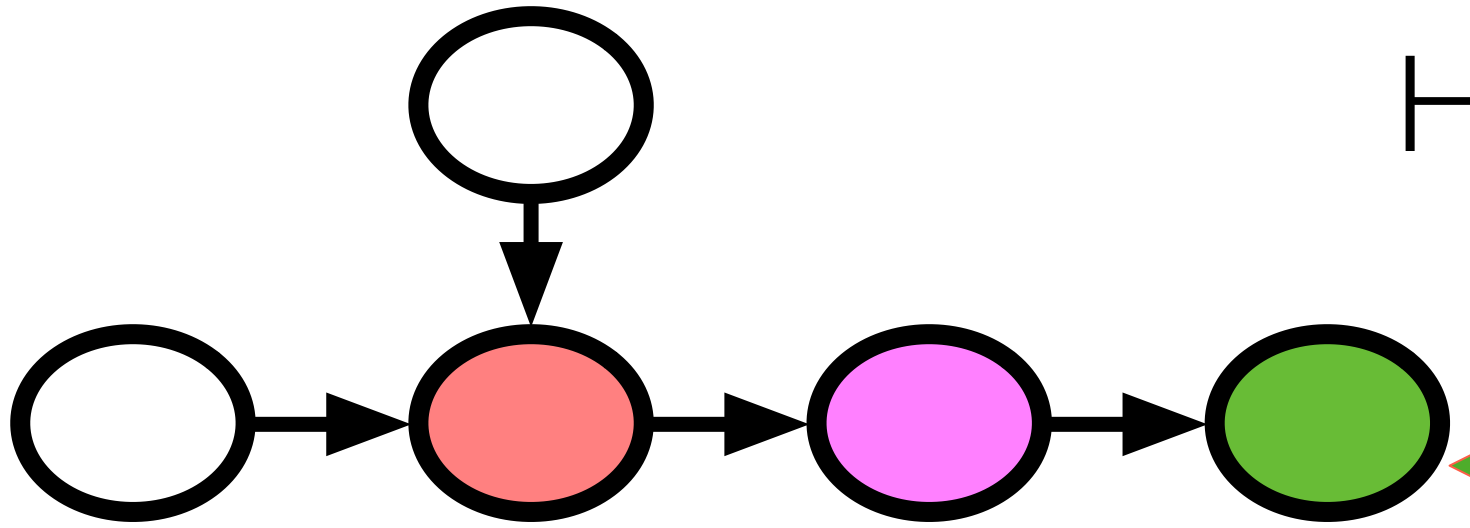


High-level data flow graph

Hardware

Existing Deep Learning Frameworks

Frameworks

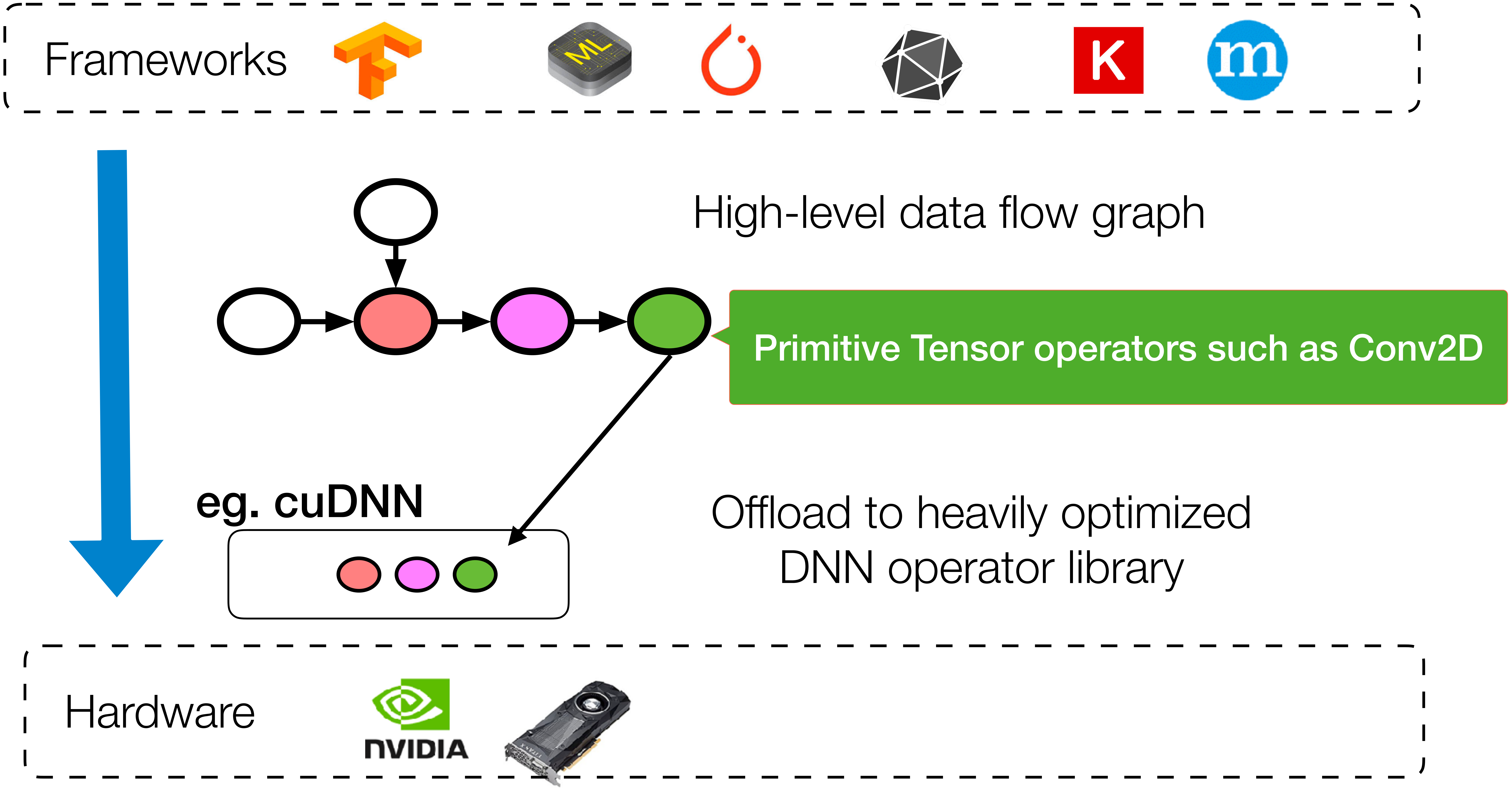


High-level data flow graph

Primitive Tensor operators such as Conv2D

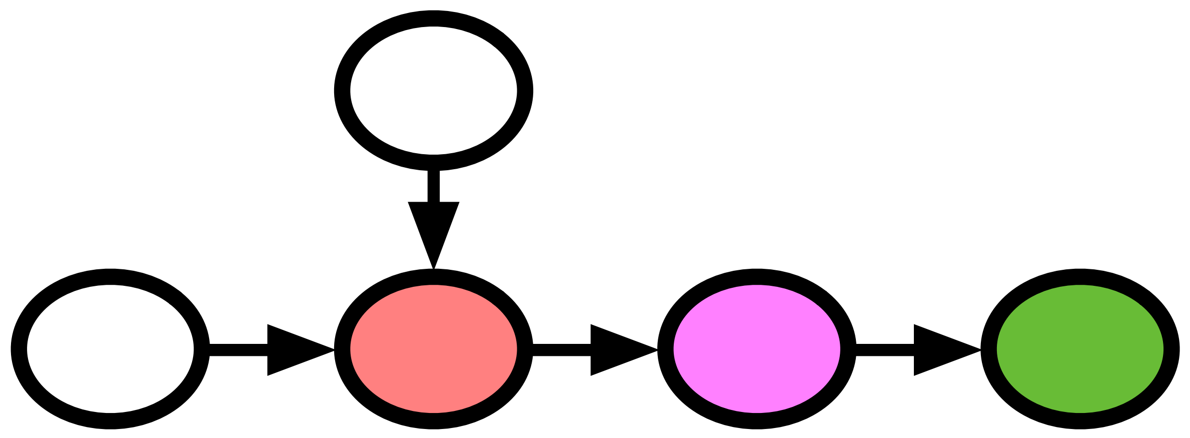
Hardware

Existing Deep Learning Frameworks



Limitations of Existing Approach

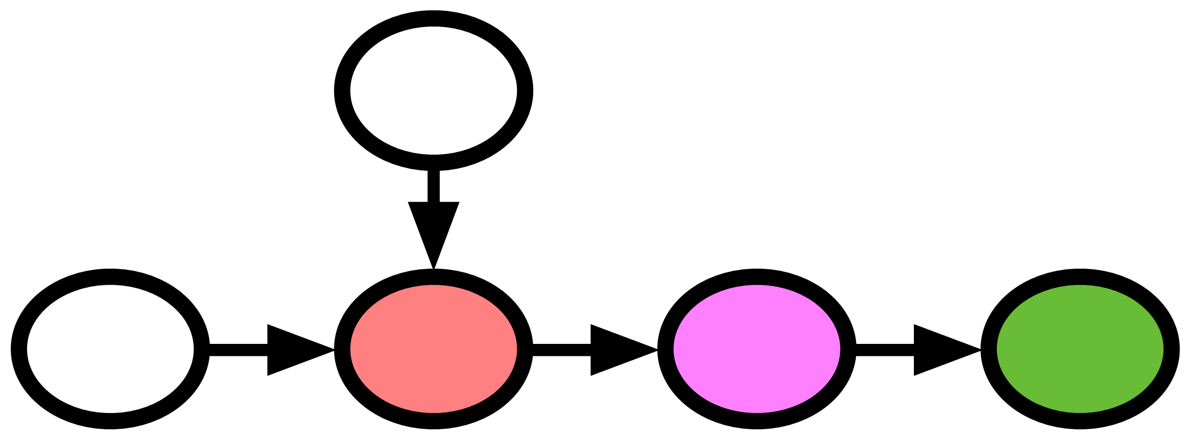
Frameworks



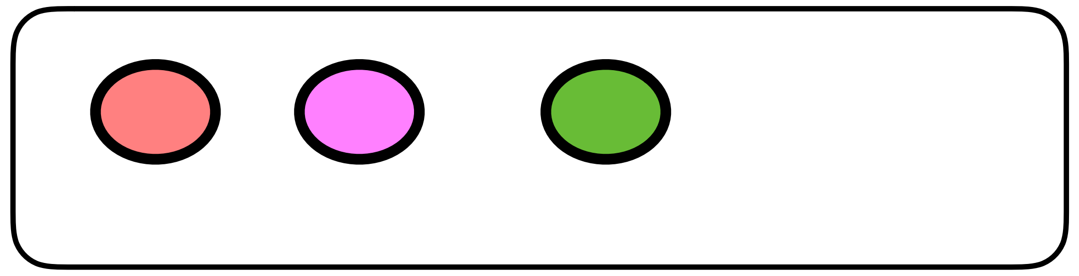
cuDNN

Limitations of Existing Approach

Frameworks



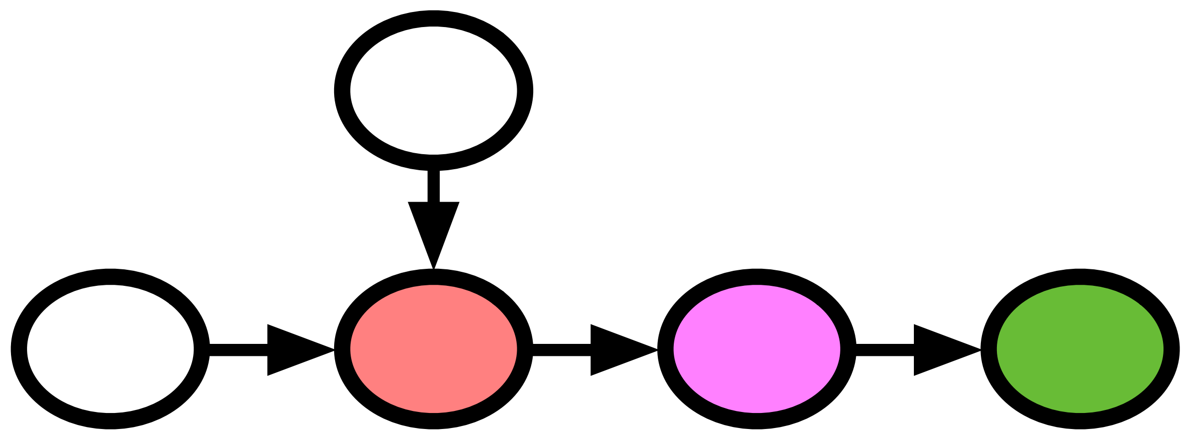
cuDNN



NVIDIA

Limitations of Existing Approach

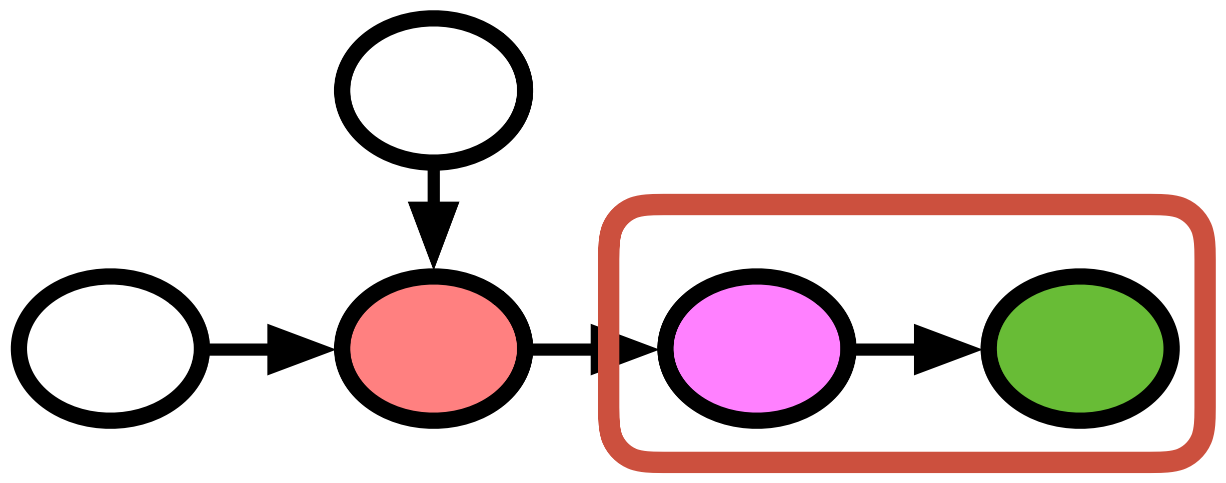
Frameworks



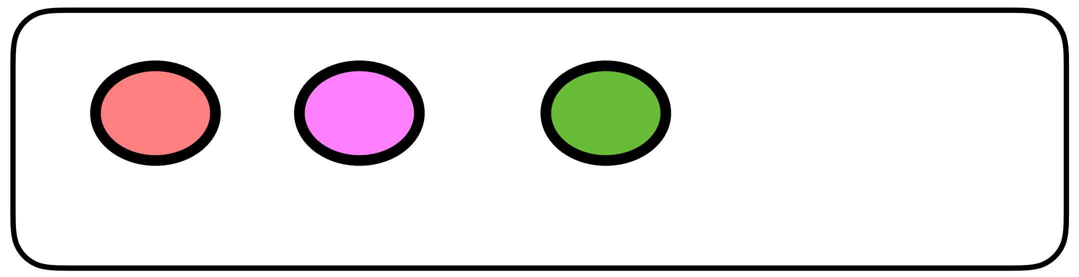
cuDNN

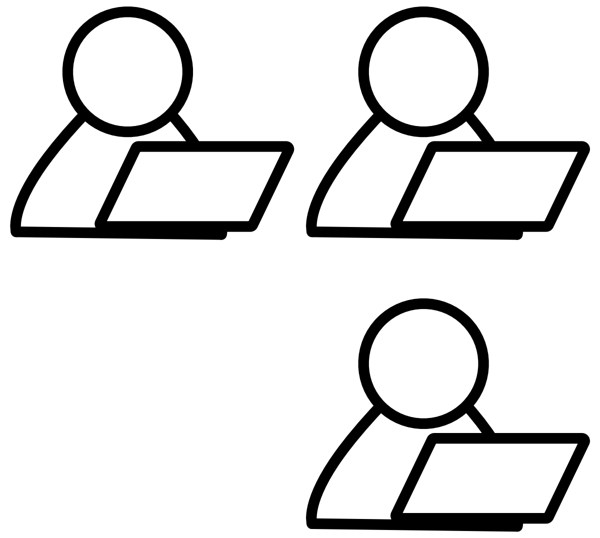
Limitations of Existing Approach

Frameworks



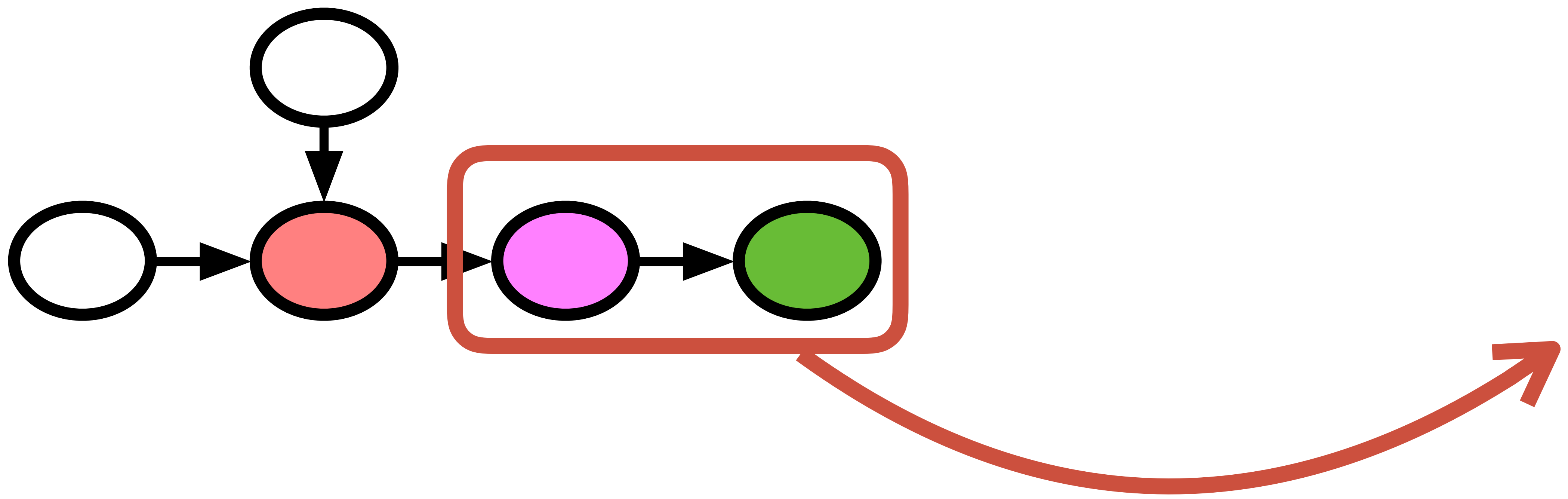
cuDNN



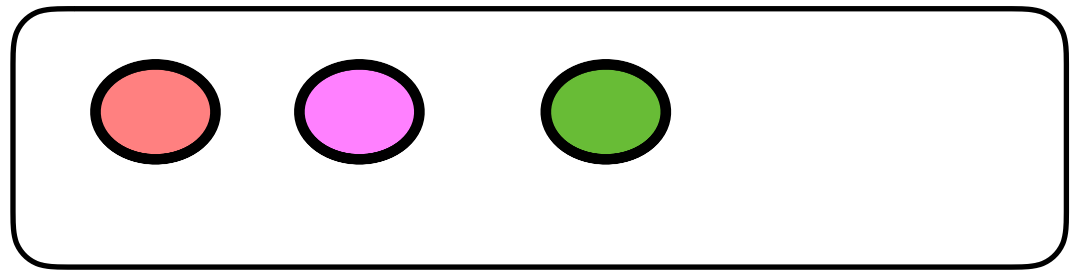


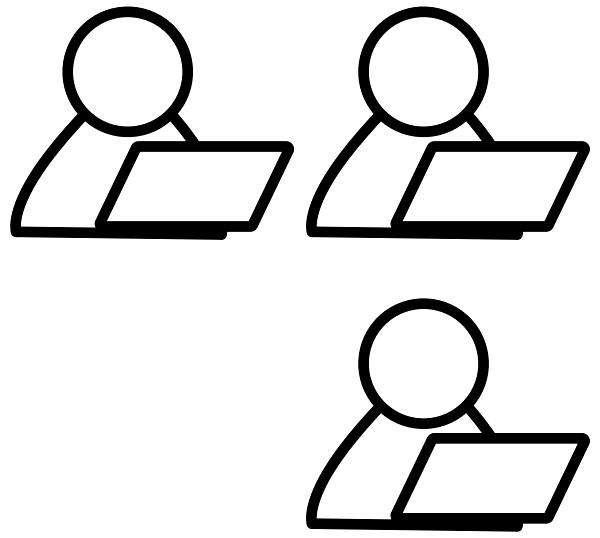
Limitations of Existing Approach

Frameworks



cuDNN



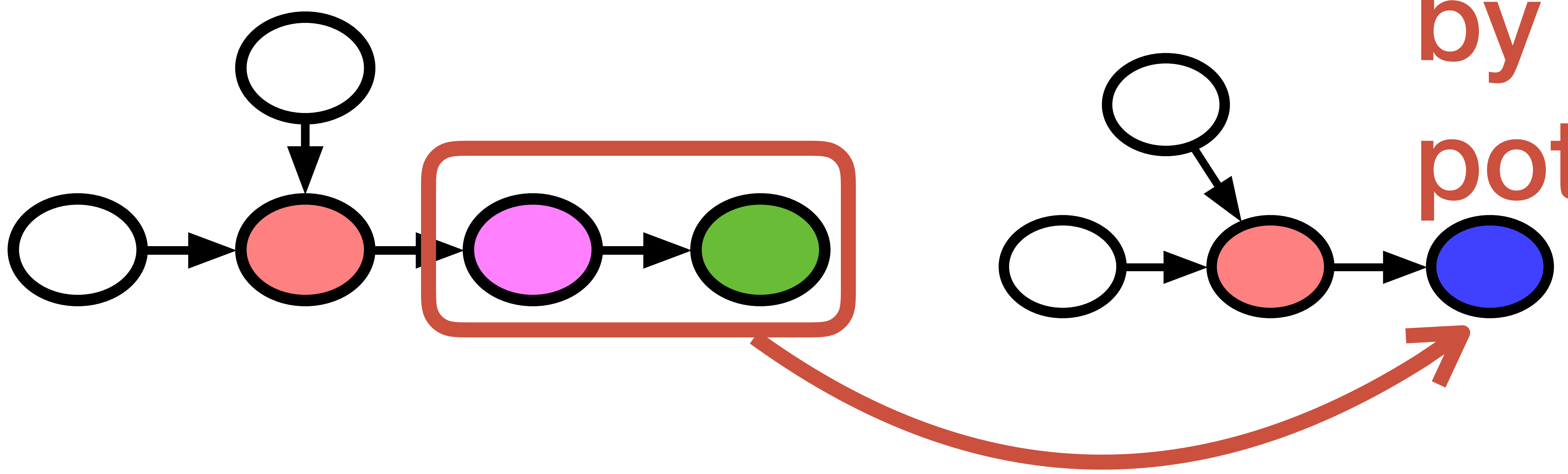


NVIDIA

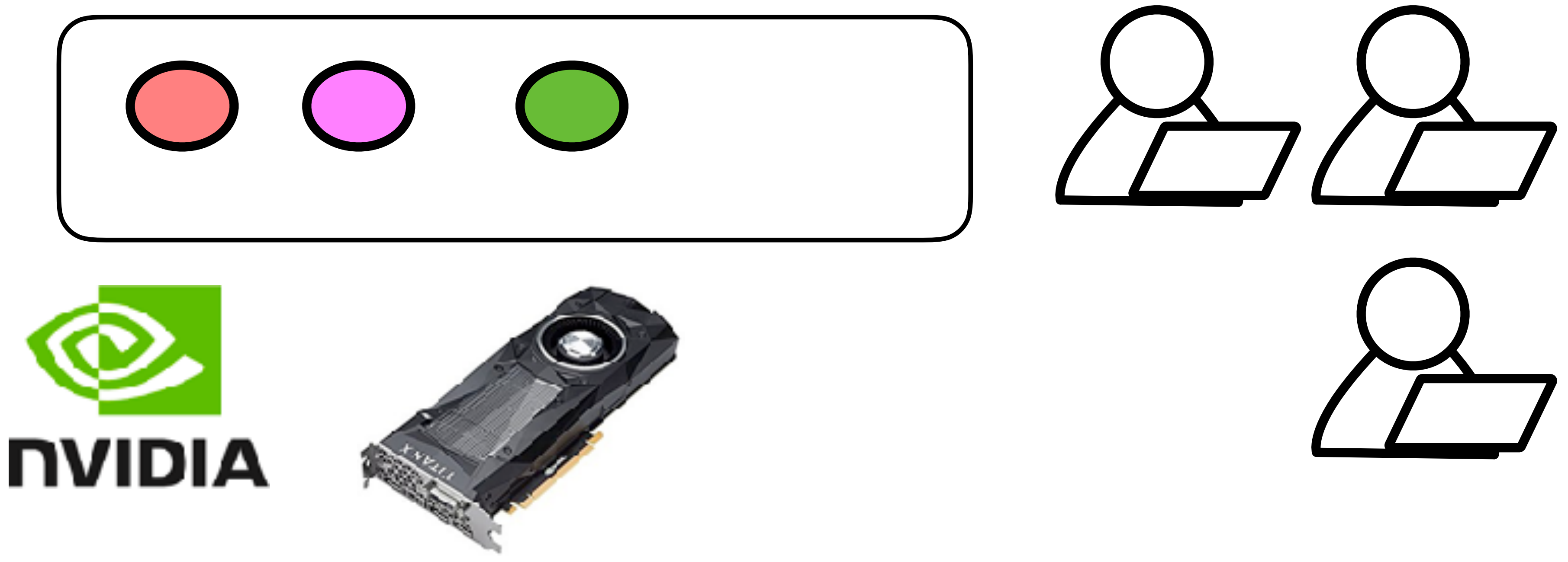
Limitations of Existing Approach

Frameworks

New operator introduced
by operator fusion optimization
potential benefit: 1.5x speedup

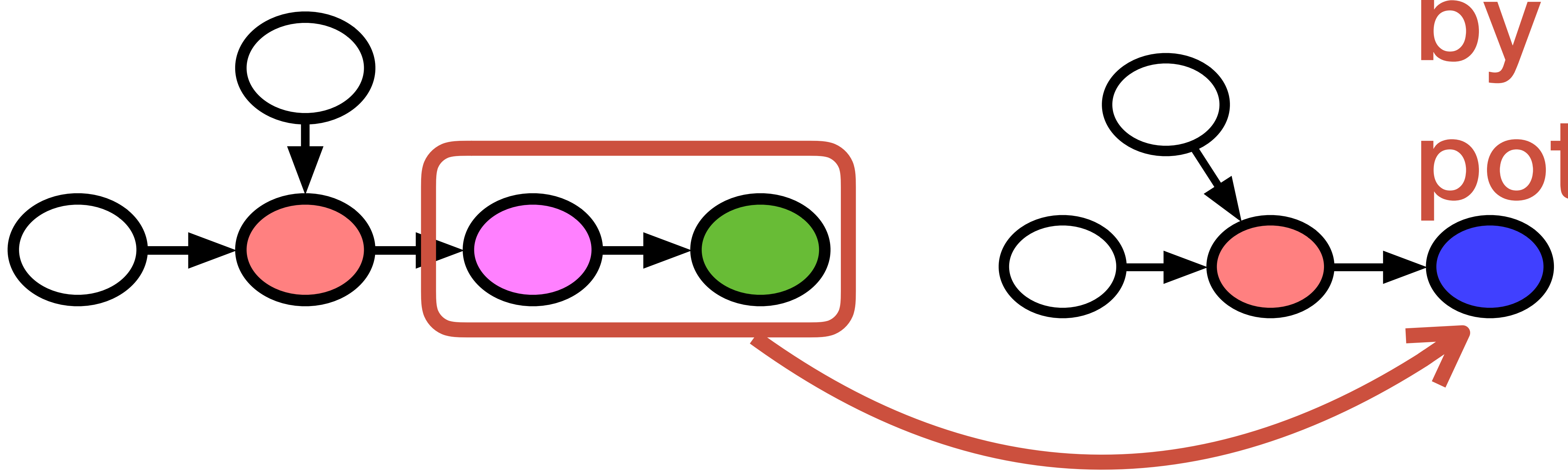


cuDNN



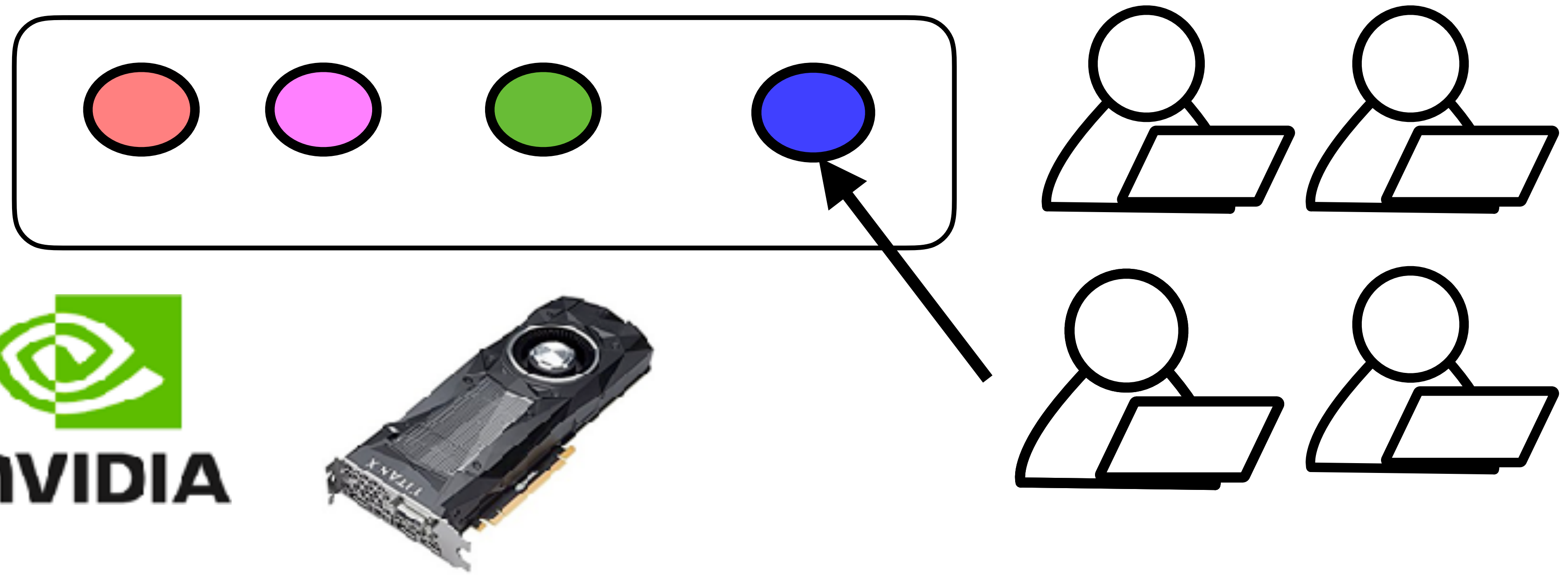
Limitations of Existing Approach

Frameworks



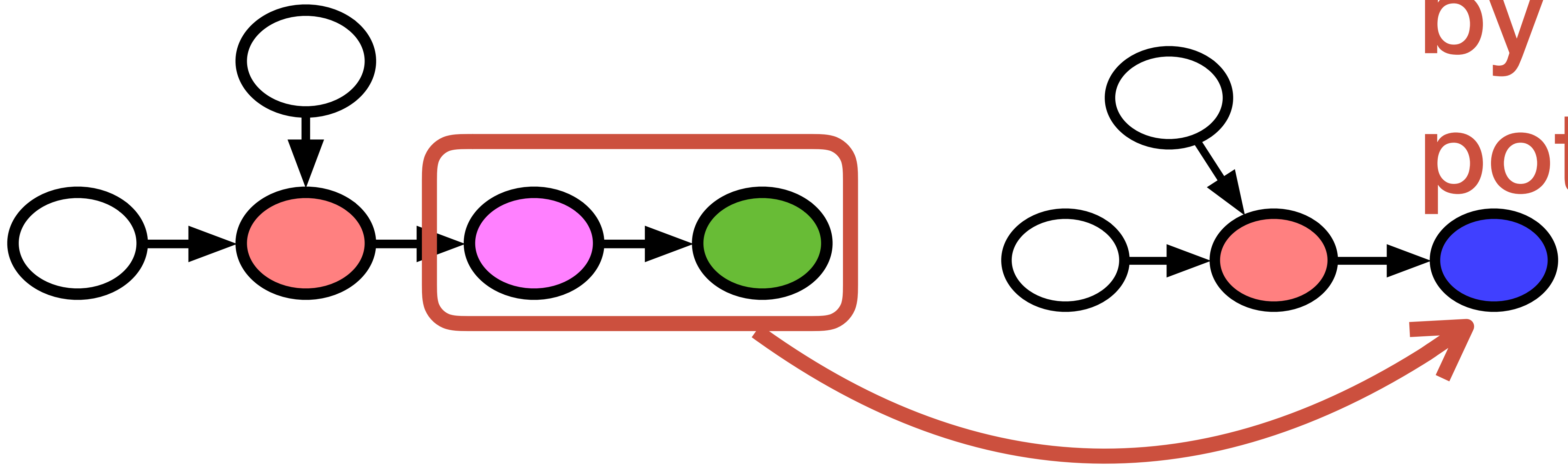
New operator introduced
by operator fusion optimization
potential benefit: 1.5x speedup

cuDNN



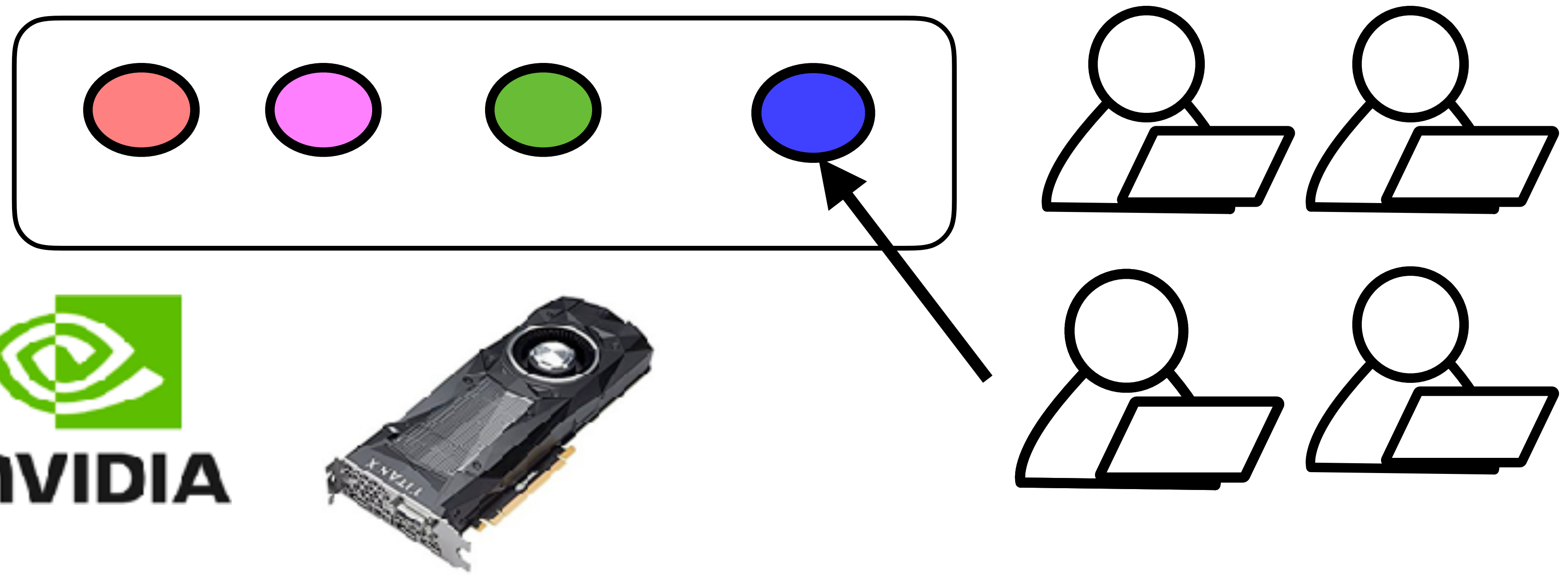
Limitations of Existing Approach

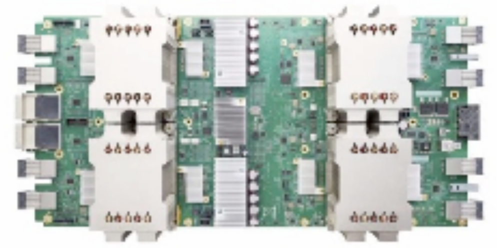
Frameworks



New operator introduced
by operator fusion optimization
potential benefit: 1.5x speedup

cuDNN

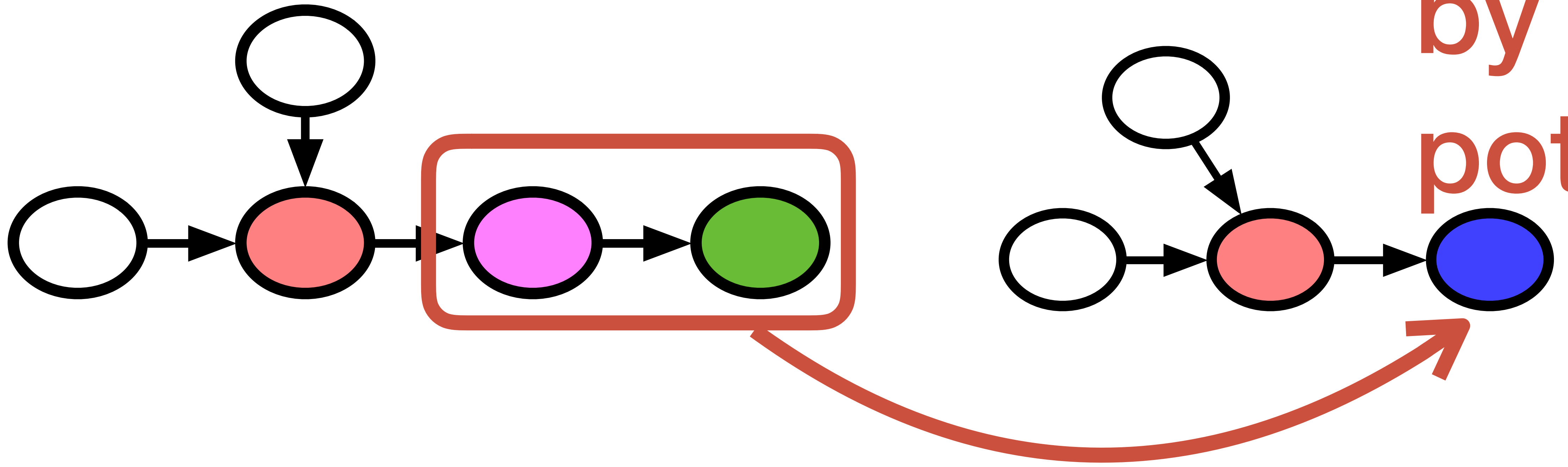




Limitations of Existing Approach

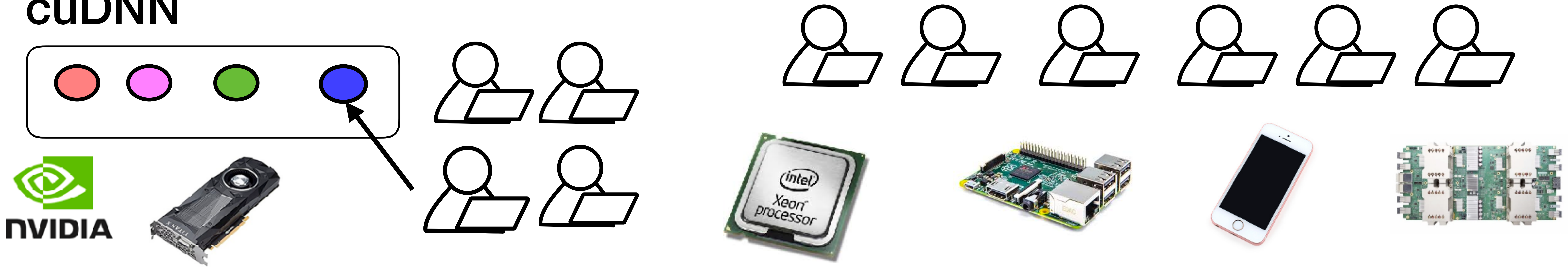
Frameworks

New operator introduced
by operator fusion optimization
potential benefit: 1.5x speedup

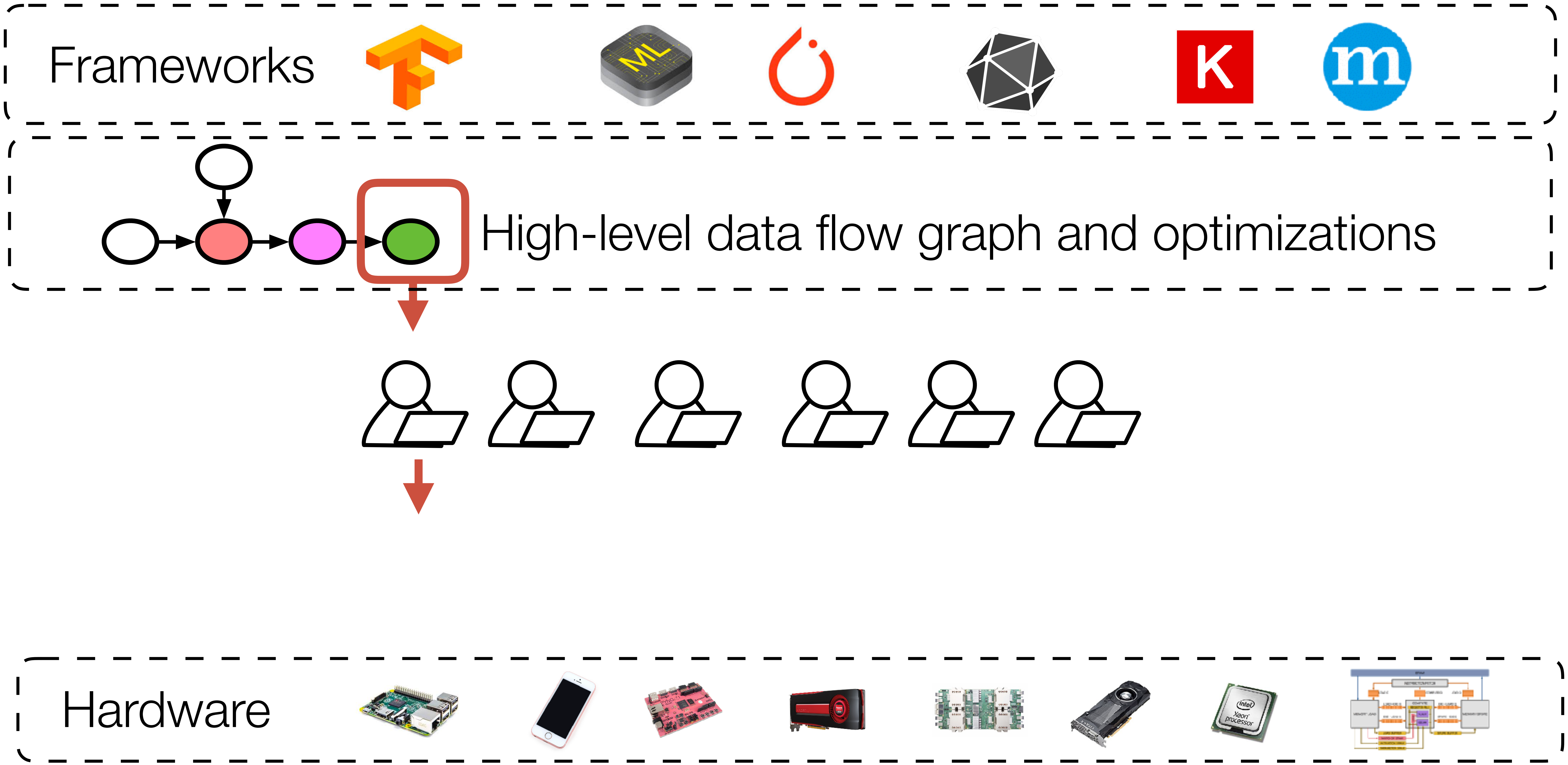


Engineering intensive

cuDNN

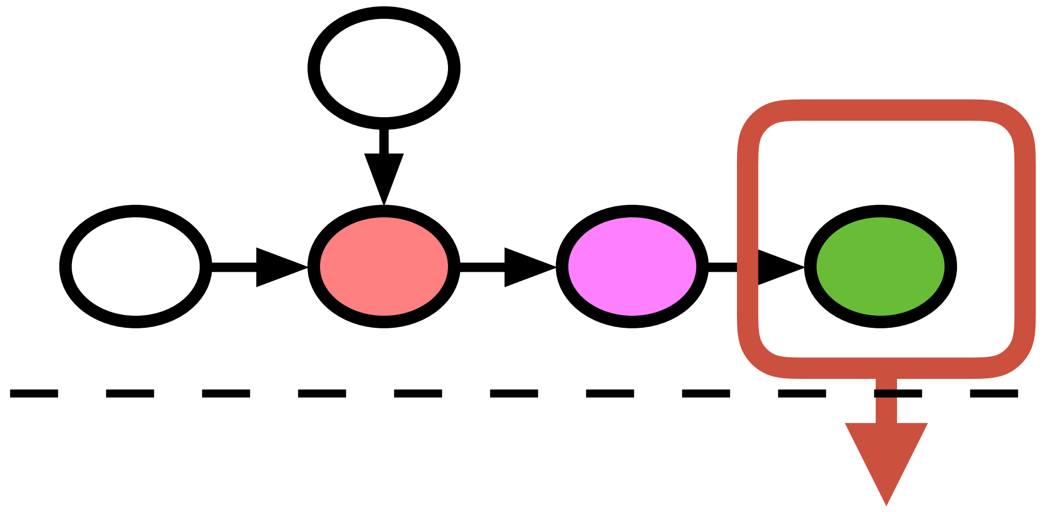


Learning-based Learning System



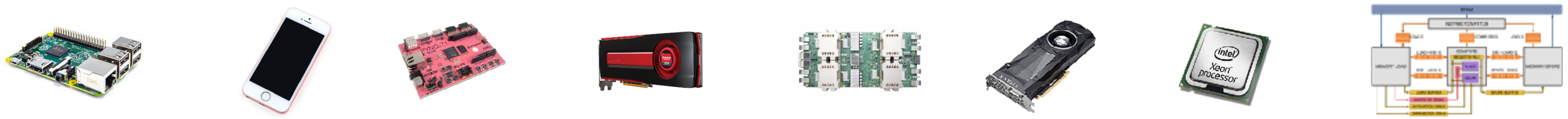
Learning-based Learning System

Frameworks

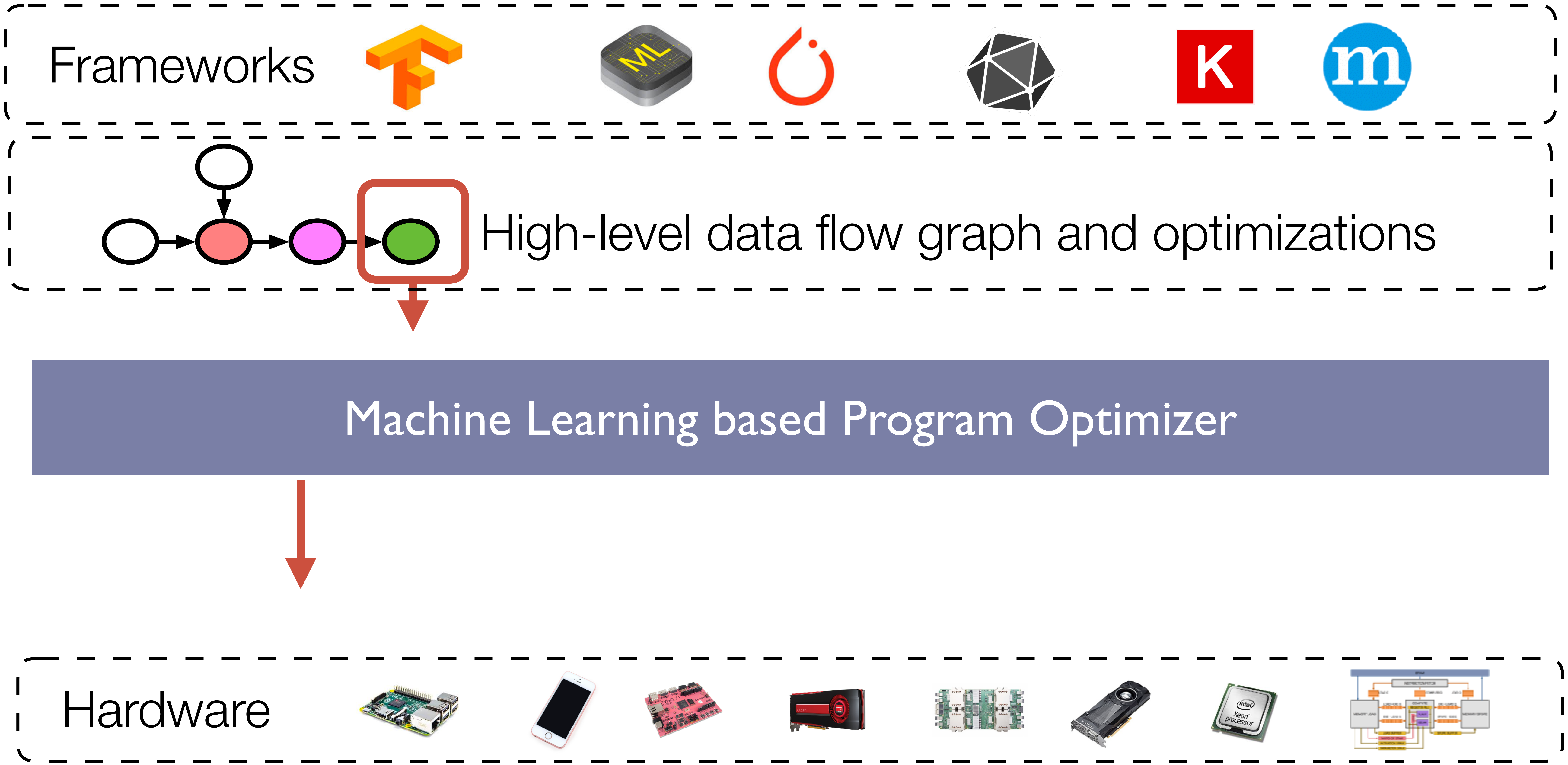


High-level data flow graph and optimizations

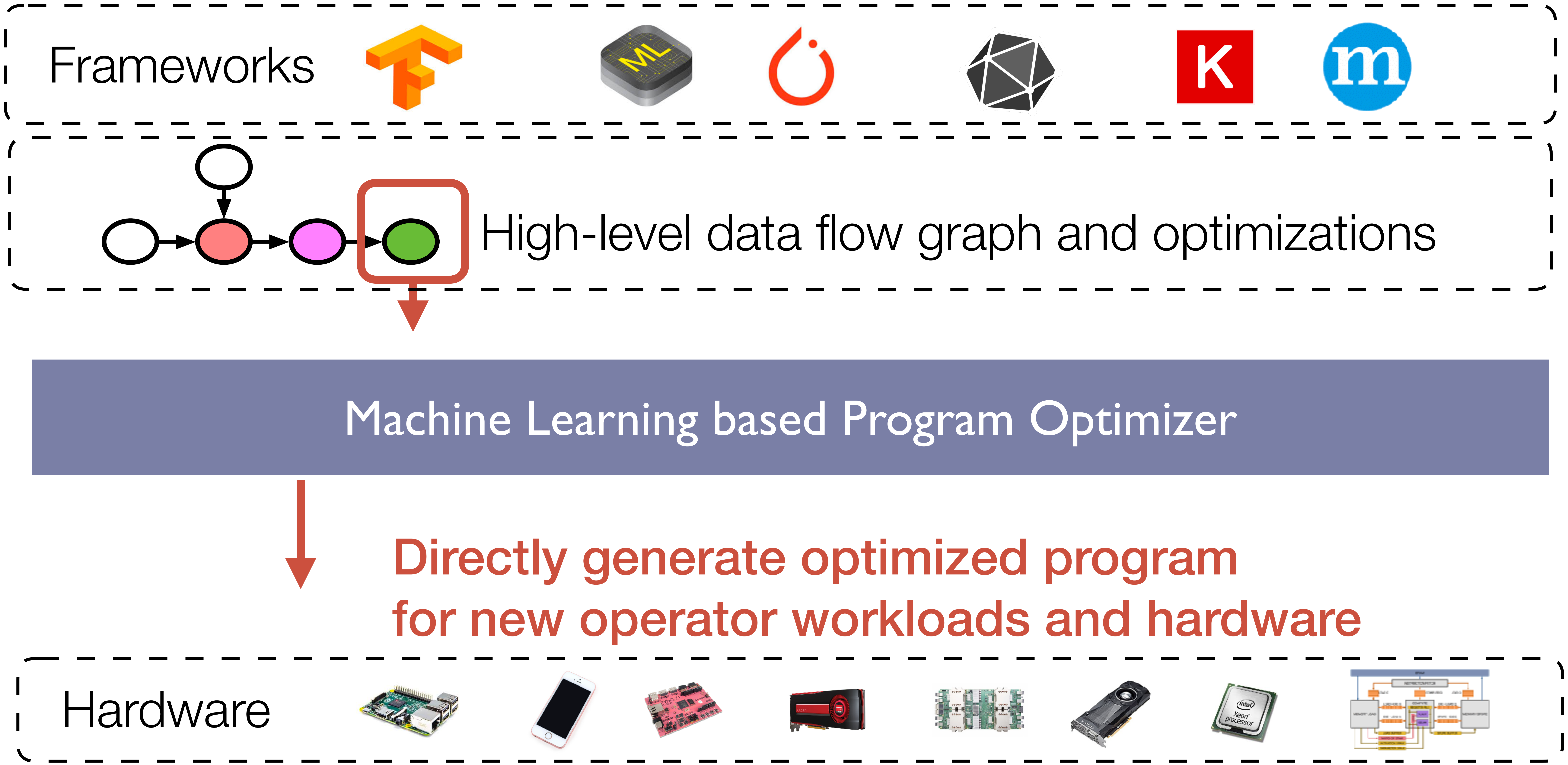
Hardware



Learning-based Learning System



Learning-based Learning System



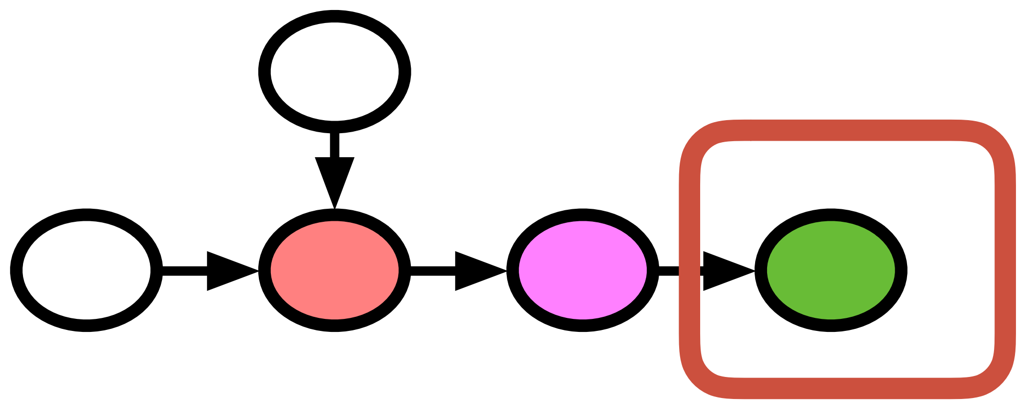
TVM: Learning-based Learning System

Why do we need machine learning for systems

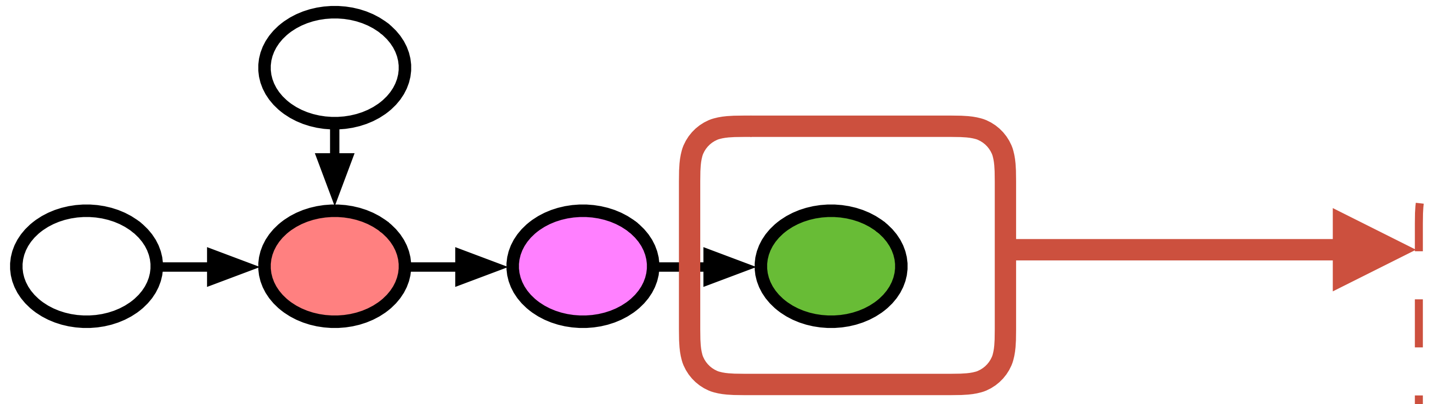
How to build intelligent systems with learning

End to end learning-based learning system stack

Problem Setting



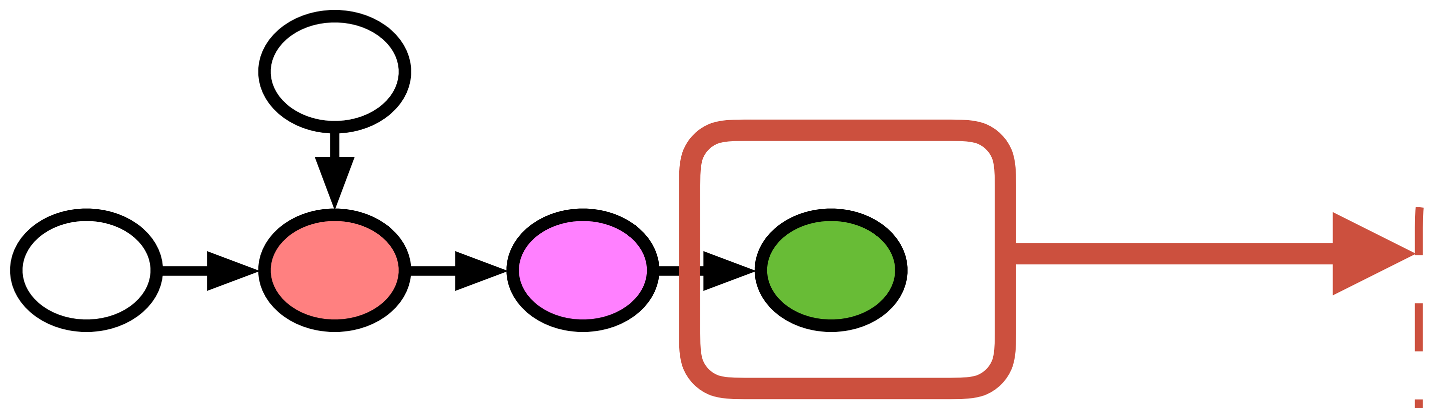
Problem Setting



Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Problem Setting

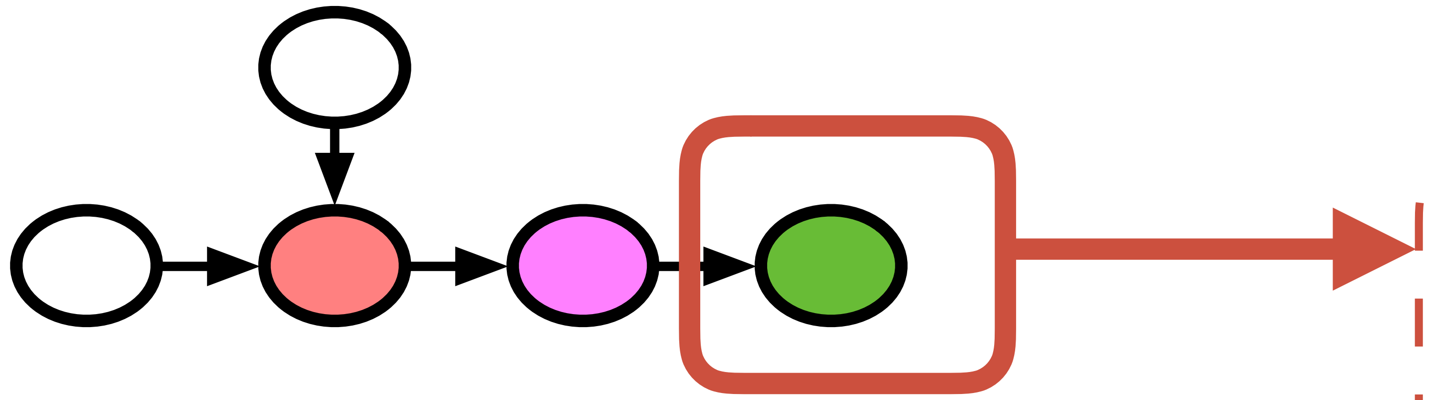


Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search Space of Possible Program Optimizations

Problem Setting



Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search Space of Possible Program Optimizations

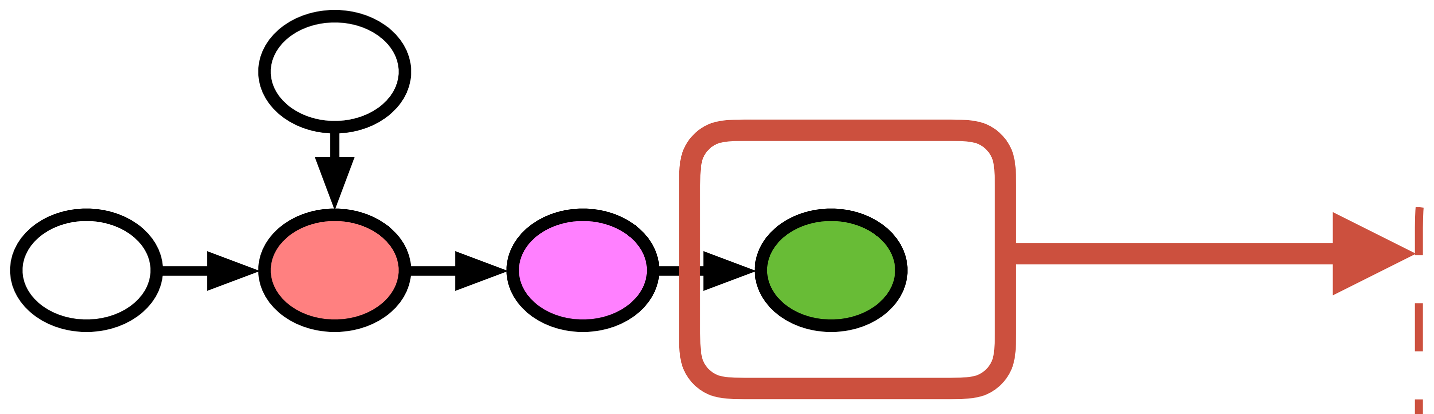
Low-level Program Variants

```
inp_buffer AL[8][8], BL[8][8]
acc_buffer CL[8][8]
for yo in range(128):
  for xo in range(128):
    vdla.fill_zero(CL)
    for ko in range(128):
      vdla.dma_copy2d(AL, A[ko*8:ko*8+8][yo*8:yo*8+8])
      vdla.dma_copy2d(BL, B[ko*8:ko*8+8][xo*8:xo*8+8])
      vdla.fused_gemm8x8_add(CL, AL, BL)
    vdla.dma_copy2d(C[yo*8:yo*8+8,xo*8:xo*8+8], CL)
```

```
for yo in range(128):
  for xo in range(128):
    C[yo*8:yo*8+8][xo*8:xo*8+8] = 0
    for ko in range(128):
      for yi in range(8):
        for xi in range(8):
          for ki in range(8):
            C[yo*8+yi][xo*8+xi] +=
               A[ko*8+ki][yo*8+yi] * B[ko*8+ki][xo*8+xi]
```

```
for y in range(1024):
  for x in range(1024):
    C[y][x] = 0
    for k in range(1024):
      C[y][x] += A[k][y] * B[k][x]
```

Example Instance in a Search Space

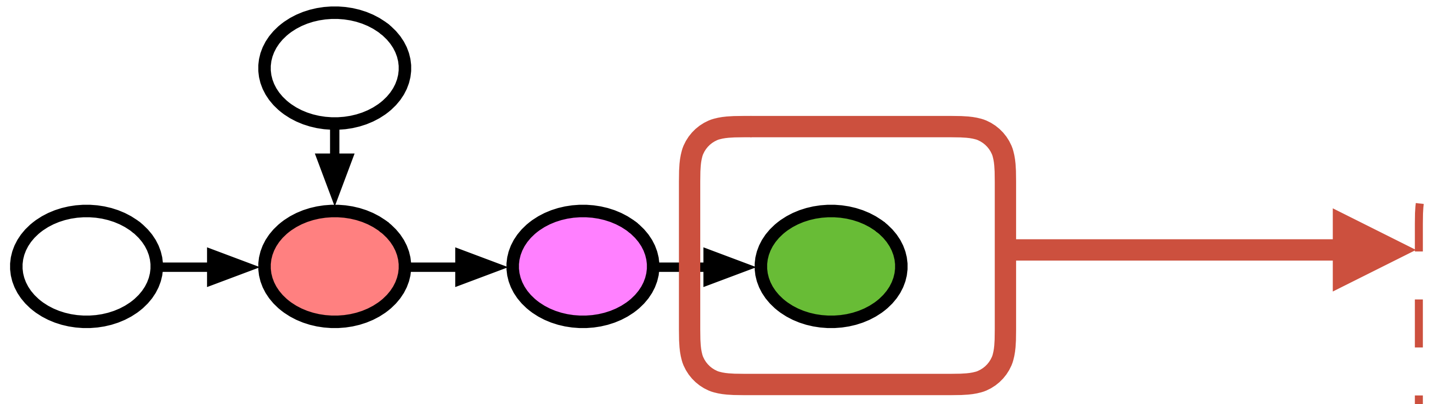


Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search Space of Possible Program Optimizations

Example Instance in a Search Space



Tensor Expression (Specification)

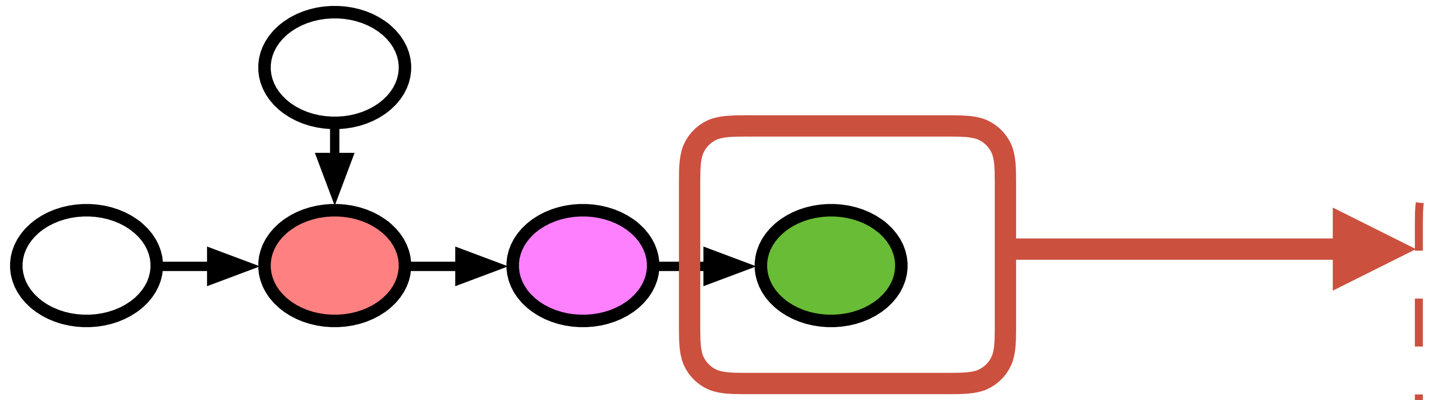
```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search Space of Possible Program Optimizations

Vanilla Code

```
for y in range(1024):
  for x in range(1024):
    C[y][x] = 0
    for k in range(1024):
      C[y][x] += A[k][y] * B[k][x]
```

Example Instance in a Search Space



Tensor Expression (Specification)

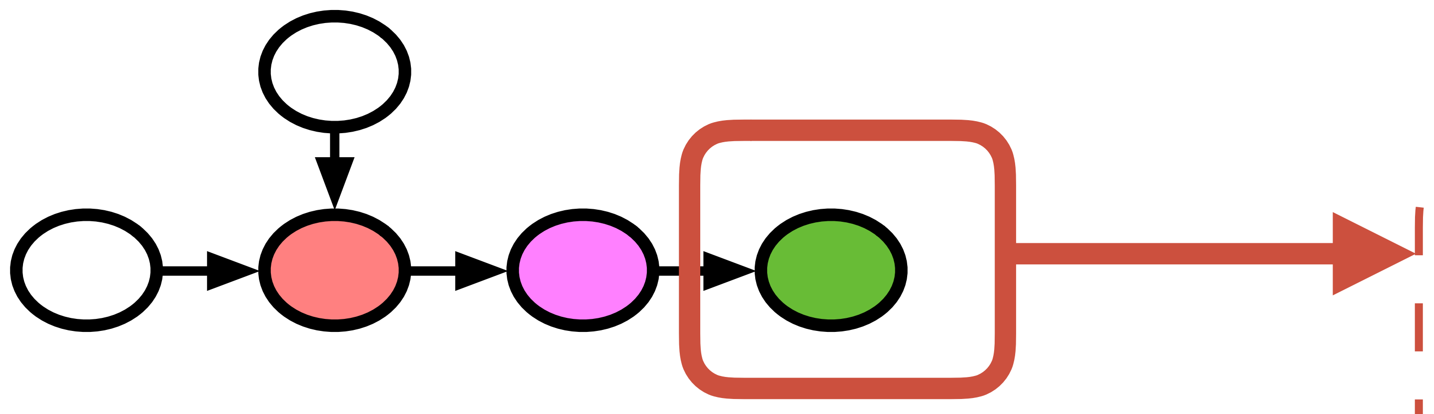
```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search Space of Possible Program Optimizations

Loop Tiling for Locality

```
for yo in range(128):
  for xo in range(128):
    C[yo*8:yo*8+8][xo*8:xo*8+8] = 0
    for ko in range(128):
      for yi in range(8):
        for xi in range(8):
          for ki in range(8):
            C[yo*8+yi][xo*8+xi] +=
               A[ko*8+ki][yo*8+yi] * B[ko*8+ki][xo*8+xi]
```

Example Instance in a Search Space



Tensor Expression (Specification)

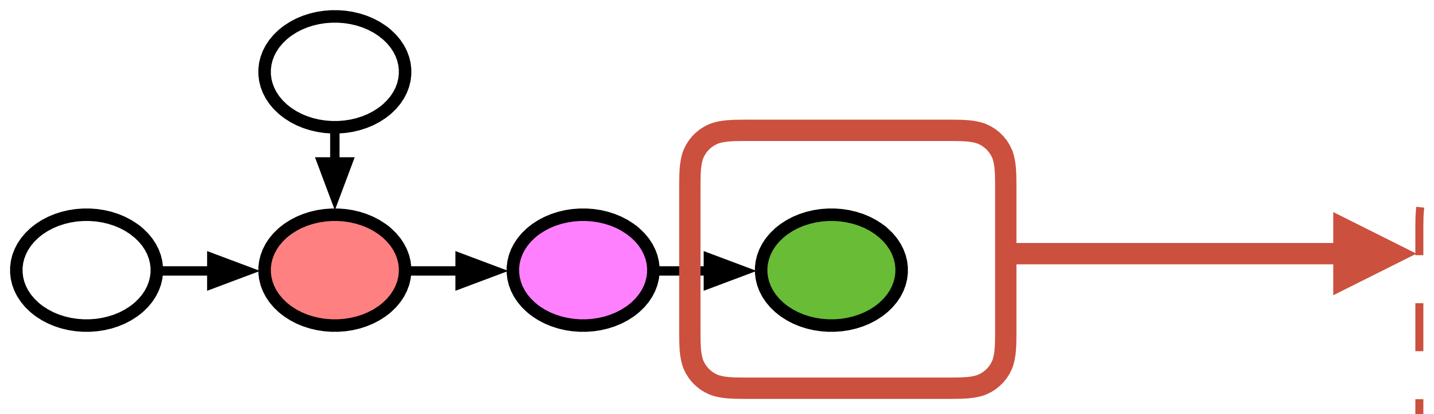
```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search Space of Possible Program Optimizations

Map to Accelerators

```
inp_buffer AL[8][8], BL[8][8]
acc_buffer CL[8][8]
for yo in range(128):
  for xo in range(128):
    vdla.fill_zero(CL)
    for ko in range(128):
      vdla.dma_copy2d(AL, A[ko*8:ko*8+8][yo*8:yo*8+8])
      vdla.dma_copy2d(BL, B[ko*8:ko*8+8][xo*8:xo*8+8])
      vdla.fused_gemm8x8_add(CL, AL, BL)
    vdla.dma_copy2d(C[yo*8:yo*8+8,xo*8:xo*8+8], CL)
```

Optimization Choices in a Search Space



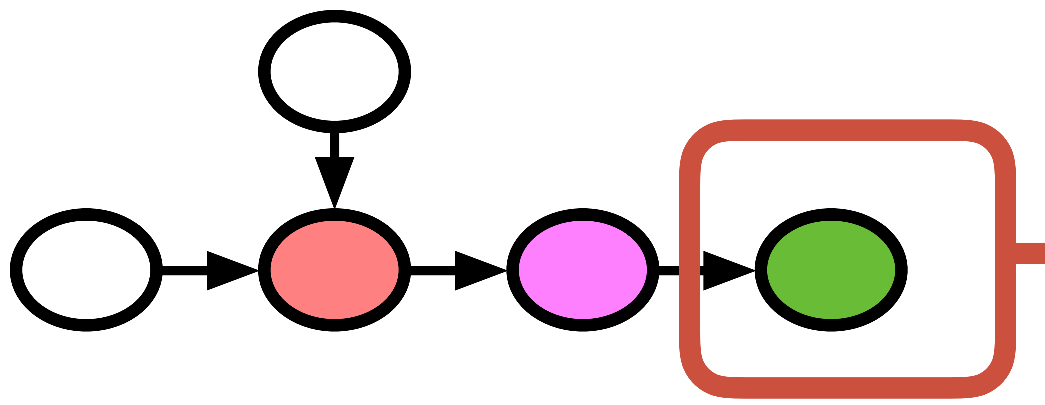
Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

- Loop Transformations
- Thread Bindings
- Cache Locality
- Thread Cooperation
- Tensorization
- Latency Hiding

More details about the search space
in the second half of the talk

Optimization Choices in a Search Space



Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Loop Transformations

Thread Bindings

Cache Locality

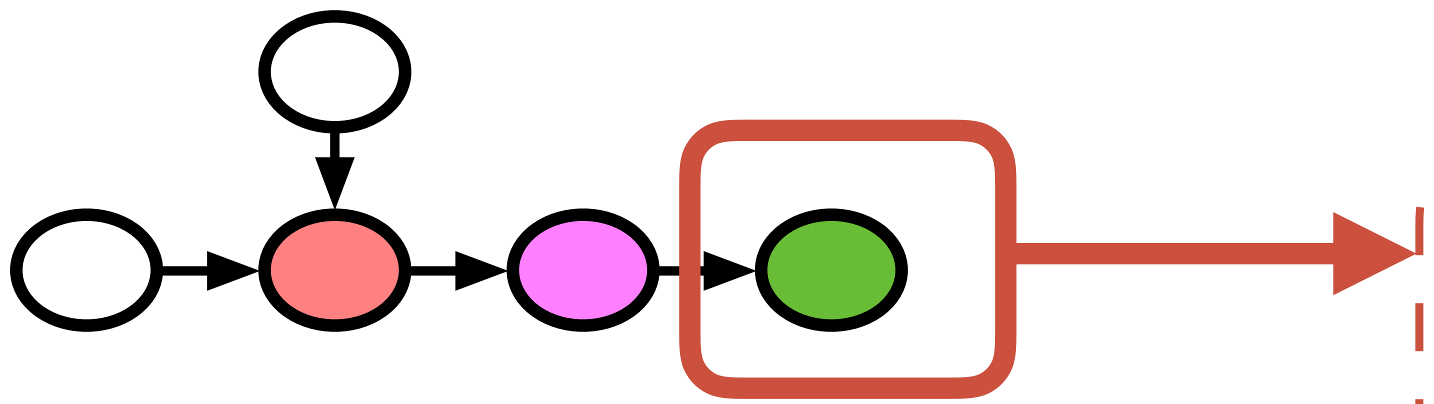
Thread Cooperation

Tensorization

Latency Hiding

More details about the search space
in the second half of the talk

Optimization Choices in a Search Space



Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Billions of possible optimization choices

- Loop Transformations
- Thread Bindings
- Cache Locality
- Thread Cooperation
- Tensorization
- Latency Hiding

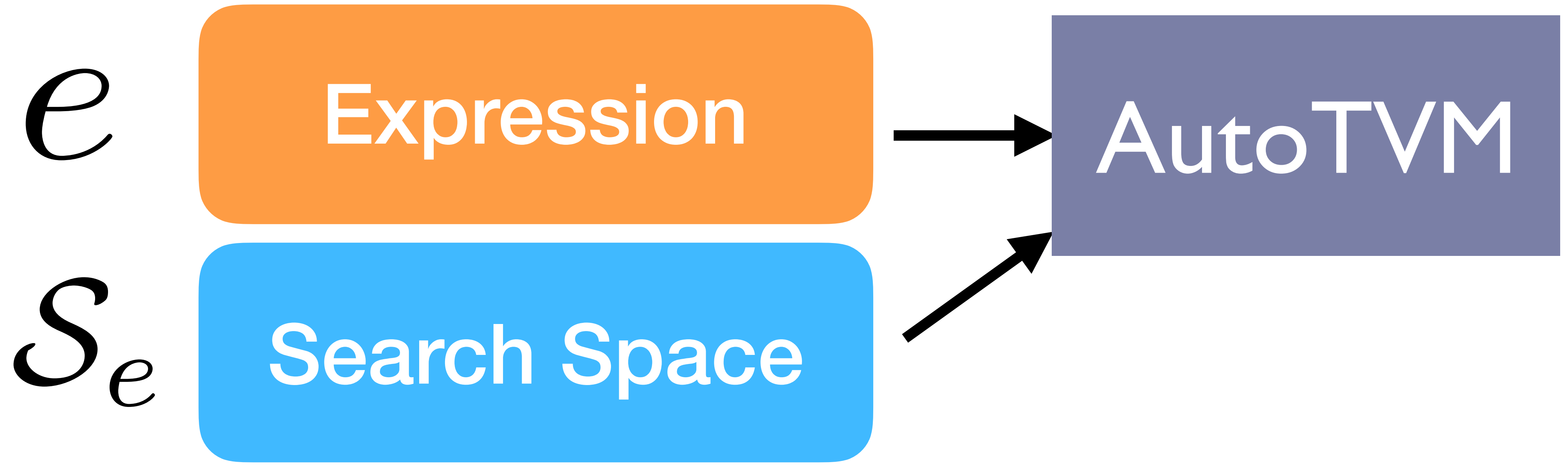
More details about the search space in the second half of the talk

Problem Formalization

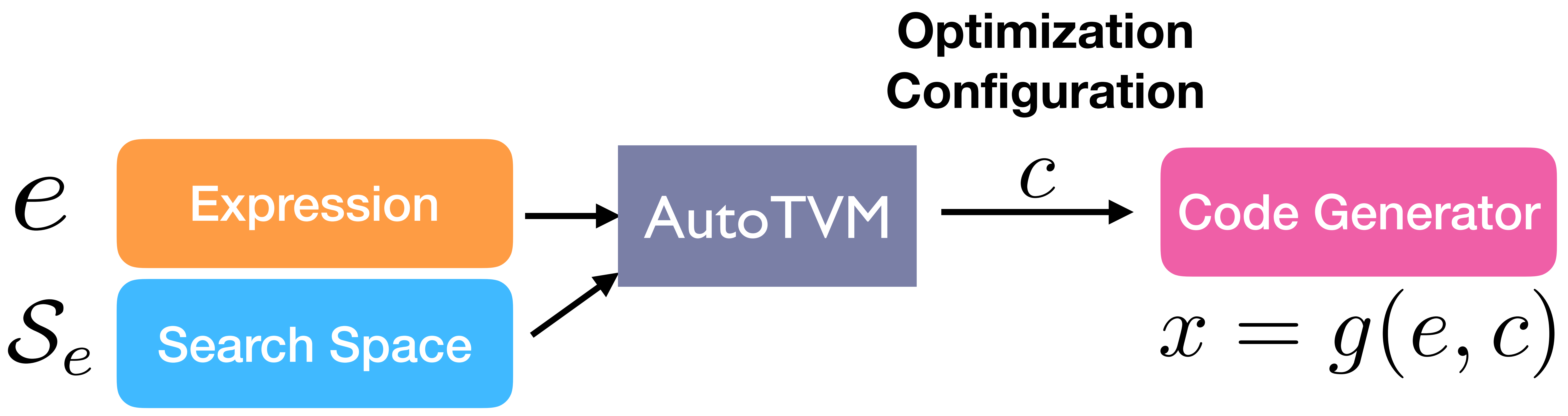
e Expression

$\mathcal{S}_e$ Search Space

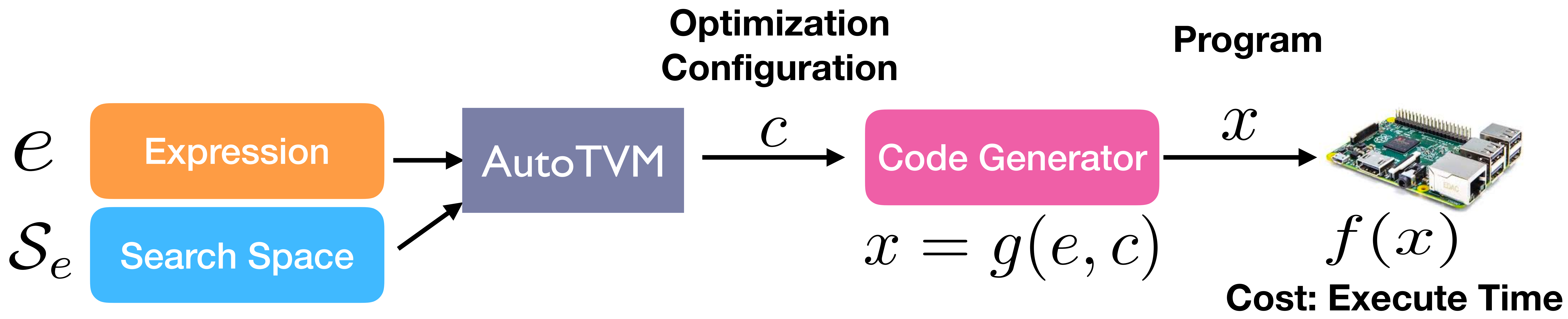
Problem Formalization



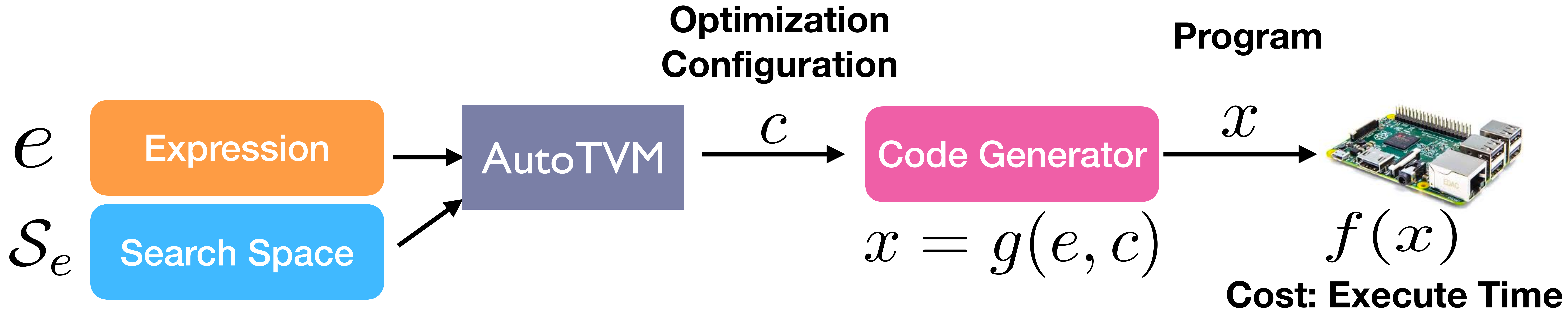
Problem Formalization



Problem Formalization



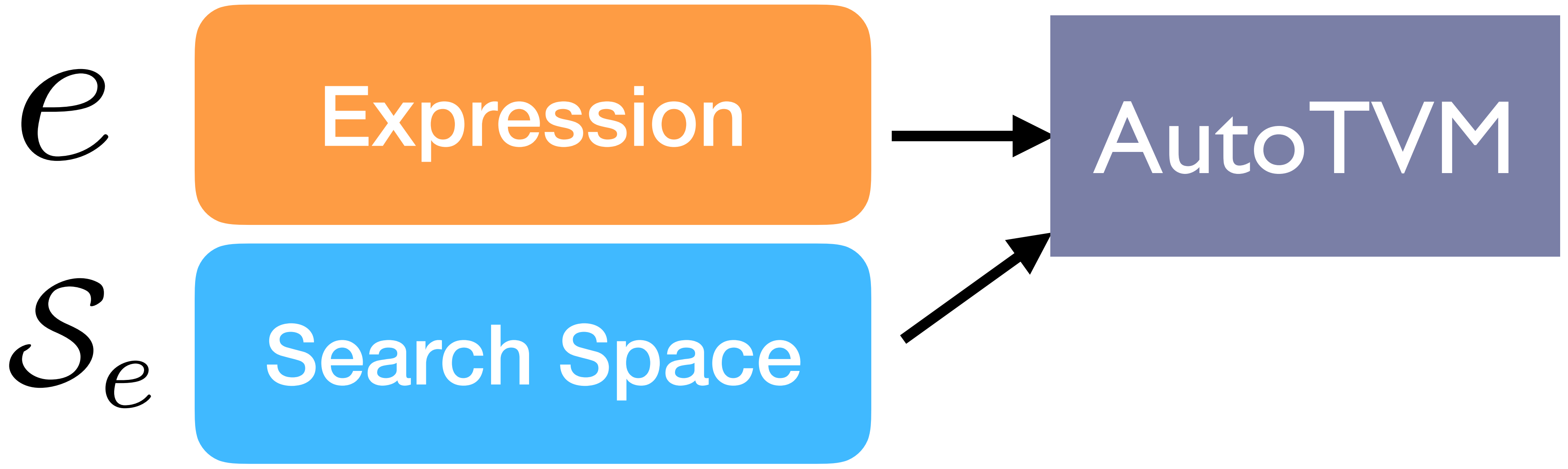
Problem Formalization



Objective $argmin_{c \in \mathcal{S}_e} f(g(e, c))$

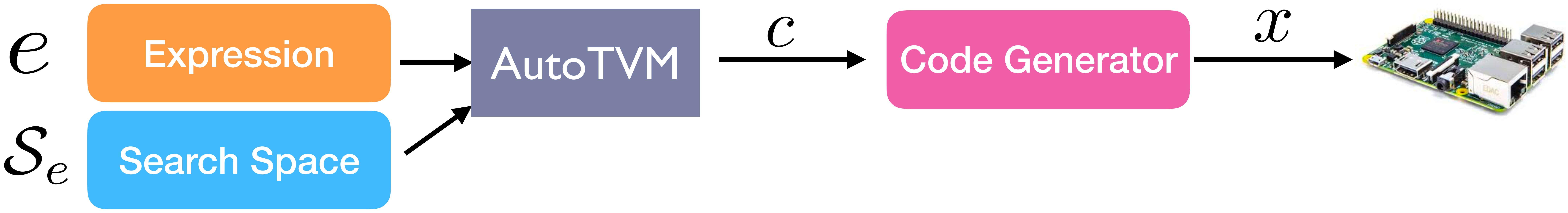
Black-box Optimization

Try each configuration c until we find a good one



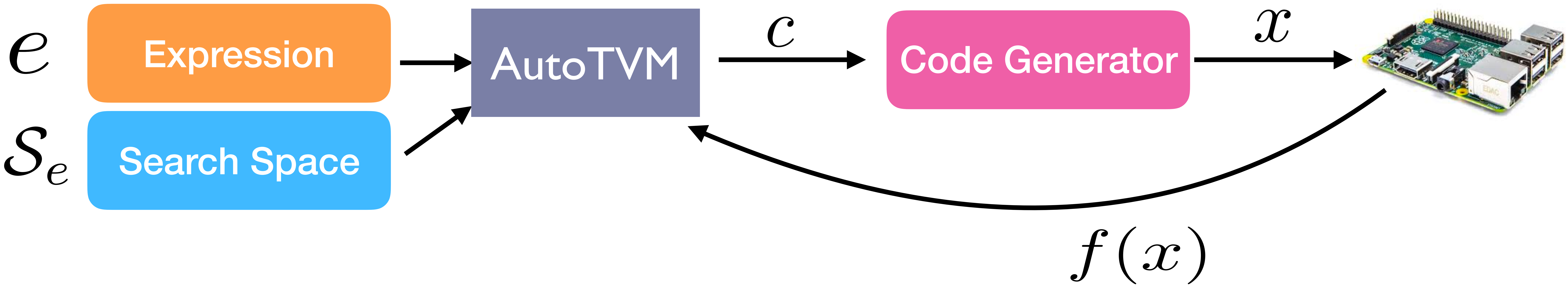
Black-box Optimization

Try each configuration c until we find a good one



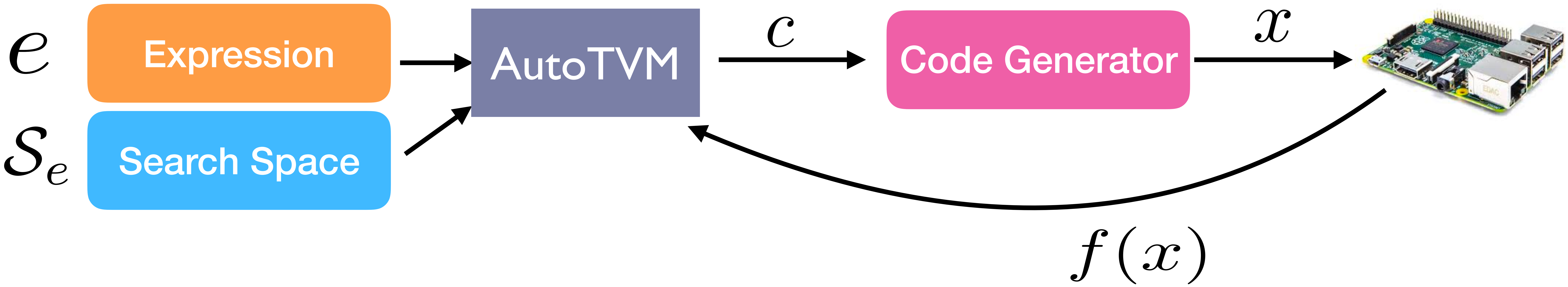
Black-box Optimization

Try each configuration c until we find a good one



Black-box Optimization

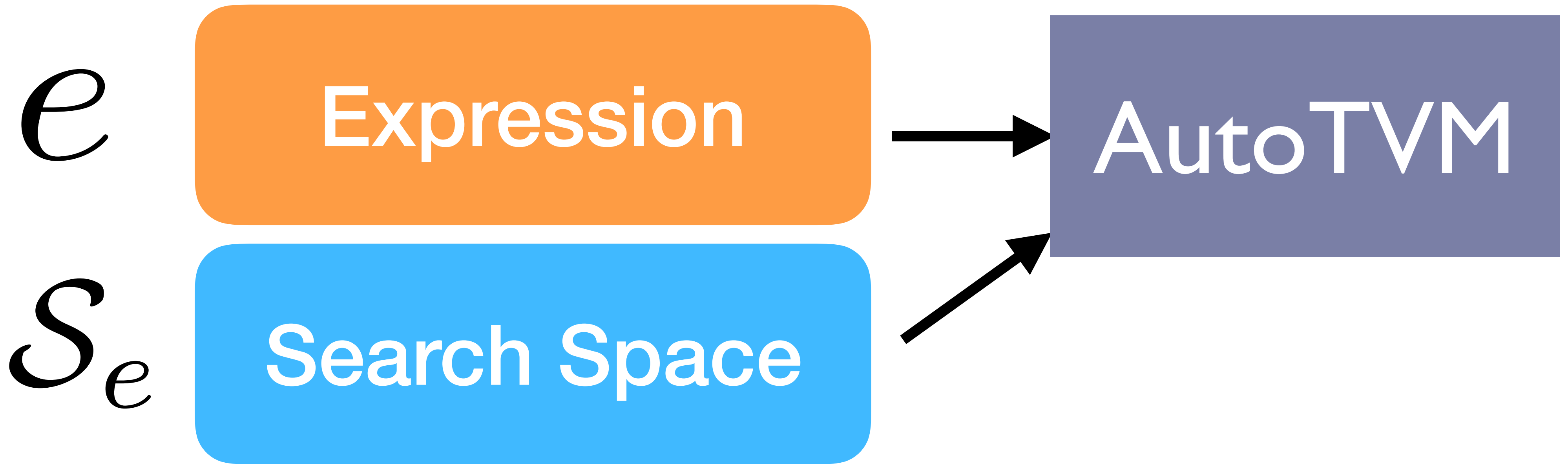
Try each configuration c until we find a good one



Challenge: lots of experimental trials, each trial costs ~1 second

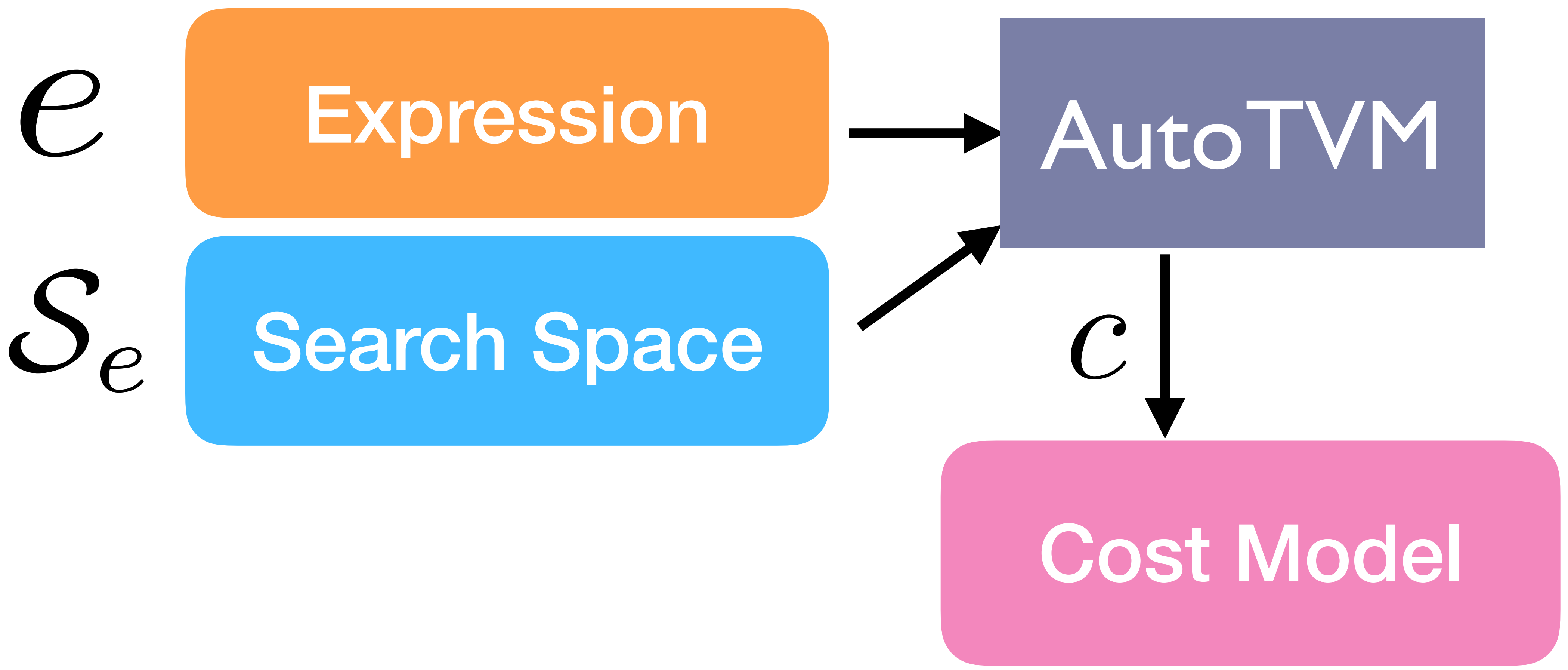
Cost-model Driven Approach

Use cost model to pick configuration



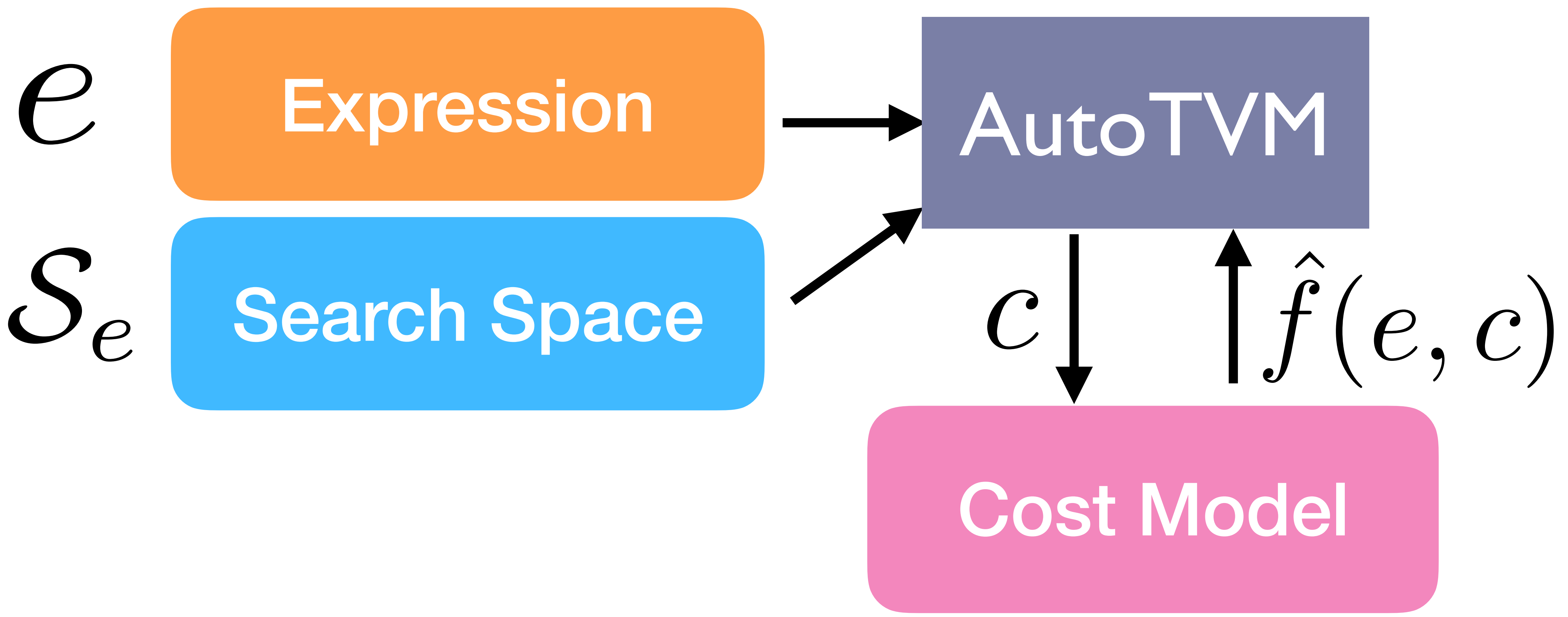
Cost-model Driven Approach

Use cost model to pick configuration



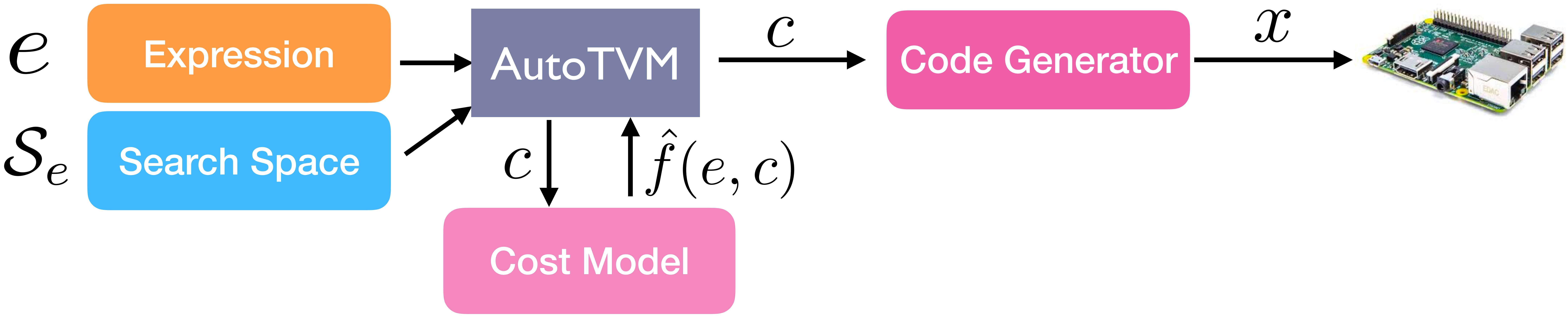
Cost-model Driven Approach

Use cost model to pick configuration



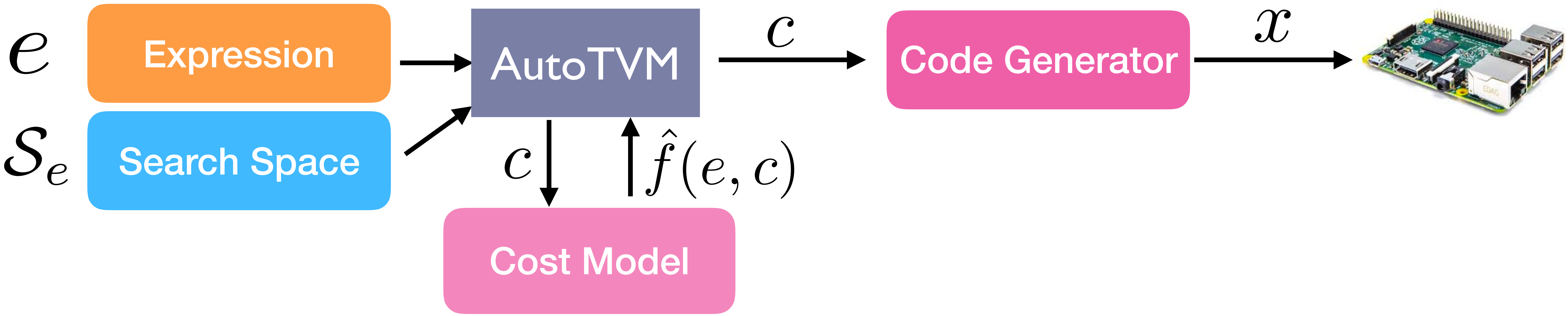
Cost-model Driven Approach

Use cost model to pick configuration



Cost-model Driven Approach

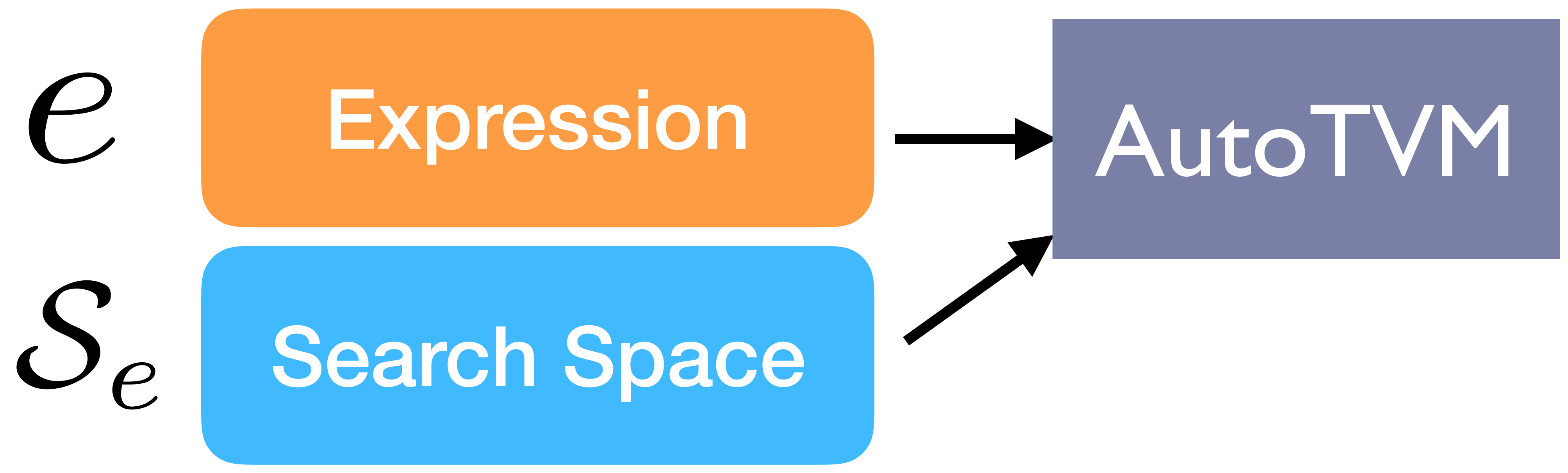
Use cost model to pick configuration



Challenge: Need reliable cost model per hardware

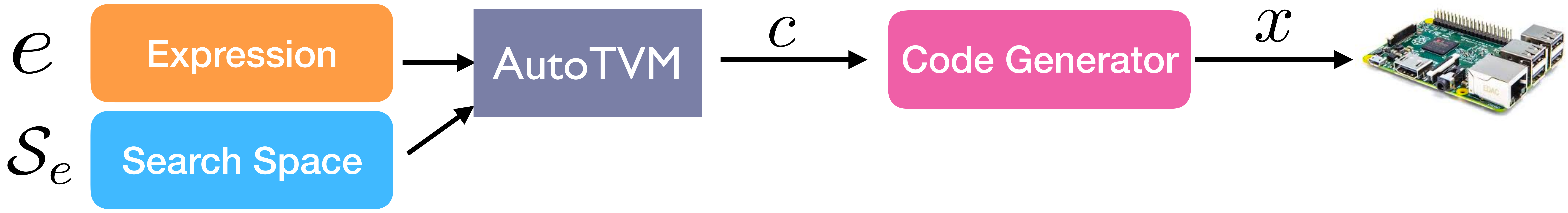
Statistical Cost Model

Use machine learning to learn a statistical cost model



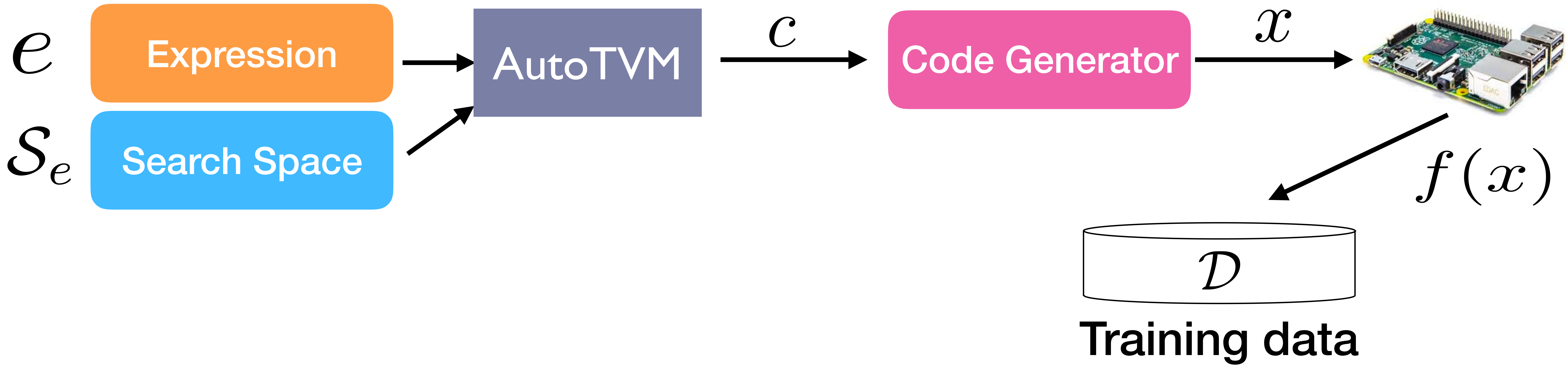
Statistical Cost Model

Use machine learning to learn a statistical cost model



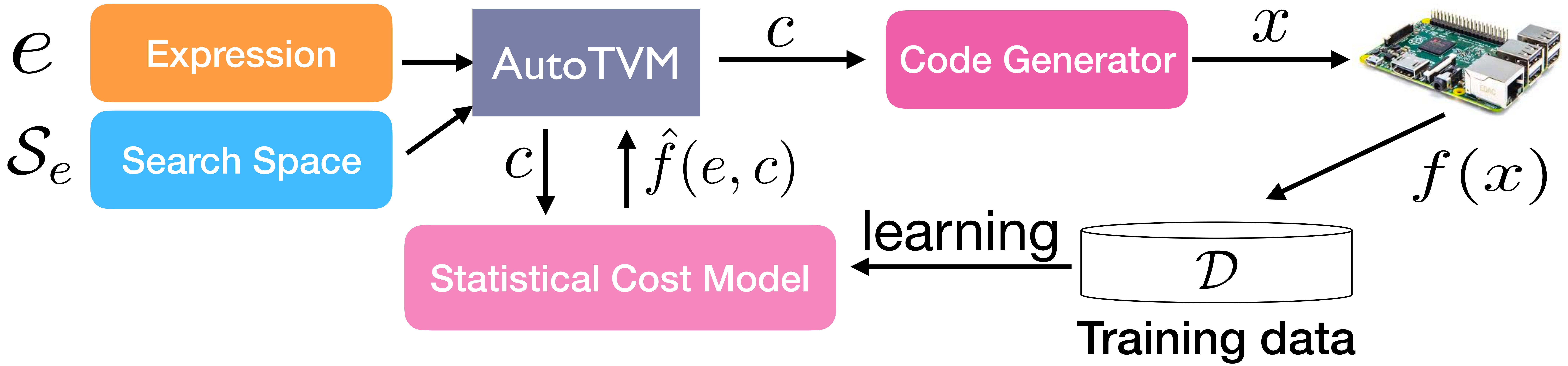
Statistical Cost Model

Use machine learning to learn a statistical cost model



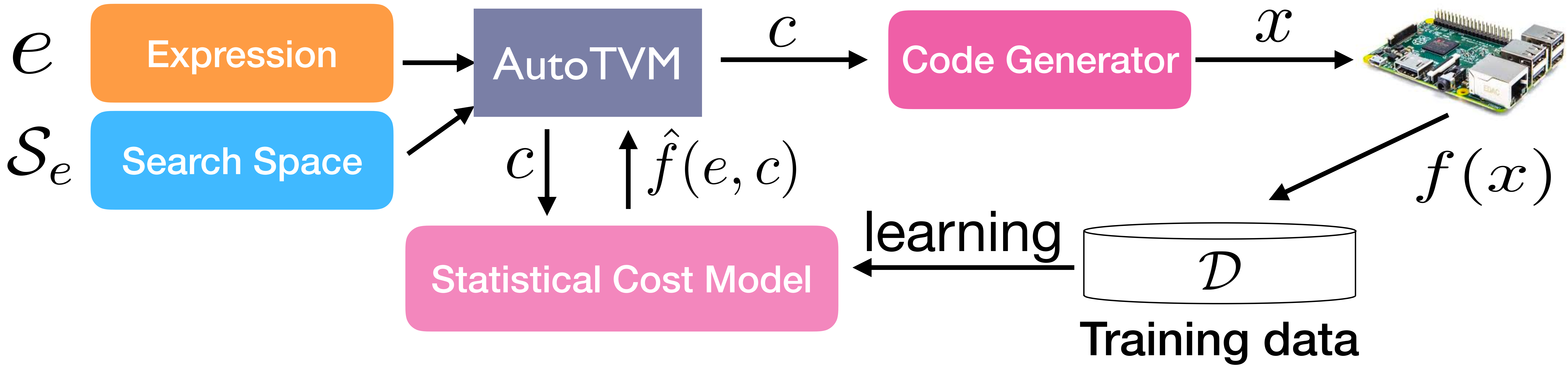
Statistical Cost Model

Use machine learning to learn a statistical cost model



Statistical Cost Model

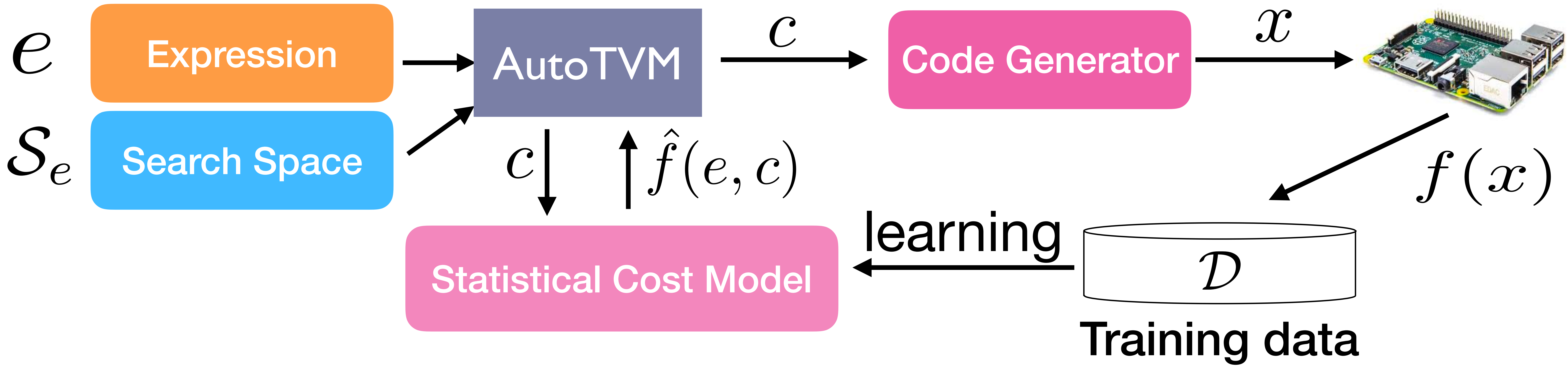
Use machine learning to learn a statistical cost model



Benefit: Automatically adapt to hardware type

Statistical Cost Model

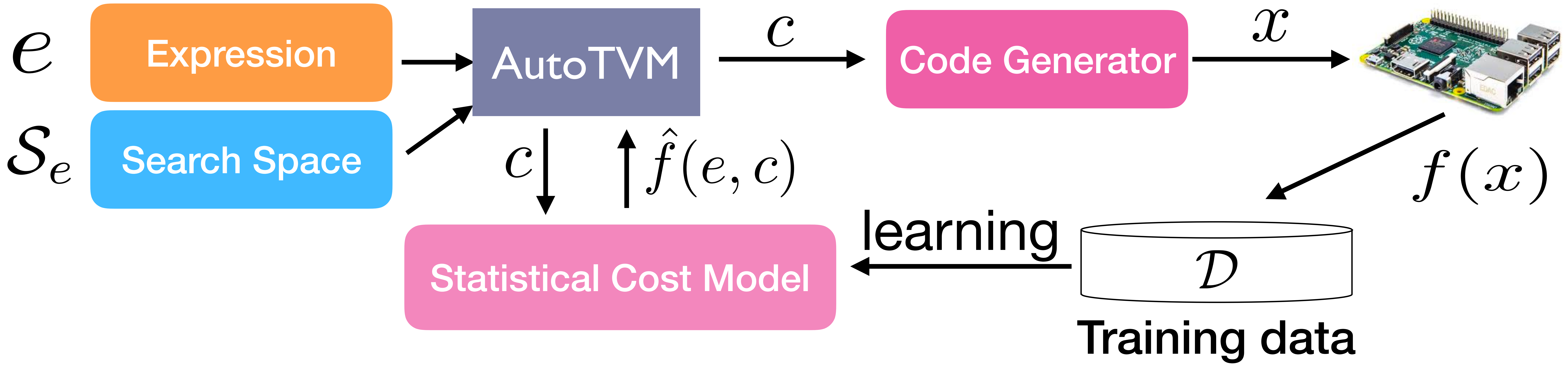
Use machine learning to learn a statistical cost model



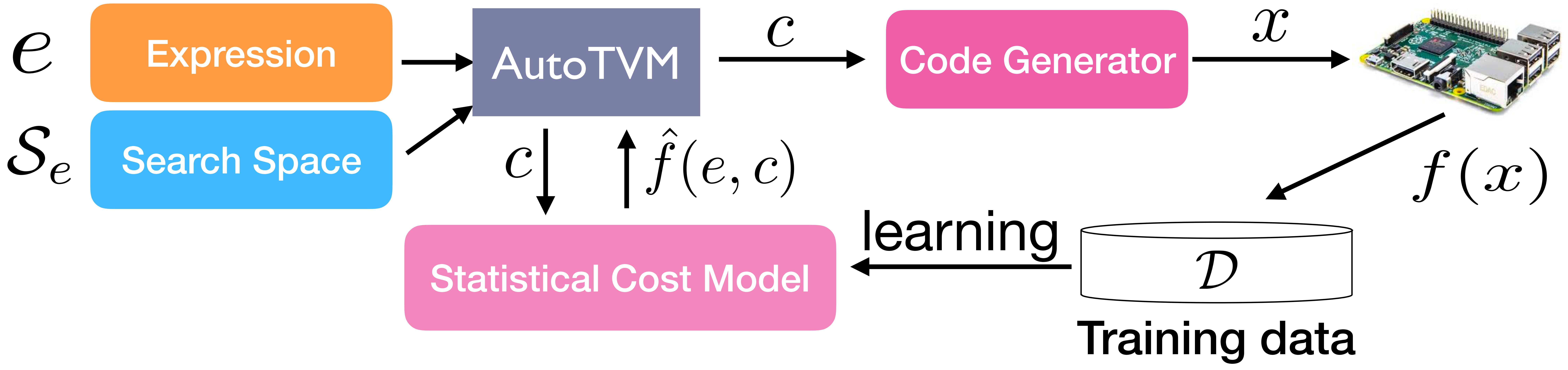
Benefit: Automatically adapt to hardware type

Challenge: How to design the cost model

Unique Problem Characteristics

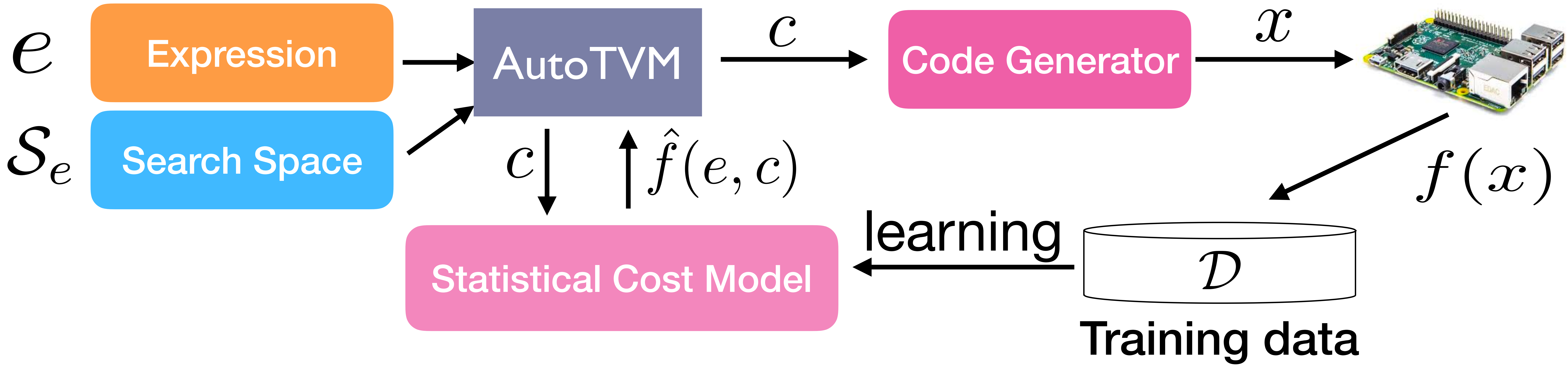


Unique Problem Characteristics



Relatively low experiment cost

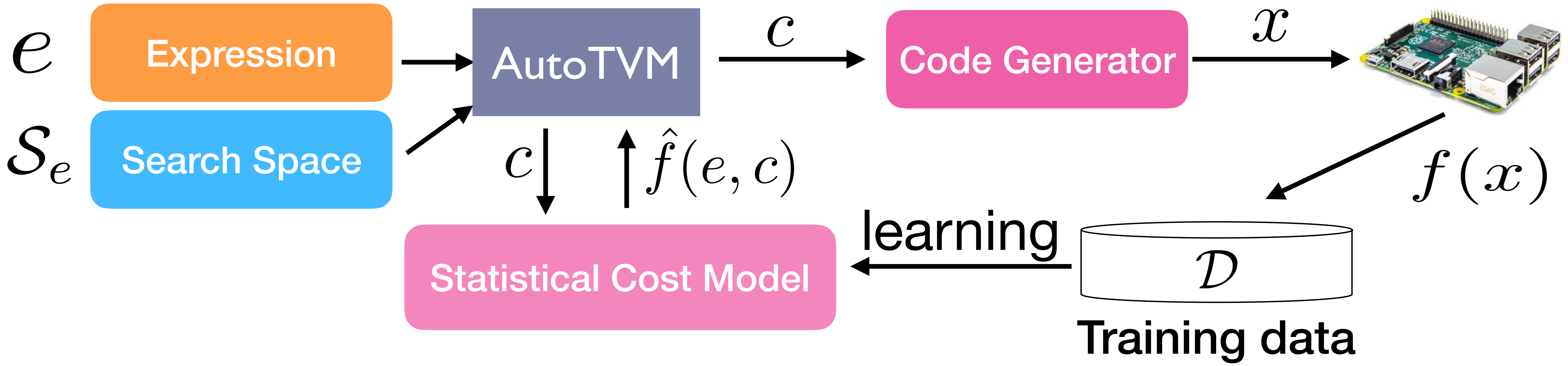
Unique Problem Characteristics



Relatively low experiment cost

Program-aware modeling

Unique Problem Characteristics

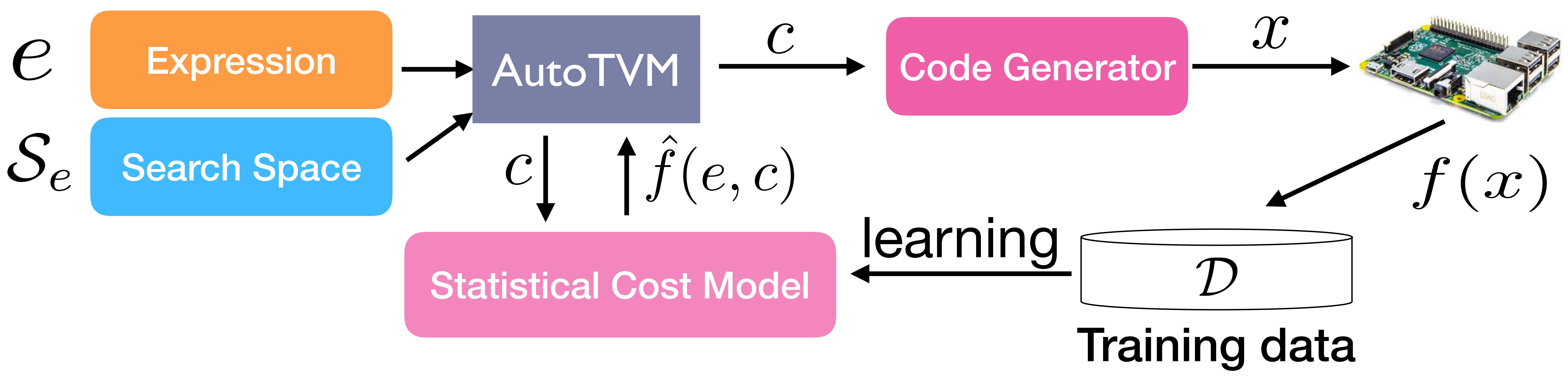


Relatively low experiment cost

Program-aware modeling

Large number of similar tasks

Unique Problem Characteristics



Relatively low experiment cost

Program-aware modeling

Large number of similar tasks

Vanilla Cost Modeling

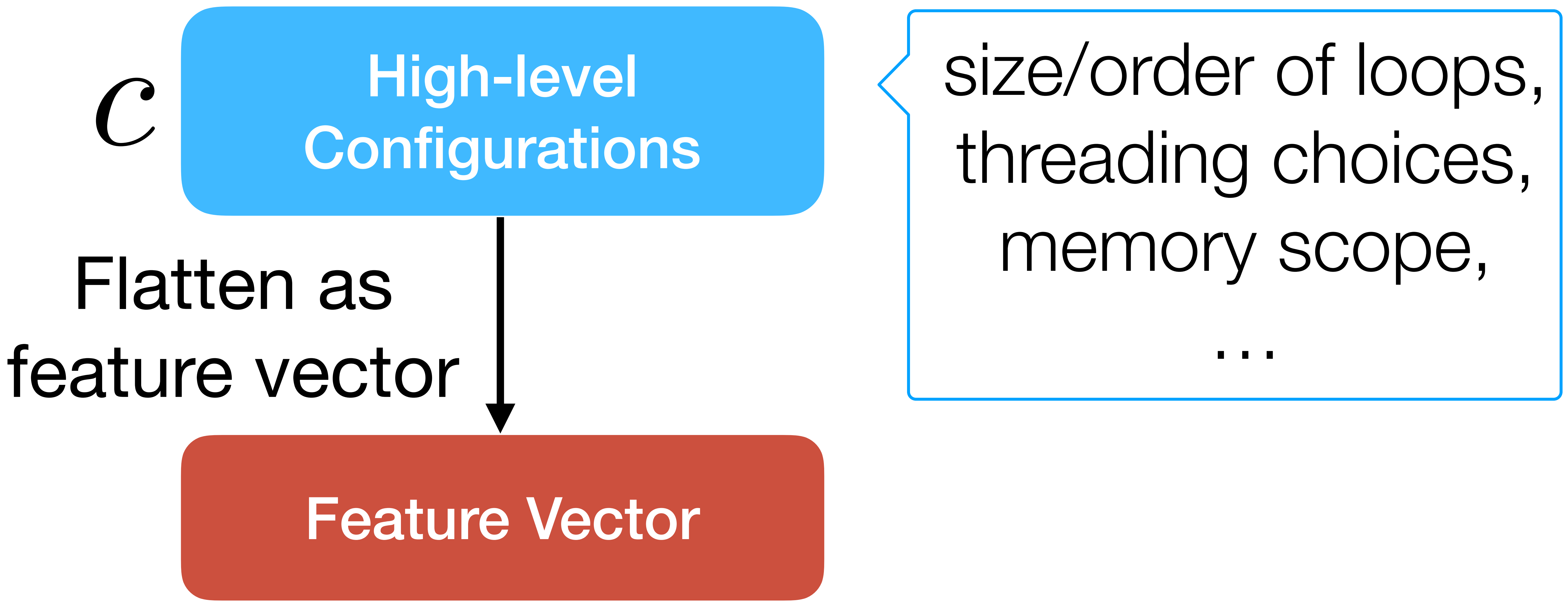
c High-level Configurations

Vanilla Cost Modeling

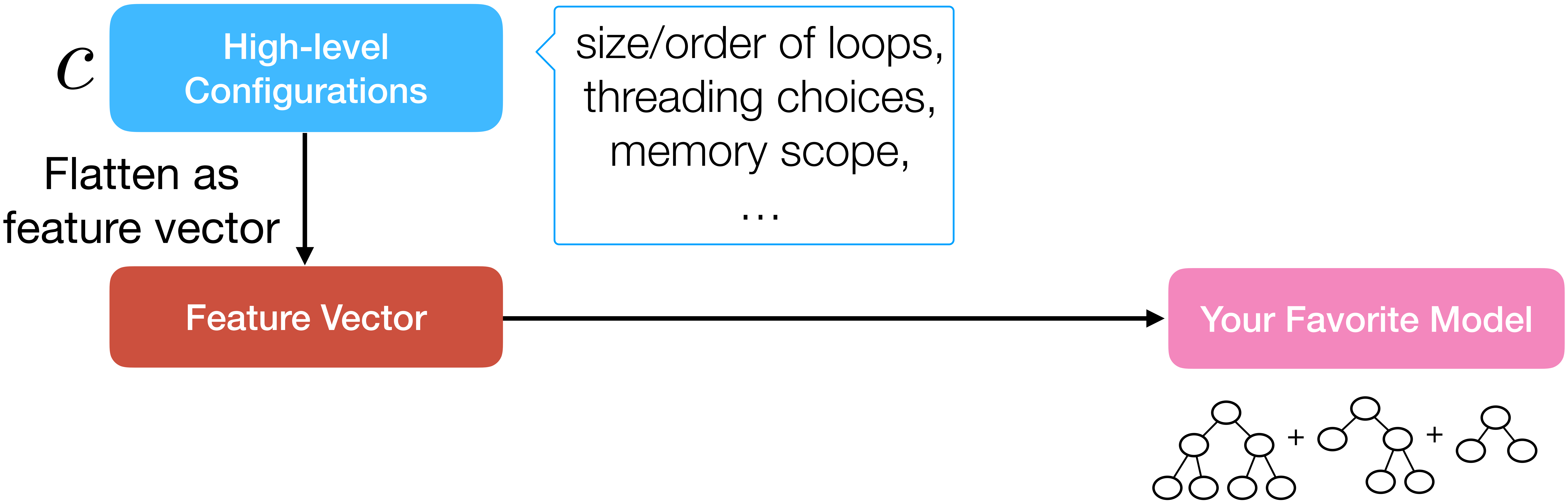
c High-level Configurations

size/order of loops,
threading choices,
memory scope,
…

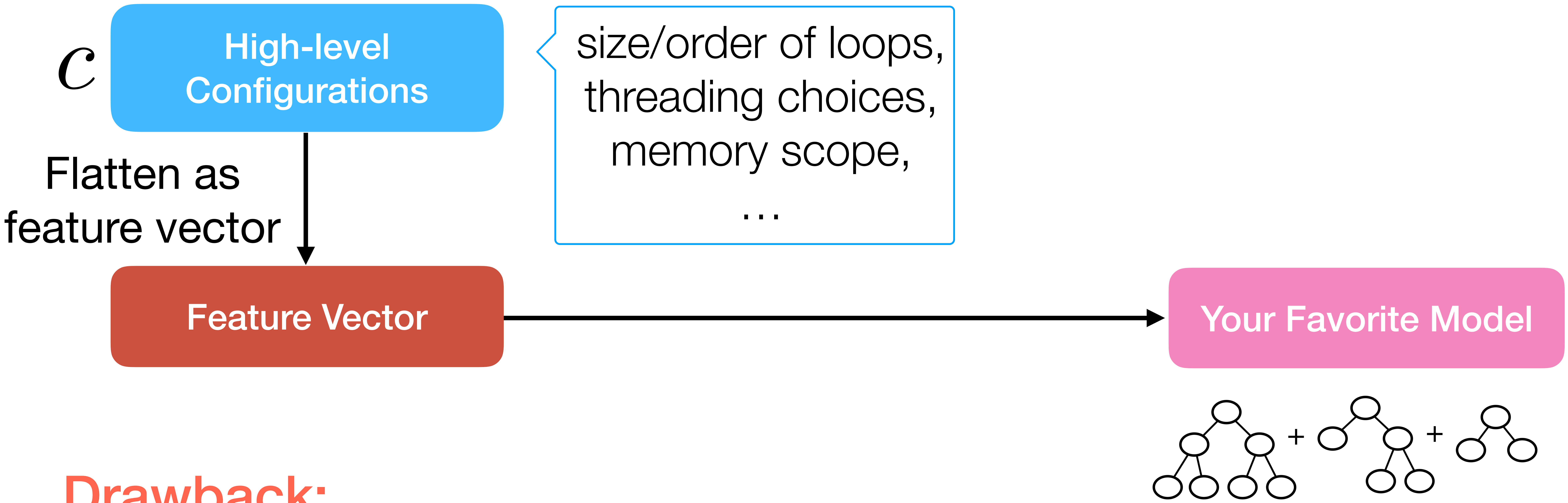
Vanilla Cost Modeling



Vanilla Cost Modeling



Vanilla Cost Modeling



Drawback:

- Ignores domain knowledge
- Set of configurations can differ per task (task dependent)

Program-aware Modeling: Tree-based Approach

c High-level Configurations

Program-aware Modeling: Tree-based Approach

c High-level Configurations

```
for y in range(8):
  for x in range(8):
    C[y][x]=0
    for k in range(8):
      C[y][x]+=A[k][y]*B[k][x]
```

Low-level
Abstract Syntax Tree (AST)

Program-aware Modeling: Tree-based Approach

c High-level Configurations

```
for y in range(8):
  for x in range(8):
    C[y][x]=0
    for k in range(8):
      C[y][x]+=A[k][y]*B[k][x]
```

Low-level
Abstract Syntax Tree (AST)

touched memory

	C	A	B
y	64	64	64
x	8	8	64
k	1	8	8

outer loop length

y	1
x	8
k	64

Statistical features
of AST

Program-aware Modeling: Tree-based Approach

c **High-level Configurations**

```
for y in range(8):
  for x in range(8):
    C[y][x]=0
    for k in range(8):
      C[y][x]+=A[k][y]*B[k][x]
```

Low-level
Abstract Syntax Tree (AST)

touched memory

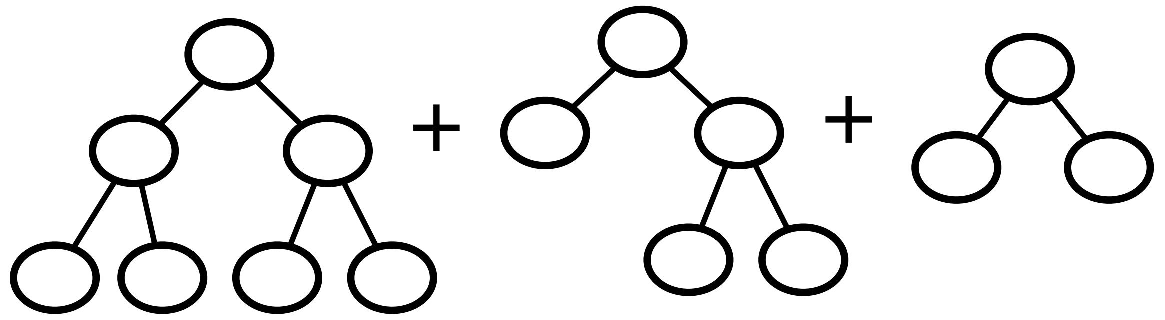
	C	A	B
y	64	64	64
x	8	8	64
k	1	8	8

outer loop length

y	1
x	8
k	64

Statistical features of AST

Your Favorite Model



Program-aware Modeling: Tree-based Approach

c **High-level Configurations**

```
for y in range(8):
  for x in range(8):
    C[y][x]=0
    for k in range(8):
      C[y][x]+=A[k][y]*B[k][x]
```

Low-level
Abstract Syntax Tree (AST)

touched memory

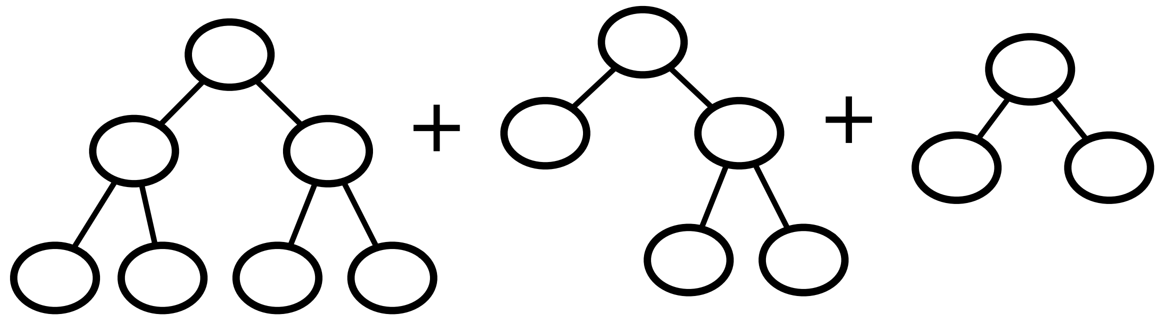
	C	A	B
y	64	64	64
x	8	8	64
k	1	8	8

outer loop length

y	1
x	8
k	64

Statistical features of AST

Your Favorite Model



Benefit: low-level AST is a common representation (task invariant)

Program-aware Modeling: Neural Approach

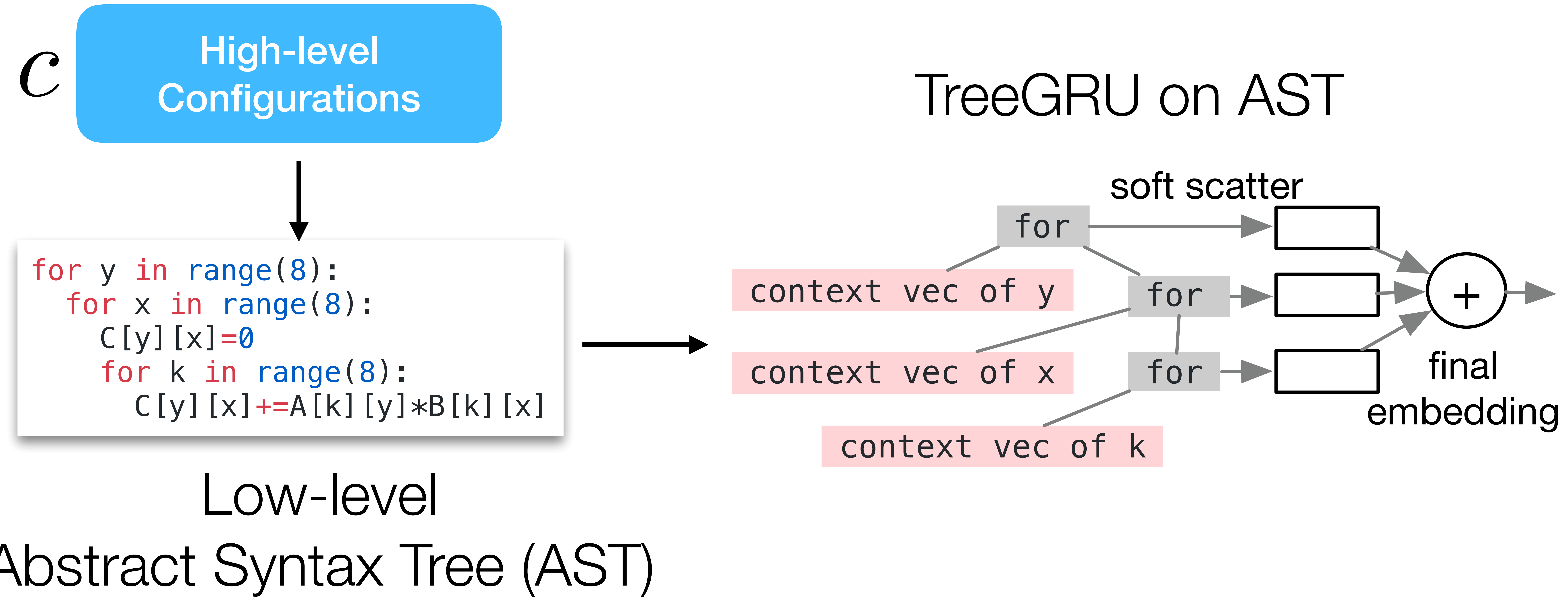
c

High-level Configurations

```
for y in range(8):
  for x in range(8):
    C[y][x]=0
    for k in range(8):
      C[y][x]+=A[k][y]*B[k][x]
```

Low-level
Abstract Syntax Tree (AST)

Program-aware Modeling: Neural Approach



Comparisons of Models

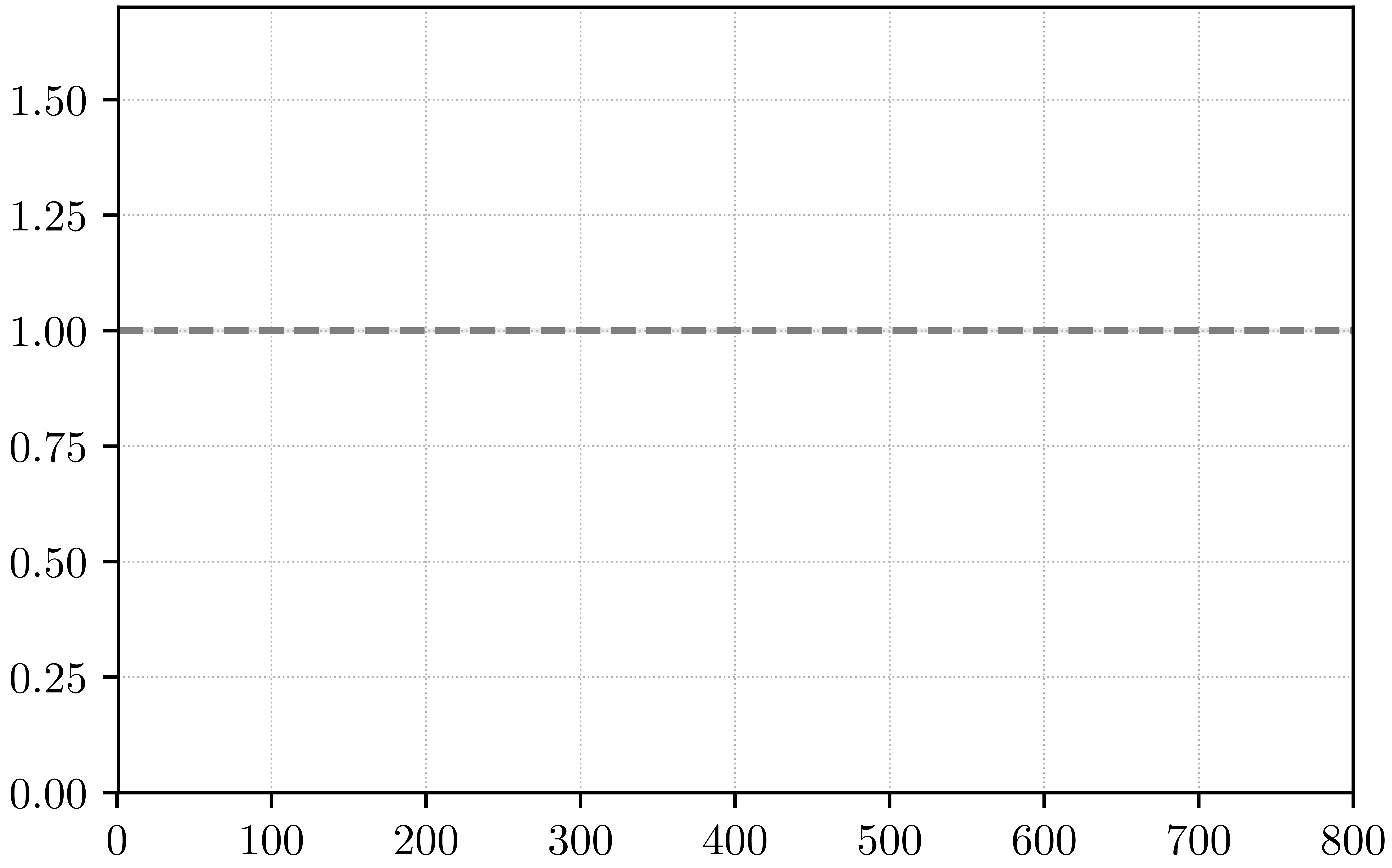
	Task Invariant	Time Cost	Predictive Accuracy
Vanilla Model	No	Low	Medium
Tree-based Model	Yes	Low	Good
Neural Model	Yes	High	Good

Comparisons of Models

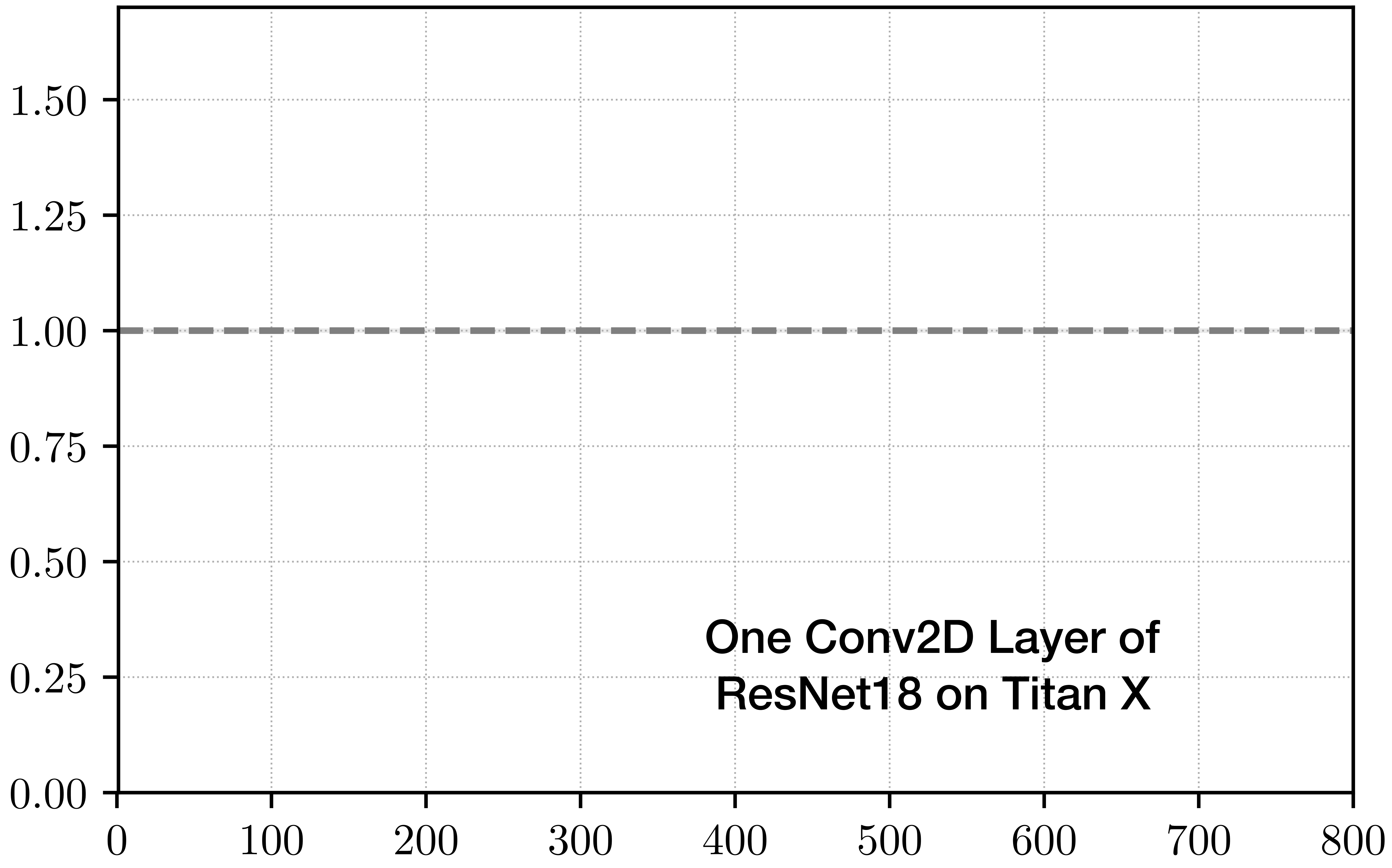
	Task Invariant	Time Cost	Predictive Accuracy
Vanilla Model	No	Low	Medium
Tree-based Model	Yes	Low	Good
Neural Model	Yes	High	Good

Choose tree-based model by default

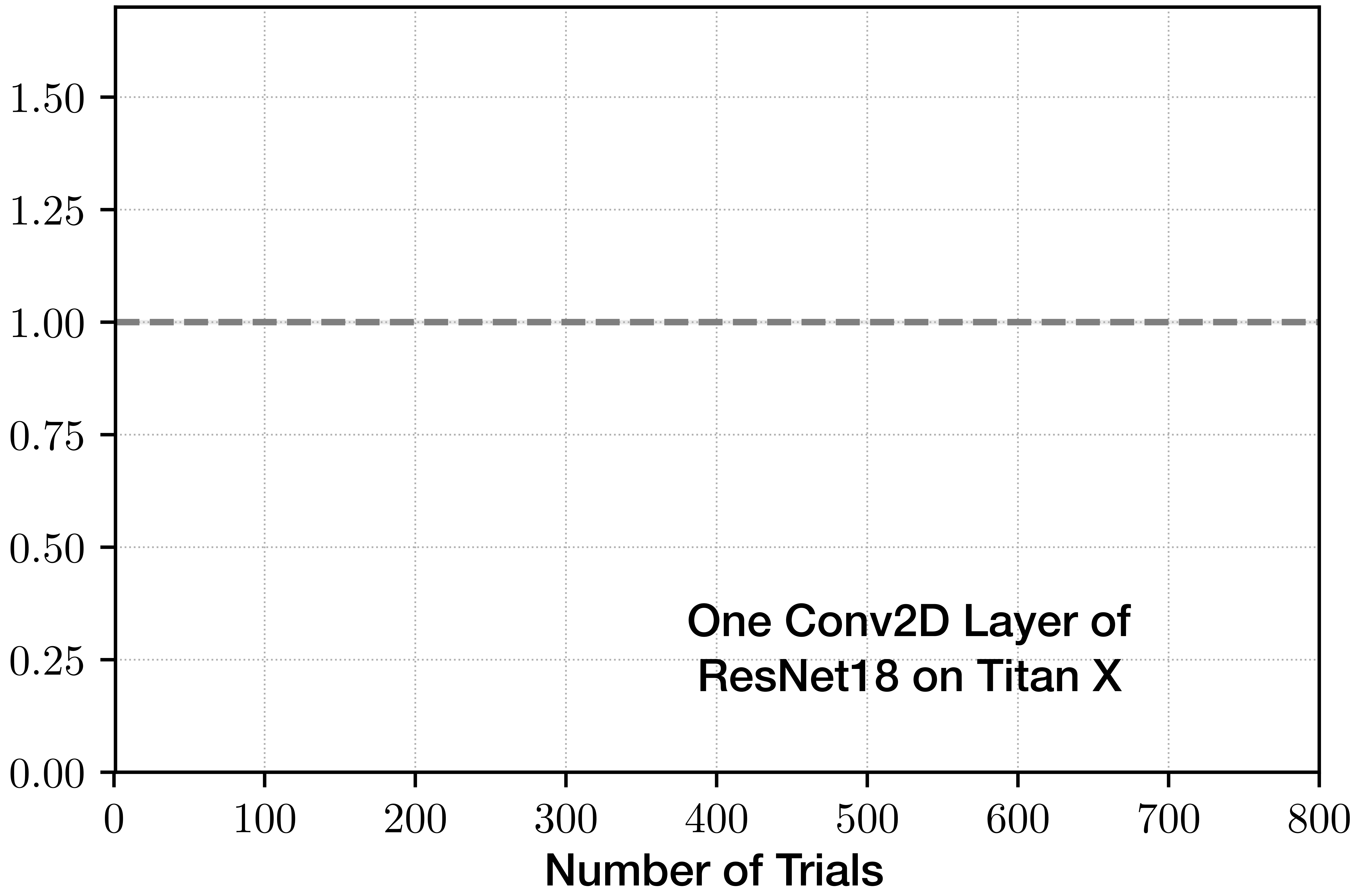
Effectiveness of ML based Model



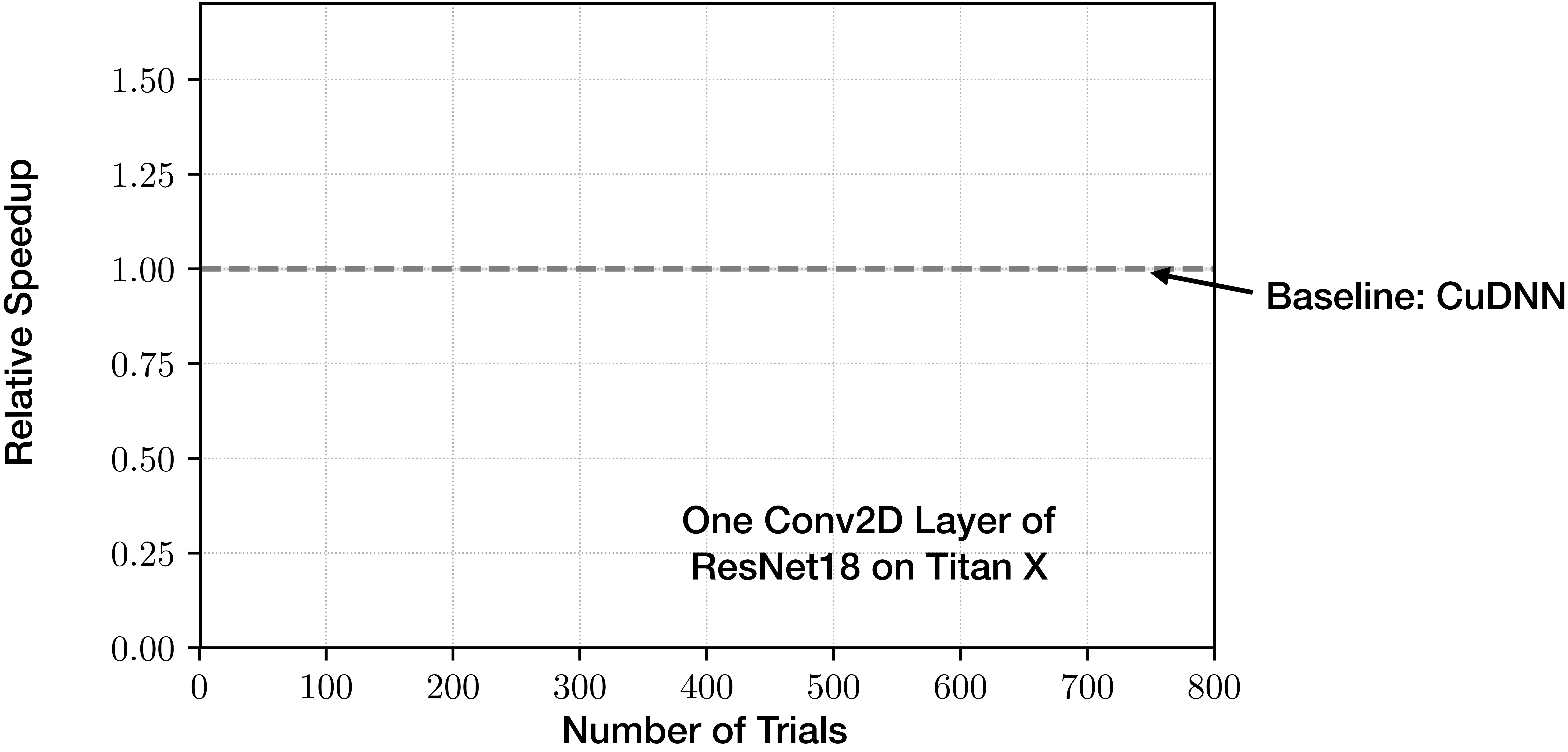
Effectiveness of ML based Model



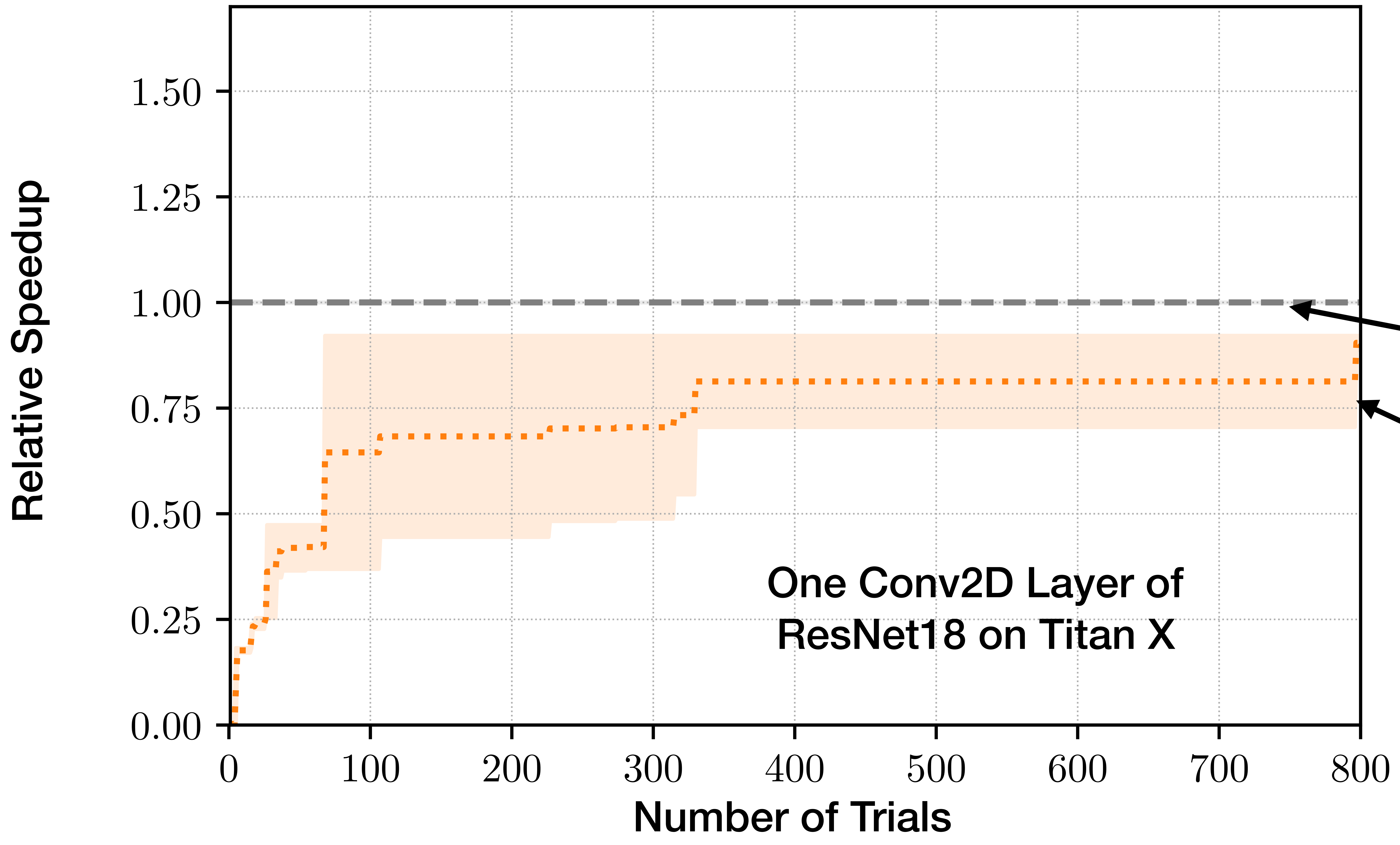
Effectiveness of ML based Model



Effectiveness of ML based Model



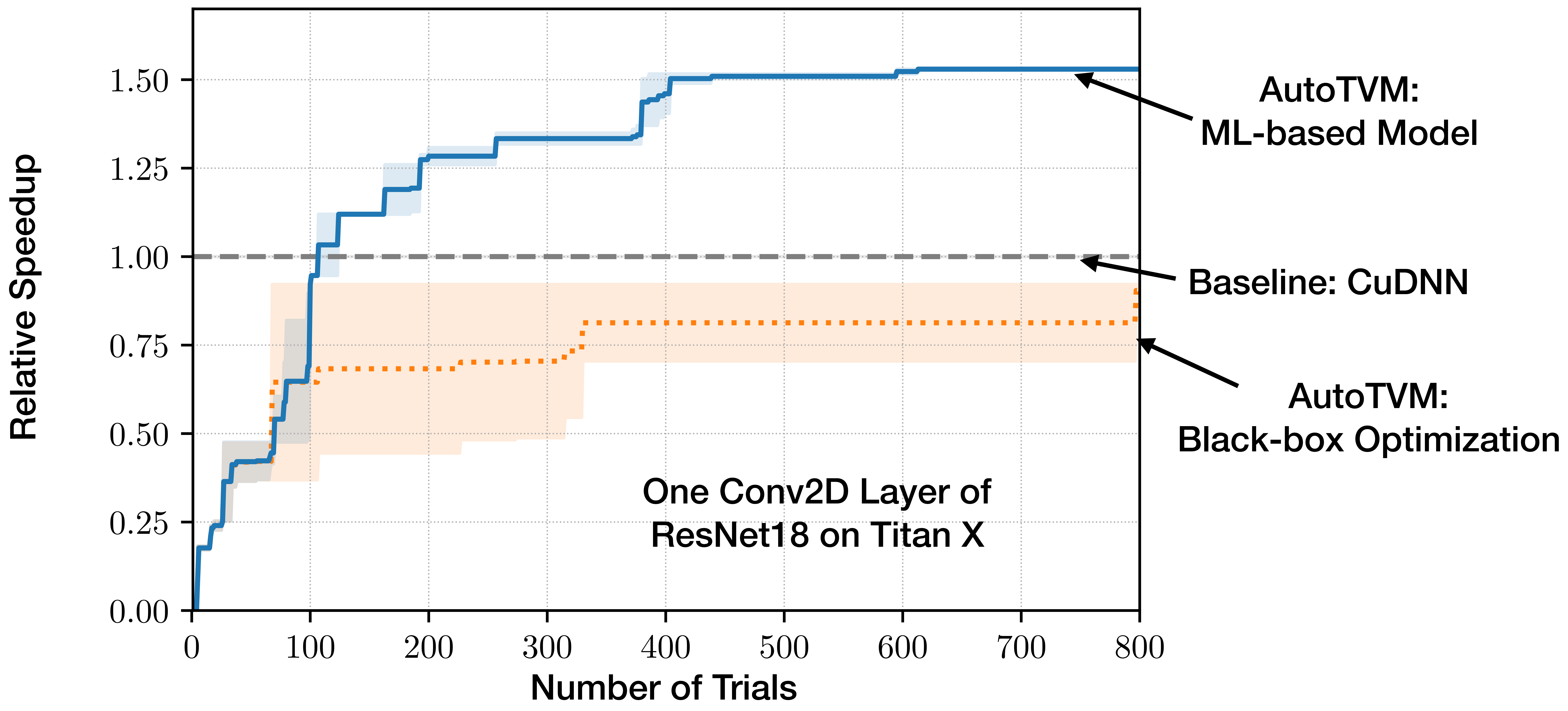
Effectiveness of ML based Model



Baseline: CuDNN

AutoTVM:
Black-box Optimization

Effectiveness of ML based Model



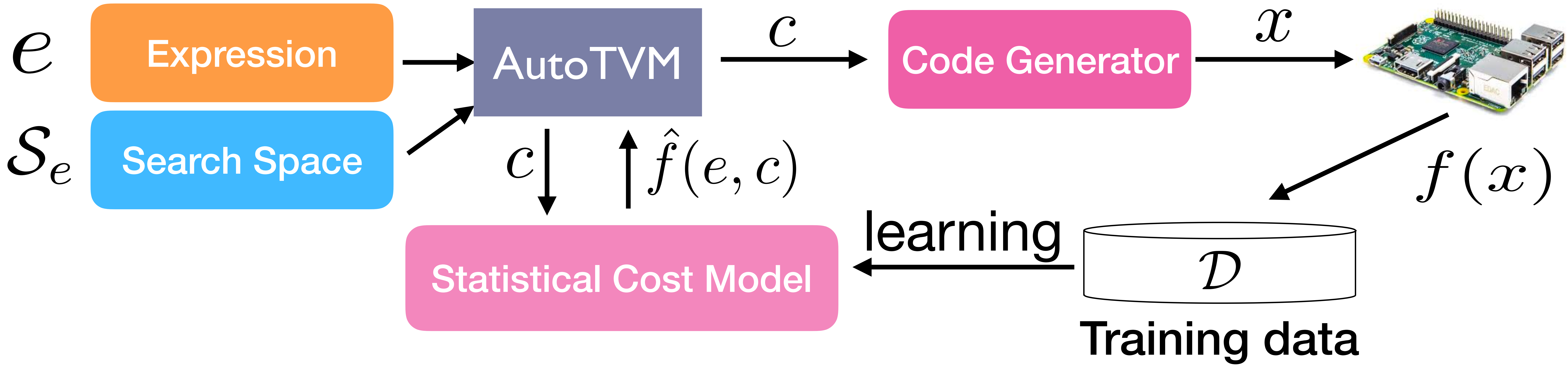
Comparisons of Models

	Task Invariant	Time Cost	Predictive Accuracy
Vanilla Model	No	Low	Medium
Tree-based Model	Yes	Low	Good
Neural Model	Yes	High	Good

Comparisons of Models

	Task Invariant	Time Cost	Predictive Accuracy
Vanilla Model	No	Low	Medium
Tree-based Model	Yes	Low	Good
Neural Model	Yes	High	Good

Unique Problem Characteristics

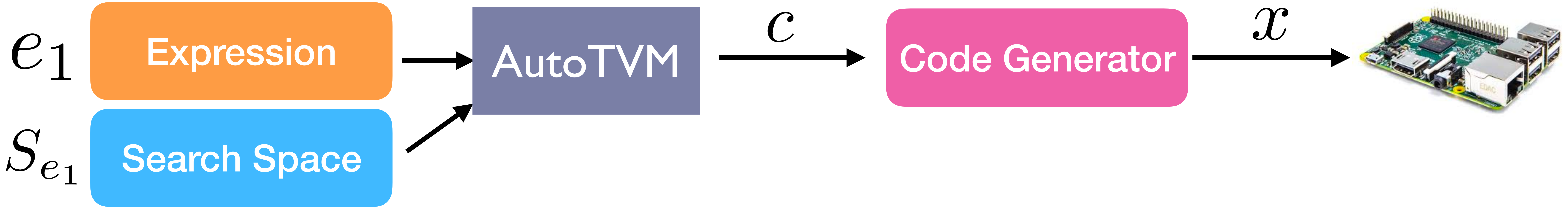


Relatively low experiment cost

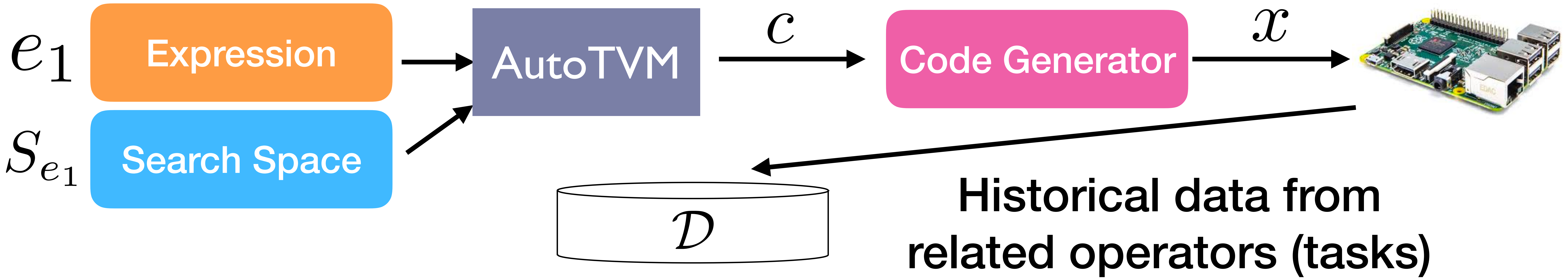
Program-aware modeling

Large number of similar tasks

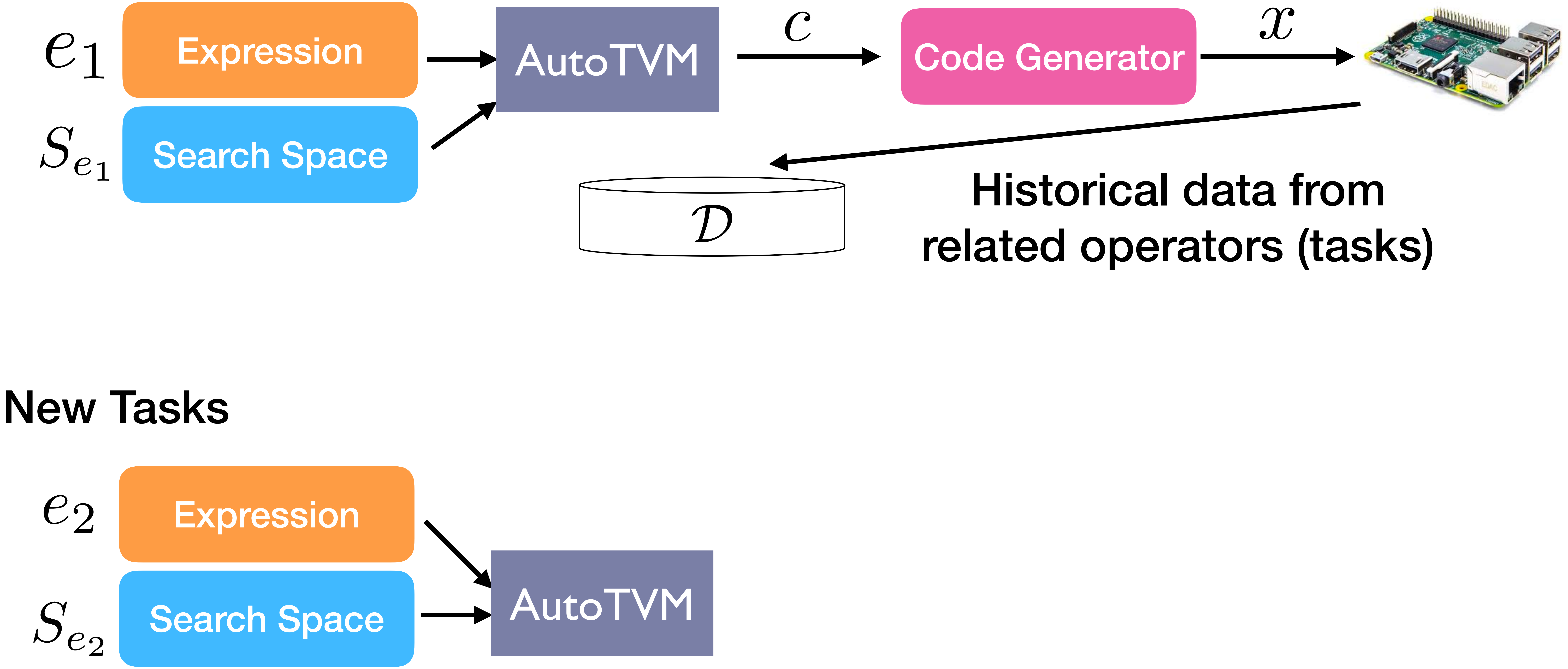
Transferable Cost Model



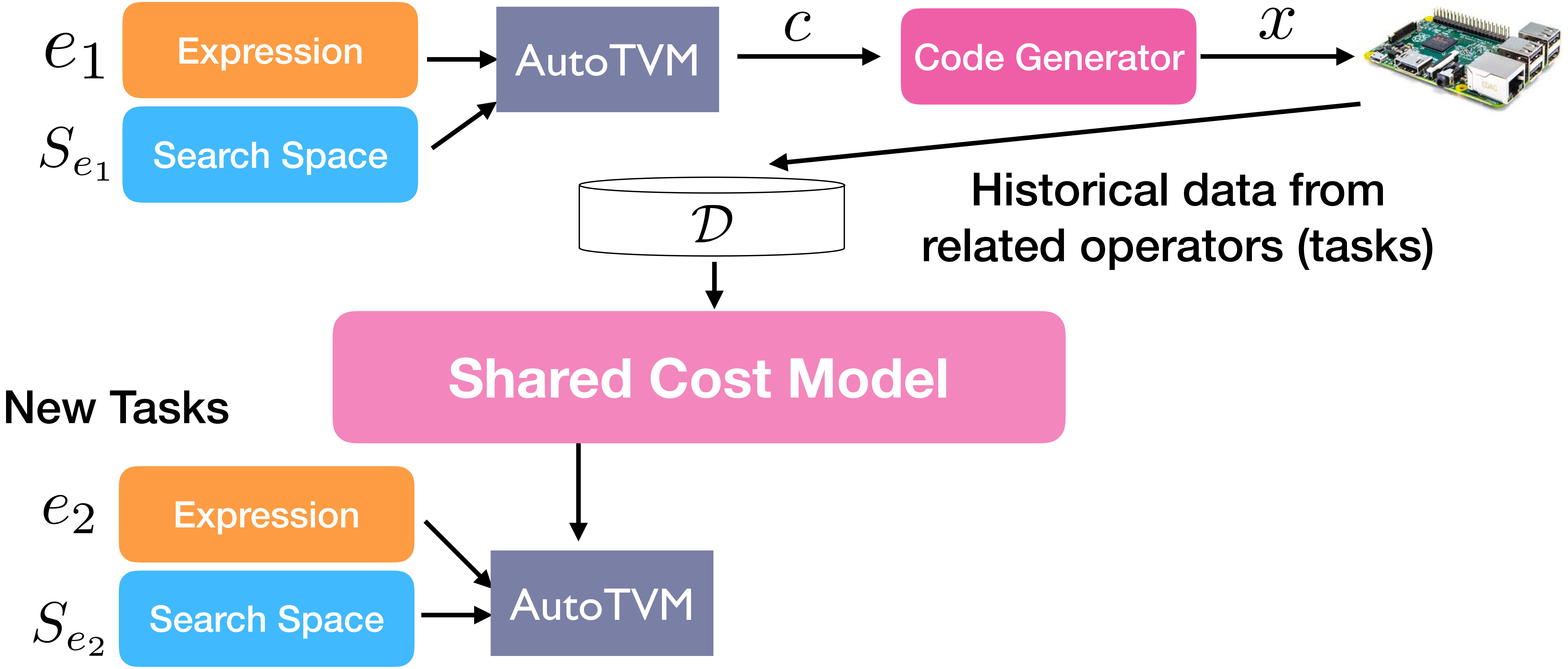
Transferable Cost Model



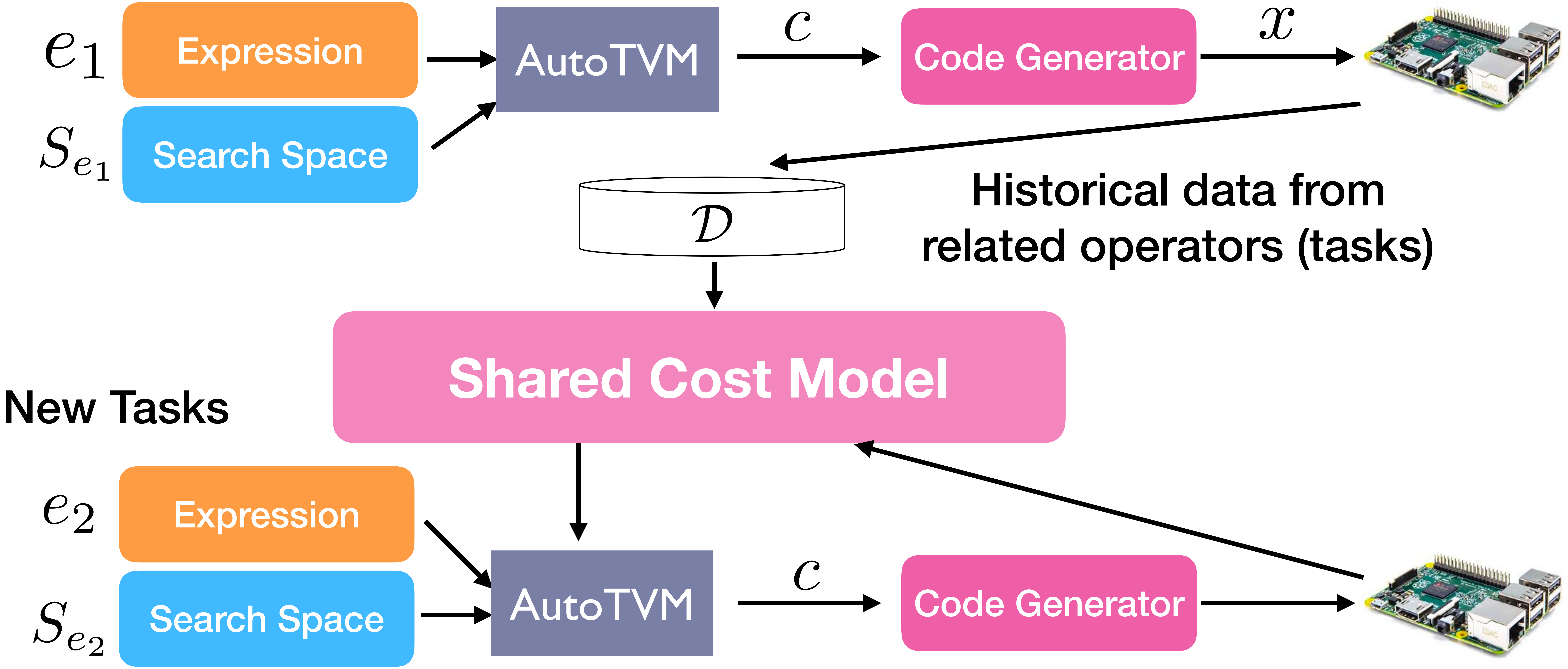
Transferable Cost Model



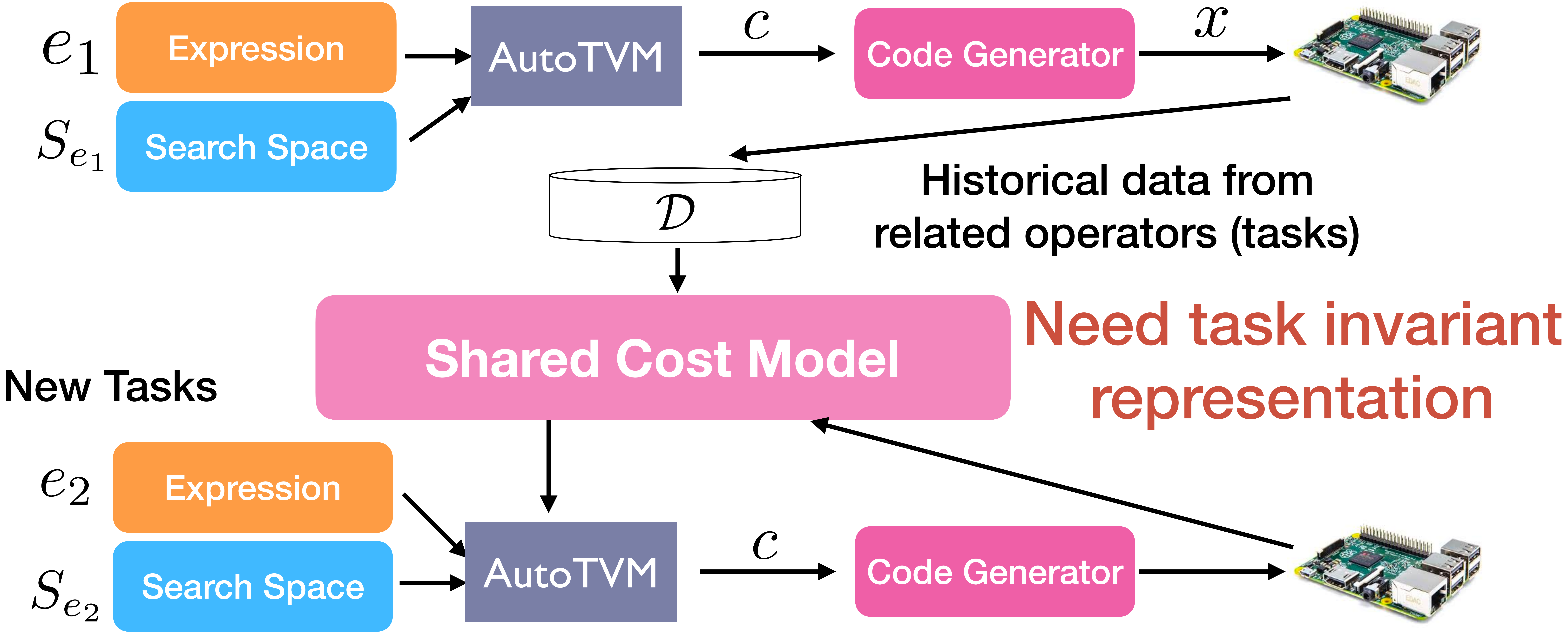
Transferable Cost Model



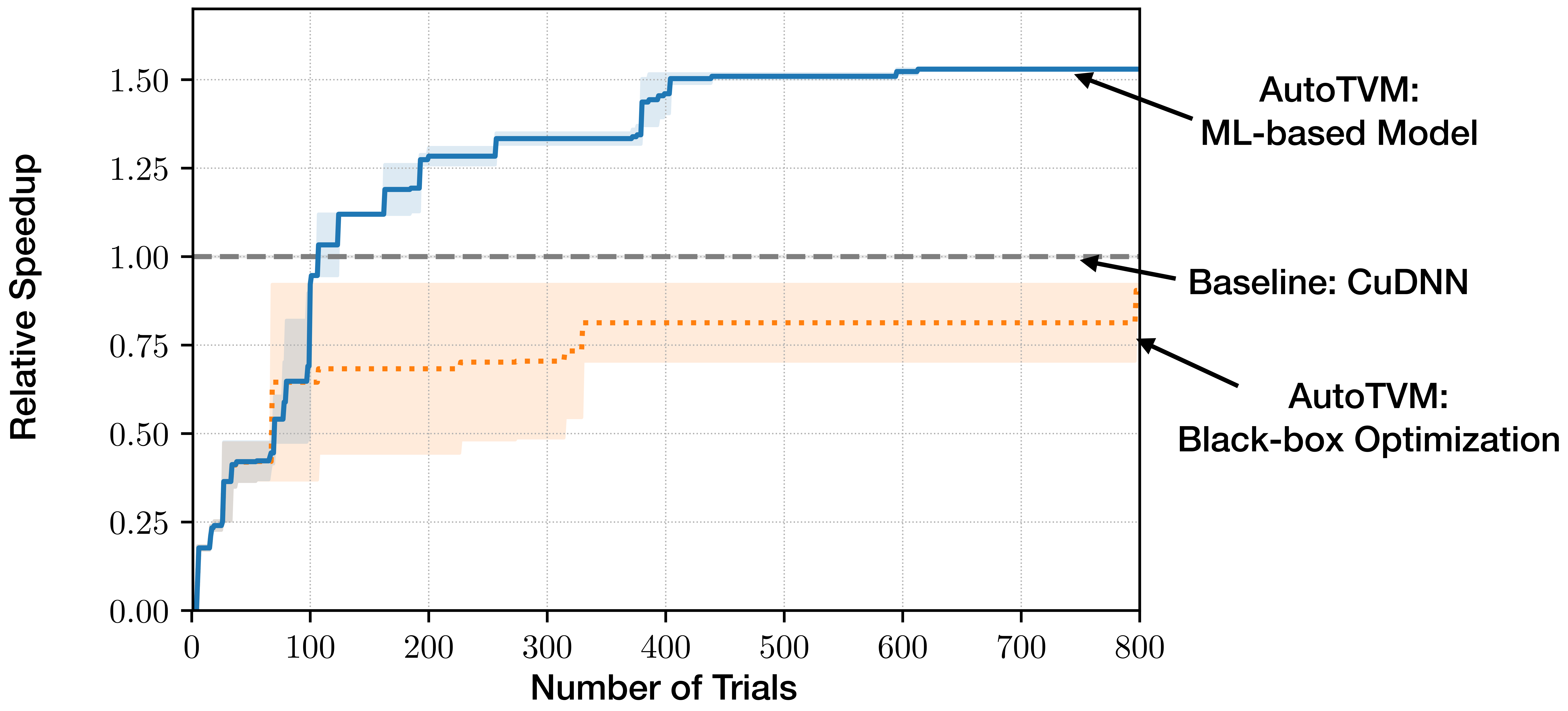
Transferable Cost Model



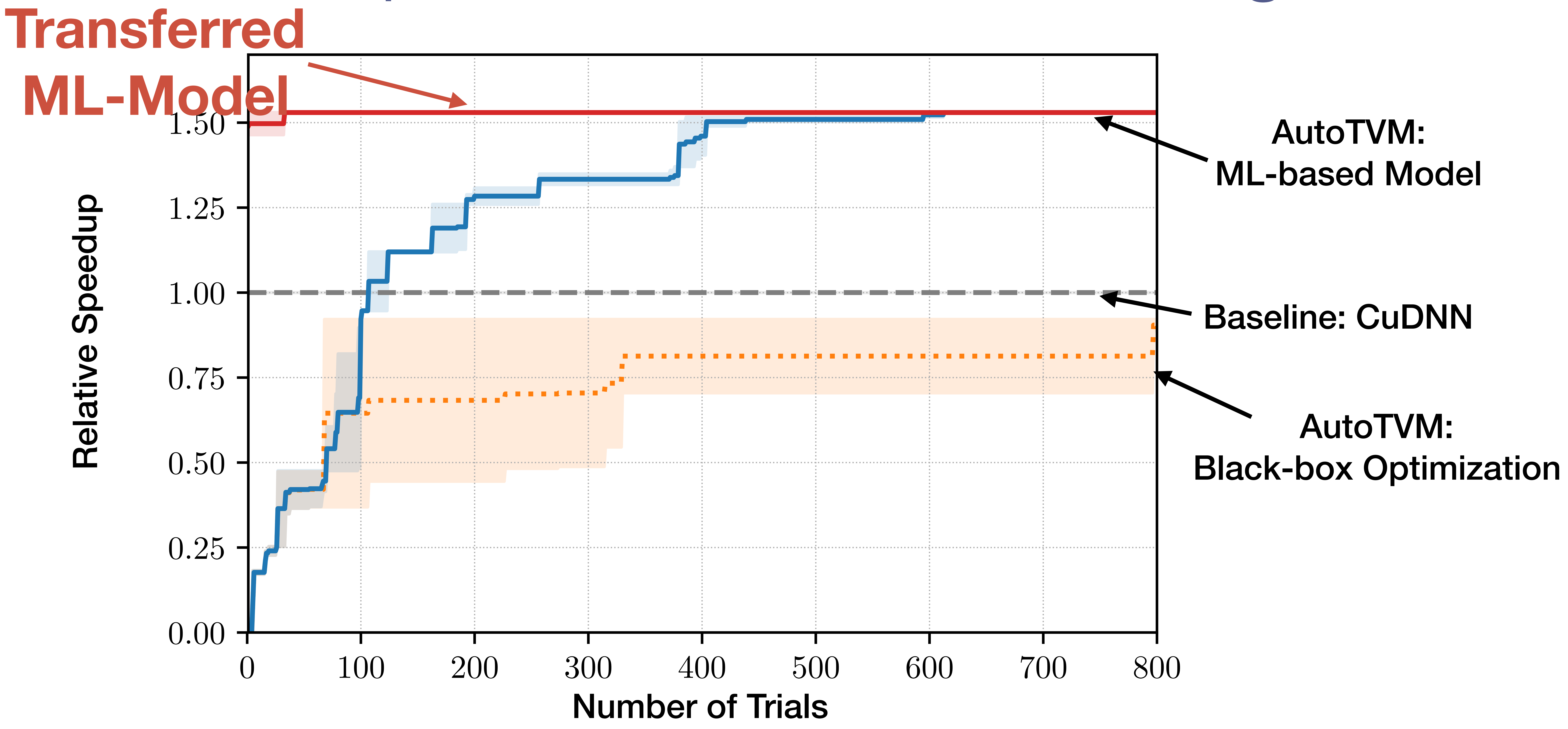
Transferable Cost Model



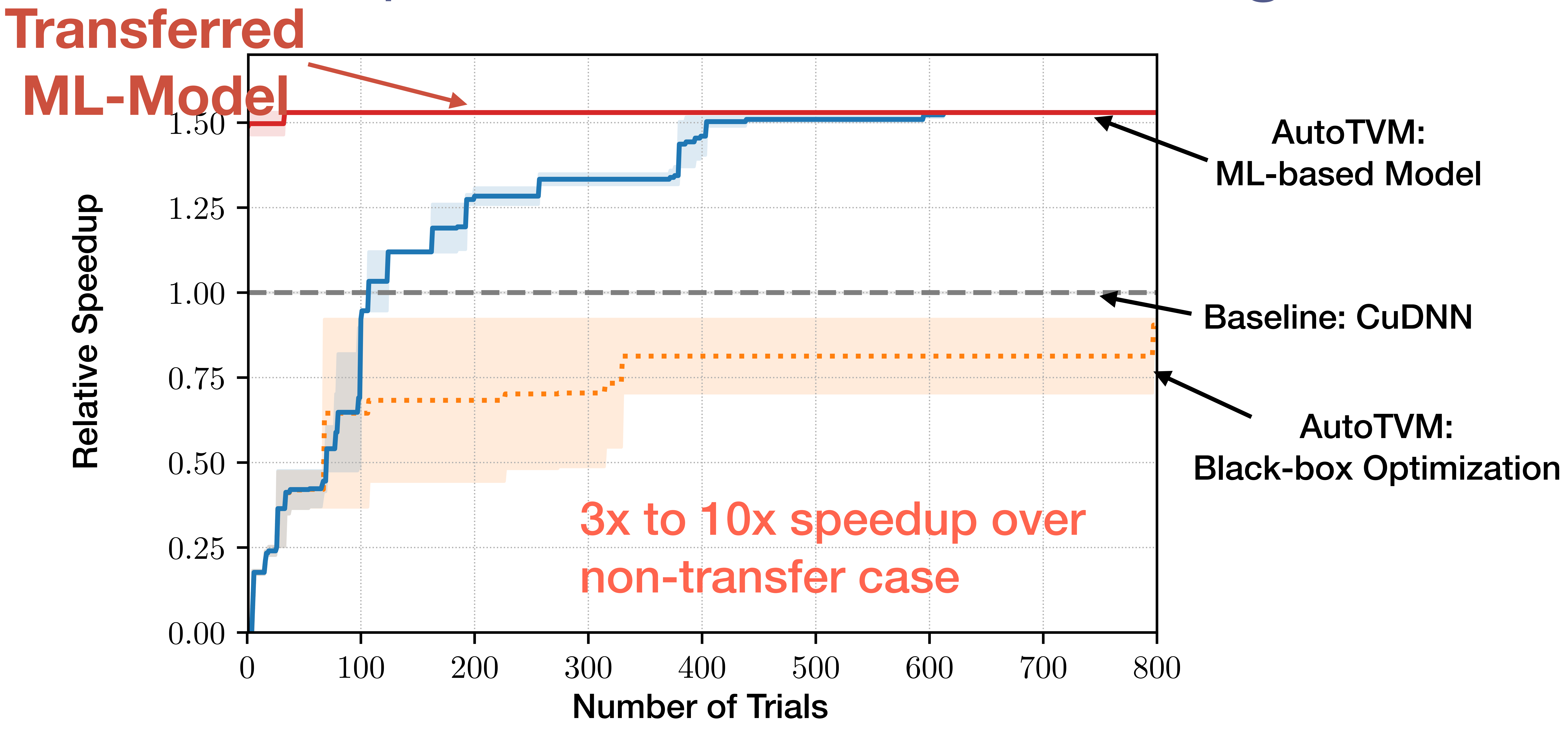
Impact of Transfer Learning



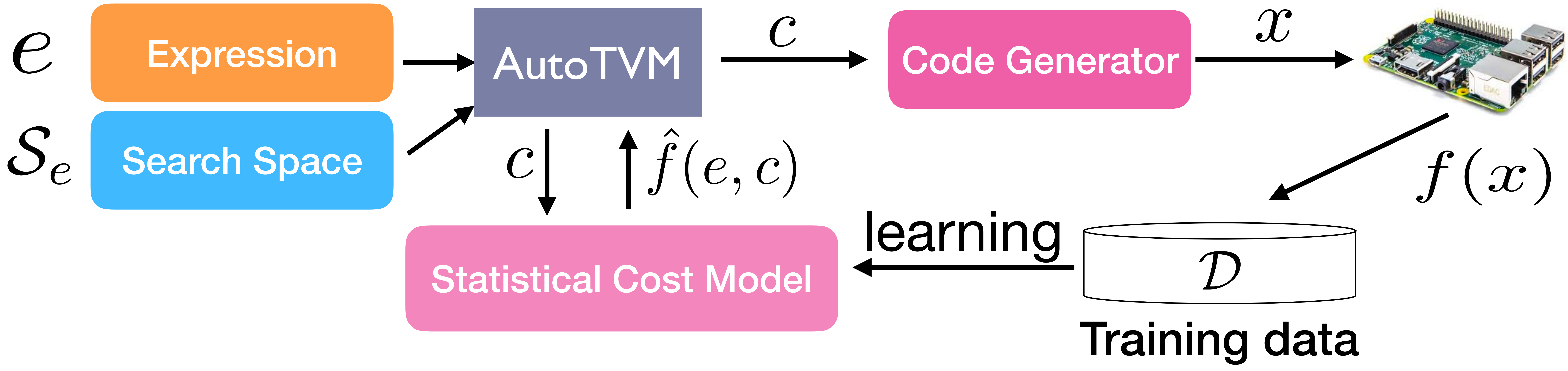
Impact of Transfer Learning



Impact of Transfer Learning



Learning to Optimize Tensor Programs



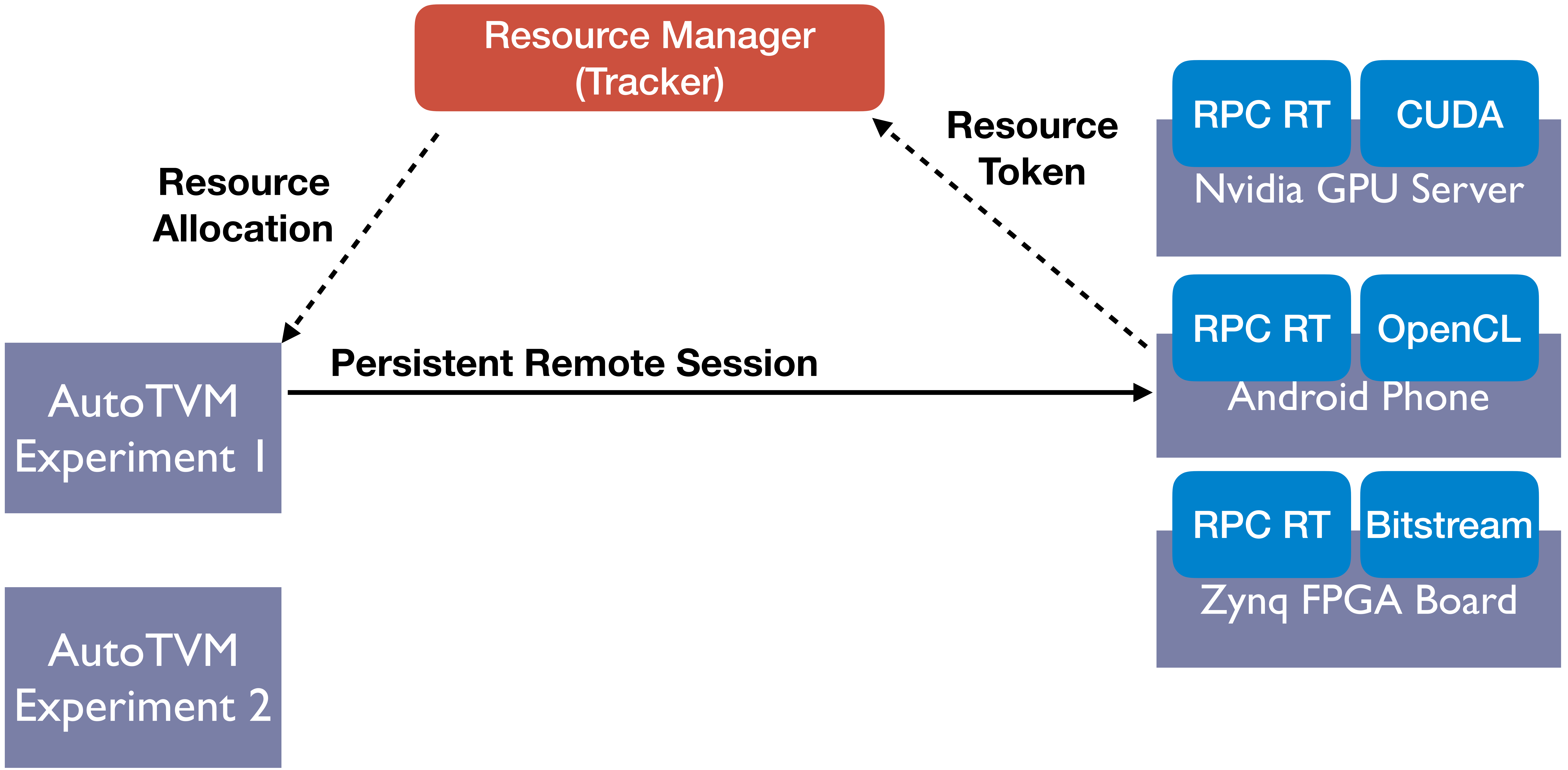
Relatively low experiment cost

Program-aware modeling

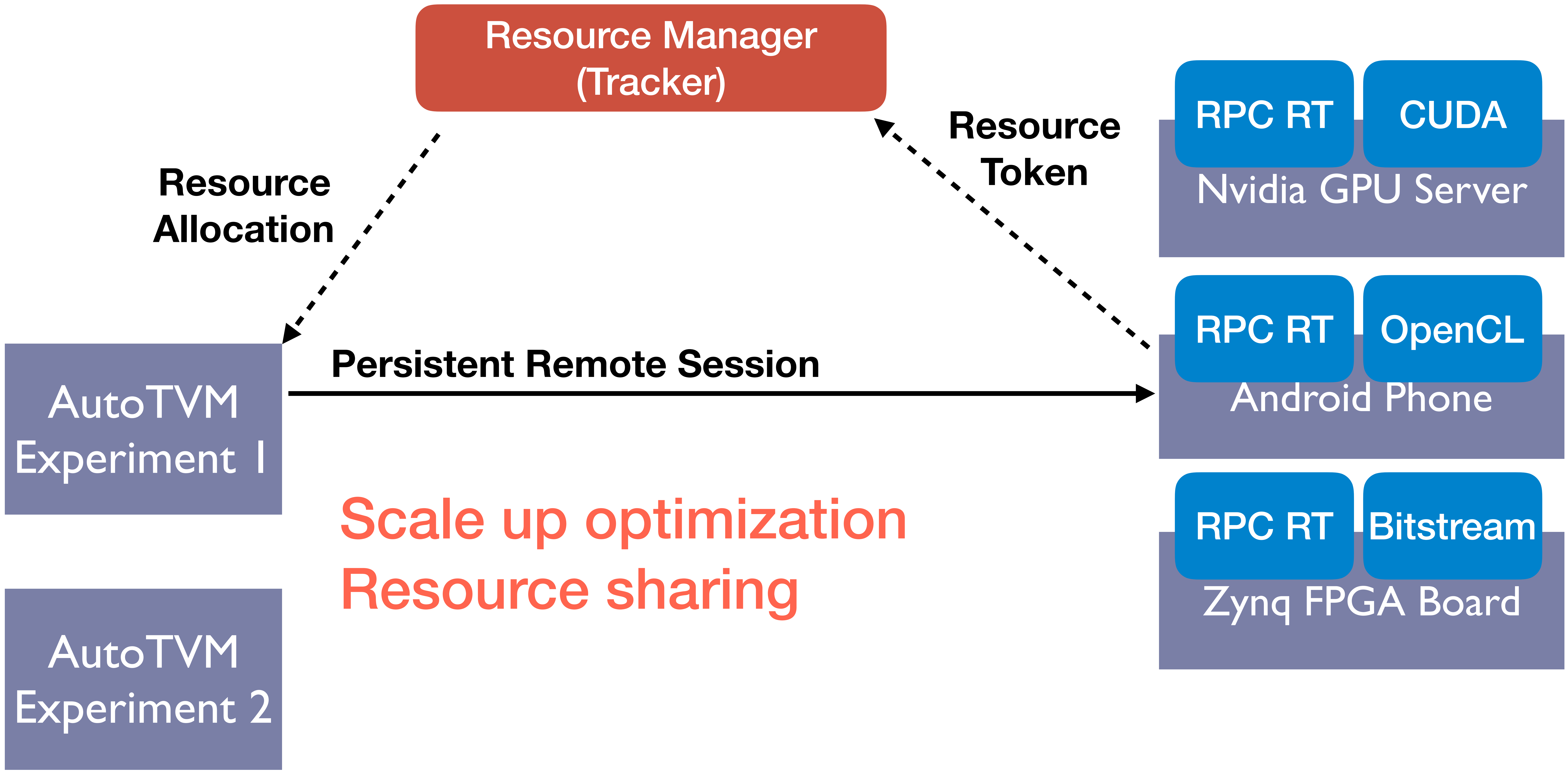
Large number of similar tasks

Learning to Optimize Tensor Programs. **Chen et al. NeurIPS 18**

Device Fleet: Distributed Test Bed for AutoTVM



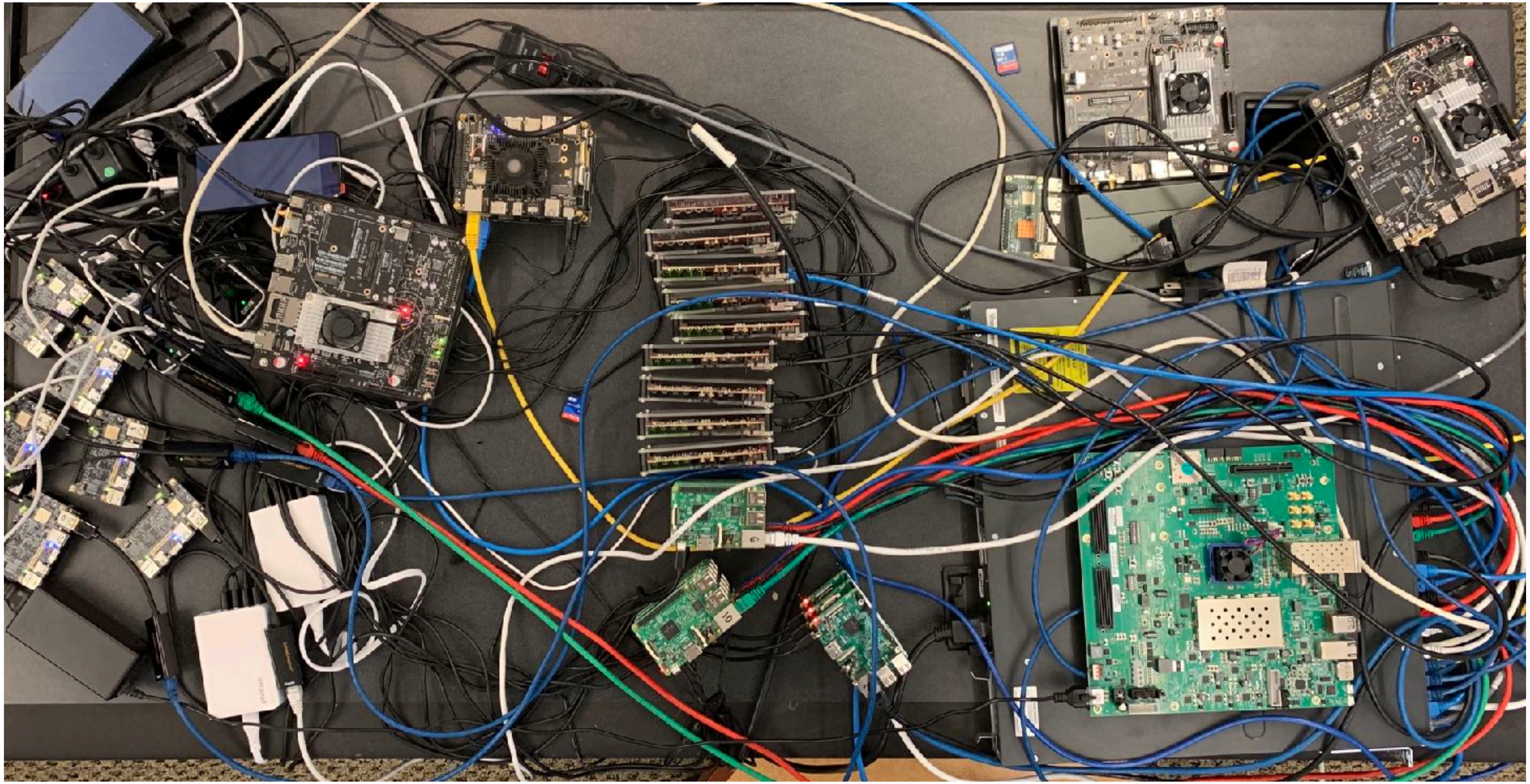
Device Fleet: Distributed Test Bed for AutoTVM



Scale up optimization

Resource sharing

Device Fleet in Action



TVM: Learning-based Learning System

Why do we need machine learning for systems

How to build intelligent systems with learning

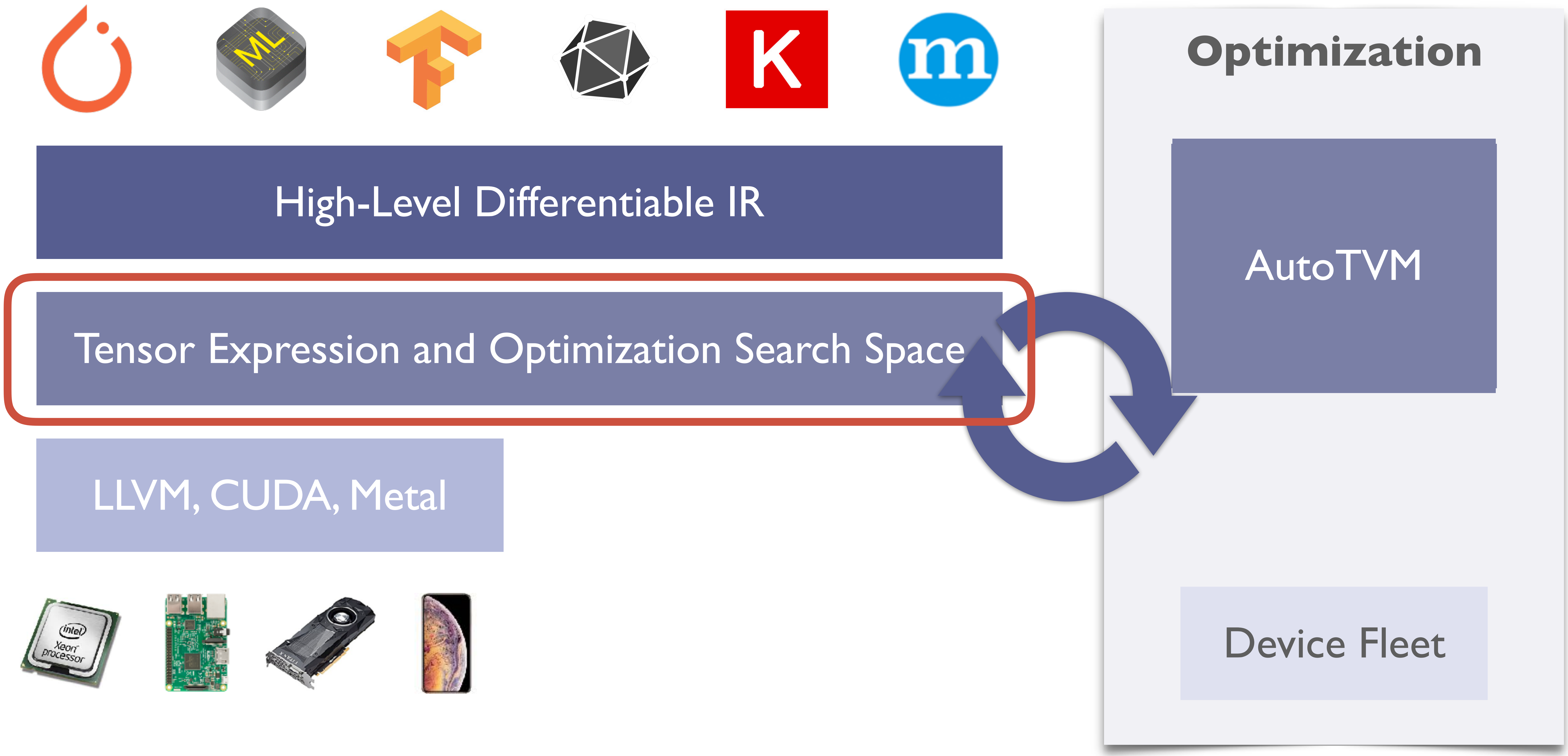
End to end learning-based learning system stack

TVM: End to End Deep Learning Compiler

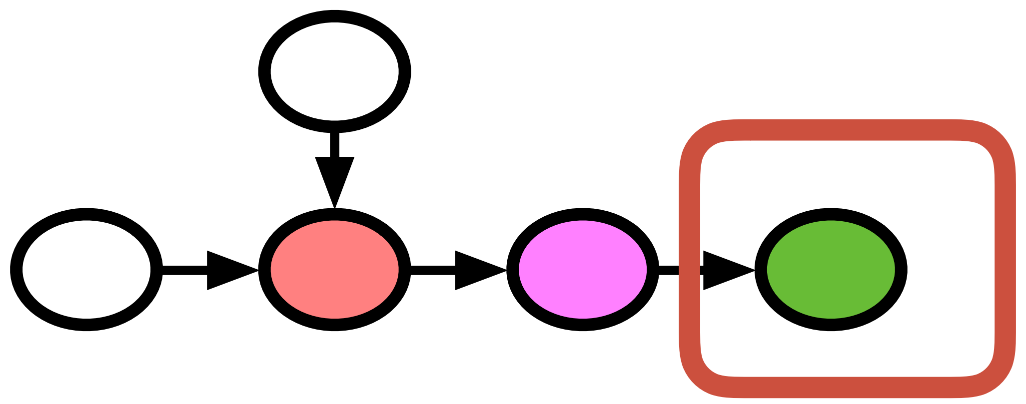
AutoTVM

TVM: End to End Deep Learning Compiler

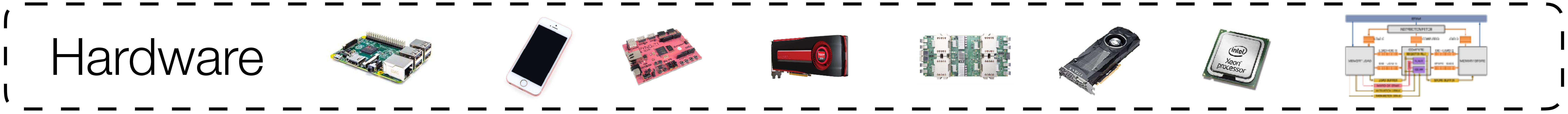
TVM: End to End Deep Learning Compiler



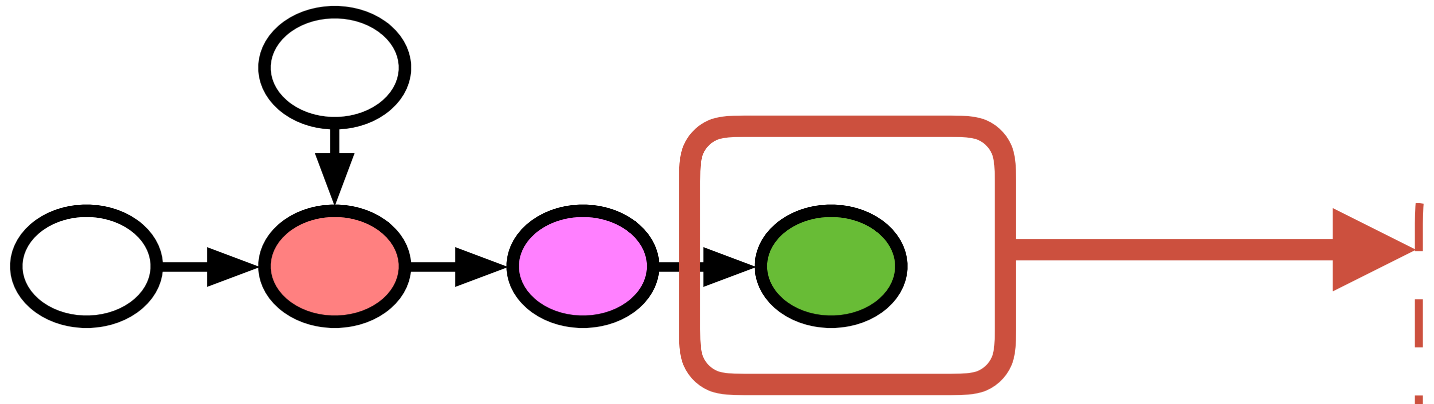
Tensor Expression and Optimization Search Space



Based on Halide's compute/schedule separation



Tensor Expression and Optimization Search Space



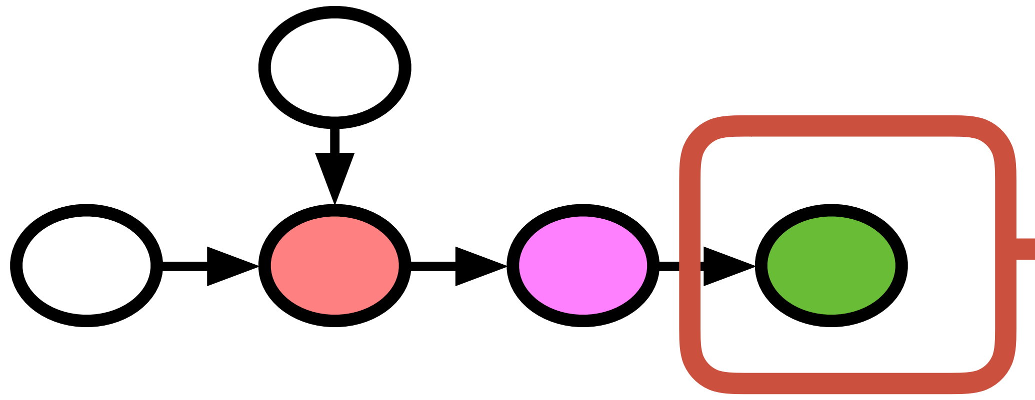
Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Based on Halide's compute/schedule separation

Hardware

Tensor Expression and Optimization Search Space



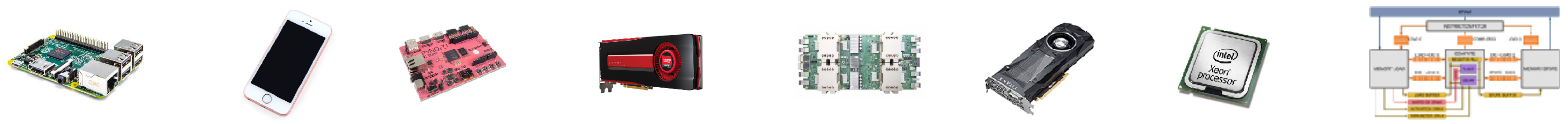
Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

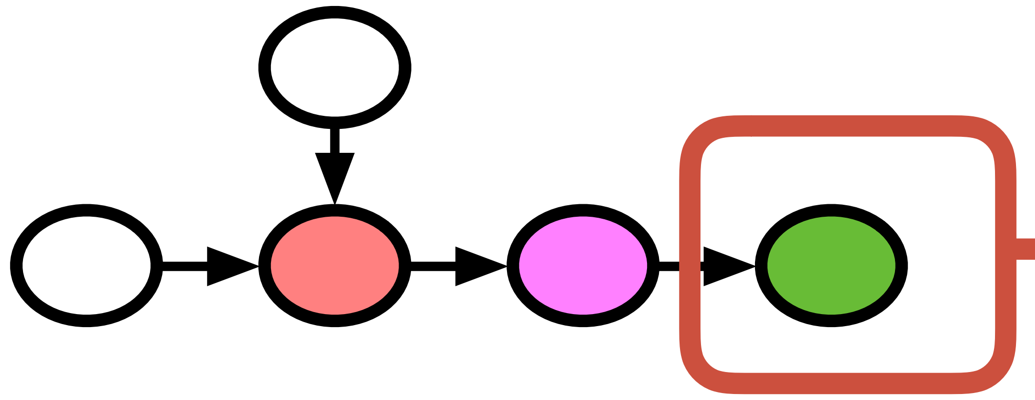
Search space:
Possible mappings from the expression to valid hardware programs

Based on Halide's compute/schedule separation

Hardware



Tensor Expression and Optimization Search Space



Tensor Expression (Specification)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Search space:
Possible mappings from the expression to valid hardware programs

Based on Halide's compute/schedule separation

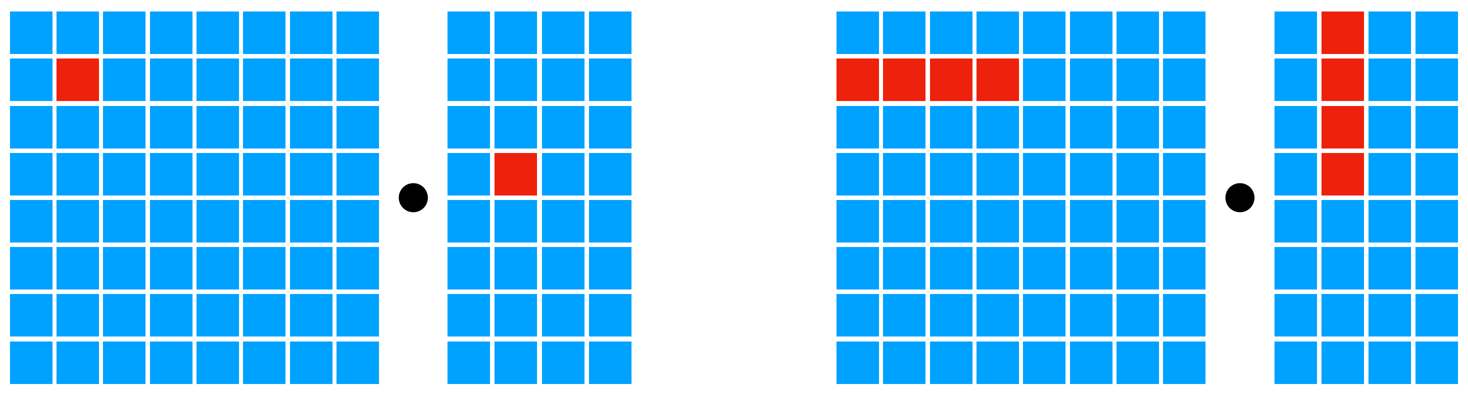
What is the search space

Hardware

Search Space for CPUs

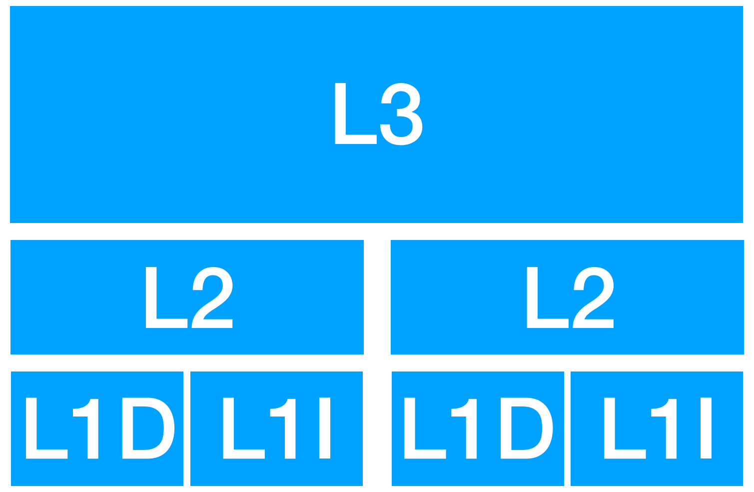
CPUs

Compute Primitives



scalar *vector*

Memory Subsystem



implicitly managed

Loop Transformations

Cache Locality

Vectorization

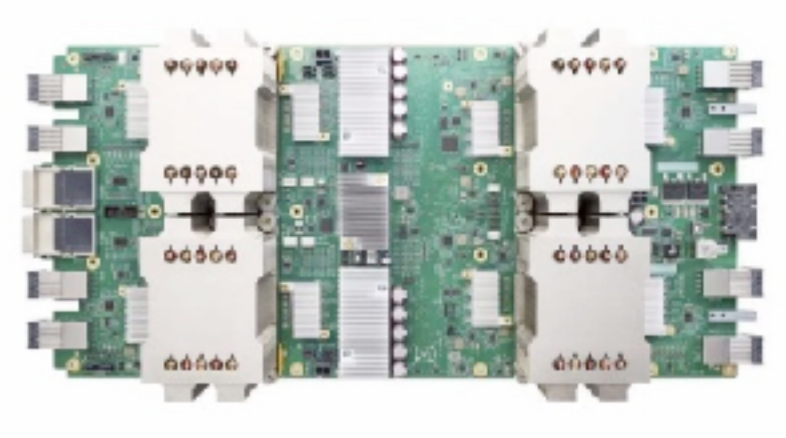
Reuse primitives from prior work:
Halide, Loopy

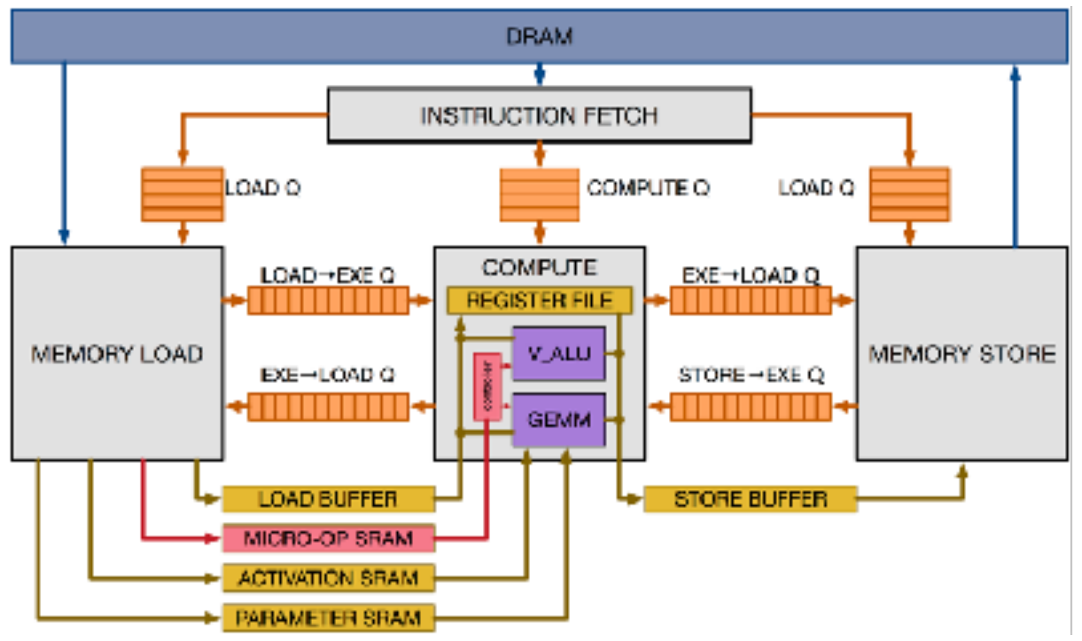
Hardware-aware Search Space

CPUs

GPUs

TPU-like specialized Accelerators

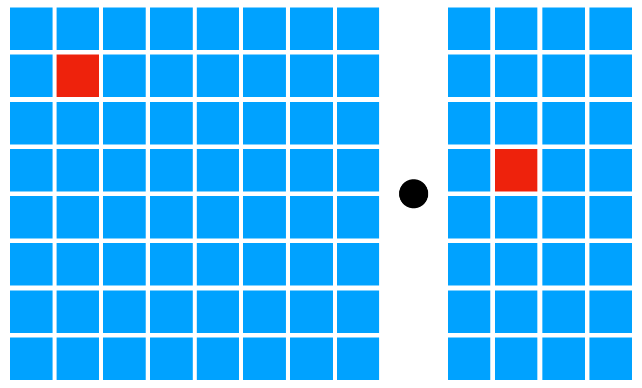




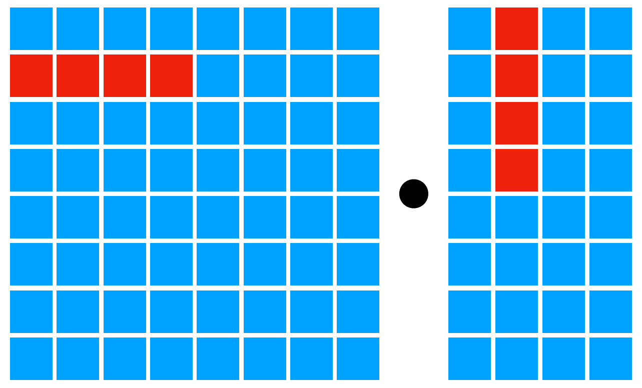
Search Space for GPUs

GPUs

Compute Primitives



scalar



vector

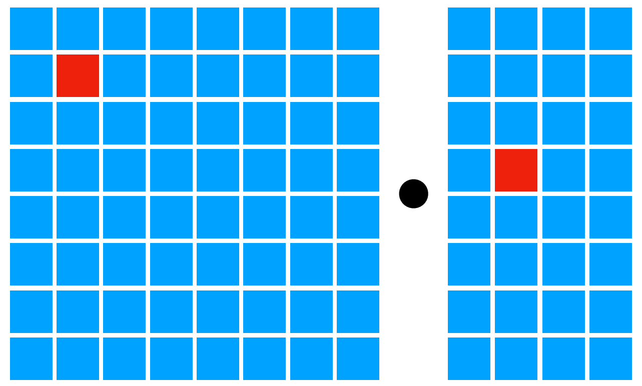
Memory Subsystem

mixed

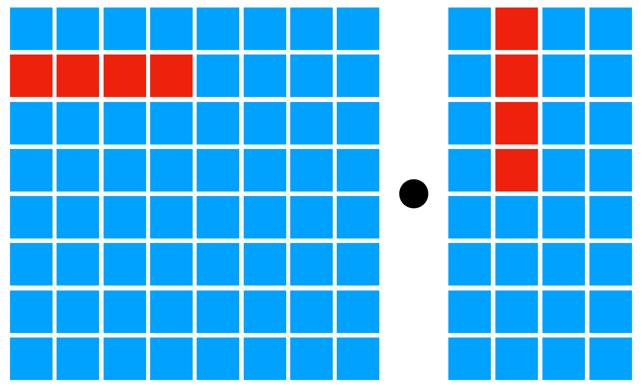
Search Space for GPUs

GPUs

Compute Primitives

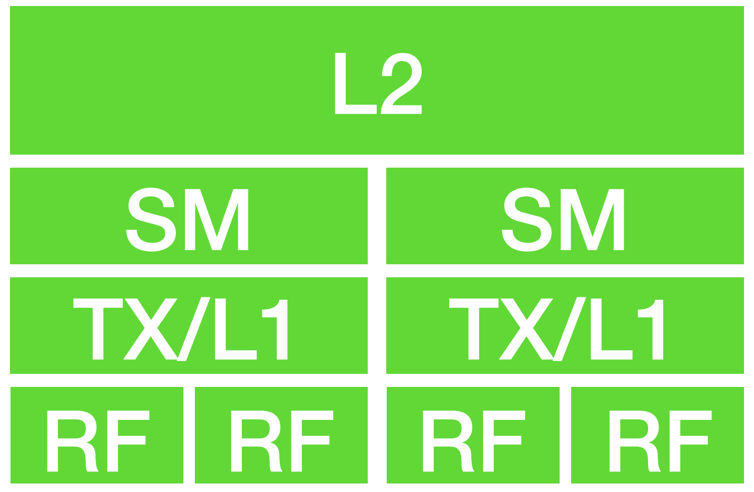


scalar



vector

Memory Subsystem



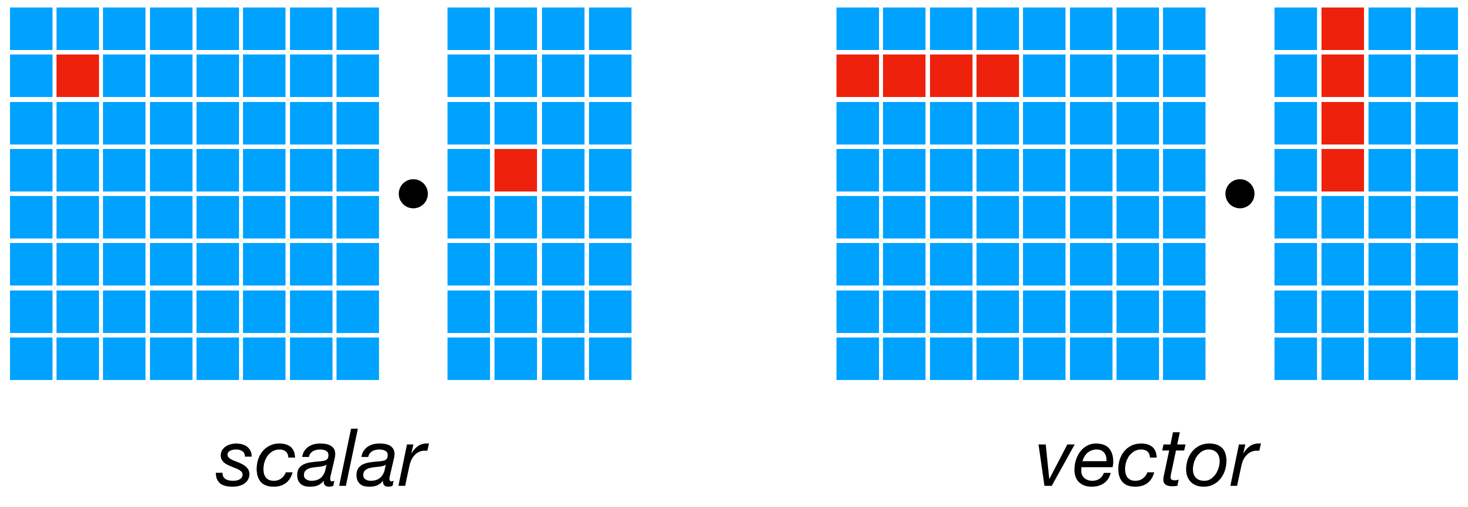
mixed

Shared memory among compute cores

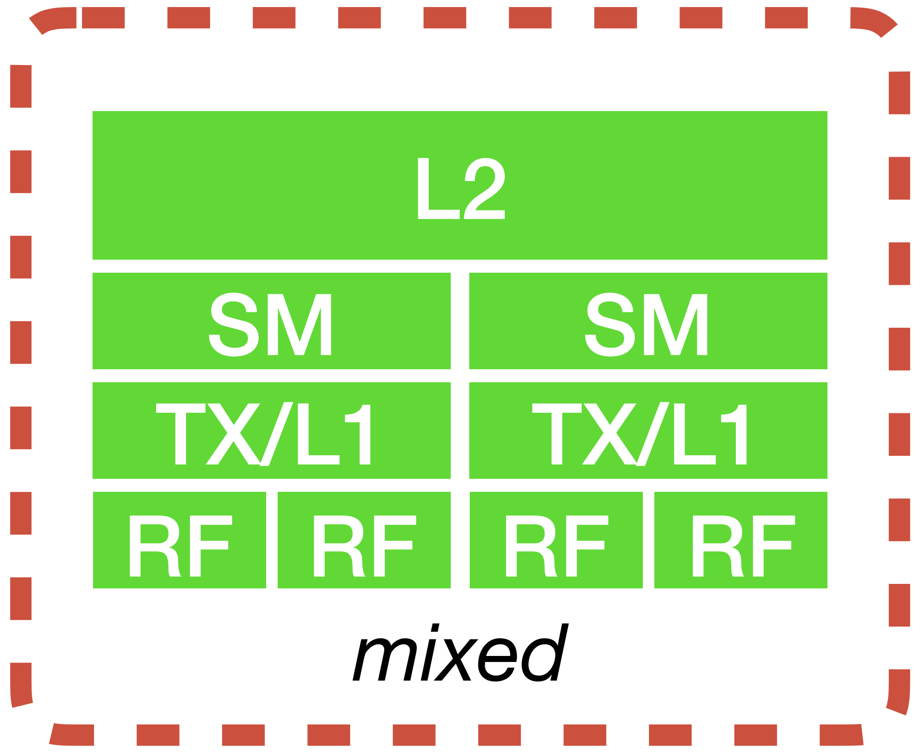
Search Space for GPUs

GPUs

Compute Primitives



Memory Subsystem



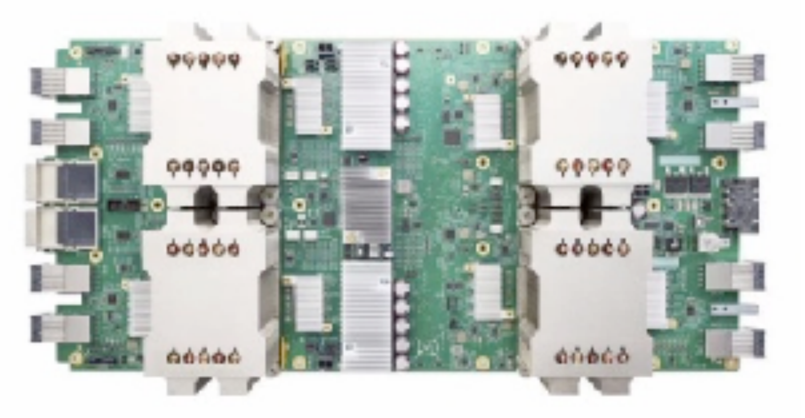
Shared memory among compute cores

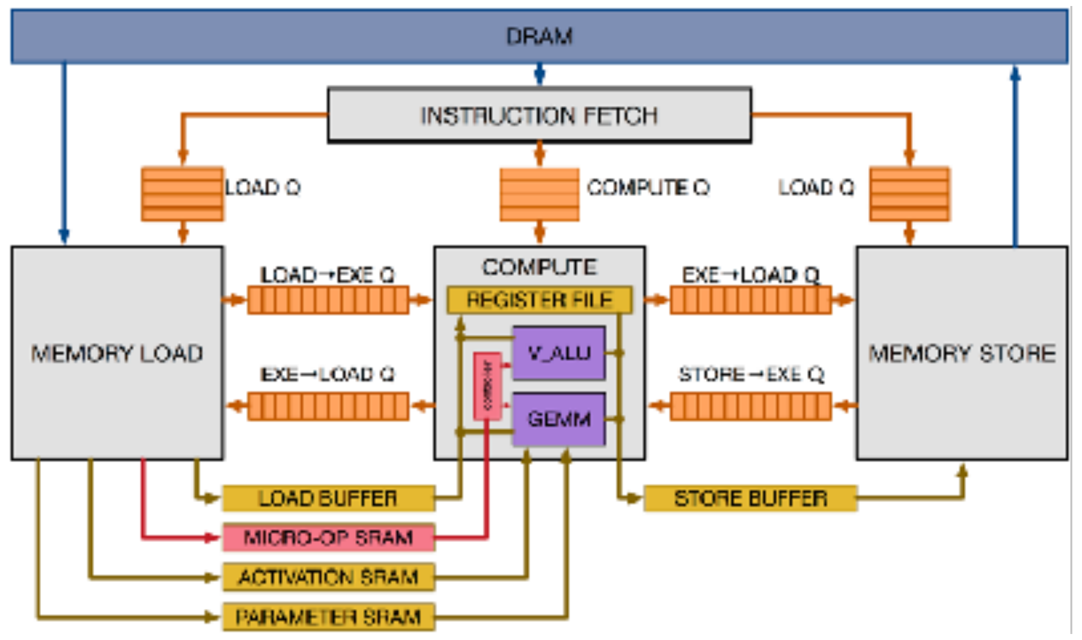
Use of Shared Memory

Thread Cooperation

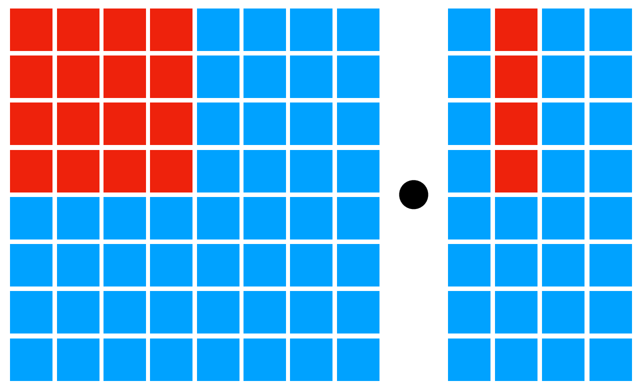
Search Space for TPU-like Specialized Accelerators

TPUs

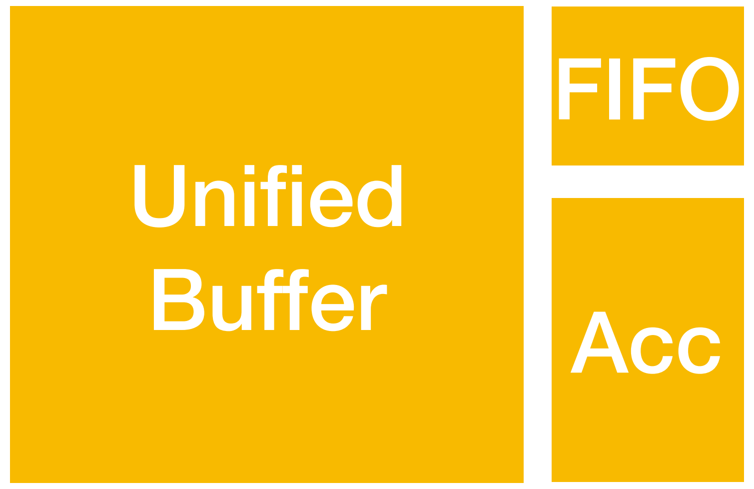




Tensor Compute Primitives

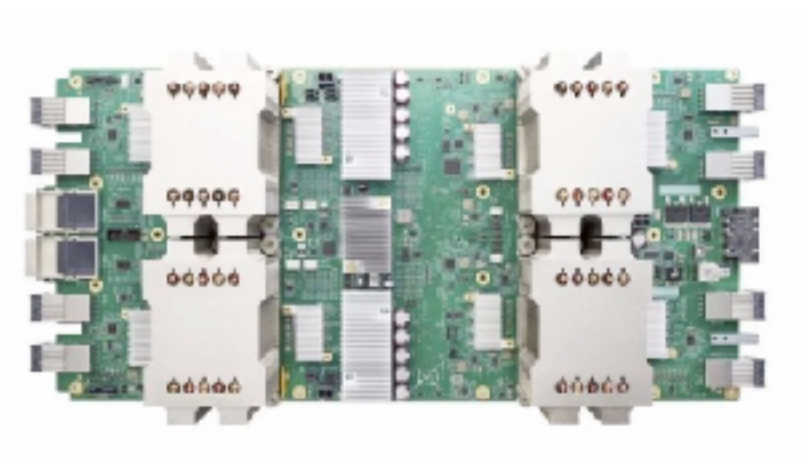


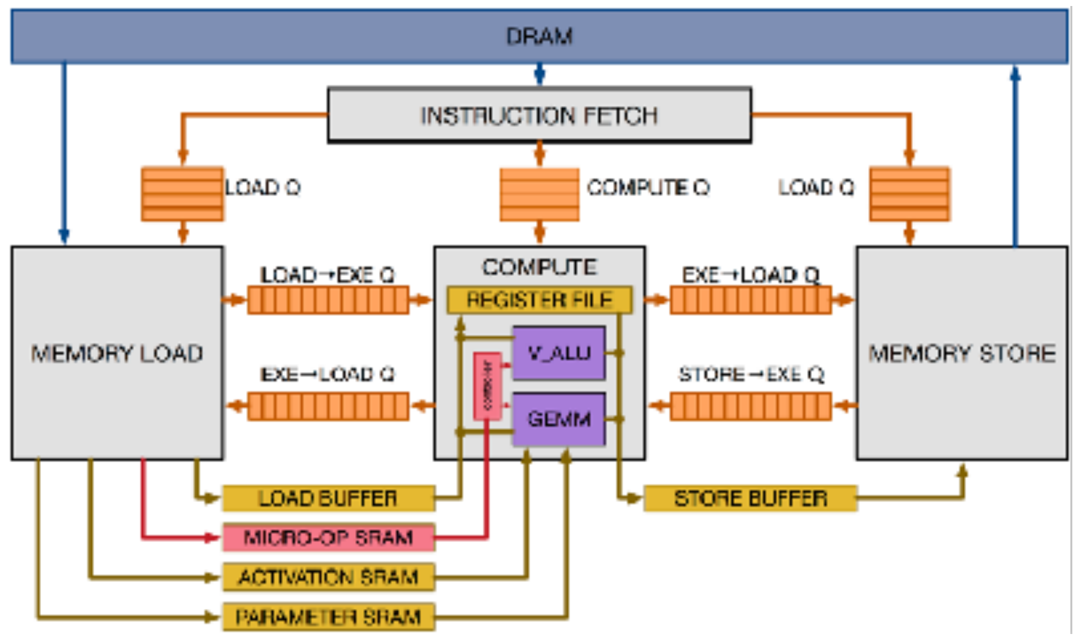
Explicitly Managed Memory Subsystem



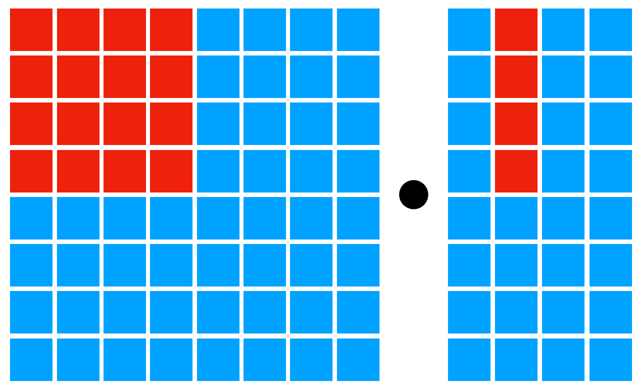
Search Space for TPU-like Specialized Accelerators

TPUs

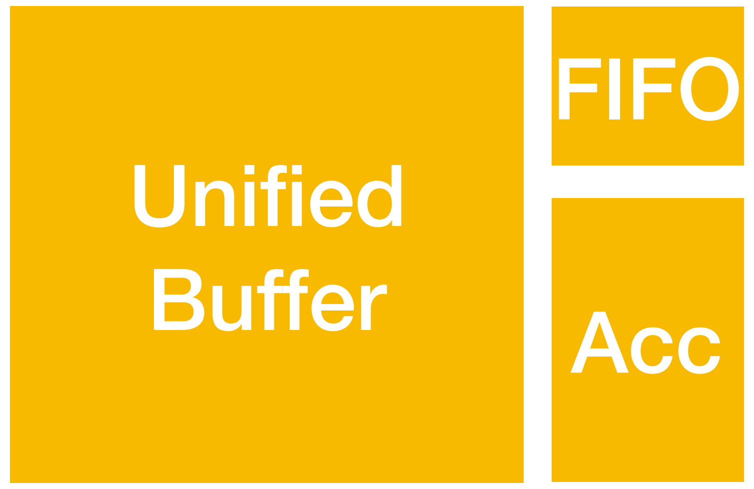




Tensor Compute Primitives



Explicitly Managed Memory Subsystem

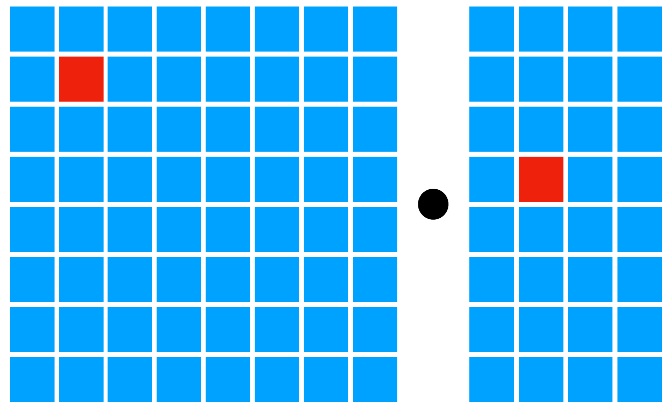


Tensorization Challenge

Compute primitives

Tensorization Challenge

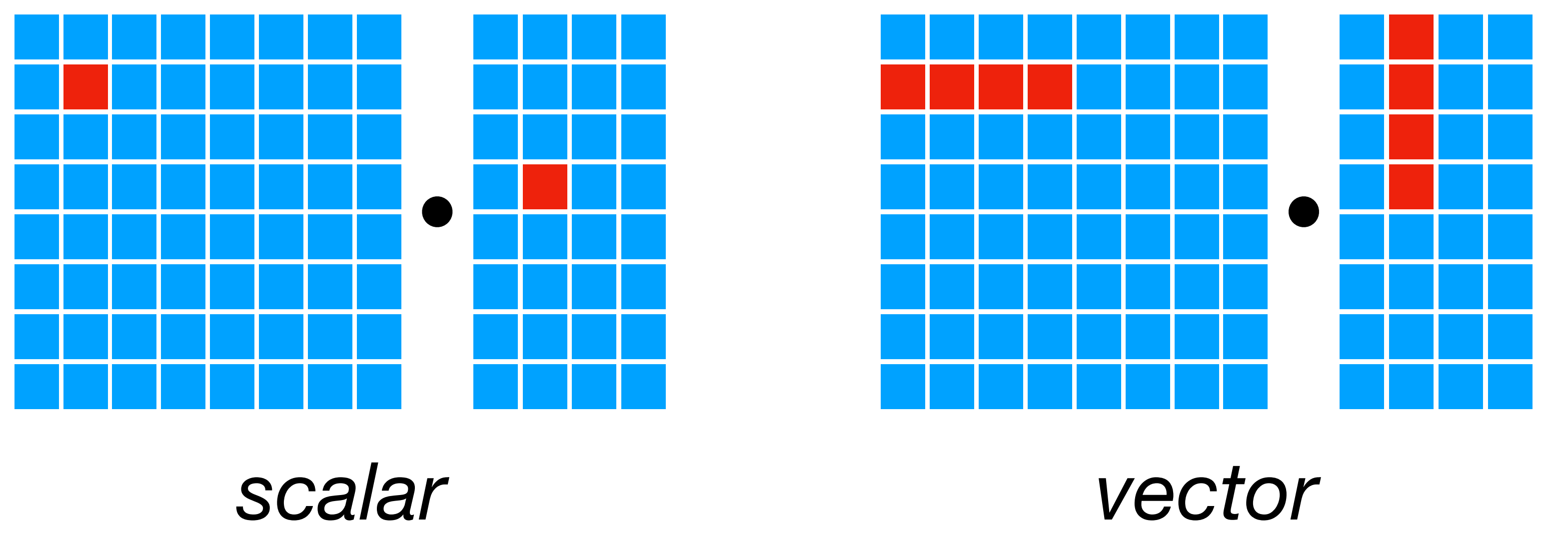
Compute primitives



scalar

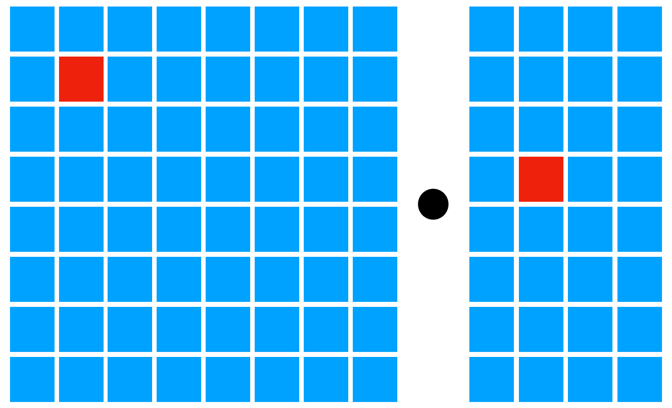
Tensorization Challenge

Compute primitives

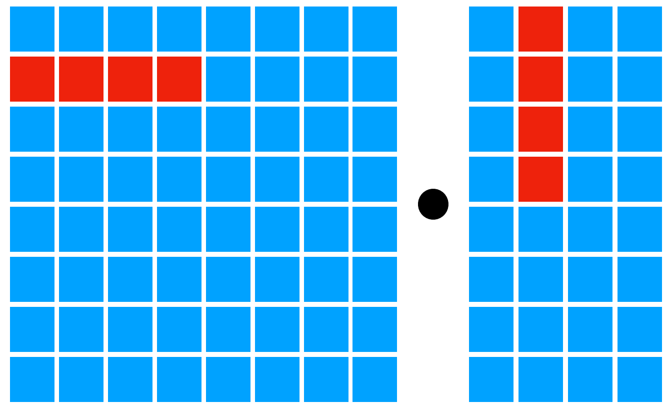


Tensorization Challenge

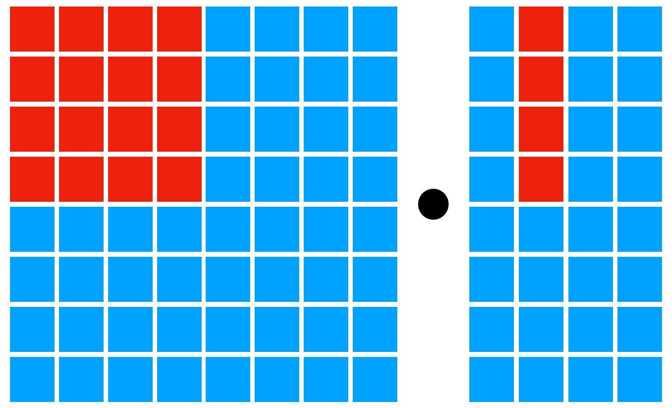
Compute primitives



scalar



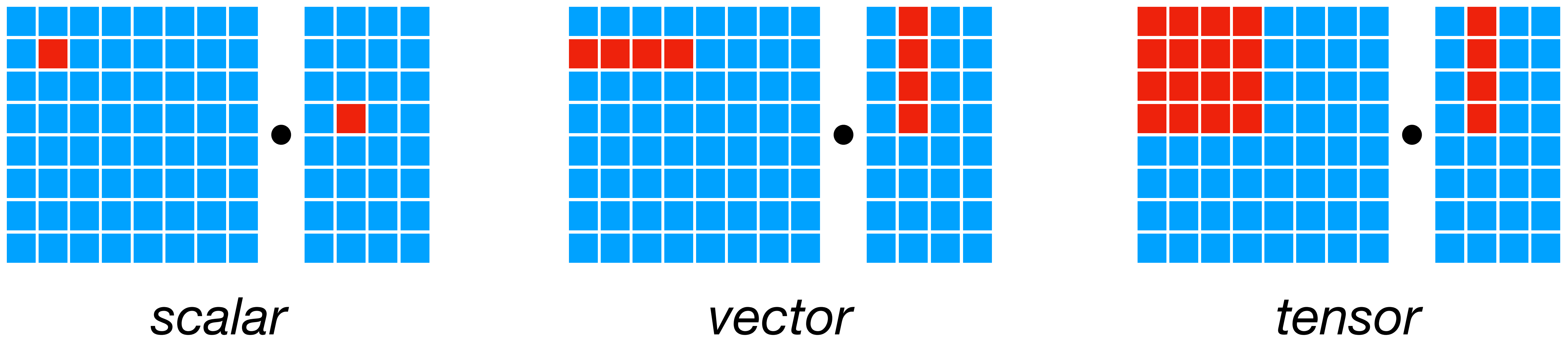
vector



tensor

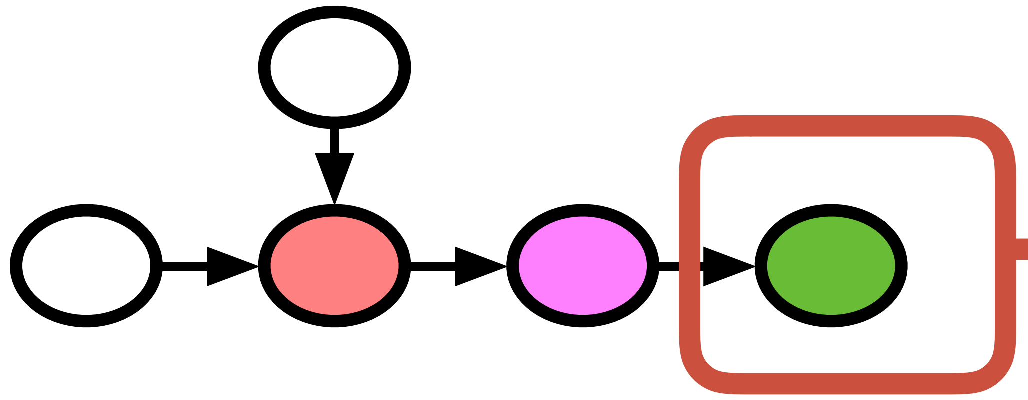
Tensorization Challenge

Compute primitives



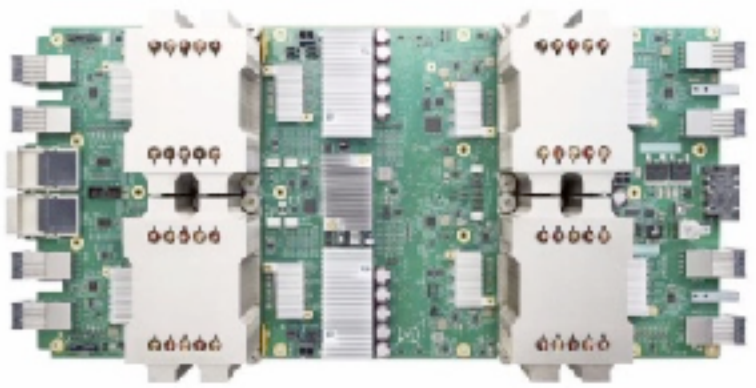
Challenge: Build systems to support emerging tensor instructions

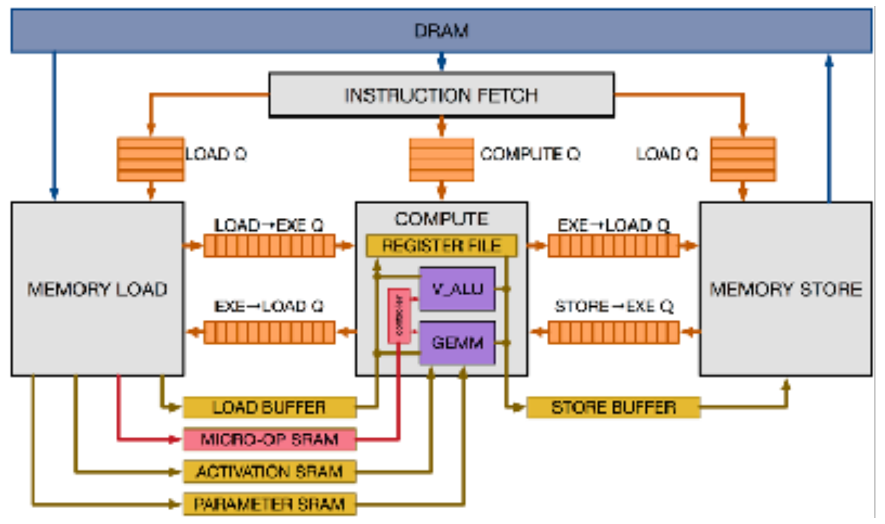
Tensorization Challenge



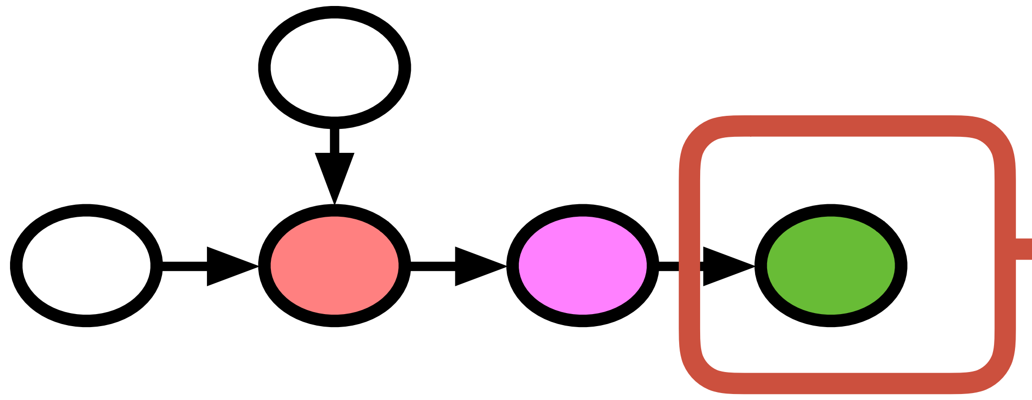
Computation Specification (Tensor Expression)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```



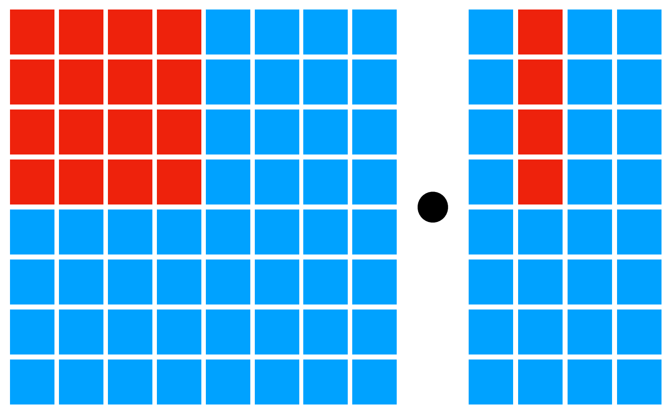


Tensorization Challenge



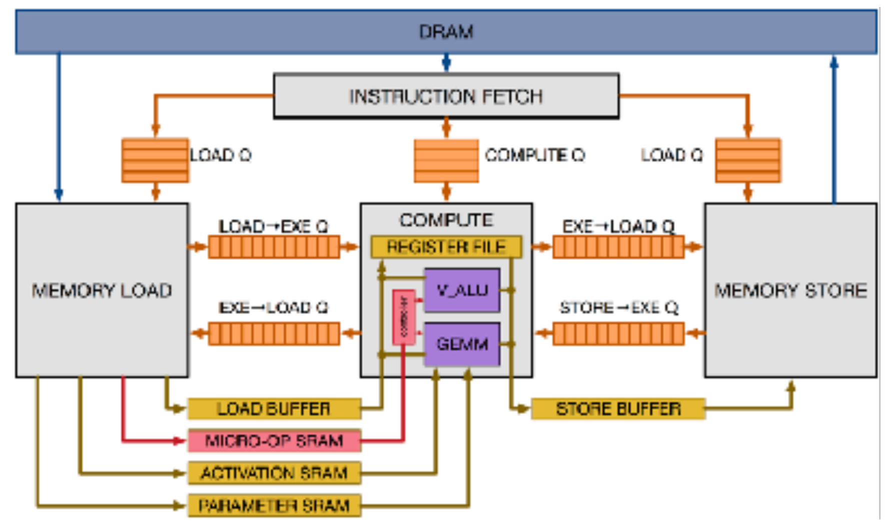
Computation Specification (Tensor Expression)

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

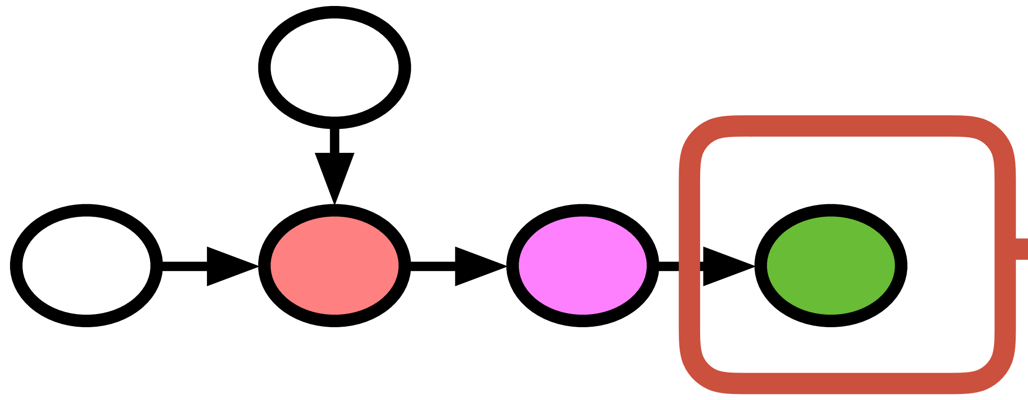


```
A = tvm.placeholder((8, 8))
B = tvm.placeholder((8,))
k = tvm.reduce_axis((0, 8))
C = tvm.compute((8, 8),
    lambda y, x: tvm.sum(A[k, y] * B[k], axis=k))
```

HW Interface Specification by Tensor Expression

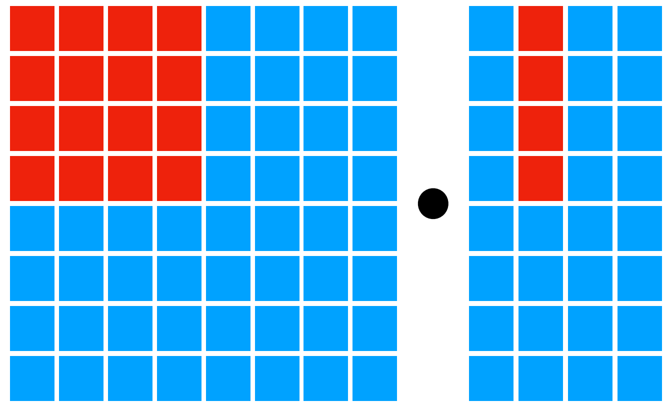


Tensorization Challenge



Computation Specification (Tensor Expression)

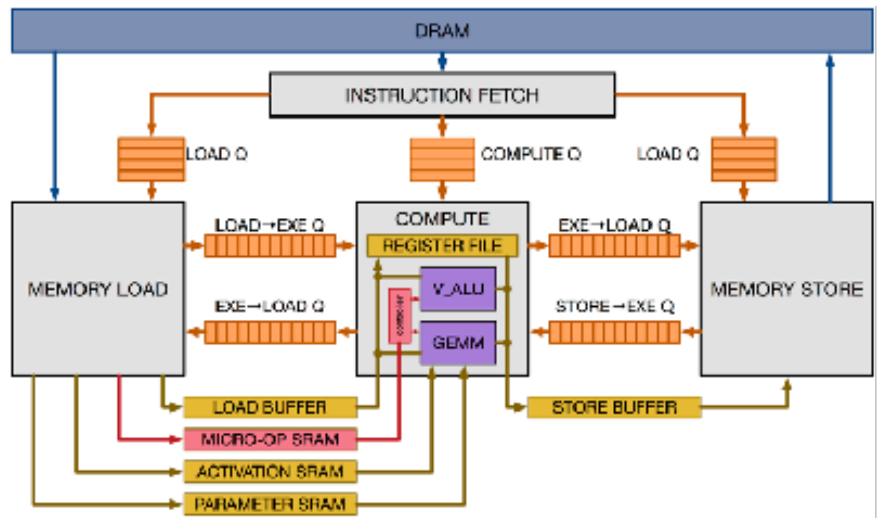
```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```



```
A = tvm.placeholder((8, 8))
B = tvm.placeholder((8,))
k = tvm.reduce_axis((0, 8))
C = tvm.compute((8, 8),
    lambda y, x: tvm.sum(A[k, y] * B[k], axis=k))
```

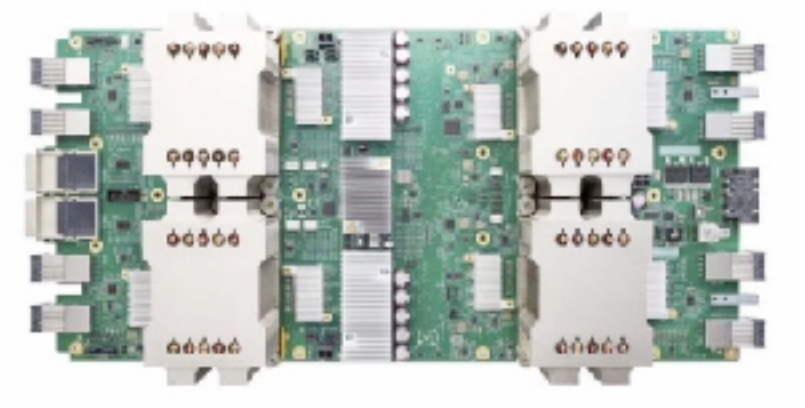
Tensorization

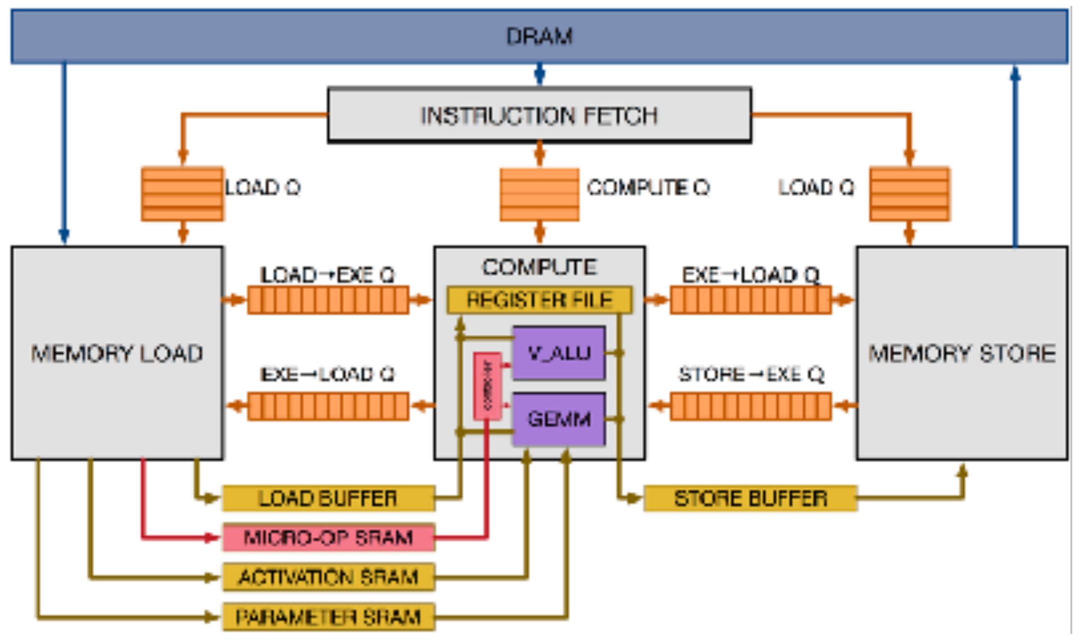
HW Interface Specification by Tensor Expression



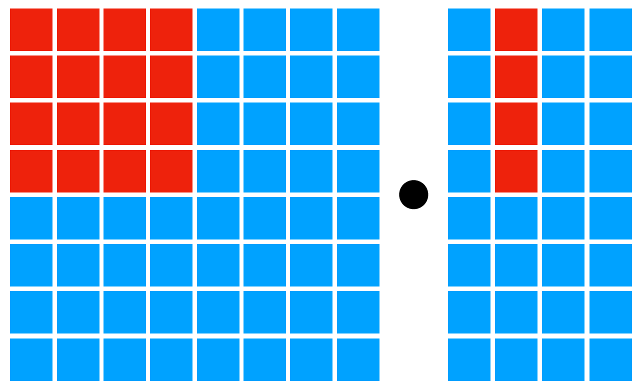
Search Space for TPU-like Specialized Accelerators

TPUs

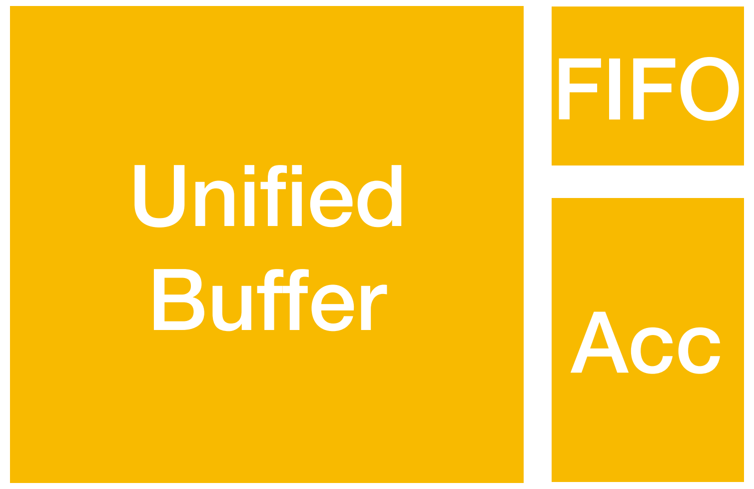




Tensor Compute Primitives

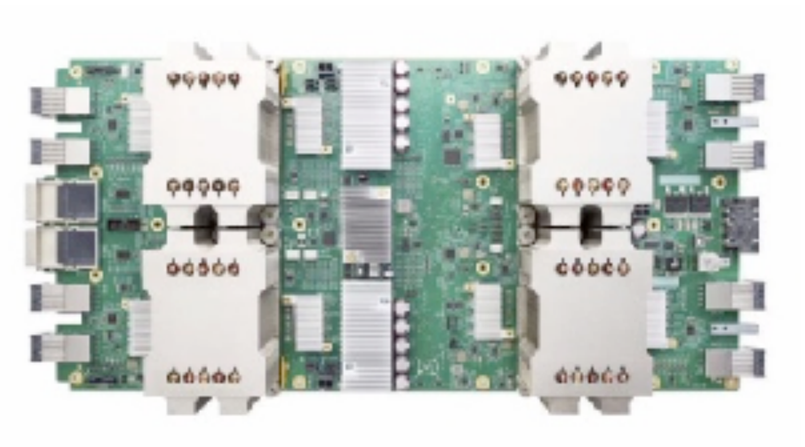


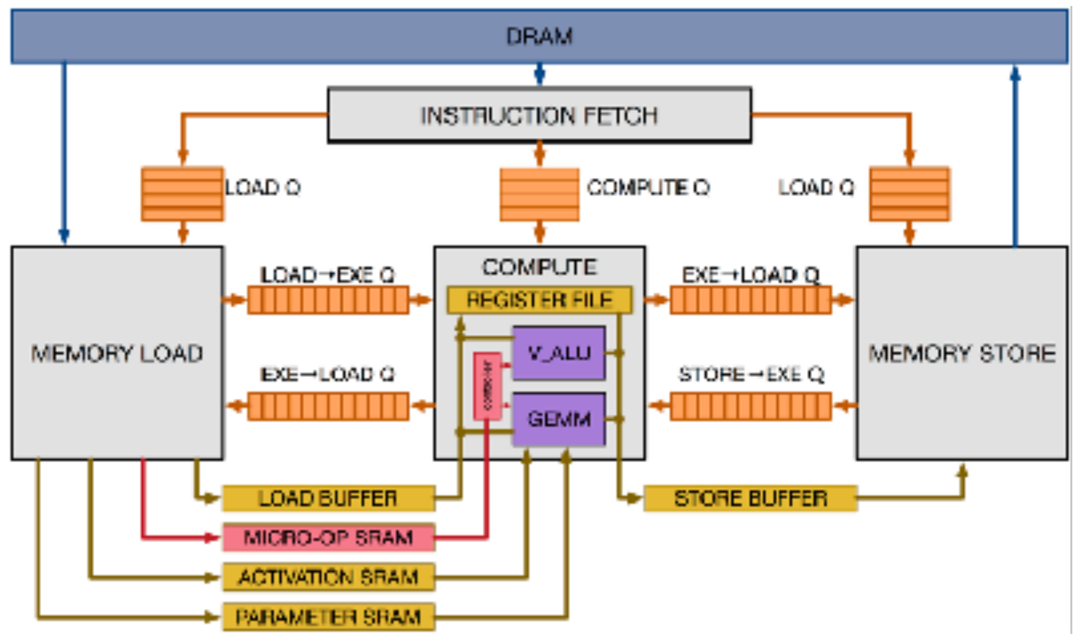
Explicitly Managed Memory Subsystem



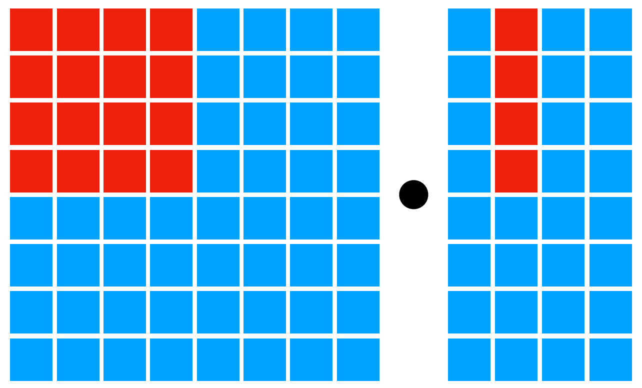
Search Space for TPU-like Specialized Accelerators

TPUs

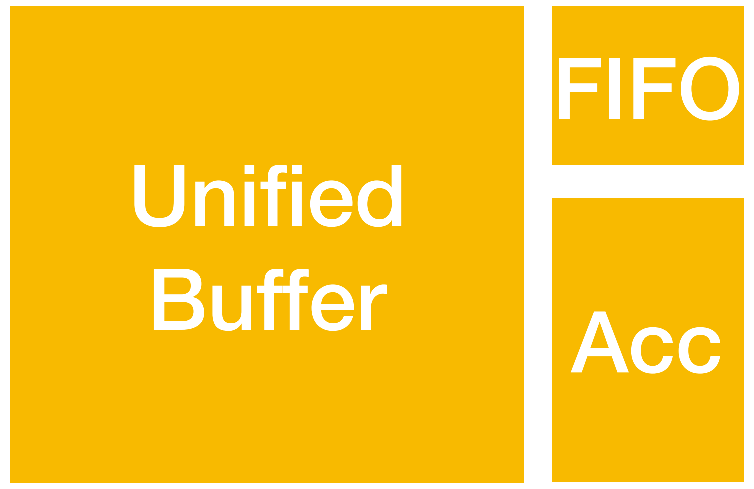




Tensor Compute Primitives



Explicitly Managed Memory Subsystem

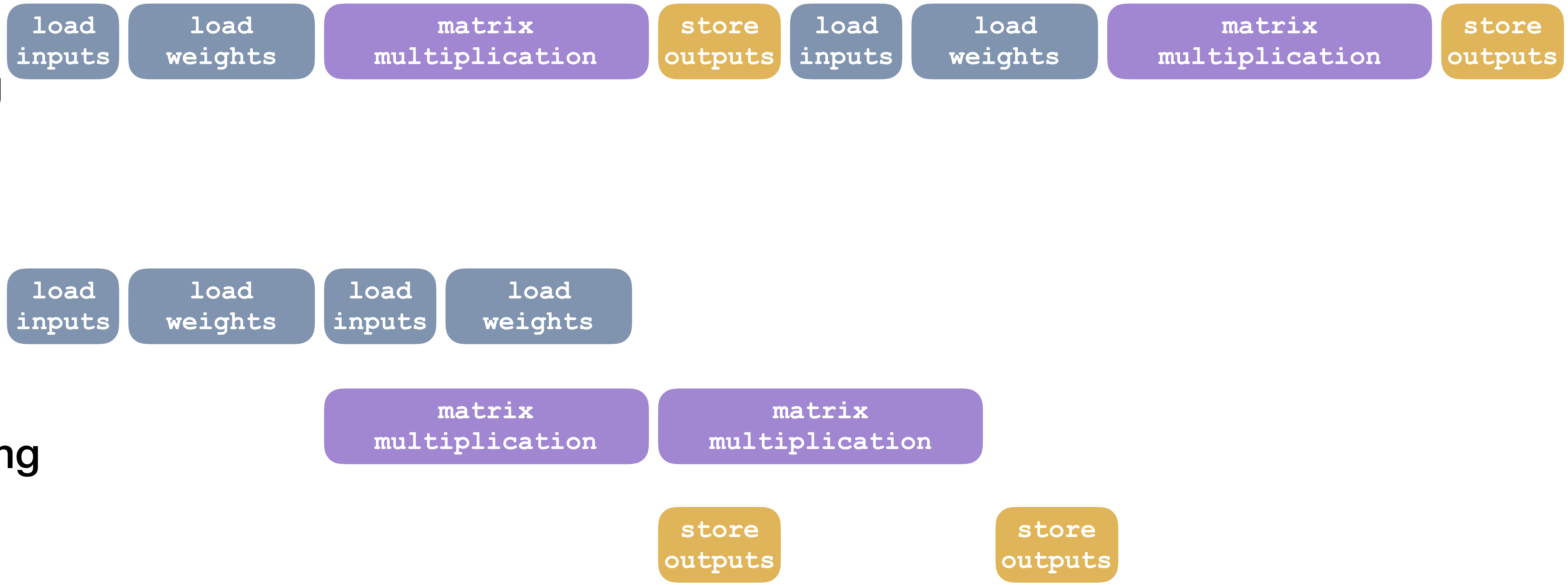


Software Support for Latency Hiding

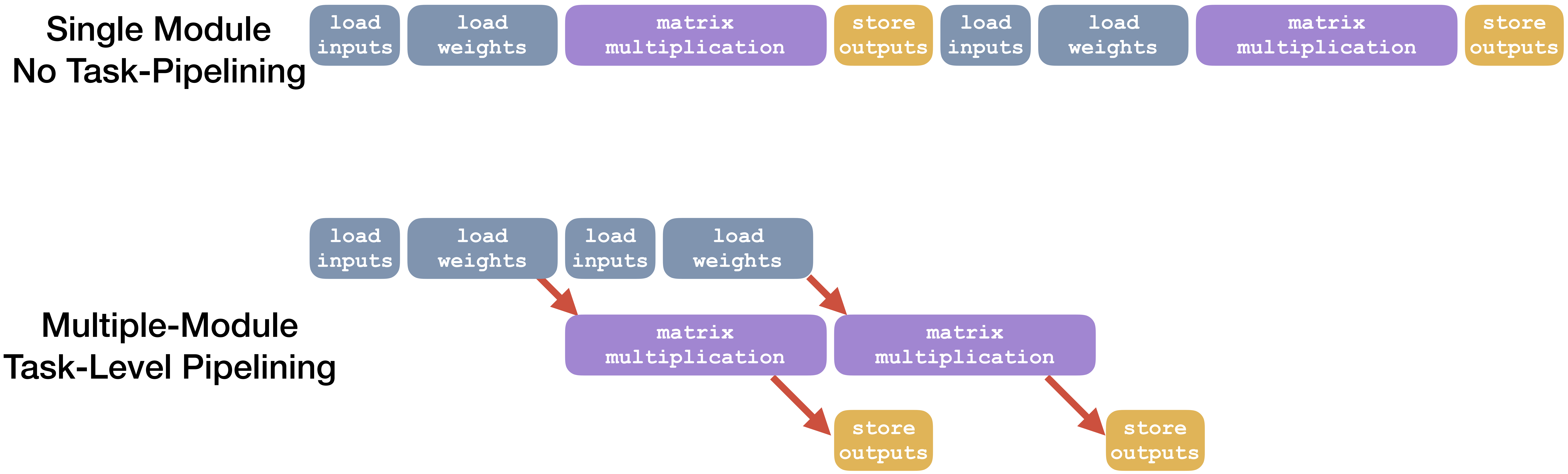
Software Support for Latency Hiding

Single Module
No Task-Pipelining

Multiple-Module
Task-Level Pipelining



Software Support for Latency Hiding

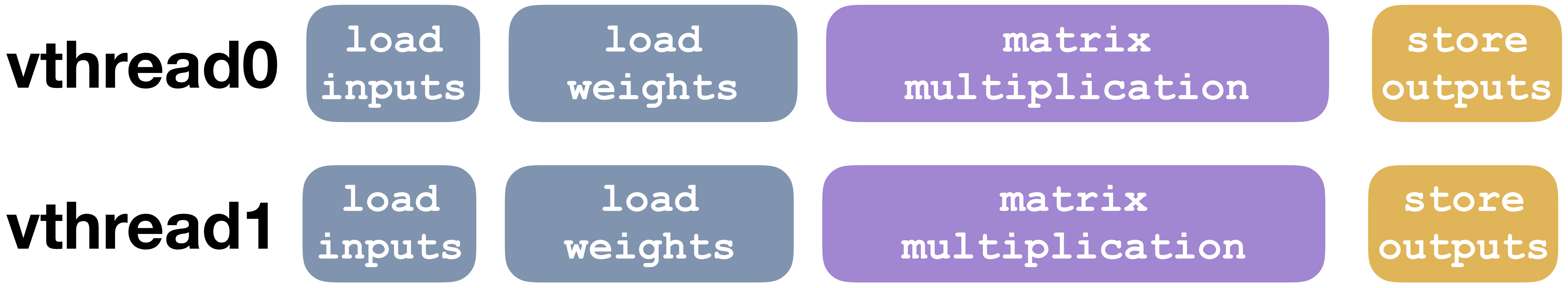


Explicit dependencies
managed by software to hide memory latency

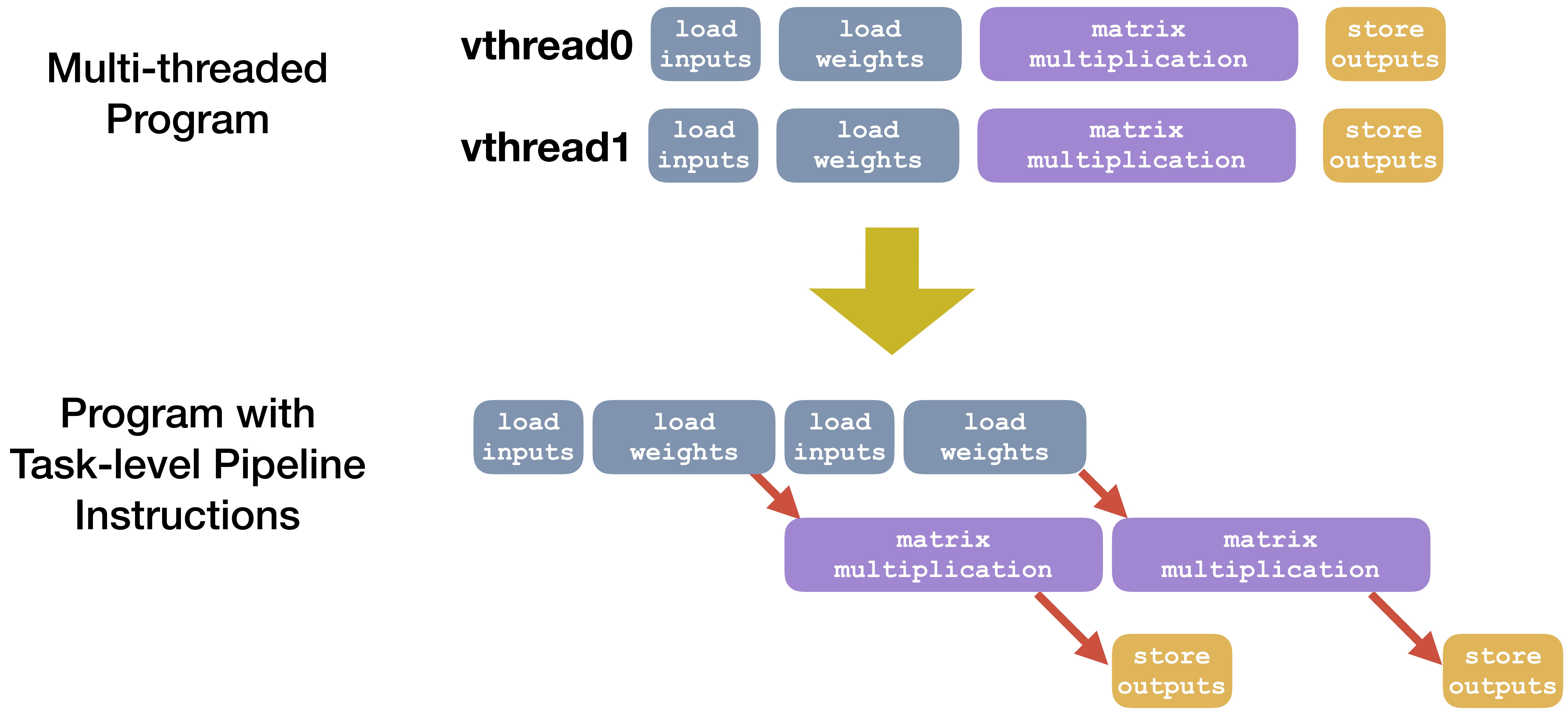
Software Support for Latency Hiding

Software Support for Latency Hiding

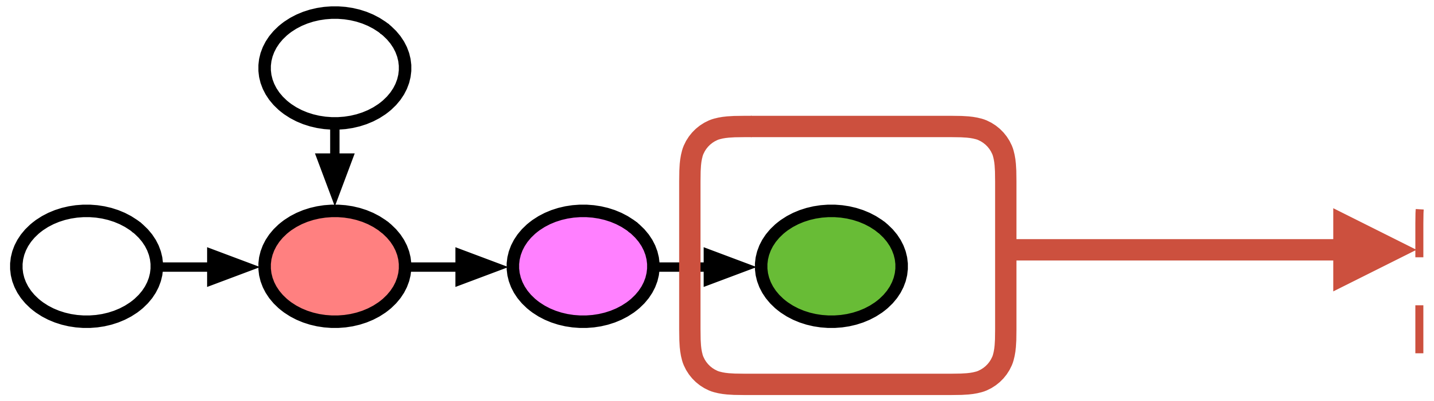
Multi-threaded Program



Software Support for Latency Hiding



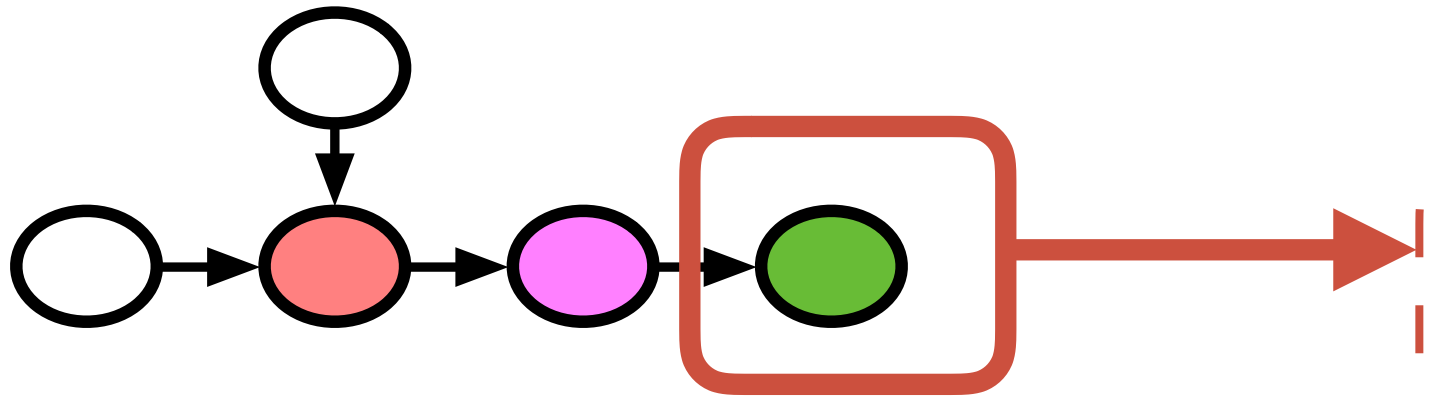
Summary: Hardware-aware Search Space



Tensor Expression Language

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

Summary: Hardware-aware Search Space



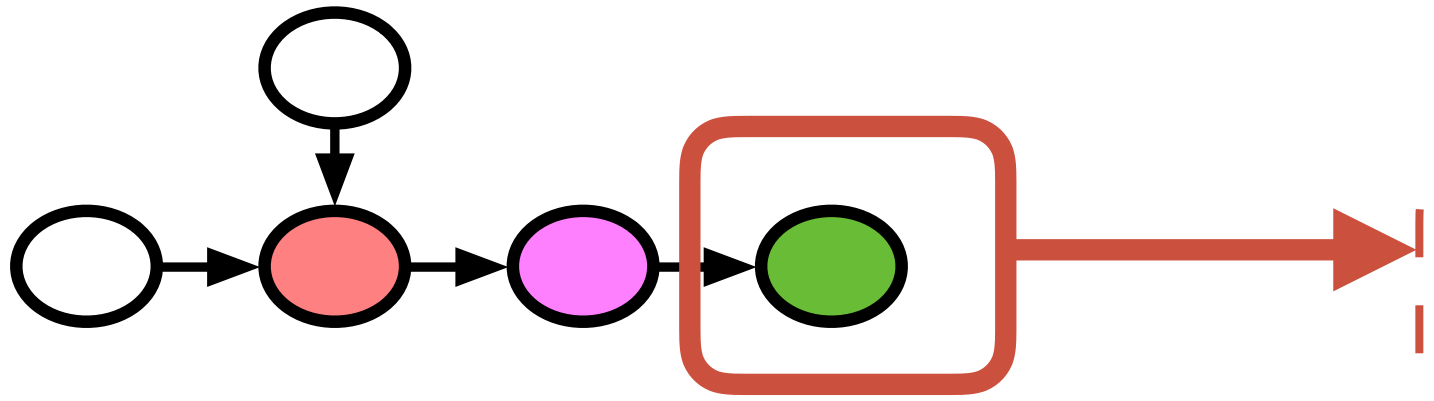
Tensor Expression Language

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

**Primitives in prior work:
Halide, Loopy**

- Loop Transformations
- Thread Bindings
- Cache Locality

Summary: Hardware-aware Search Space



Tensor Expression Language

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

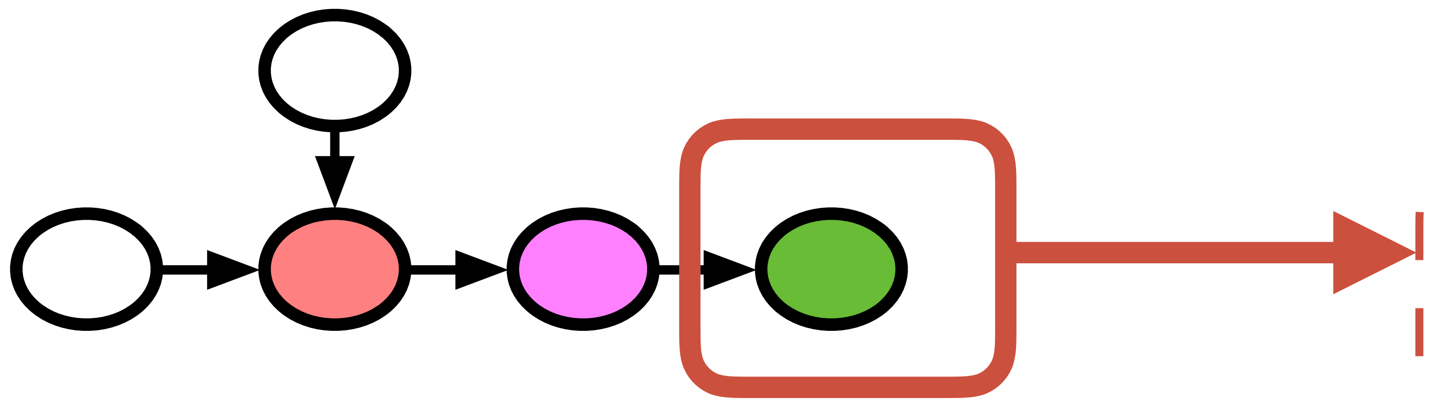
Primitives in prior work: Halide, Loopy

- Loop Transformations
- Thread Bindings
- Cache Locality

New primitives for GPUs, and enable TPU-like Accelerators

- Thread Cooperation
- Tensorization
- Latency Hiding
- ...

Summary: Hardware-aware Search Space



Tensor Expression Language

```
C = tvm.compute((m, n),
    lambda y, x: tvm.sum(A[k, y] * B[k, x], axis=k))
```

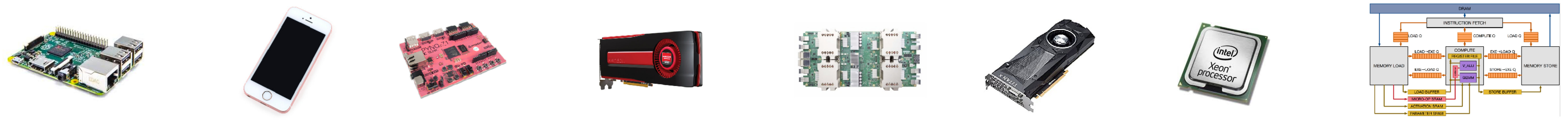
Primitives in prior work:
Halide, Loopy

- Loop Transformations
- Thread Bindings
- Cache Locality

New primitives for GPUs, and enable TPU-like Accelerators

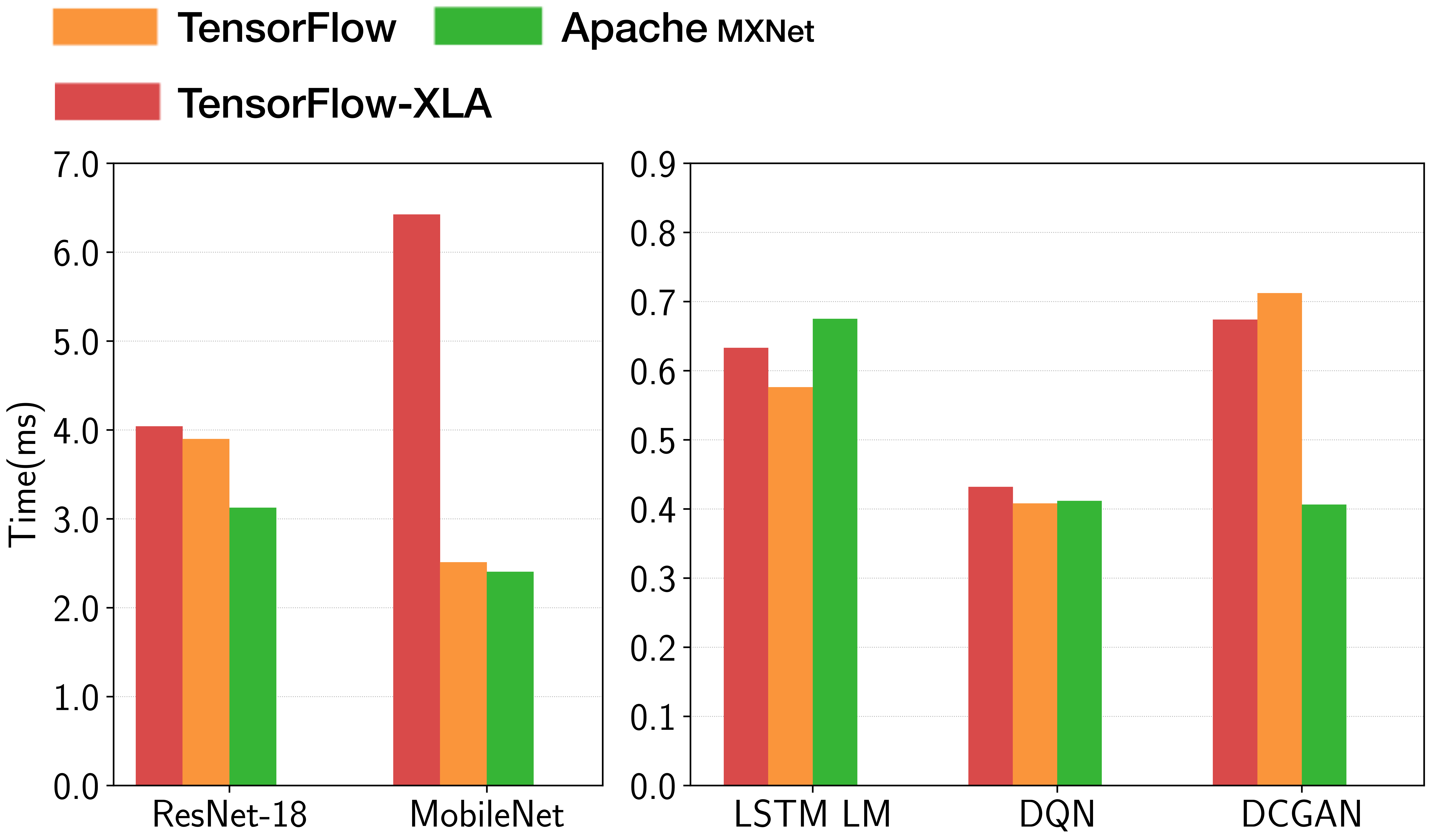
- Thread Cooperation
- Tensorization
- Latency Hiding
- ...

Hardware

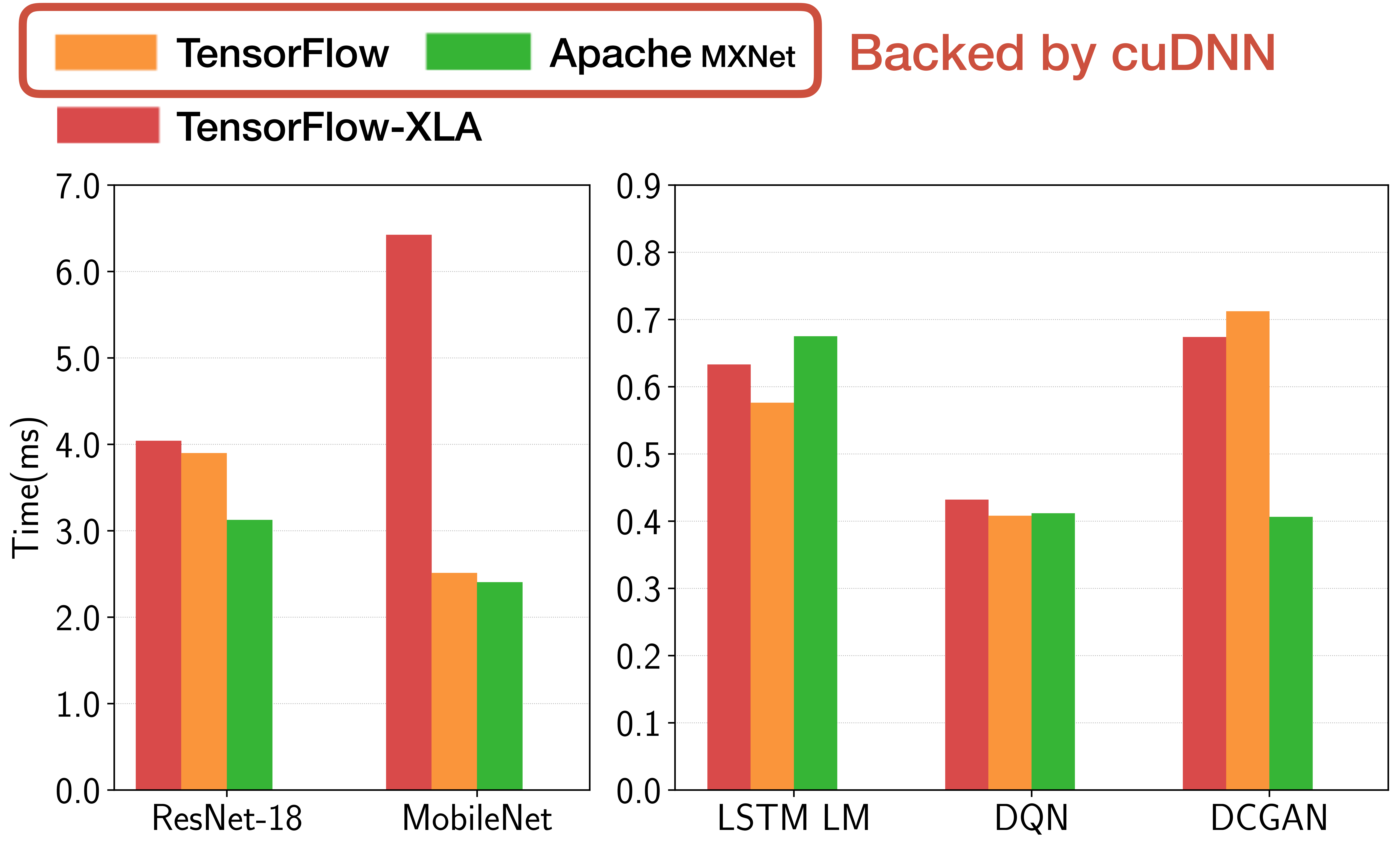


TVM: End to End Deep Learning Compiler

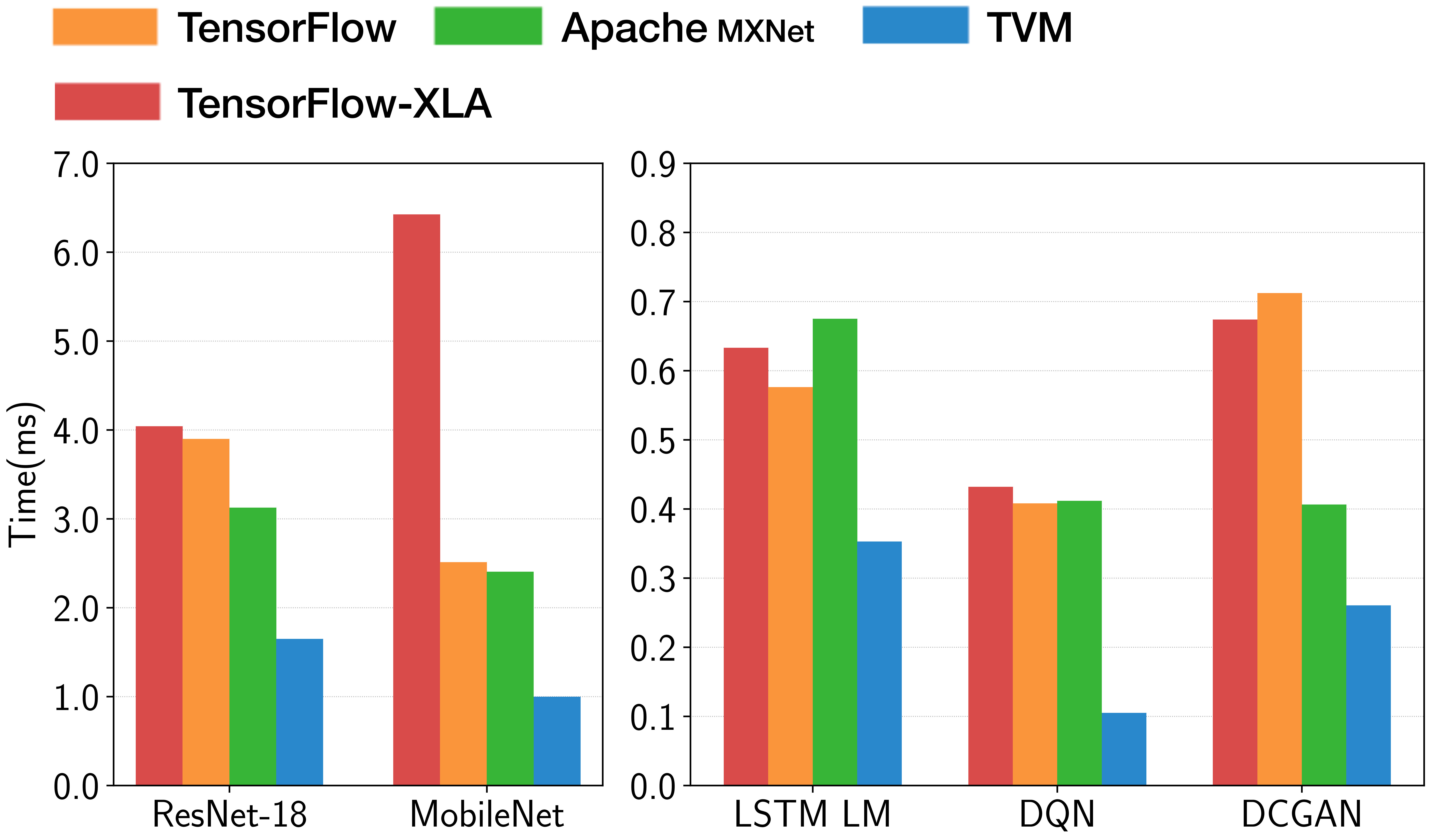
End to End Inference Performance (Nvidia Titan X)



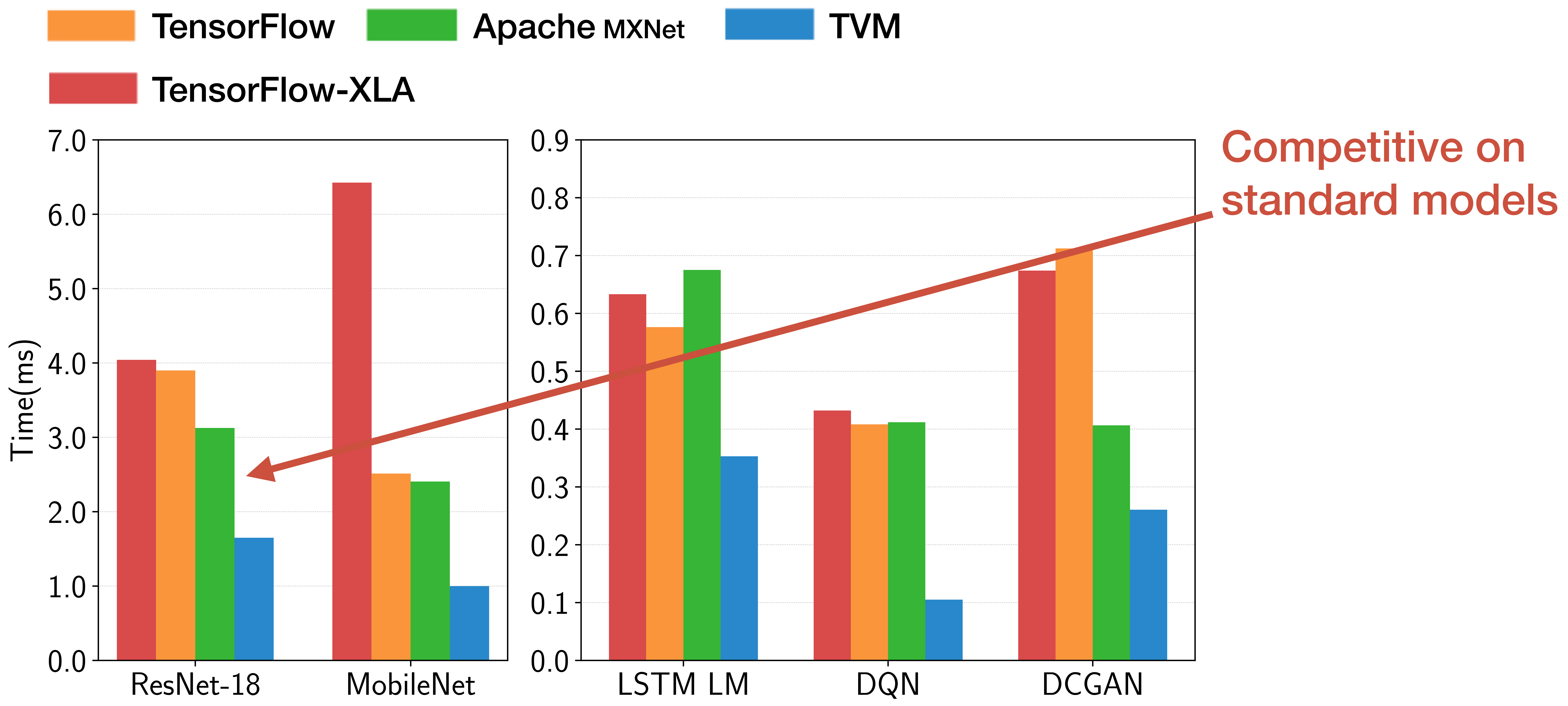
End to End Inference Performance (Nvidia Titan X)



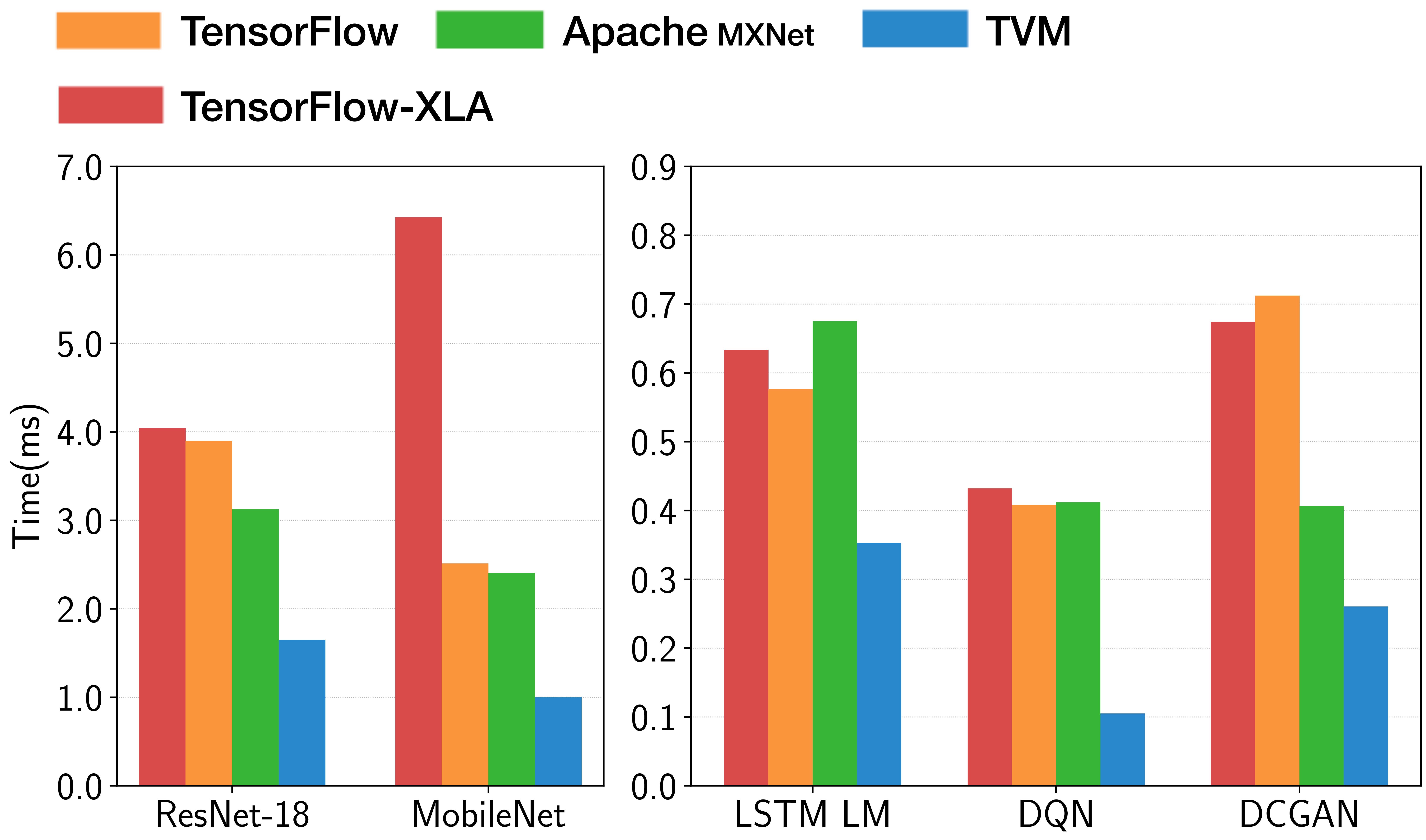
End to End Inference Performance (Nvidia Titan X)



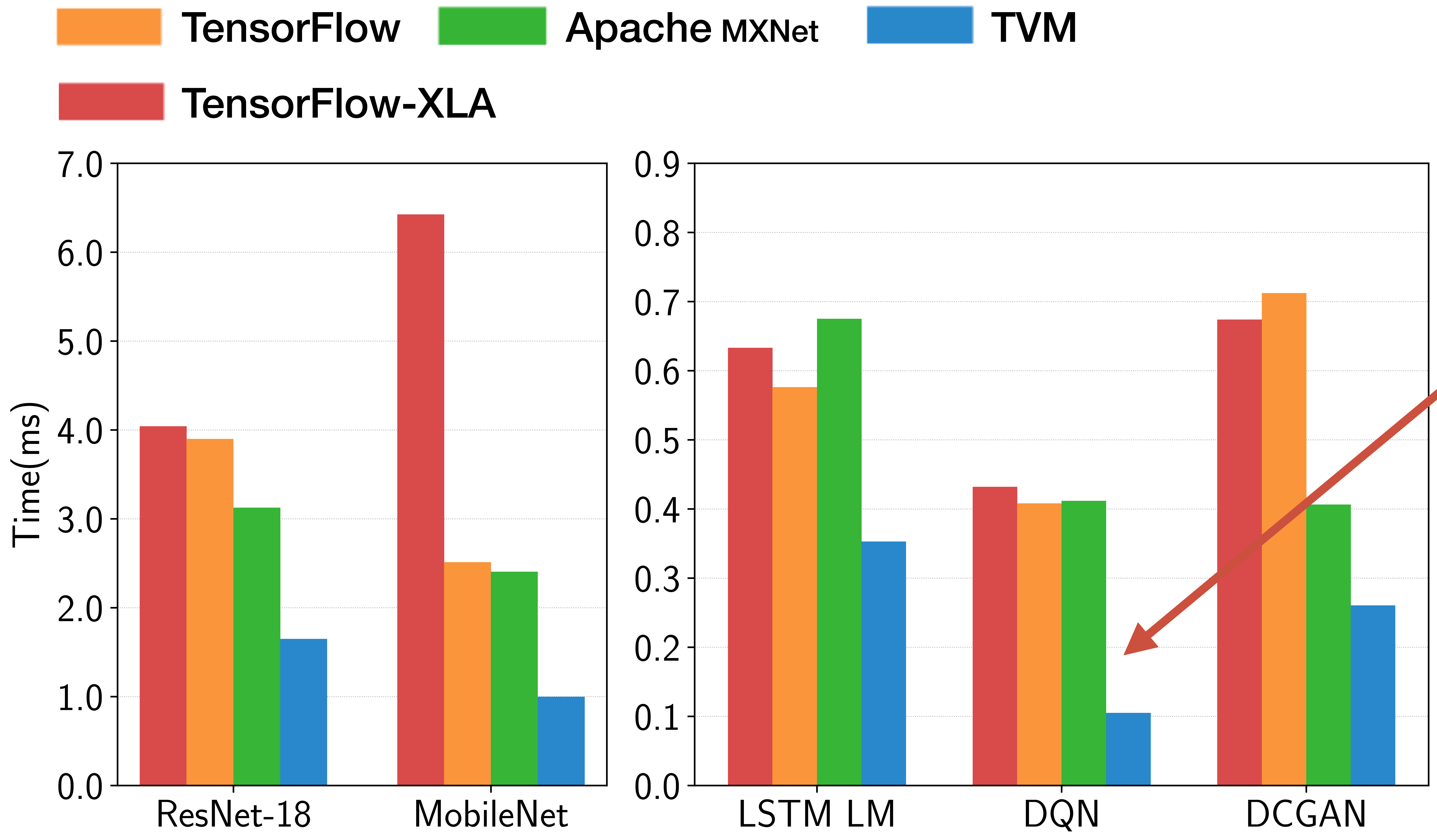
End to End Inference Performance (Nvidia Titan X)



End to End Inference Performance (Nvidia Titan X)

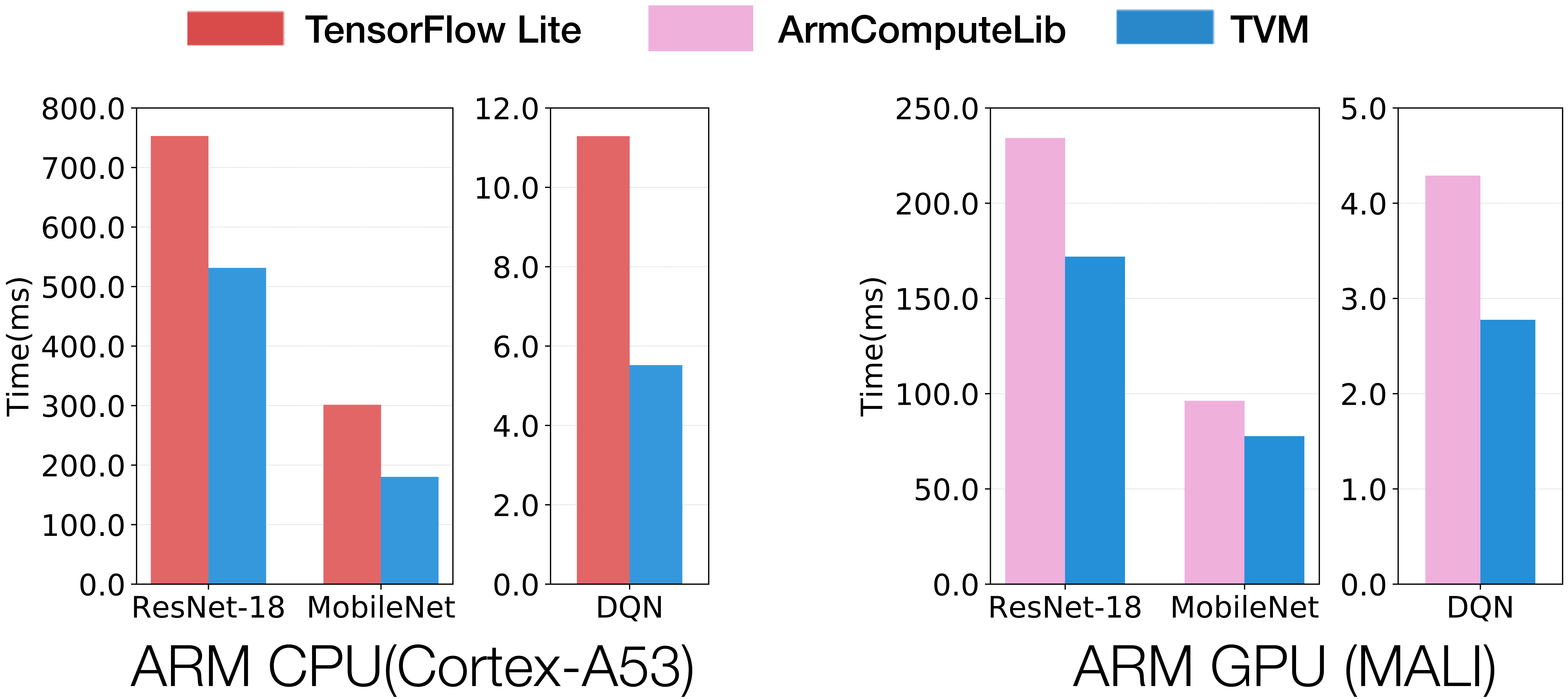


End to End Inference Performance (Nvidia Titan X)



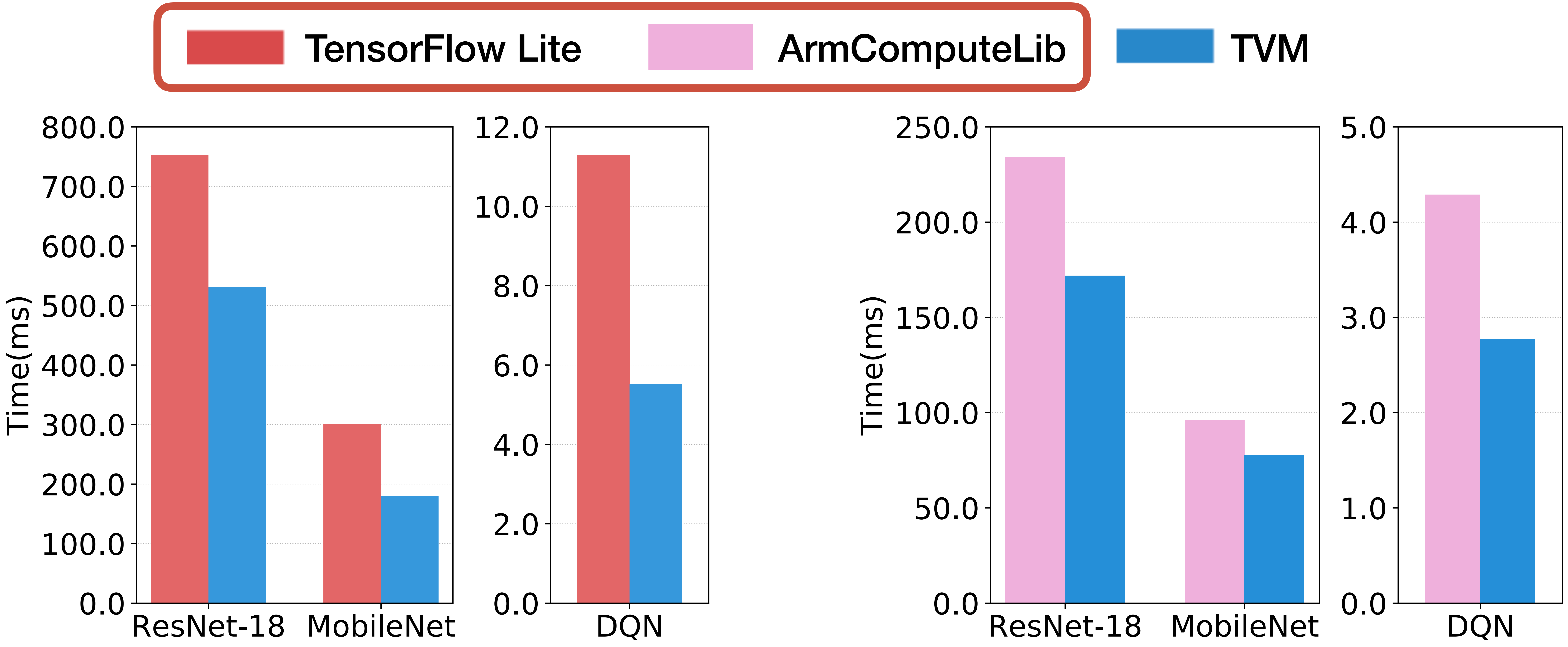
3x better on emerging models

Portable Performance Across Hardware Platforms



Portable Performance Across Hardware Platforms

Special frameworks for the particular hardware platform



ARM CPU(Cortex-A53)

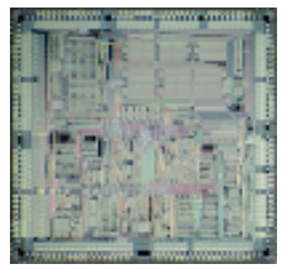
ARM GPU (MALI)

TVM: End to End Deep Learning Compiler

What about Accelerator Support?

VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

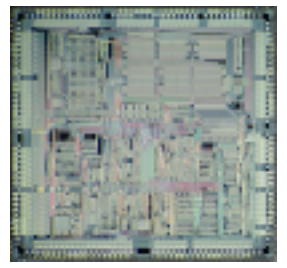


Moreau, Chen, et al. work in progress

VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

VTA MicroArchitecture



Moreau, Chen, et al. work in progress

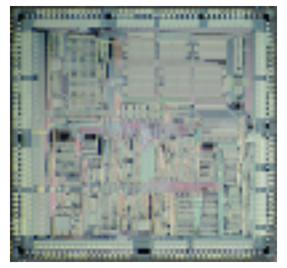
VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

VTA Hardware/Software Interface (ISA)

VTA MicroArchitecture

amazon webservices



Moreau, Chen, et al. work in progress

VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

VTA Runtime & JIT Compiler

VTA Hardware/Software Interface (ISA)

VTA MicroArchitecture

Moreau, Chen, et al. work in progress

VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

VTA Runtime & JIT Compiler

VTA Hardware/Software Interface (ISA)

VTA MicroArchitecture | VTA Simulator

Moreau, Chen, et al. work in progress

VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

VTA Runtime & JIT Compiler

VTA Hardware/Software Interface (ISA)

VTA MicroArchitecture | VTA Simulator

Moreau, Chen, et al. work in progress

- Runtime JIT compile accelerator micro code
- Support heterogenous devices, 10x better than CPU on the same board.
- Move hardware complexity to software

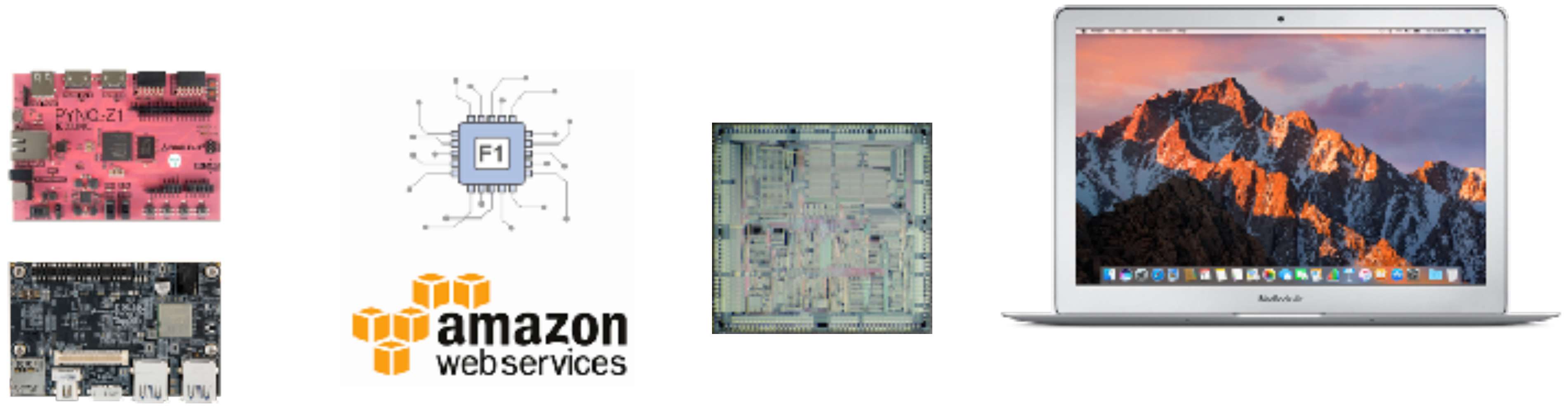
VTA: Open & Flexible Deep Learning Accelerator

Current TVM Stack

VTA Runtime & JIT Compiler

VTA Hardware/Software Interface (ISA)

VTA MicroArchitecture | VTA Simulator

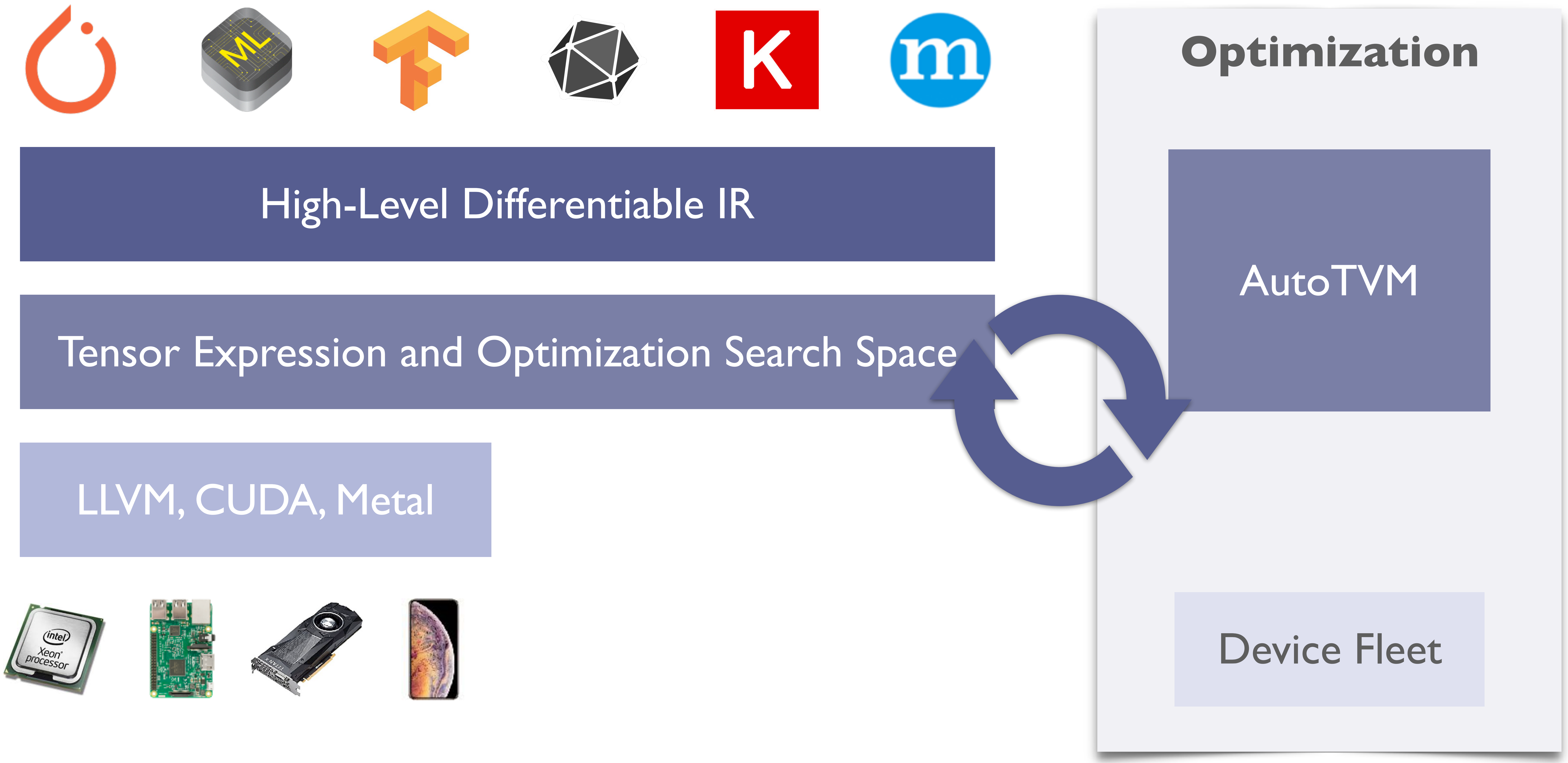


Moreau, Chen, et al. work in progress

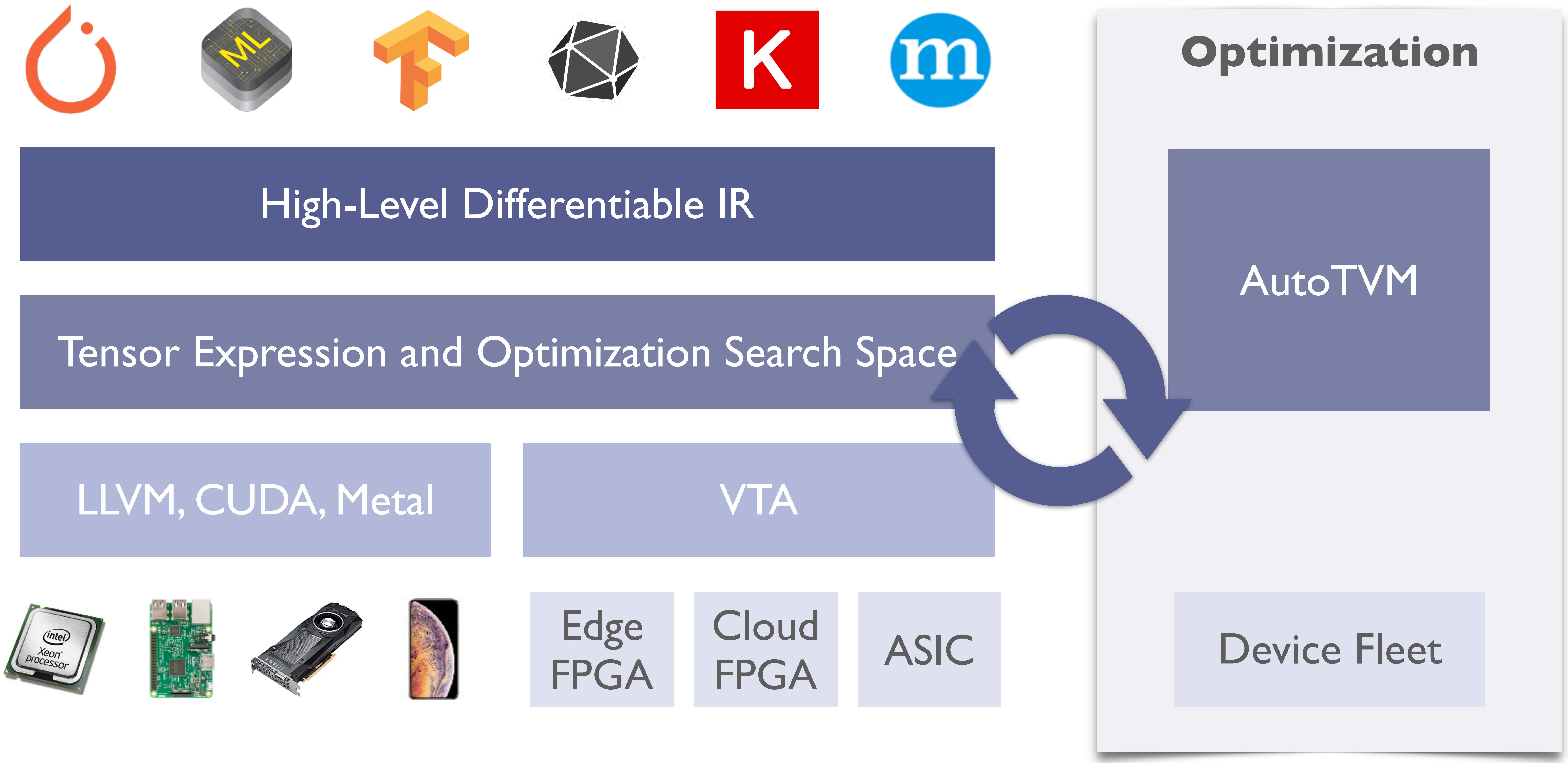
- Runtime JIT compile accelerator micro code
- Support heterogenous devices, 10x better than CPU on the same board.
- Move hardware complexity to software

compiler, driver,
hardware design
full stack open source

TVM: End to End Deep Learning Compiler



TVM: End to End Deep Learning Compiler



TVM Impact

TVM Impact

Open source: 202 contributors from UW, Berkeley, Cornell, UCLA, AWS, Huawei, NTT, Facebook, Qualcomm, …

TVM Impact

Open source: 202 contributors from UW, Berkeley, Cornell, UCLA, AWS, Huawei, NTT, Facebook, Qualcomm, …

Used in production

TVM Enables New Research Frontiers

TVM Enables New Research Frontiers

- PL: New high-level differentiable programming IR (UW)

TVM Enables New Research Frontiers

- PL: New high-level differentiable programming IR (UW)
- Architecture: New deep learning ASICs, RISC-V (UW, Cornell)

TVM Enables New Research Frontiers

- PL: New high-level differentiable programming IR (UW)
- Architecture: New deep learning ASICs, RISC-V (UW, Cornell)
- Security: trusted enclave for private aware ML. (Berkeley)

TVM Enables New Research Frontiers

- PL: New high-level differentiable programming IR (UW)
- Architecture: New deep learning ASICs, RISC-V (UW, Cornell)
- Security: trusted enclave for private aware ML. (Berkeley)
- Machine learning: test bed for automatic optimization. (UW)

TVM Enables New Research Frontiers

- PL: New high-level differentiable programming IR (UW)
- Architecture: New deep learning ASICs, RISC-V (UW, Cornell)
- Security: trusted enclave for private aware ML. (Berkeley)
- Machine learning: test bed for automatic optimization. (UW)

Reseach Group sampl

TVM Enables New Research Frontiers

- PL: New high-level differentiable programming IR (UW)
- Architecture: New deep learning ASICs, RISC-V (UW, Cornell)
- Security: trusted enclave for private aware ML. (Berkeley)
- Machine learning: test bed for automatic optimization. (UW)

Reseach Group sampl

TVM Conference
180 attendees, 20+ talks

Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

Scale up
deep learning

tvm

Deploy AI
everywhere

Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

Scale up
deep learning

tvm

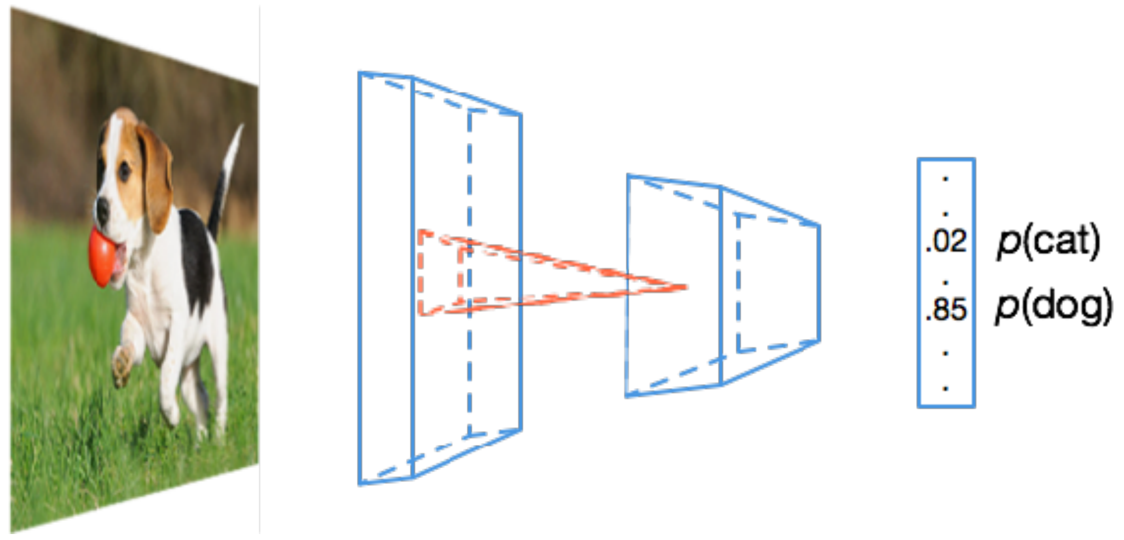
Deploy AI
everywhere

What's Next

Learning-based Learning System

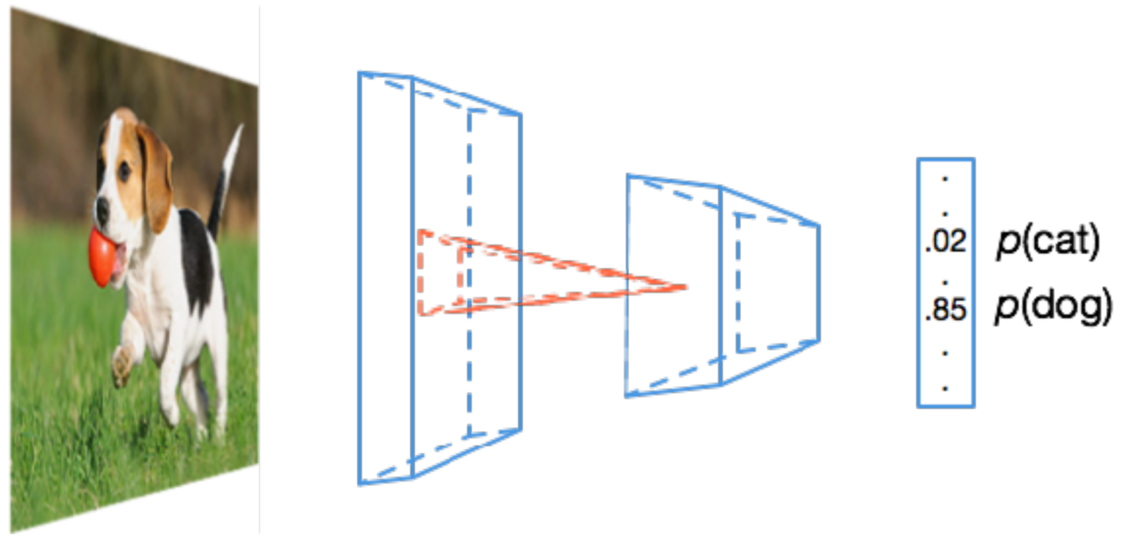
Learning-based Learning System

Application



Learning-based Learning System

Application

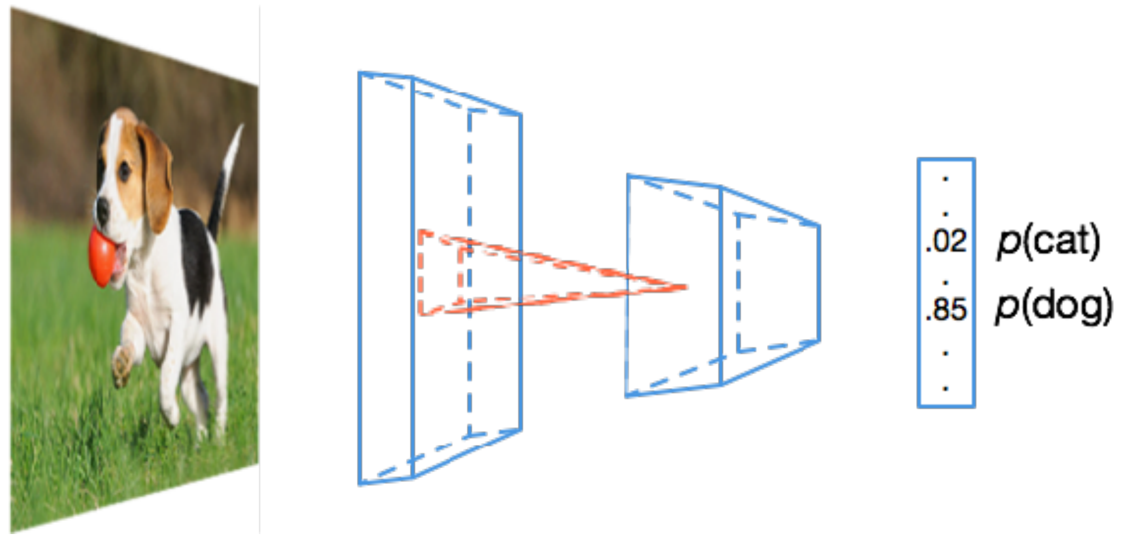


Model

MobileNet-V2

Learning-based Learning System

Application



Model

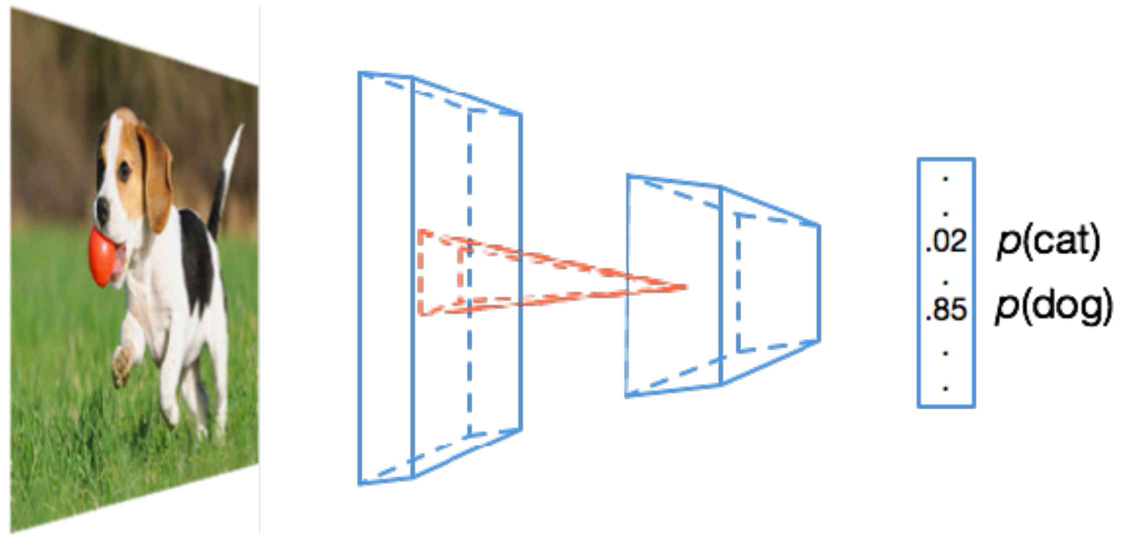
MobileNet-V2

Hardware

ARM Cortex A53

Learning-based Learning System

Application



Model

MobileNet-V2

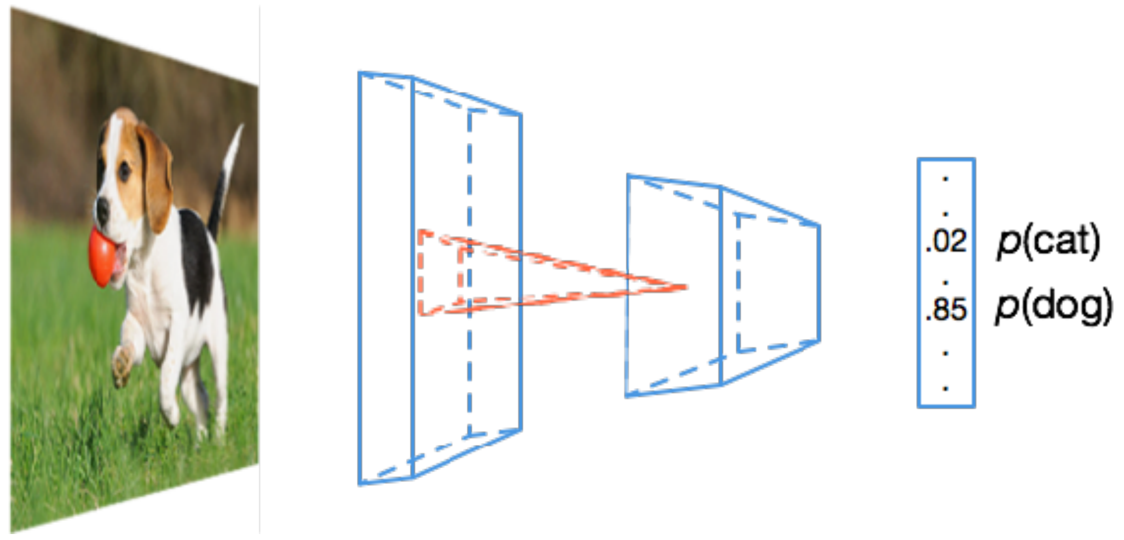
Space of Tensor Programs

Hardware

ARM Cortex A53

Learning-based Learning System

Application



Model

MobileNet-V2

Space of Tensor Programs

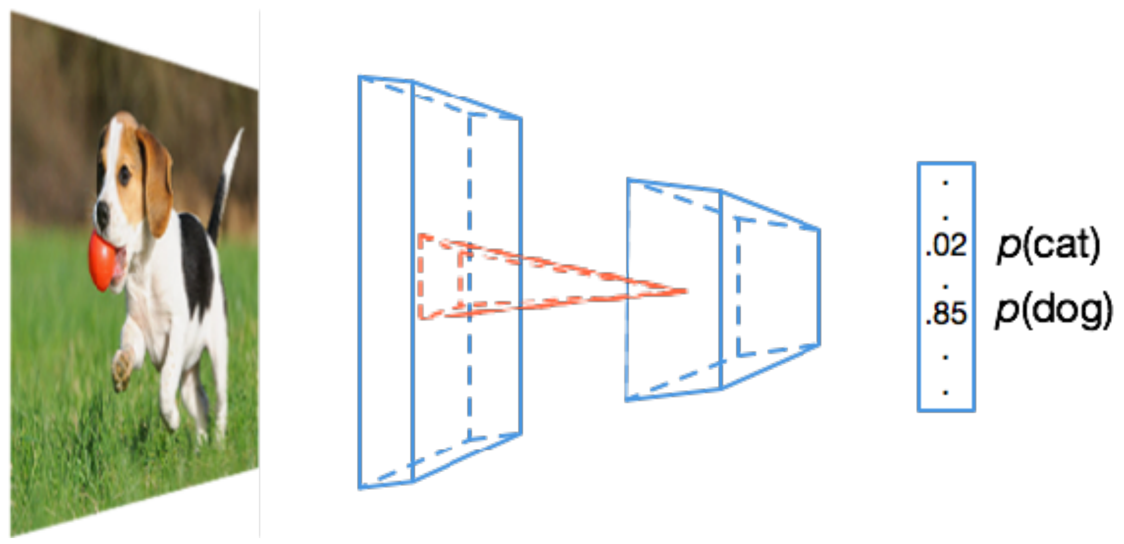
AutoTVM

Hardware

ARM Cortex A53

Learning-based Learning System

Application



Model

MobileNet-V2

Space of Tensor Programs

→ **AutoTVM** → Optimized Tensor Program

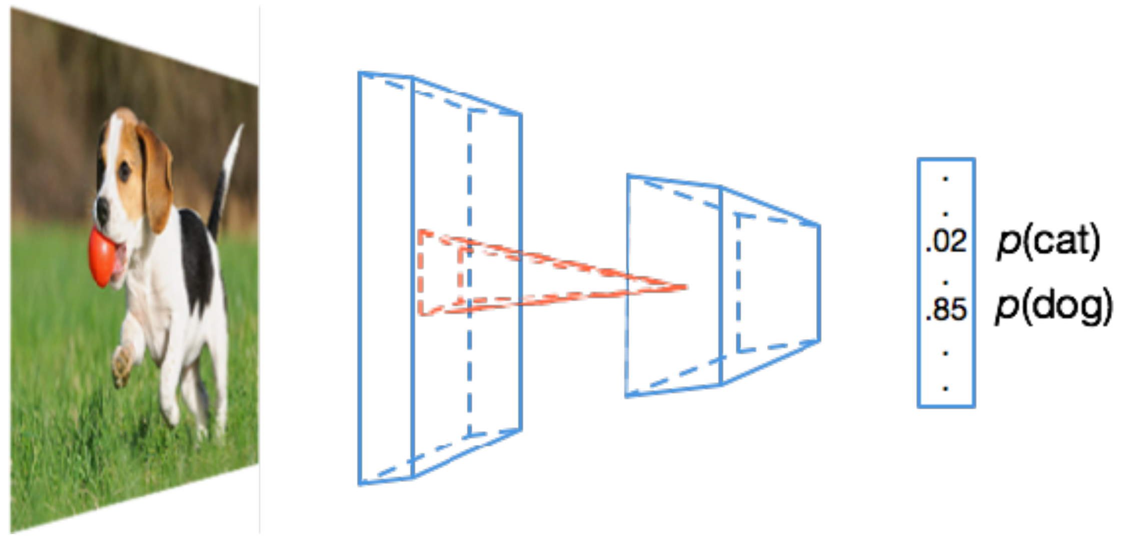
Hardware

ARM Cortex A53

Full Stack Learning-based Learning System

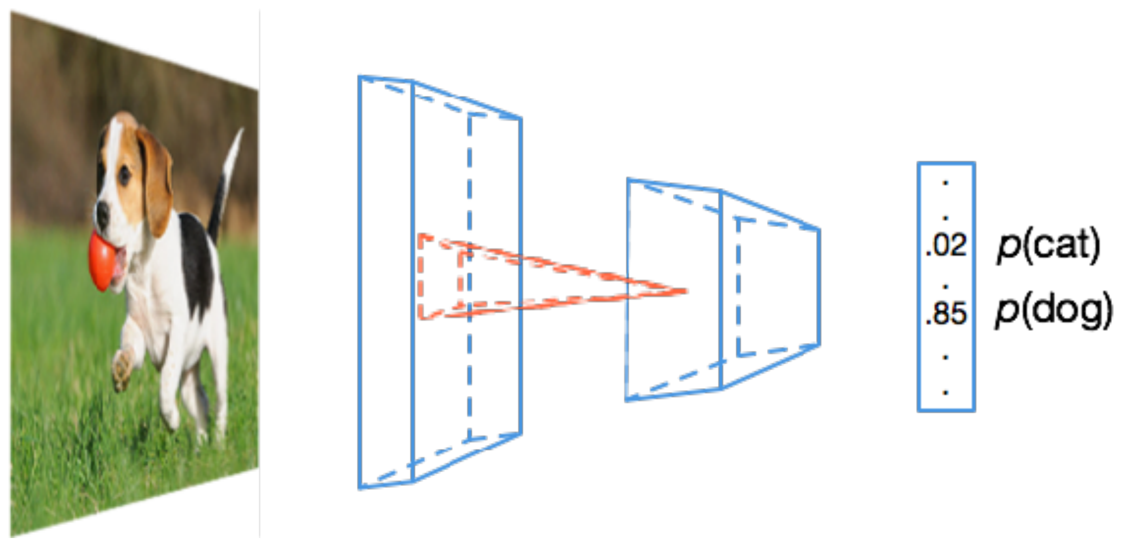
Full Stack Learning-based Learning System

Application



Full Stack Learning-based Learning System

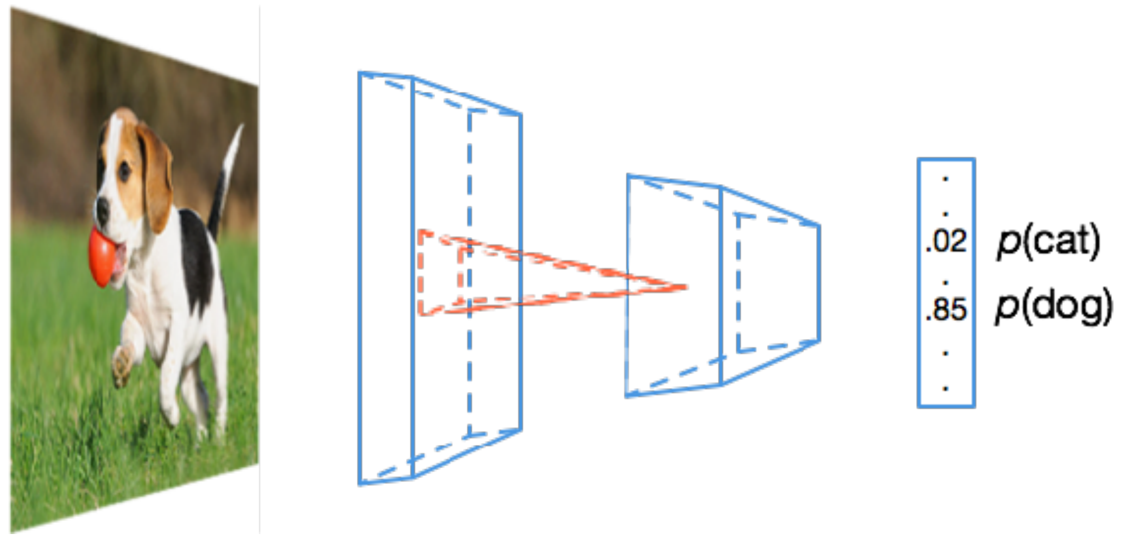
Application



Space of Models

Full Stack Learning-based Learning System

Application

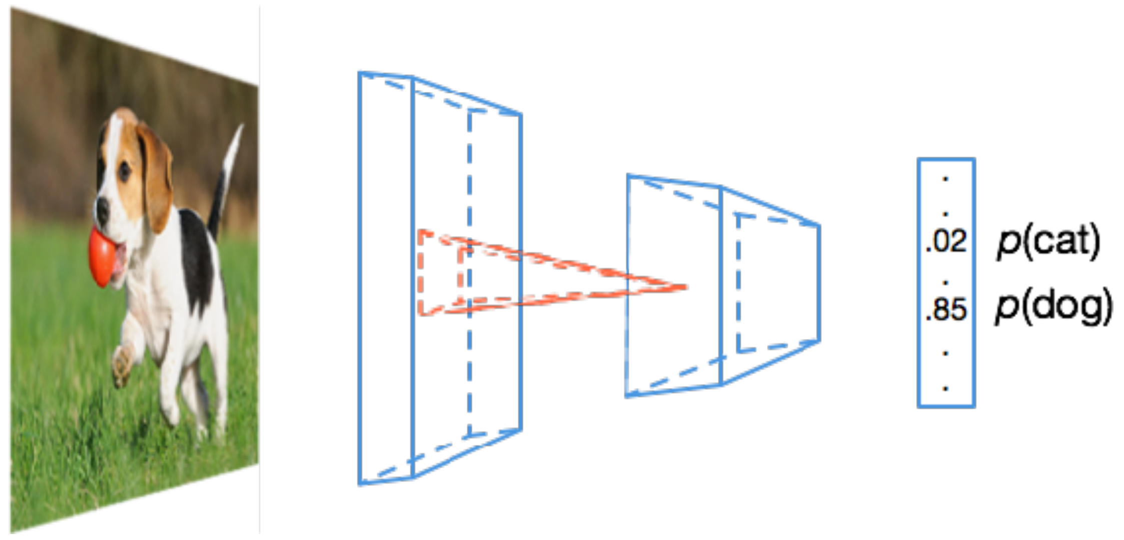


Space of Models

Space of
Tensor Programs

Full Stack Learning-based Learning System

Application



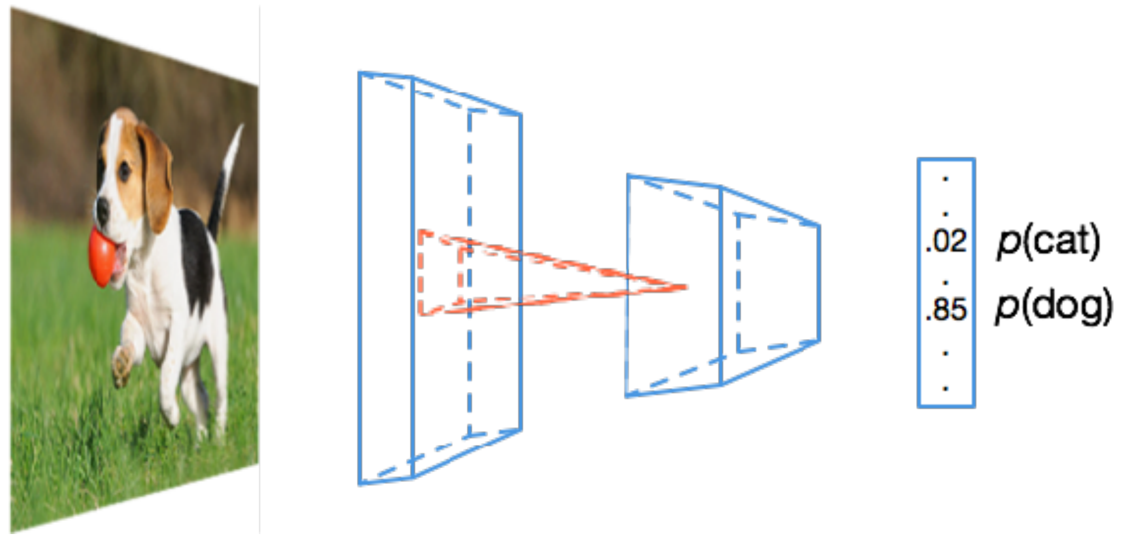
Space of Models

Space of
Tensor Programs

Space of Hardware
Variants

Full Stack Learning-based Learning System

Application



Space of Models

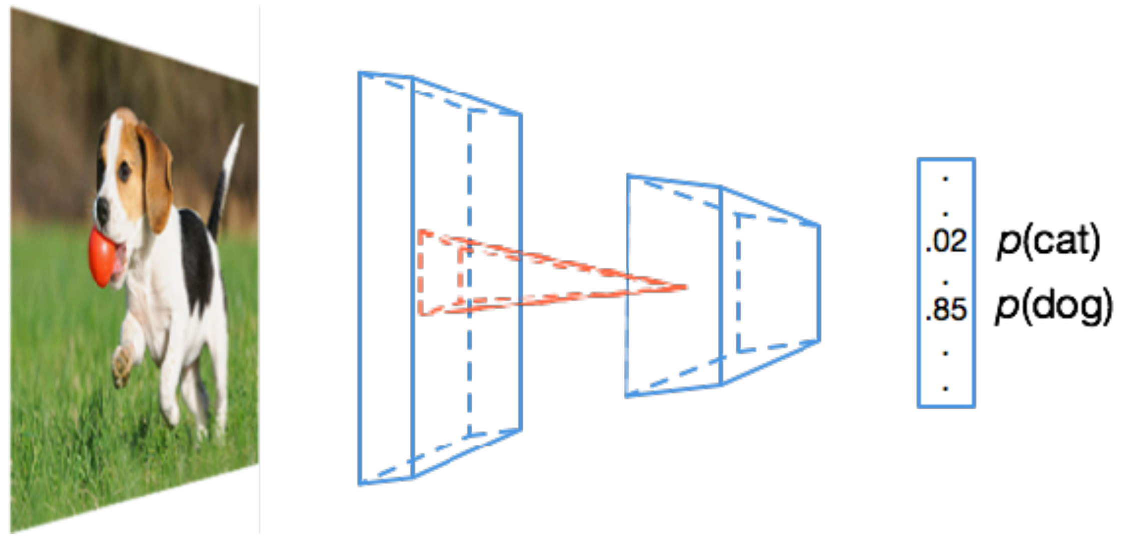
Space of Tensor Programs

Space of Hardware Variants

Full-Stack AutoTVM

Full Stack Learning-based Learning System

Application



Space of Models

Space of Tensor Programs

Space of Hardware Variants

Full-Stack AutoTVM

Auto Optimized Net

Optimized Tensor Program

Auto Hardware Variant

Full Stack Learning-based Learning System

Full Stack Learning-based Learning System

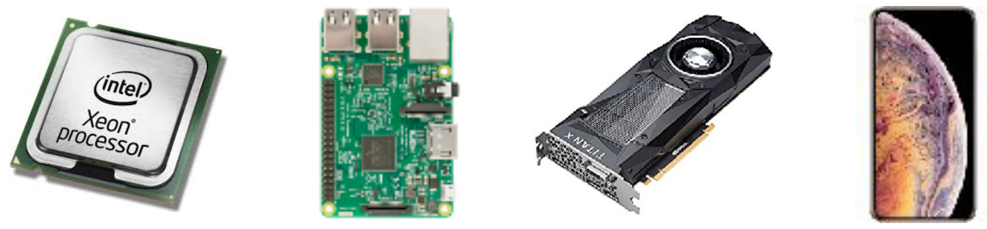
ML Models

High-Level Differentiable IR

Tensor Expression IR

LLVM, CUDA | VTA

System Optimizations



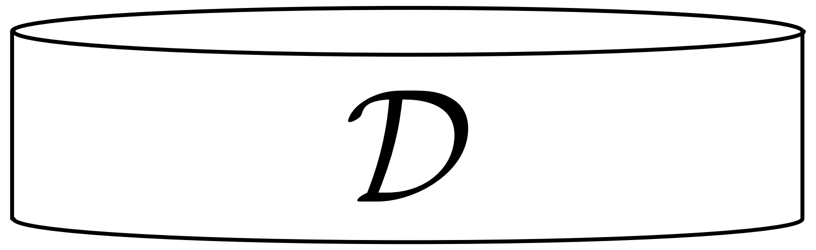
Edge FPGA | Cloud FPGA | ASIC

Hardware Design

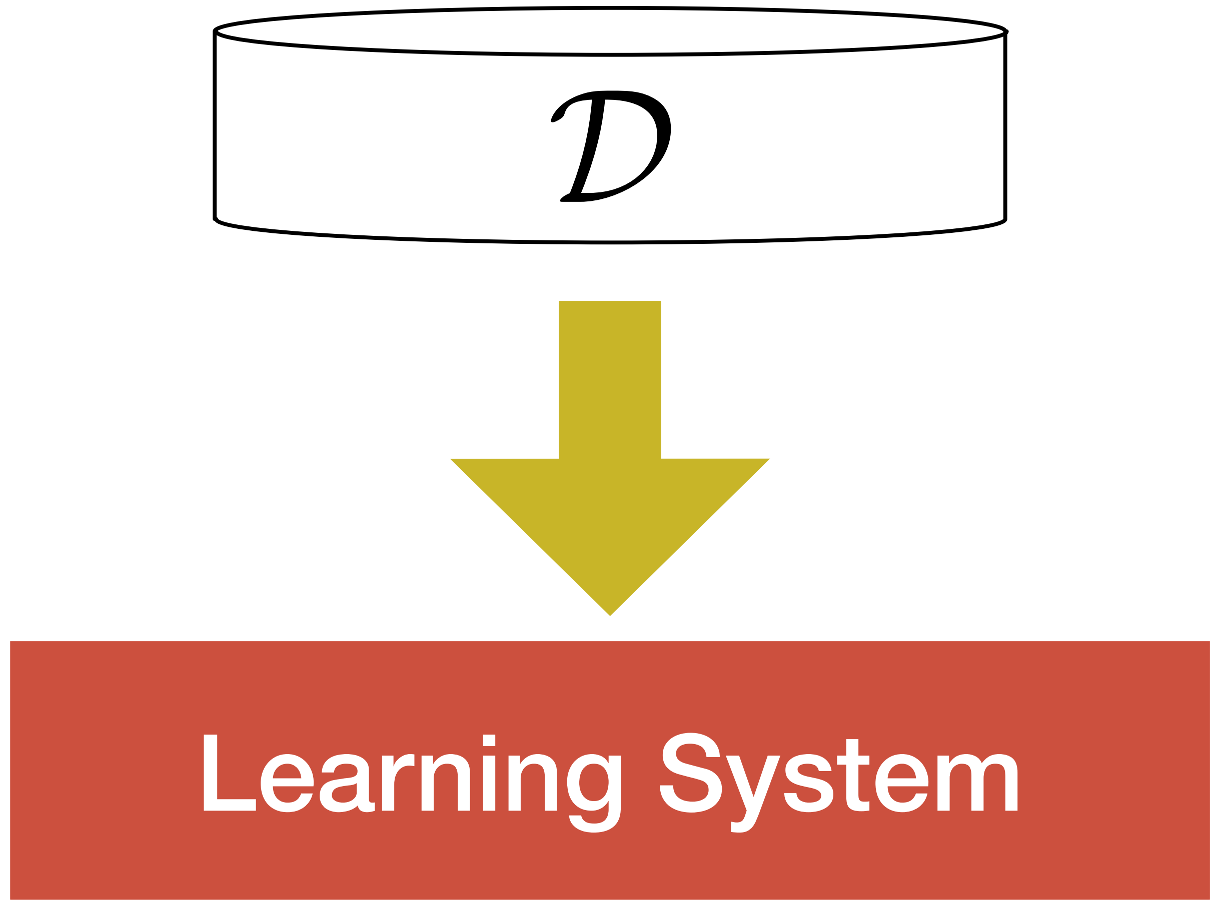
Full-stack co-design

ML as the first-class citizen

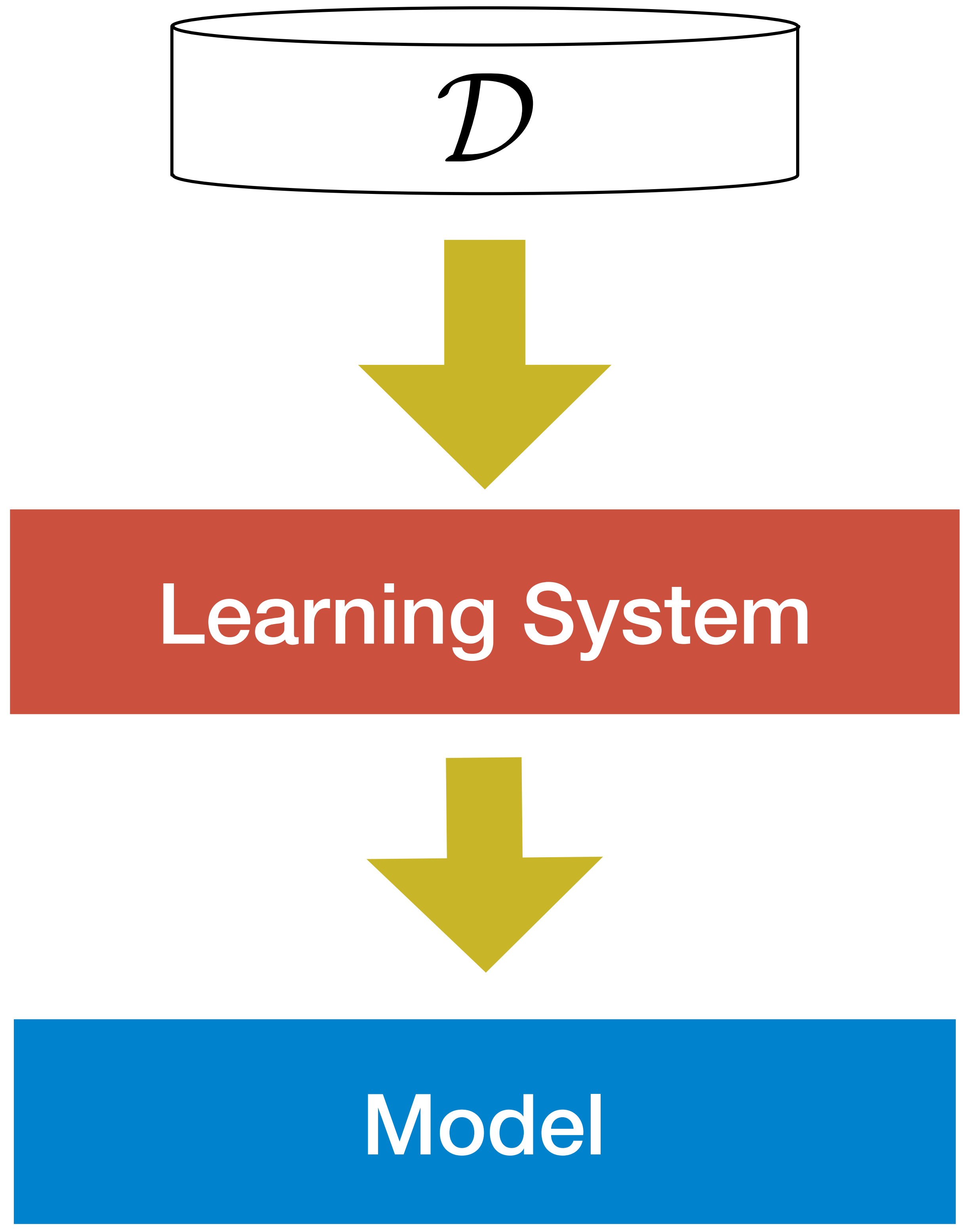
Lifecycle of Intelligent Applications



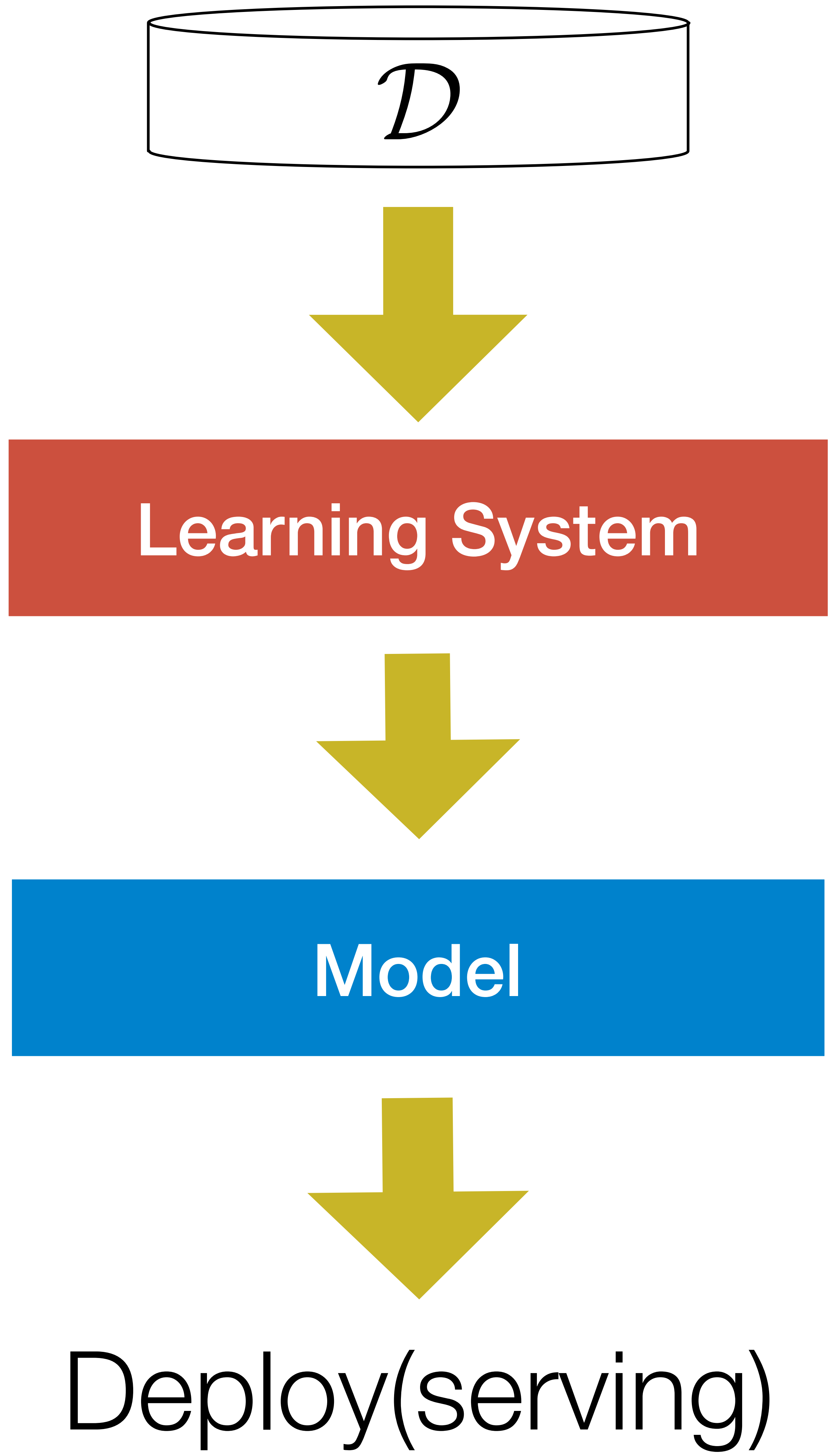
Lifecycle of Intelligent Applications



Lifecycle of Intelligent Applications



Lifecycle of Intelligent Applications



Lifelong Learning Systems

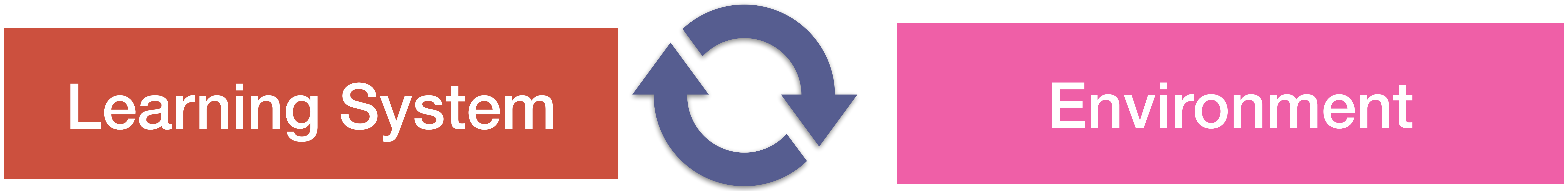
Learning System

Lifelong Learning Systems

Learning System

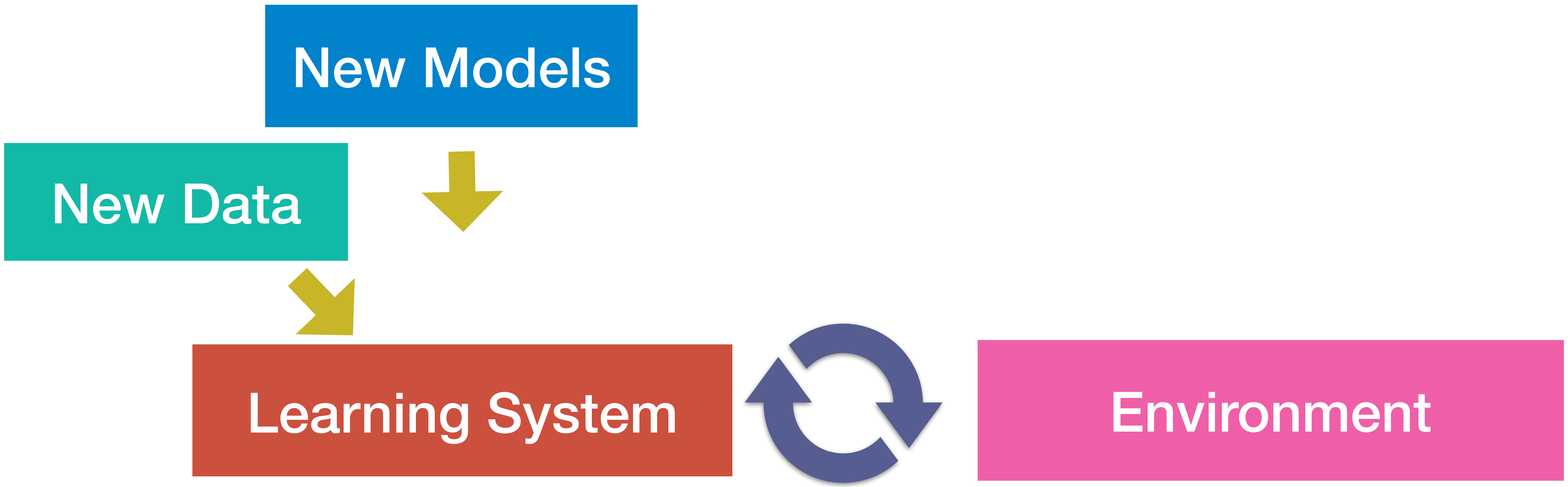
Environment

Lifelong Learning Systems

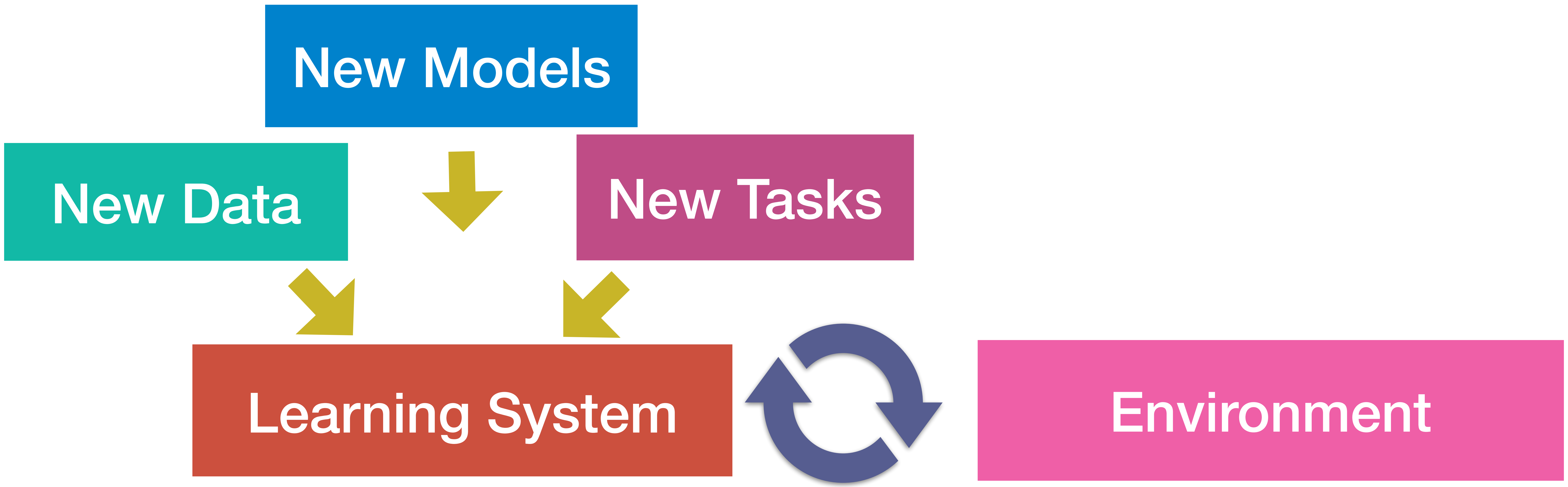


Lifelong Learning Systems

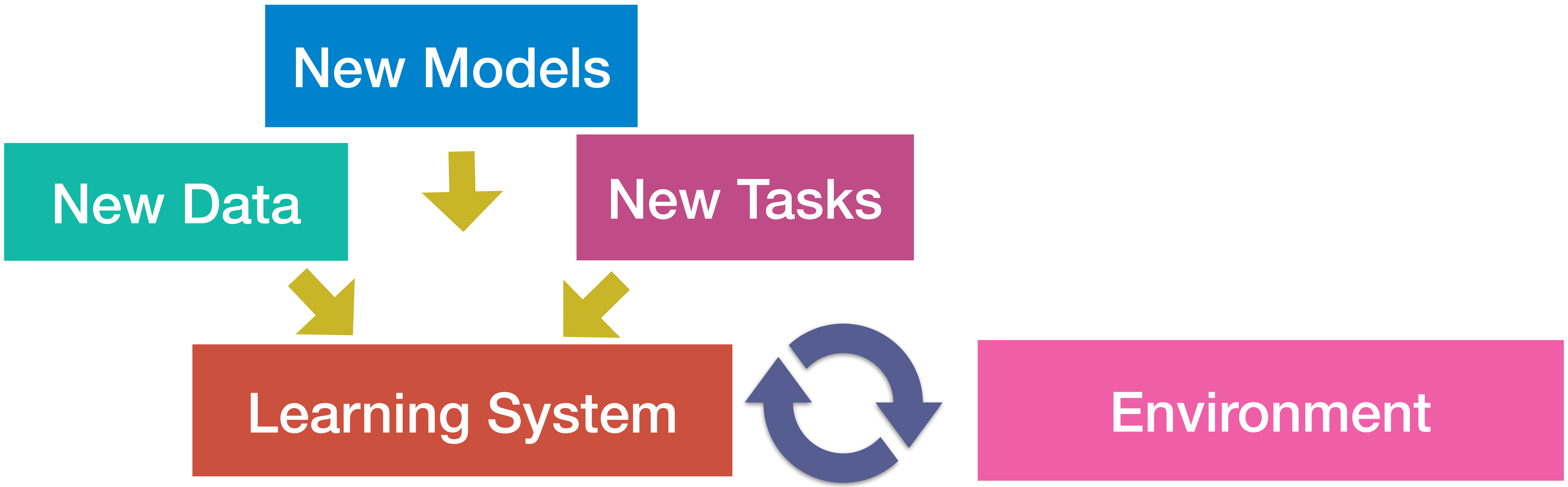
Lifelong Learning Systems



Lifelong Learning Systems



Lifelong Learning Systems



Lifelong evolution of model, data and system optimizations

Challenges in Lifelong Learning Research

Challenges in Lifelong Learning Research

Model transfer as model complexity grows

Net2Net: Accelerating learning via knowledge transfer. **Chen, et al. ICLR 16**

Challenges in Lifelong Learning Research

Model transfer as model complexity grows

Net2Net: Accelerating learning via knowledge transfer. **Chen, et al. ICLR 16**

Smart data acquisition, task prioritization

Challenges in Lifelong Learning Research

Model transfer as model complexity grows

Net2Net: Accelerating learning via knowledge transfer. **Chen, et al. ICLR 16**

Smart data acquisition, task prioritization

Build real-world learning systems as test beds

Learning-based learning systems are ideal starting points

Learning-based Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

Scale up
deep learning

tvm

Deploy AI
everywhere

Learning-based Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

Scale up
deep learning

tvm

Deploy AI
everywhere

**Full-stack Learning-based
Learning System**

Learning-based Learning Systems

dmlc XGBoost

Data science
for everyone

mxnet

Scale up
deep learning

tvm

Deploy AI
everywhere

Full-stack Learning-based Learning System

Life-long learning Systems

Take Aways: Elements of Future Learning Systems

Beside being **accessible** and **scalable**

Intelligent automated by machine learning

Full stack model, systems and hardware co-design

Lifelong consider the entire life-cycle of learning

dmlc XGBoost mxnet tvm

Take Aways: Elements of Future Learning Systems

Beside being **accessible** and **scalable**

Intelligent automated by machine learning

Full stack model, systems and hardware co-design

Lifelong consider the entire life-cycle of learning

dmlc XGBoost mxnet tvm