# Ansor : Generating High-Performance Tensor Programs for Deep Learning

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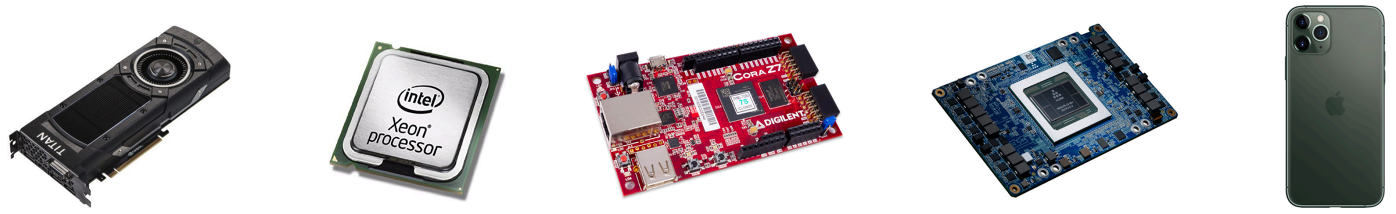
# Deep Learning System Stack

PyTorch TensorFlow mxnet

**Operator Library** (CuDNN, MKL-DNN, ARM Compute Library, ...)



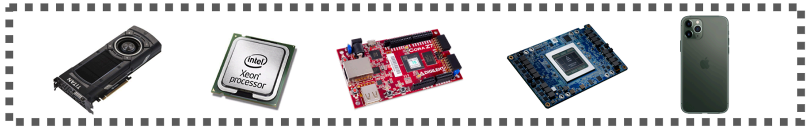
# Introducing Compiler

PyTorch TensorFlow mxnet

Compute declaration

**compiler**

Optimized code



A dense layer with ReLU activation

- **Math expression:**

$$dense_{b,o} = \sum_i data_{b,i} \times weight_{o,i}$$

$$relu(b,o) = \max(dense_{b,o}, 0)$$

- **Declaration**:

Halide

```
dense(o, b) += data(i, b) * weight(i, o);
relu(o, b) = max(dense(o, b), 0.0)
```

TVM

```
dense = compute(shape, lambda b, o: sum(data[b,i] * weight[o,i], i))
relu  = compute(shape, lambda b, o: max(dense[b,o], 0.0))
```

**Billions of possible implementations for it!**

# Related Work on Generating High-Performance Tensor Programs

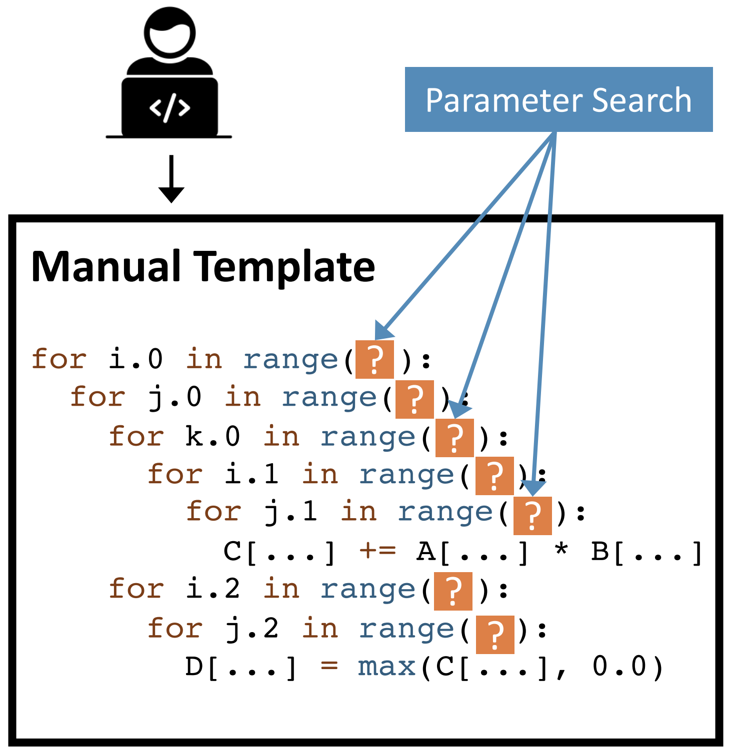
# TVM's Approach

## AutoTVM: Template-guided search

Use **templates** to define the search space for every operator

## Drawbacks

- Not fully-automated -> Requires huge manual effort
- Limited search space -> Does not achieve optimal performance



# Halide’s Auto-scheduler

## Sequential Construction Based Search

Use beam search to generate the programs sequentially

## Drawbacks

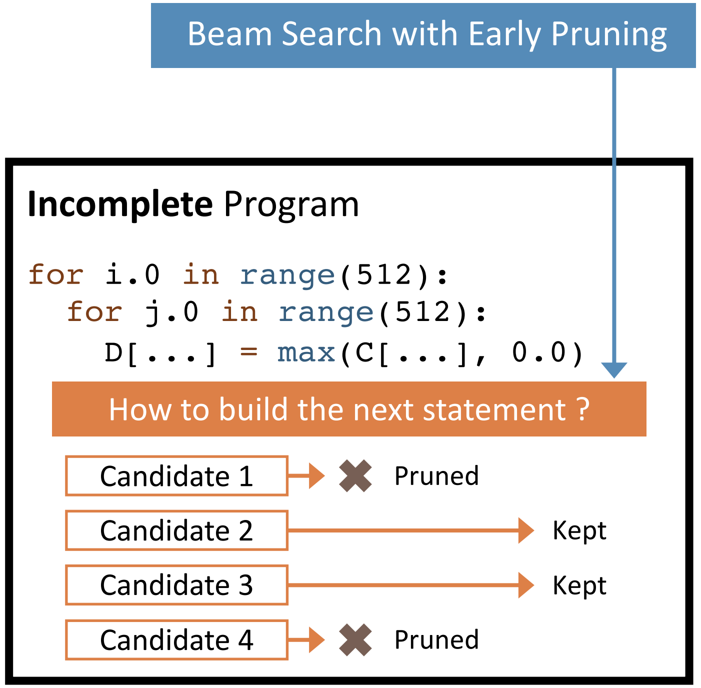
- Intermediate candidates are incomplete programs

  -> The cost model cannot do accurate prediction

- Sequential order

  -> The error accumulates

  -> Limits the design of the search space



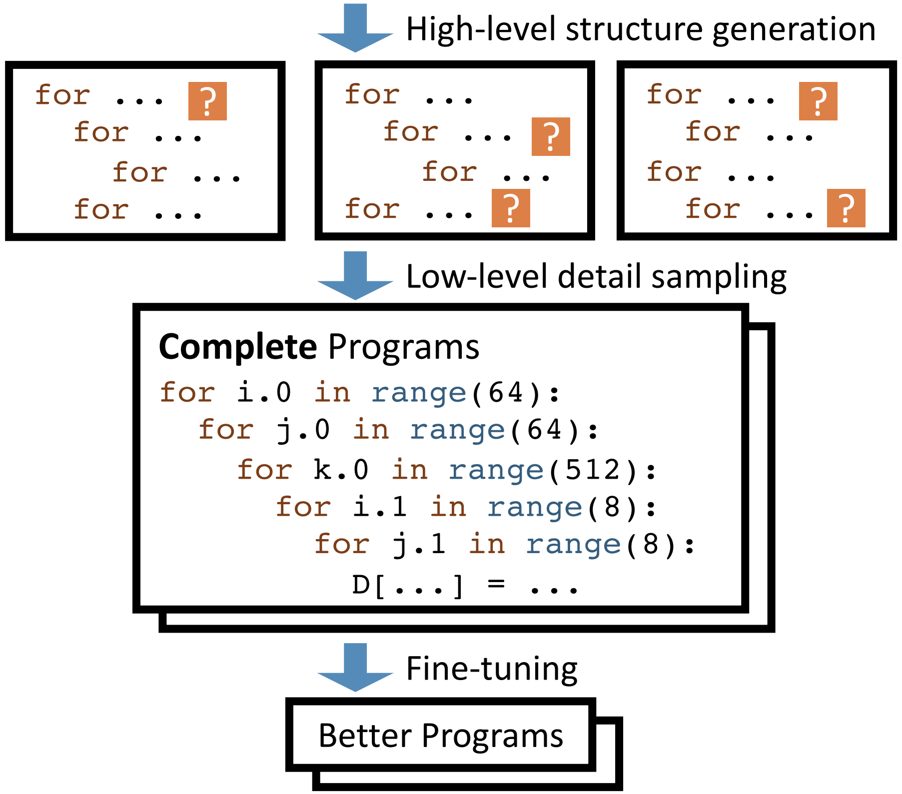
# Challenges and our approach

**C1: How to build a large search space automatically?**

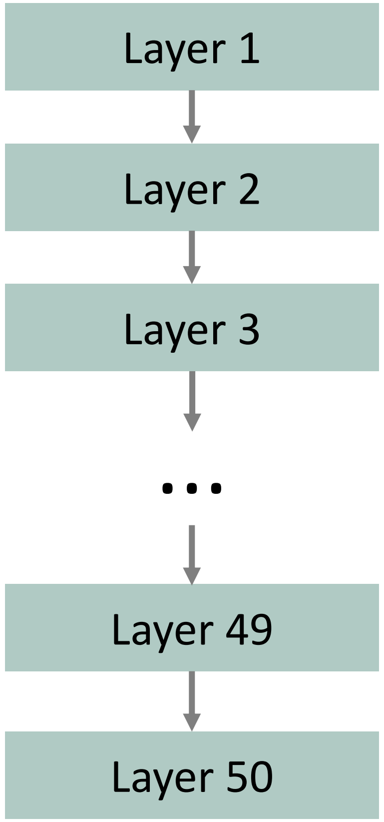
- Use a hierarchical search space

**C2: How to search efficiently?**

- Sample complete programs and fine-tune them



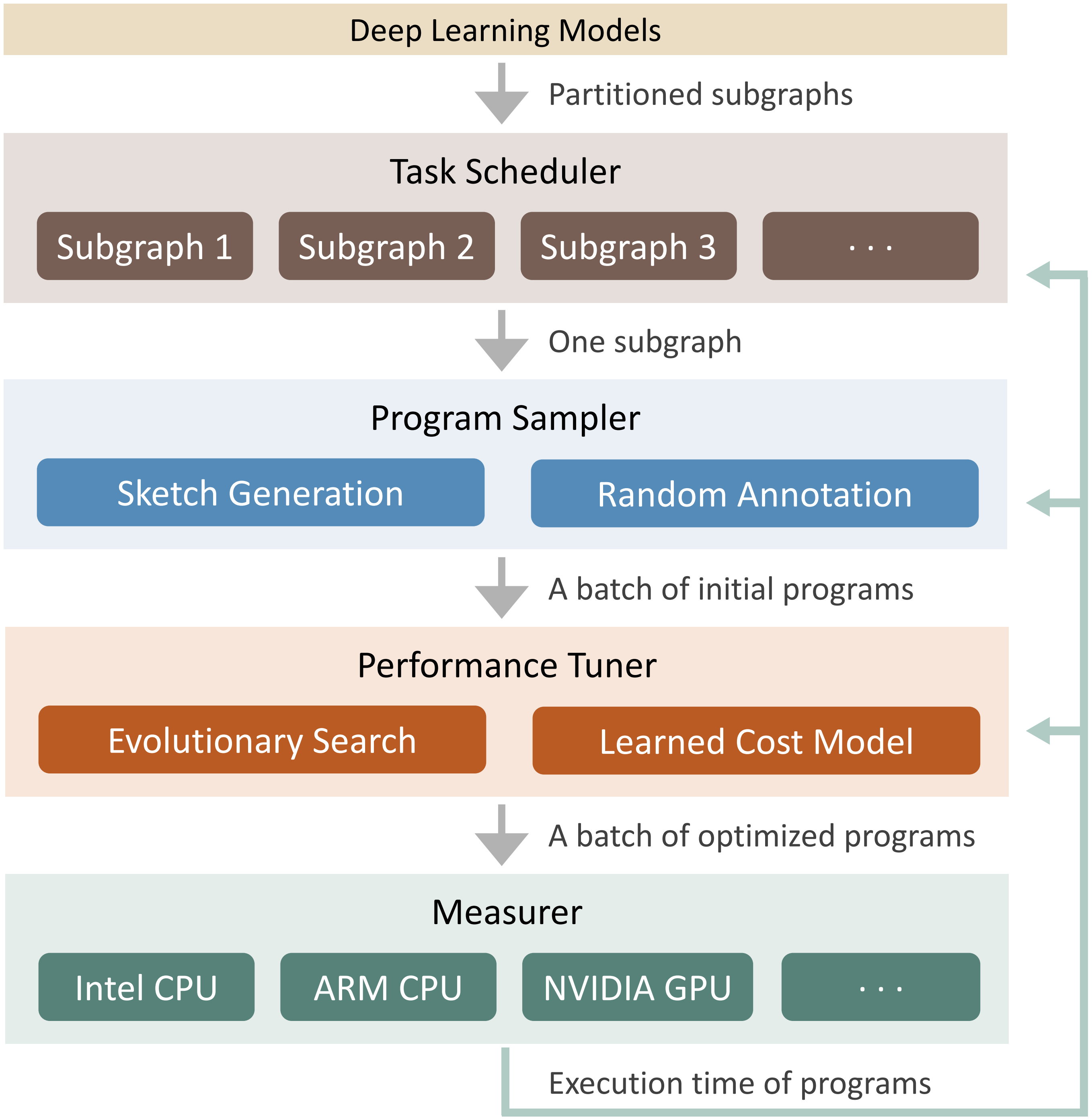
# Challenges and our approach



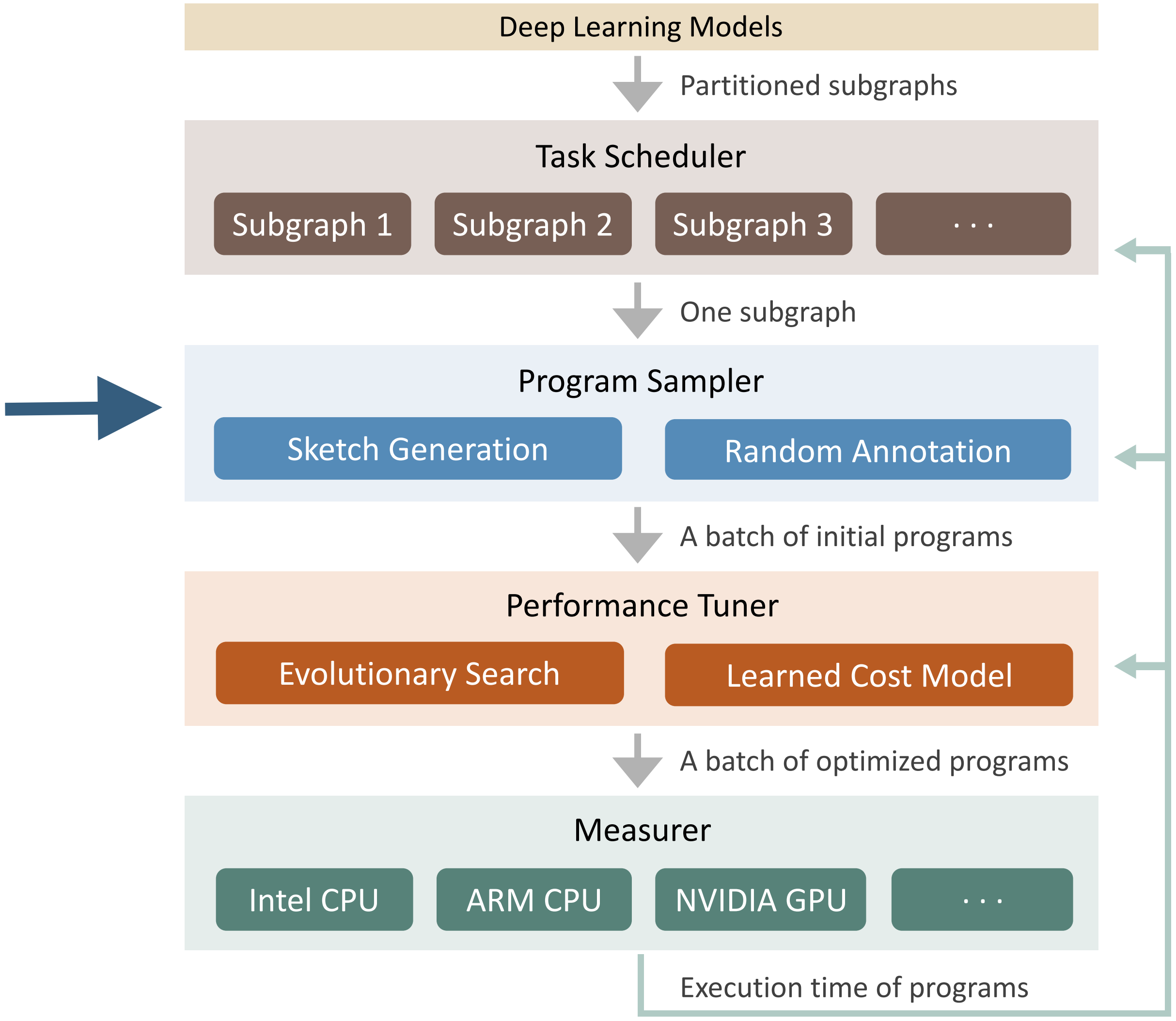

Need to generate programs for all layers -> A lot of search tasks

- **C3: How to allocate resource for many search tasks?**
  - Utilize a task scheduler to prioritize important tasks

# System Overview


Deep Learning Models
Partitioned subgraphs
Task Scheduler
Subgraph 1
Subgraph 2
Subgraph 3
· · ·
One subgraph
Program Sampler
Sketch Generation
Random Annotation
A batch of initial programs
Performance Tuner
Evolutionary Search
Learned Cost Model
A batch of optimized programs
Measurer
Intel CPU
ARM CPU
NVIDIA GPU
· · ·
Execution time of programs

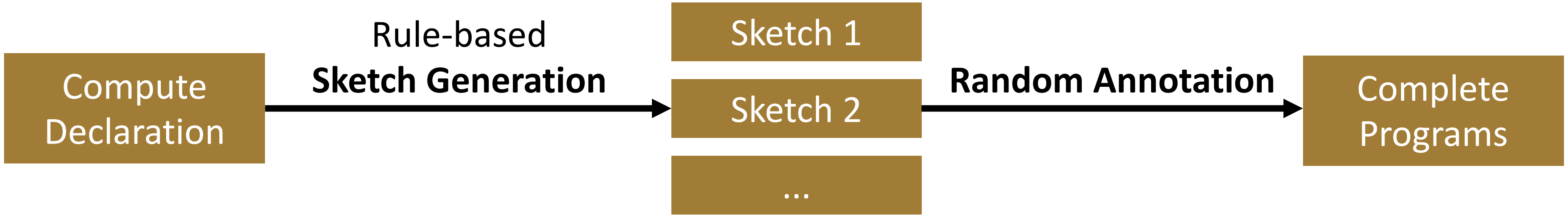
# Program Sampling



# Program Sampling

- **Goal**: automatically construct a large search space and uniformly sample from the space

- **Approach**
  - Two-level hierarchical search space: **Sketch** + **Annotation**
    - **Sketch:** a few good high-level structures
    - **Annotation:** billions of low-level details
  - Sampling process:



# Sketch Generation Examples 1/2

Example Input 1:

*** The mathmetical expression:**

$$C[i,j] = \sum_k A[i,k] \times B[k,j]$$

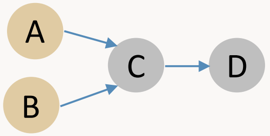
$$D[i,j] = \max(C[i,j], 0.0)$$

where $0 \leq i,j,k < 512$

*** The corresponding naïve program:**

```
for i in range(512):
  for j in range(512):
    for k in range(512):
      C[i, j] += A[i, k] * B[k, j]
for i in range(512):
  for j in range(512):
    D[i, j] = max(C[i, j], 0.0)
```

*** The corresponding DAG:**




Derivation:

$$Input\ 1 \rightarrow \sigma(S_0, i=4) \xrightarrow{\text{Rule 1}} \sigma(S_1, i=3) \xrightarrow{\text{Rule 4}} \sigma(S_2, i=2) \xrightarrow{\text{Rule 1}} \sigma(S_3, i=1) \xrightarrow{\text{Rule 1}} Sketch\ 1$$

Generated sketch 1

```
for i.0 in range(TILE_I0):
  for j.0 in range(TILE_J0):
    for i.1 in range(TILE_I1):
      for j.1 in range(TILE_J1):
        for k.0 in range(TILE_K0):
          for i.2 in range(TILE_I2):
            for j.2 in range(TILE_J2):
              for k.1 in range(TILE_I1):
                for i.3 in range(TILE_I3):
                  for j.3 in range(TILE_J3):
                    C[...] += A[...] * B[...]
        for i.4 in range(TILE_I2 * TILE_I3):
          for j.4 in range(TILE_J2 * TILE_J3):
            D[...] = max(C[...], 0.0)
```

"SSRSRSS" multi-level tiling + fusion

# Sketch Generation Examples 2/2

**Example Input 2:**

*** The mathmetical expression:**

$$B[i,l] = \max(A[i,l], 0.0)$$

$$C[i,k] = \begin{cases} B[i,k], & k < 400 \\ 0\ , & k \geq 400 \end{cases}$$

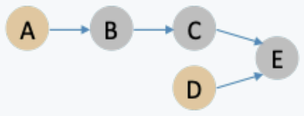
$$E[i,j] = \sum_k C[i,k] \times D[k,j]$$

where $0 \leq i < 8,\ 0 \leq j < 4,$
$0 \leq k < 512, 0 \leq l < 400$

*** The corresponding naïve program:**

```
for i in range(8):
  for l in range(400):
    B[i, l] = max(A[i, l], 0.0)
for i in range(8):
  for k in range(512):
    C[i, k] = B[i, k] if k < 400 else 0
for i in range(8):
  for j in range(4):
    for k in range(512):
      E[i, j] += C[i, k] * D[k, j]
```

*** The corresponding DAG:**




**Generated sketch 2**

```
for i in range(8):
  for k in range(512):
    C[i, j] = max(A[i,k], 0.0) if k<400 else 0
for i.0 in range(TILE_I0):
  for j.0 in range(TILE_J0):
    for i.1 in range(TILE_I1):
      for j.1 in range(TILE_J1):
        for k.0 in range(TILE_K0):
          for i.2 in range(TILE_I2):
            for j.2 in range(TILE_J2):
              for k.1 in range(TILE_I1):
                for i.3 in range(TILE_I3):
                  for j.3 in range(TILE_J3):
                    E.cache[...] += C[...] * D[...]
        for i.4 in range(TILE_I2 * TILE_I3):
          for j.4 in range(TILE_J2 * TILE_J3):
            E[...] = E.cache[...]
```

$$\textit{Input 2} \rightarrow \sigma(S_0, i=5) \xrightarrow{\text{Rule 5}} \sigma(S_1, i=5) \xrightarrow{\text{Rule 4}} \sigma(S_2, i=4) \xrightarrow{\text{Rule 1}} \sigma(S_3, i=3) \xrightarrow{\text{Rule 1}} \sigma(S_4, i=2) \xrightarrow{\text{Rule 2}} \sigma(S_5, i=1) \xrightarrow{\text{Rule 1}} \textit{Sketch 2}$$

**Generated sketch 3**

```
for i in range(8):
  for k in range(512):
    C[i, k] = max(A[i, k], 0.0) if k < 400 else 0
for i in range(8):
  for j in range(4):
    for k_o in range(TILE_K0):
      for k_i in range(TILE_KI):
        E.rf[...] += C[...] * D[...]
for i in range(8):
  for j in range(4):
    for k_i in range(TILE_KI):
      E[...] += E.rf[...]
```

$$\textit{Input 2} \rightarrow \sigma(S_0, i=5) \xrightarrow{\text{Rule 6}} \sigma(S_1, i=4) \xrightarrow{\text{Rule 1}} \sigma(S_2, i=3) \xrightarrow{\text{Rule 1}} \sigma(S_3, i=2) \xrightarrow{\text{Rule 2}} \sigma(S_4, i=1) \xrightarrow{\text{Rule 1}} \textit{Sketch 3}$$

# Random Annotation Examples

Generated sketch 1

```
for i.0 in range(TILE_I0):
  for j.0 in range(TILE_J0):
    for i.1 in range(TILE_I1):
      for j.1 in range(TILE_J1):
        for k.0 in range(TILE_K0):
          for i.2 in range(TILE_I2):
            for j.2 in range(TILE_J2):
              for k.1 in range(TILE_I1):
                for i.3 in range(TILE_I3):
                  for j.3 in range(TILE_J3):
                    C[...] += A[...] * B[...]
        for i.4 in range(TILE_I2 * TILE_I3):
          for j.4 in range(TILE_J2 * TILE_J3):
            D[...] = max(C[...], 0.0)
```

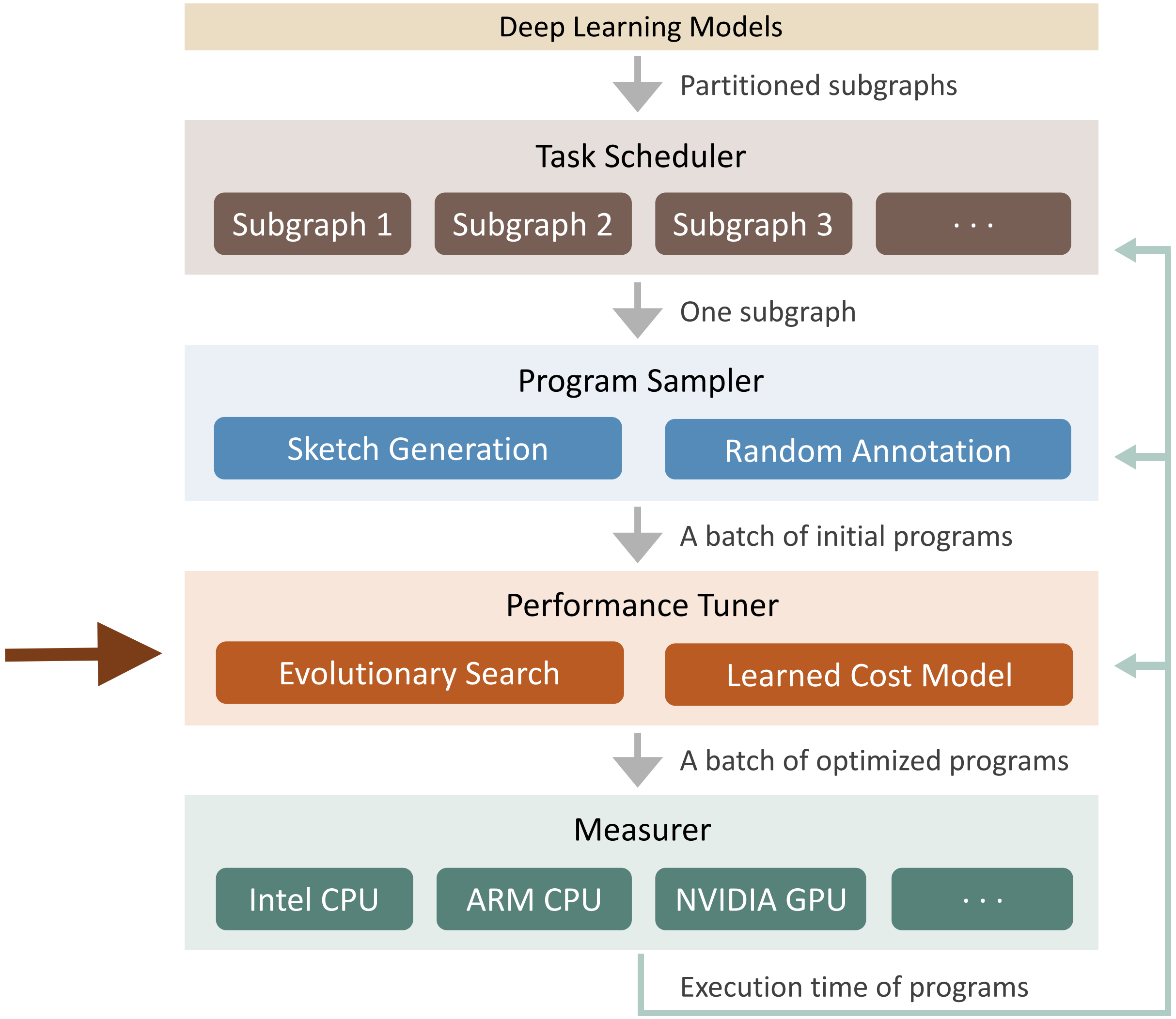
Sampled program 1

```
parallel i.0@j.0@i.1@j.1 in range(256):
  for k.0 in range(32):
    for i.2 in range(16):
      unroll k.1 in range(16):
        unroll i.3 in range(4):
          vectorize j.3 in range(16):
            C[...] += A[...] * B[...]
  for i.4 in range(64):
    vectorize j.4 in range(16):
      D[...] = max(C[...], 0.0)
```

Sampled program 2

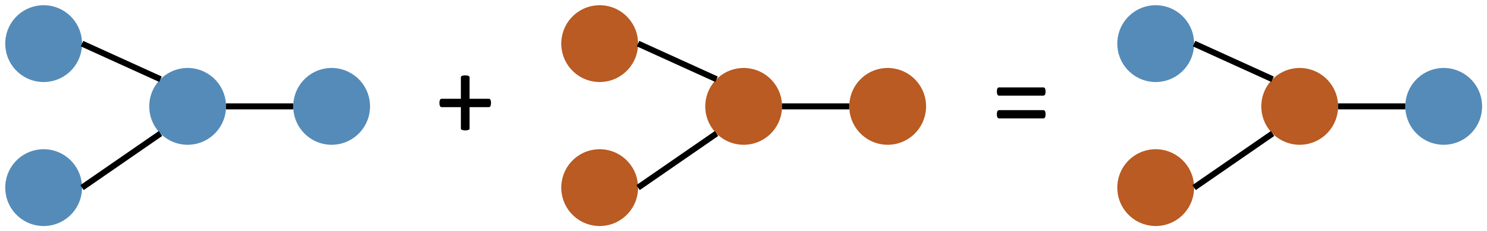
```
parallel i.2 in range(16):
  for j.2 in range(128):
    for k.1 in range(512):
      for i.3 in range(32):
        vectorize j.3 in range(4):
          C[...] += A[...] * B[...]
parallel i.4 in range(512):
  for j.4 in range(512):
    D[...] = max(C[...], 0.0)
```

# Performance Fine-tuning



# Evolutionary Search

- Random sampling does not guarantee the performance
- Perform evolutionary search with learned cost model on sampled programs
  - **mutation**
    - Randomly mutate tile size
    - Randomly mutate parallel/unroll/vectorize factor and granularity
    - Randomly mutate computation location
  - **crossover**



# Learned Cost Model

- Predict the score of each non-loop innermost statement

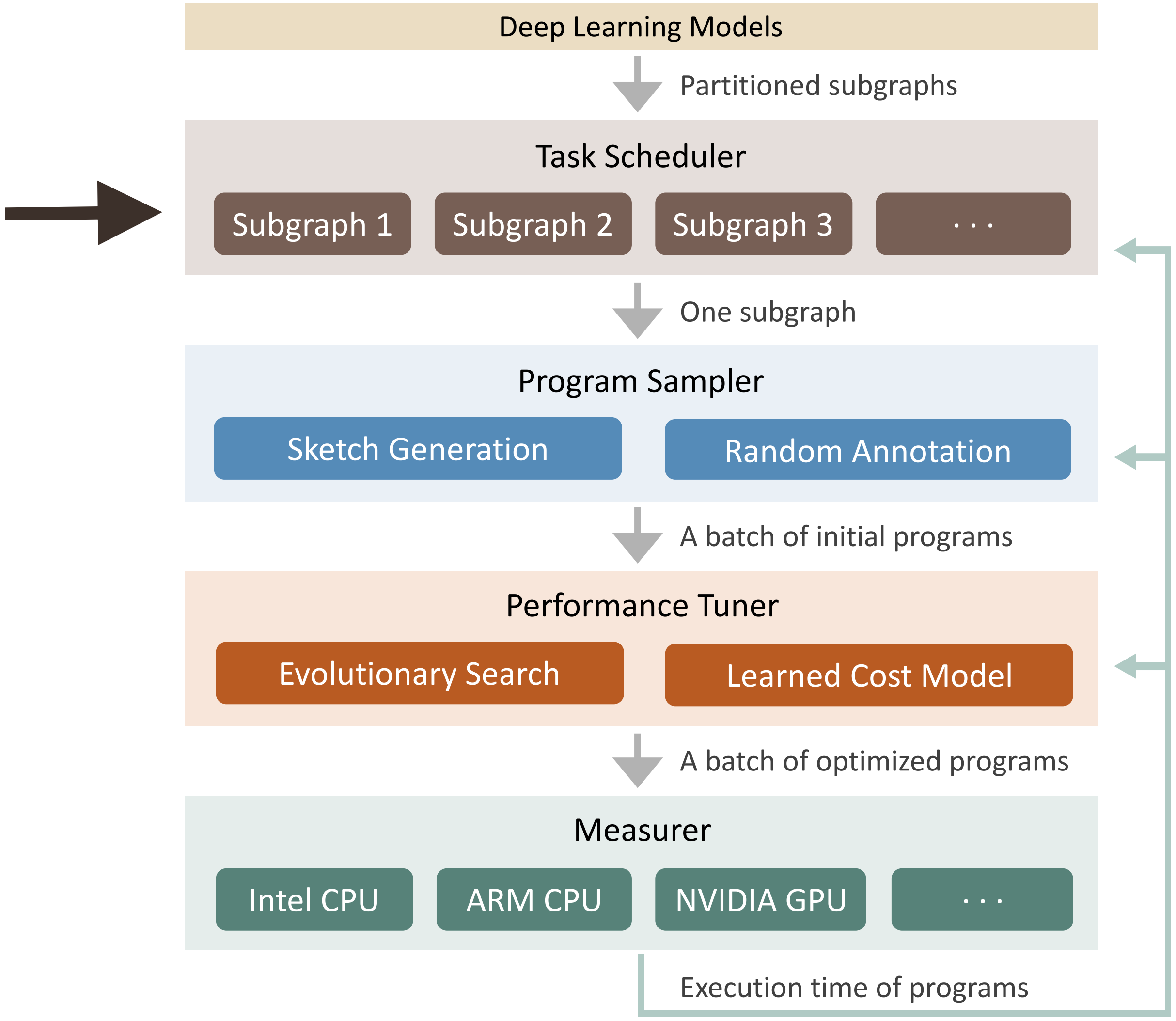
**Example:**

```
                     for i in range(10):
                       for j in range(10):
Statement B:              B[i][j] = A[i] * 2
                     for i in range(10):
Statement C:           C[i] = B[i][i] - 3
```

Cost = Cost of Statement B + Cost of Statement C

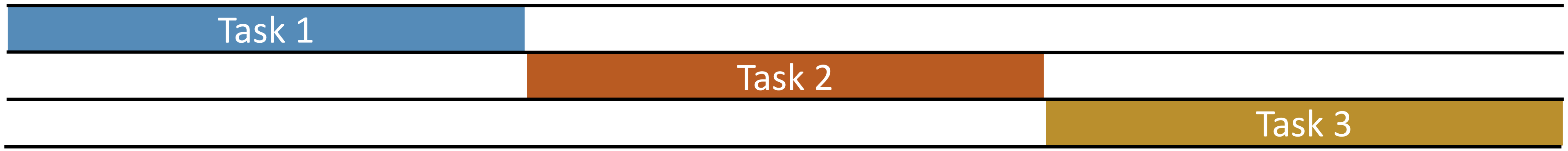
- Extract features for every non-loop innermost statement:
  - used cache lines, used memory, reuse distance, arithmetic intensity, ...
- Train on-the-fly with measured programs (typically less than 30,000)

# Task Scheduler

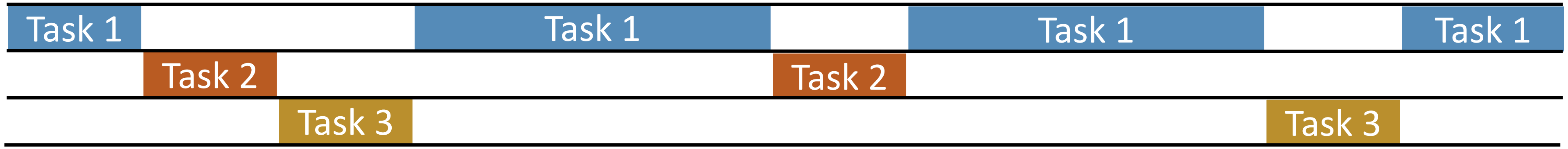


# Task Scheduler

- There are many **subgraphs** (search tasks) in a network
  - Example: ResNet-50 has 29 unique subgraphs after partition
- **Existing systems**: sequential optimization with a fixed allocation




- **Our task scheduler**: slice the time and prioritize important subgraphs




- Predict each task's impact on the end-to-end objective function
  - Using optimistic guess and similarity between tasks

# Evaluation Results

**Three levels** : single operator, subgraph and network

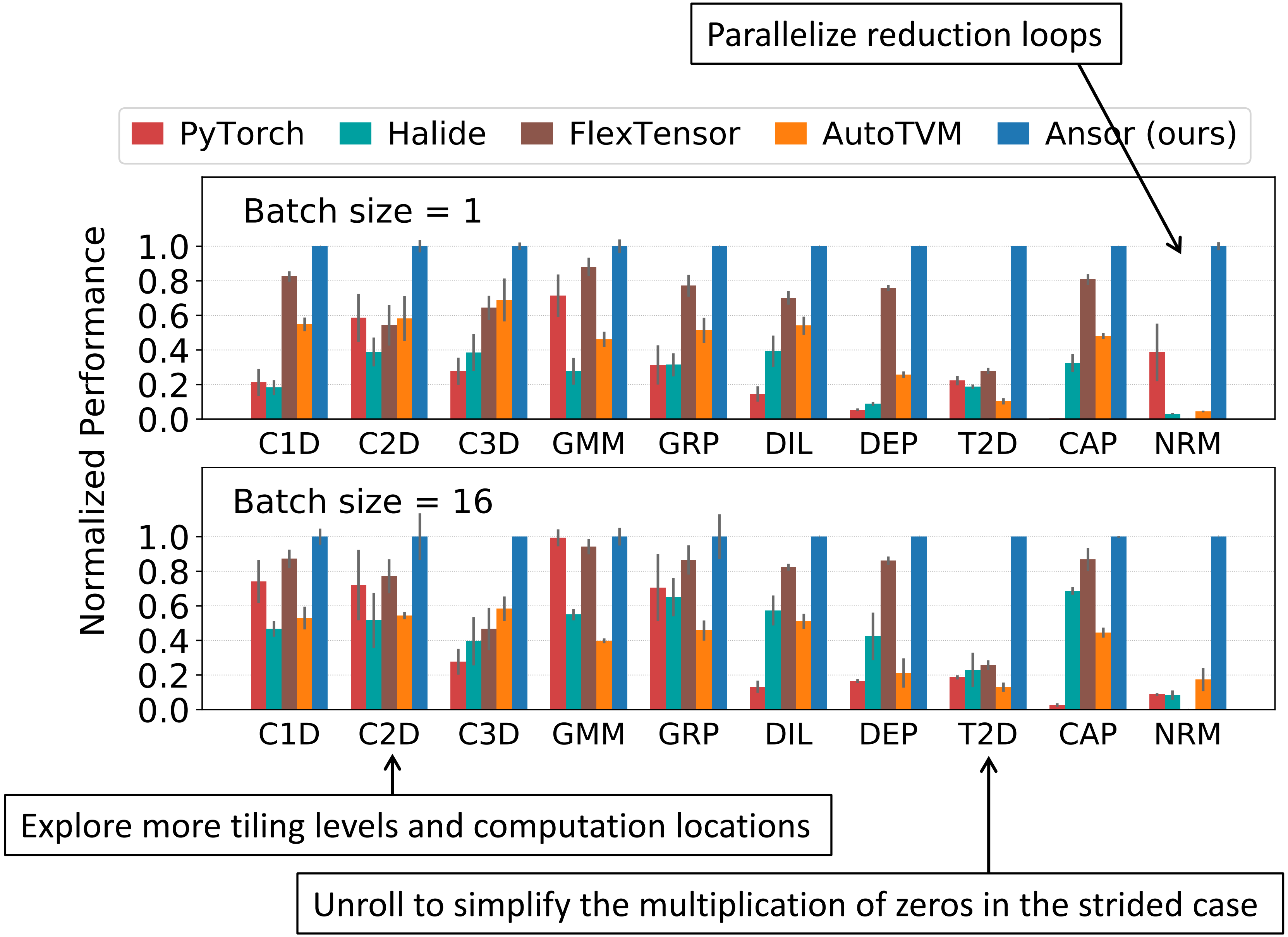
# Single Operator

**Platform:**

Intel-Platinum 8124M (18 cores)

**Operators:**

conv1d (C1D), conv2d (C2D),
conv3d (C3D), matmul (GMM)
group conv2d (GRP),
dilated conv2d (DIL)
depthwise conv2d (DEP),
conv2d transpose (T2D),
capsule conv2d (CAP),
matrix 2-norm (NRM)




**Analysis**:

For most test cases, the best programs found by Ansor are outside the search space of existing search-based frameworks.

# Subgraph

**Platforms:**

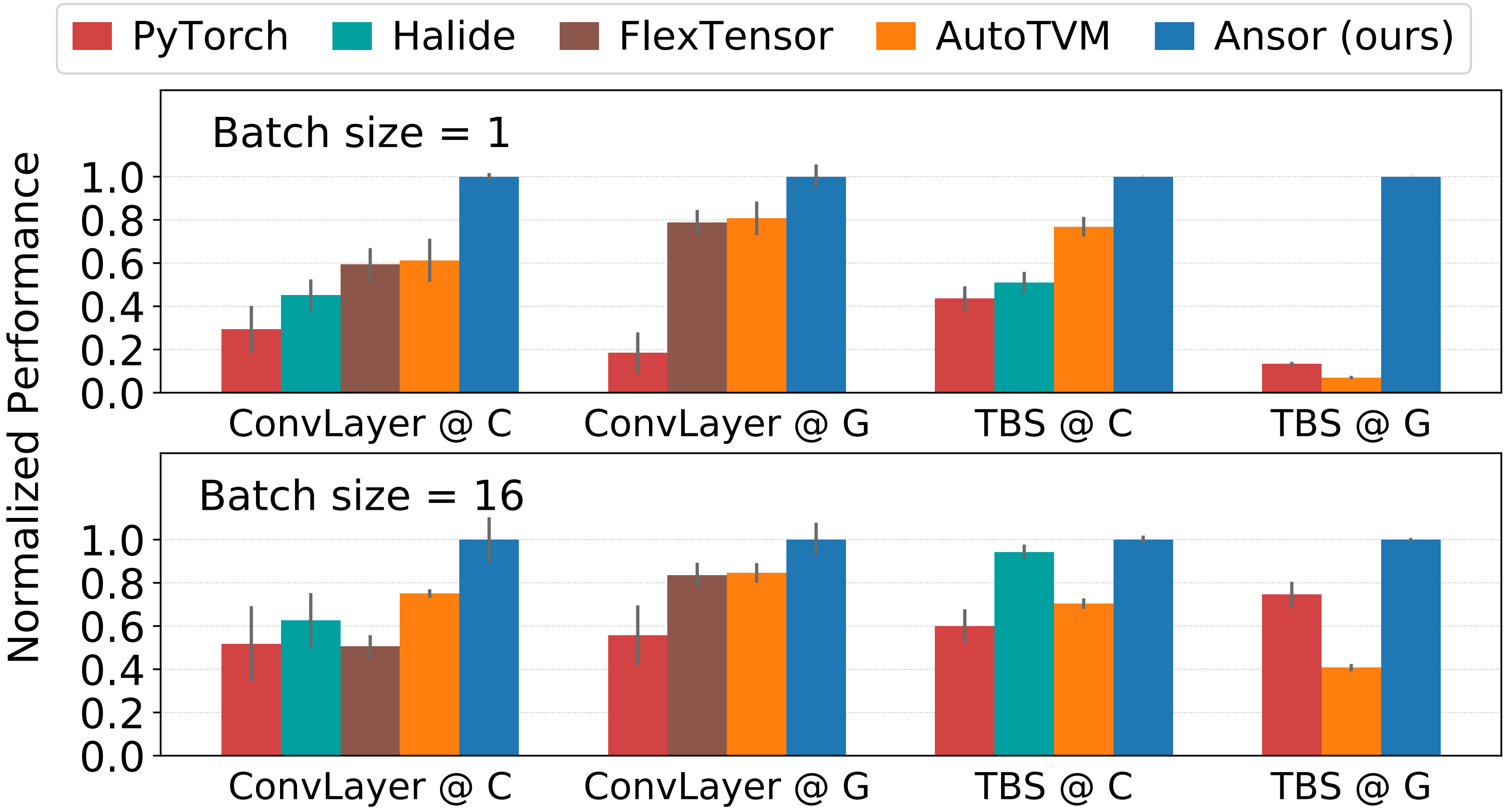
"@C" for Intel CPU (8124M)

"@G" for NVIDIA (V100)

**Subgraphs:**

ConvLayer = conv2d + bn + relu

TBS = transpose + batch_matmul + softmax




**Analysis:**

Comprehensive coverage of the search space gives 1.1 – 14.2× speedup against the best alternative.

# Network

**Platforms:**

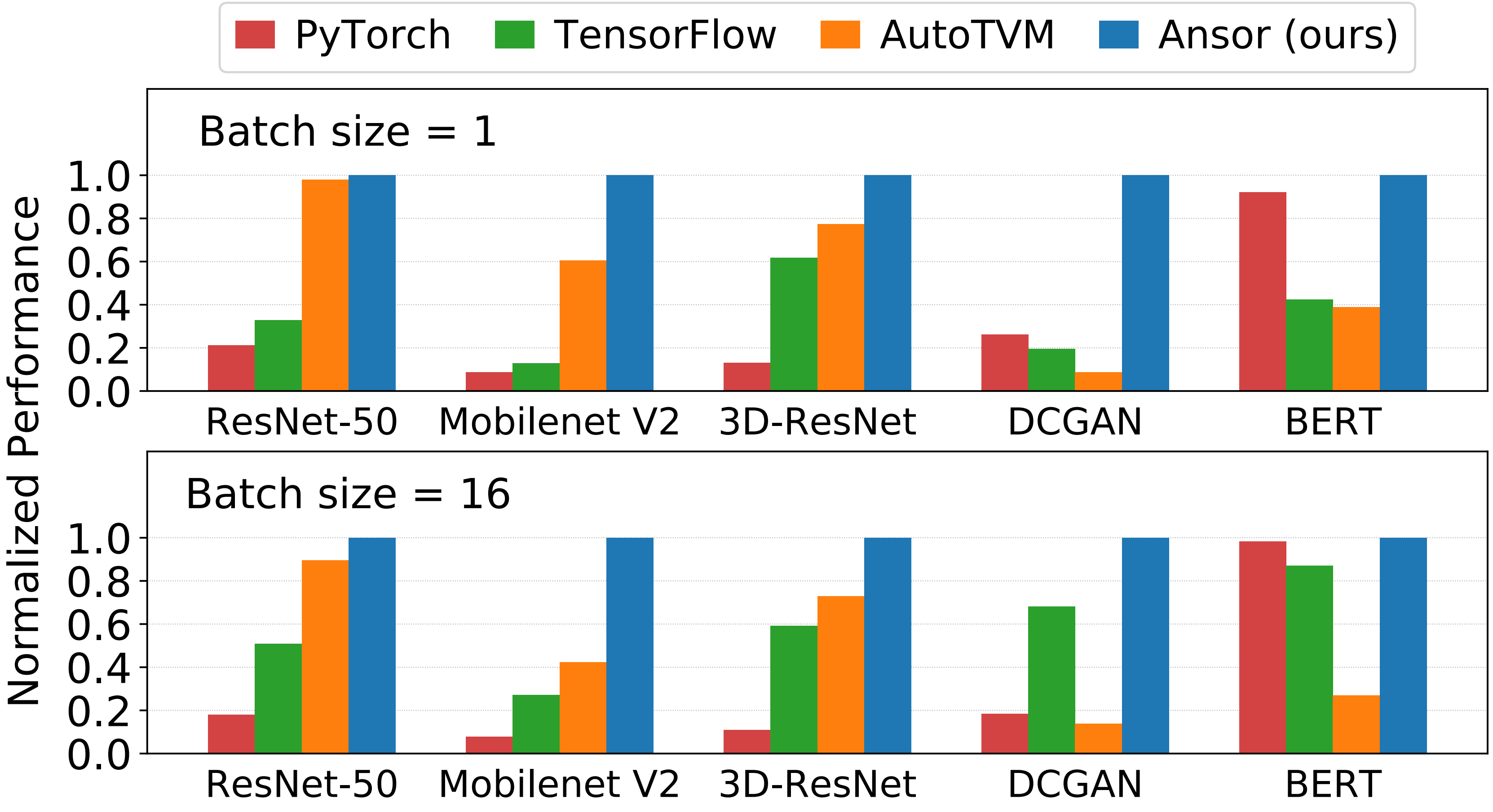
Intel CPU (8124M)

NVIDIA GPU (V100)

ARM CPU (A53)

**Networks:**

ResNet-50, Mobilenet V2, 3D-ResNet, DCGAN, BERT




**Intel CPU**

**Analysis**

- Ansor performs best or equally the best in all test cases with up to **3.8x** speedup

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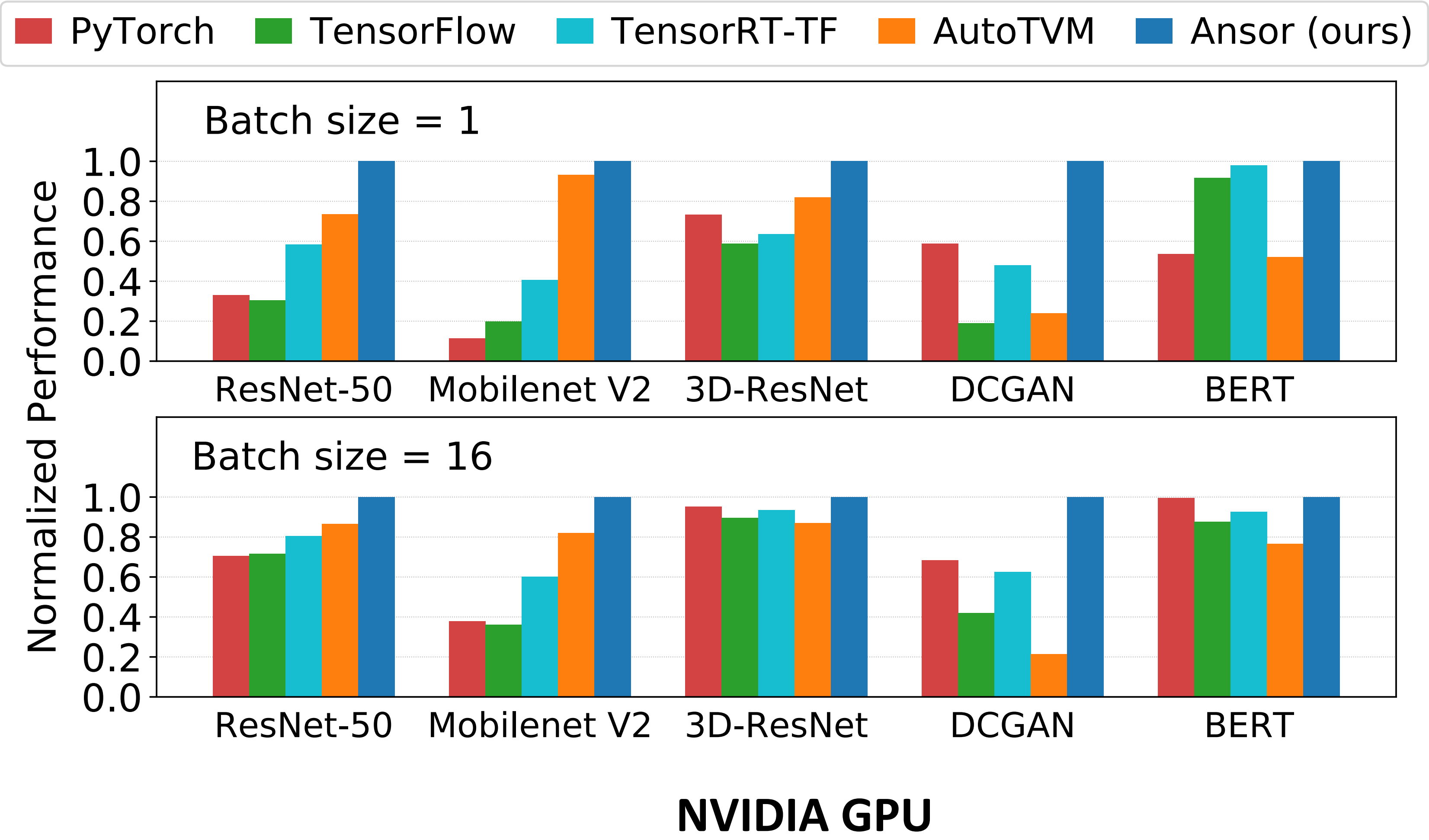


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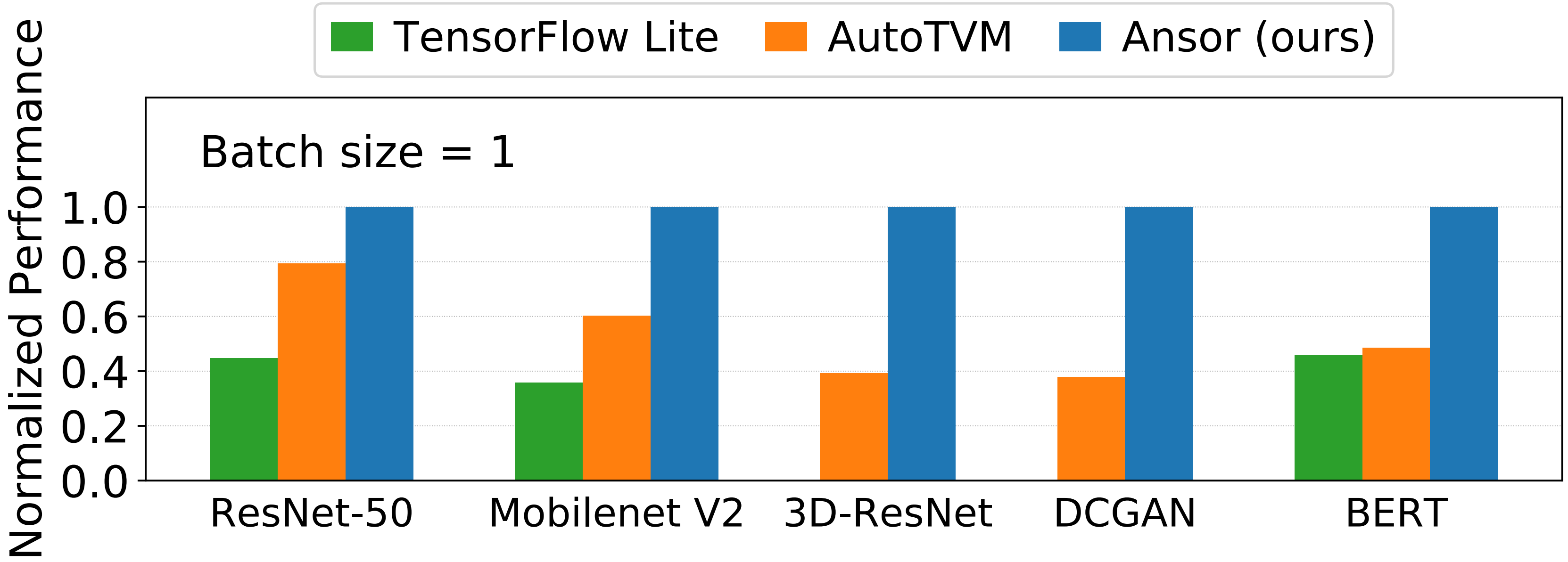
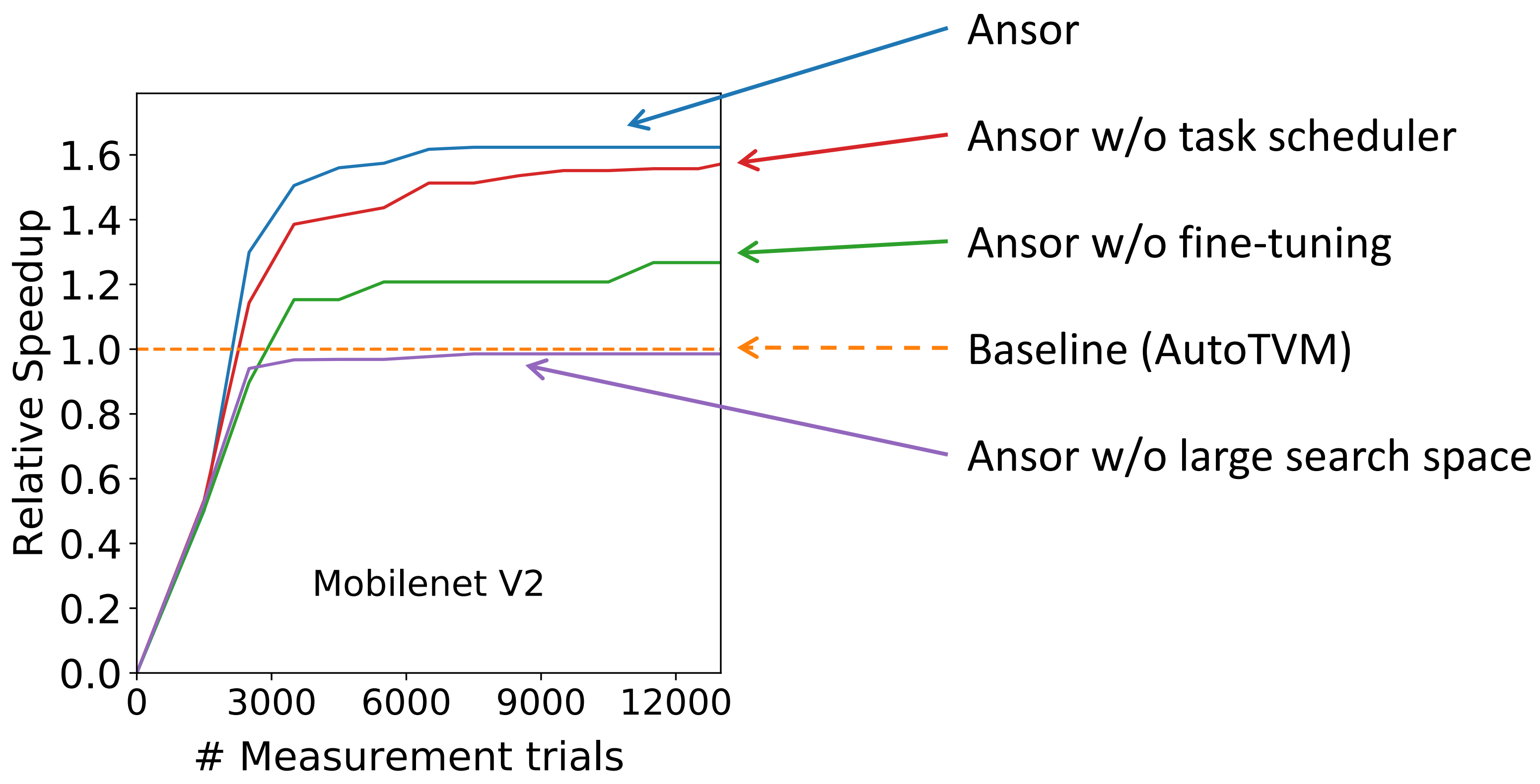



**ARM CPU**

**Analysis**

- Ansor performs best or equally the best in all test cases with up to **3.8x** speedup
- Ansor delivers portable performance

# Ablation Study




**Analysis**

- The most important factor is the search space
- Fine-tuning improves the search results significantly
- Task scheduler accelerates the search
- Match the performance of AutoTVM with 10x less search time

# Summary

- Search-based compilation enables to generate high-performance tensor programs for deep learning

- Ansor introduces techniques to improve the search in three aspects:
  - Large search space
  - Efficient search algorithm
  - Smart search scheduling

- Thank you for listening
- Email me to ask follow-up questions: lianminzheng@gmail.com