Ansor: Generating High-Performance Tensor Programs for Deep Learning

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R244 Presentation

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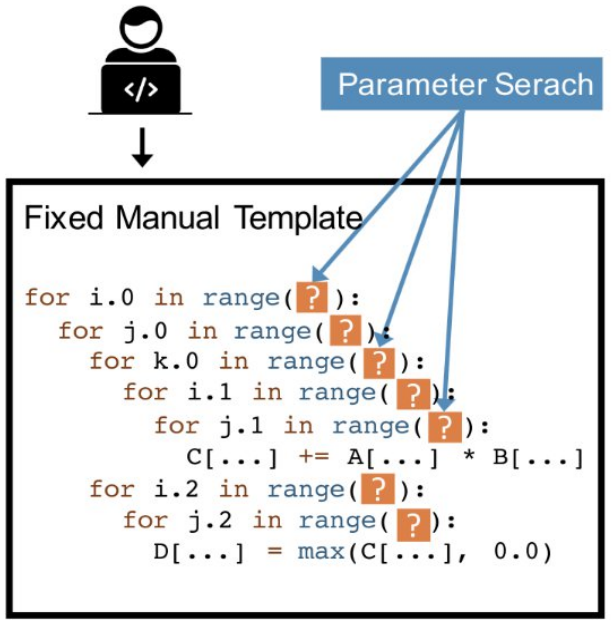
Motivation — High-performance Tensor Programs

- High-performance tensor programs are crucial for efficiently executing deep learning models
- Deep learning models are being deployed on a variety of hardware platforms (CPUs, GPUs, TPUs, FPGAs, ASICs, etc.)
- It is difficult to obtain high-performance tensor programs for different operators across various hardware platforms
- It typically requires a significant amount of engineering work to develop hardware-platform-specific optimized code
- We need automated methods to find (generate) high-performance tensor programs

Previous Work — Template-guided search

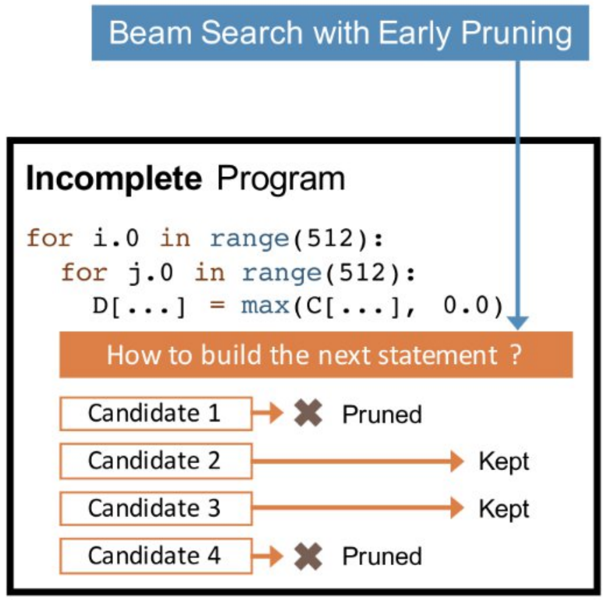
- The search space is defined by templates manually written by users
- Example: TVM [5] (An Automated End-to-End Optimizing Compiler for Deep Learning)
- Templates define tensor program structures with adjustable parameters
- The compiler searches for the best values of these parameters for the specific input shape configuration and specific hardware target
- Developing these templates requires substantial efforts
- TVM repository contains over 15K lines of code for these templates
- Constructing quality templates requires expertise in both tensor operators and hardware
- Only cover limited program structures (manually enumerating all optimization choices is prohibitive)



```
for i.0 in range(?):
  for j.0 in range(?):
    for k.0 in range(?):
      for i.1 in range(?):
        for j.1 in range(?):
          C[...] += A[...] * B[...]
    for i.2 in range(?):
      for j.2 in range(?):
        D[...] = max(C[...], 0.0)
```

Previous Work — Sequential construction based search

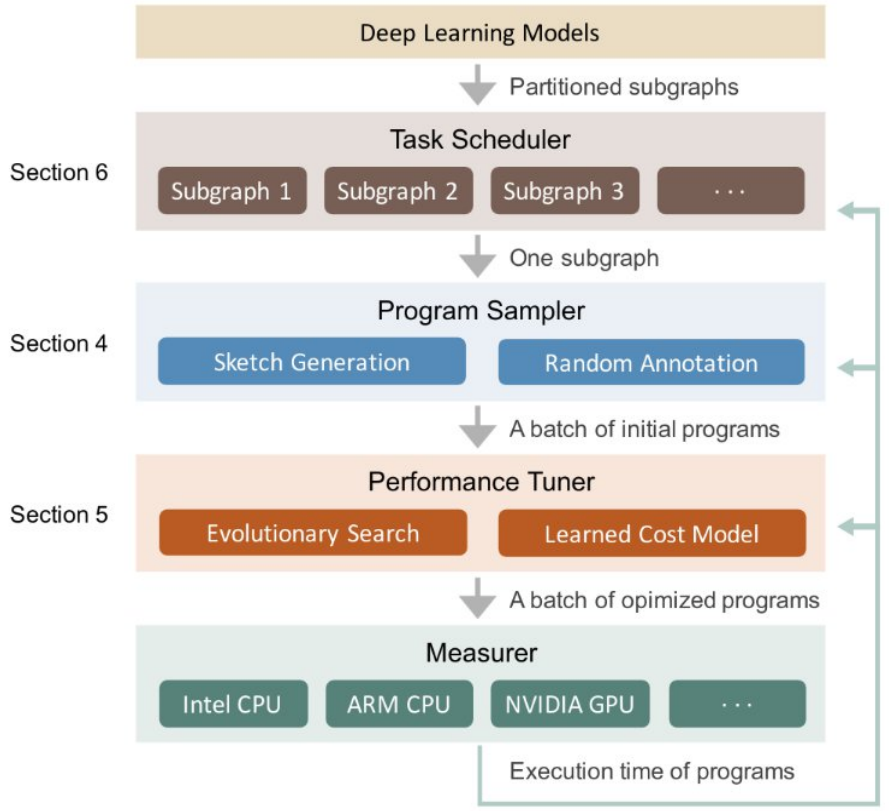
- The search space is defined by decomposing the program into a fixed sequence of decisions
- Example: Halide Auto-Scheduler [1]
- The compiler constructs a tensor program by sequentially unfolding all nodes in the computation graph and making decisions at each node, using algorithms such as beam search to search for good decisions
- When making decisions, the program is incomplete, and cost models trained on complete programs cannot accurately predict performance
- The fixed order of sequential decisions limits the design of the search space
- Sequential construction based search is not scalable



```
for i.0 in range(512):
  for j.0 in range(512):
    D[...] = max(C[...], 0.0)
```

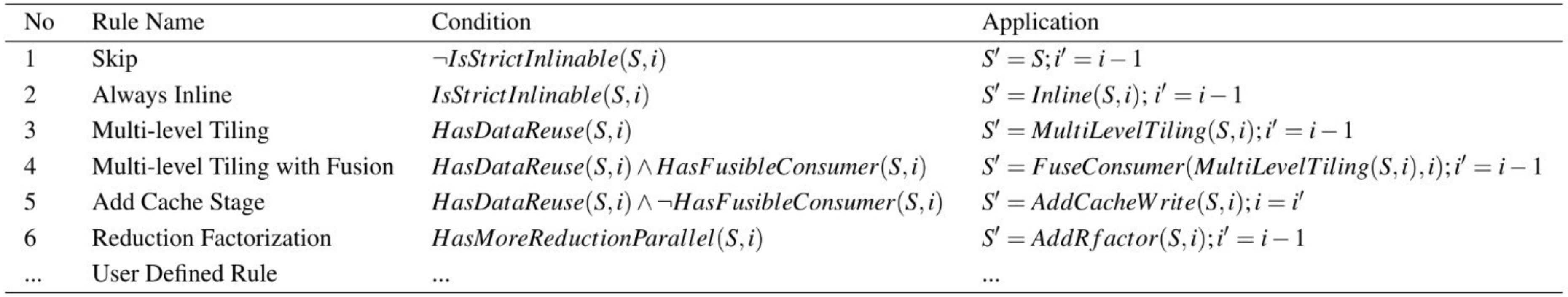
Ansor — Design Overview

- Ansor, a framework for automated tensor program generation
- The input of Ansor is a set of to be optimized DNNs
- Program Sampler
  - Constructs a large search space and samples diverse programs from it
- Performance Tuner
  - Fine-tunes the performance of sampled programs
- Task Scheduler
  - Allocates time resources for optimizing multiple subgraphs in the DNNs



Program Sampler — Sketch Generation

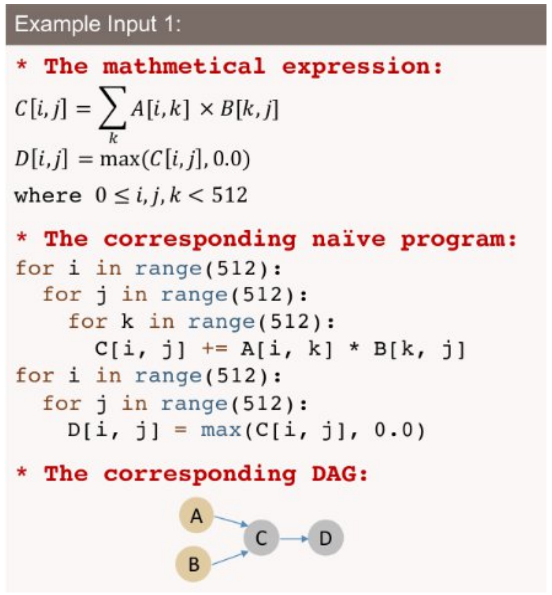
- To sample programs that can cover a large search space, Ansor define a hierarchical search space with two levels: **sketch** and **annotation**
- The high-level structure of a program is defined as sketches
- Ansor generates sketches by recursively applying a few derivation rules
- Ansor allows users to register new derivation rules and integrate them seamlessly with existing rules to adapt to emerging algorithms and hardware



No	Rule Name	Condition	Application
1	Skip	$\neg IsStrictInlinable(S,i)$	$S' = S; i' = i-1$
2	Always Inline	$IsStrictInlinable(S,i)$	$S' = Inline(S,i);\ i' = i-1$
3	Multi-level Tiling	$HasDataReuse(S,i)$	$S' = MultiLevelTiling(S,i); i' = i-1$
4	Multi-level Tiling with Fusion	$HasDataReuse(S,i) \land HasFusibleConsumer(S,i)$	$S' = FuseConsumer(MultiLevelTiling(S,i),i); i' = i-1$
5	Add Cache Stage	$HasDataReuse(S,i) \land \neg HasFusibleConsumer(S,i)$	$S' = AddCacheWrite(S,i); i = i'$
6	Reduction Factorization	$HasMoreReductionParallel(S,i)$	$S' = AddRfactor(S,i); i' = i-1$
...	User Defined Rule	...	...

Program Sampler — Random Annotation

- The sketches generated are incomplete programs because they only have tile structures
- Billions of low-level choices (e.g., tile size, parallel, unroll annotations) as annotations
- Ansor randomly annotates these sketches to get complete programs for fine-tuning and evaluation
- Ansor allows users to give simple hints in the computation definition to adjust the annotation policy


Example Input 1:

* The mathmetical expression:

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

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

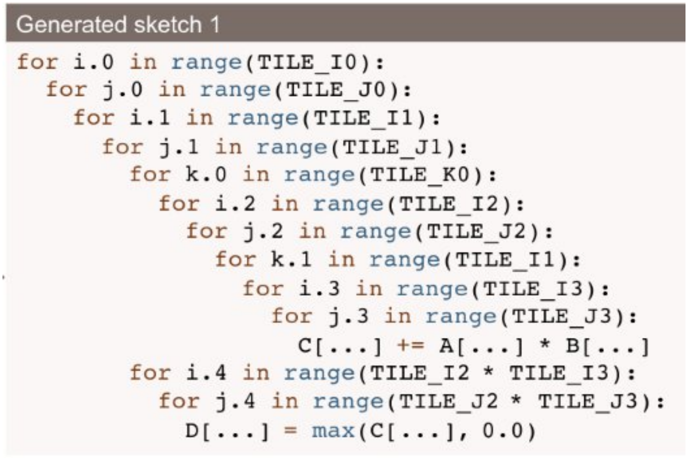
where $0 \le i,j,k < 512$

* The corresponding naïve program:

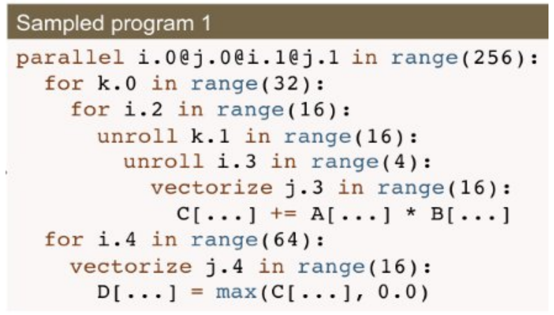
```
for i in range(512):
  for j in range(512):
    for k in range(512):
      C[i, j] += A[i, k] * B[k, j]
for i in range(512):
  for j in range(512):
    D[i, j] = max(C[i, j], 0.0)
```

* The corresponding DAG:

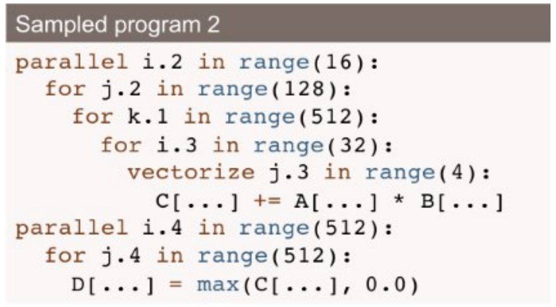
$$\begin{tikzcd} A \arrow[dr] & & \\ & C \arrow[r] & D \\ B \arrow[ur] & & \end{tikzcd}$$


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 Tuner — Evolutionary Search

- The quality of the program sampled randomly by the program sampler cannot be guaranteed
- Ansor needs to fine-tune the performance of the sampled program through the performance tuner
- The performance tuner performs fine-tuning via **evolutionary search** and a **learned cost model**
- Initial population used in the evolutionary search:
  - randomly sampled programs
  - high-quality programs from the previous measurement
- Evolution operations in the evolutionary search:
  - Tile size mutation
  - Parallel, vectorization mutation
  - Node-based crossover

Performance Tuner — Learned Cost Model

- The learned cost model is used to predict the fitness of each program
- In Ansor, fitness is the throughput of programs
- The evolutionary search iteratively finds a small batch of promising programs based on the learned cost model, then measures their actual execution time costs on hardware
- The cost model is orders of magnitude faster than the actual measurement, allowing us to compare tens of thousands of programs in the search space in seconds
- The profiling data got from measurement is used to re-train the cost model to make it more accurate
- The evolutionary search gradually generates higher-quality programs for the target hardware

Task Scheduler

- For some subgraphs, spending time in tuning them does not improve the end-to-end DNN performance significantly
  - The subgraph is not a performance bottleneck
  - Tuning brings only minimal improvement in the subgraph’s performance
- Ansor needs to avoid wasting time tuning unimportant (low returns) subgraphs
- Ansor uses a gradient descent-based scheduling algorithm to efficiently optimize the objective function (predefined or user-provided)
- Ansor prioritizes subgraphs with high initial latency, optimistically guessing to quickly reduce its latency. If Ansor spends many iterations on the subgraph without observing a decrease in latency, Ansor leaves the subgraph

Evaluation

The authors evaluated tensor programs generated by Ansor on Intel CPU, ARM CPU, NVIDIA GPU

- Single Operator Benchmark
  - Common deep learning operators: C1D, C2D, C3D, GMM, GRP, etc.
  - Ansor outperforms existing search frameworks by 1.1 −32.7x
- Subgraph Benchmark
  - Two common subgraphs in DNNs: ConvLayer and TBG
  - Ansor outperforms manual libraries and other search frameworks by 1.1 −1.8x
- End-to-End Network Benchmark
  - The end-to-end inference execution time of several DNNs: ResNet-50, MobileNet-V2, etc.
  - Ansor performs the best or equally the best on 24 out of 25 cases

Conclusion & Key Contributions

- Proposed Ansor, a high-performance tensor program generation framework
- Proposed a hierarchical representation mechanism that can cover a large tensor program search space
- Proposed an evolutionary search with a learned cost model to fine-tune the performance of sampled tensor programs
- Proposed a scheduling algorithm based on gradient descent to prioritize important subgraphs
- Evaluated Ansor in common deep learning operators, subgraphs, and end-to-end networks
- Ansor outperforms state-of-the-art systems

Agree & Strength

- Covering large search spaces via hierarchical search space representation without relying on manually defined templates
- Efficiently fine-tune sampled programs via evolutionary search with learned cost model
- Avoid wasting time on low-return fine-tuning via gradient descent-based task scheduler
- Encouraging performance, larger search space, and generation of higher-performance tensor programs in a shorter time
- Ansor enables automatic extensions to new operators
- All Ansor source code is publicly available

Disagree & Weaknesses

- No sufficiently diverse hardware was evaluated. Only evaluated on Intel CPUs, ARM CPUs, and NVIDIA GPUs. Can Ansor work well on other GPUs (such as AMD GPUs) or TPUs?
- Only evaluated common deep learning operators such as C1D, GMM, etc, but did not consider user-defined operators. Can Ansor optimize user-defined operators?
- Only evaluated the ConvLayer and TBG subgraphs, which is very limited. Can the Ansor work well on other subgraphs?
- In the learned cost model, the fitness only considers throughput. In actual deployment, more factors need to be considered, such as memory consumption, energy consumption, etc.
- The scenario of multi-GPU or distributed environments has not been considered. For example, model parallelism, data parallelism, communication overhead, synchronization, etc.

Related Research

- This paper was influenced by previous works:
  - Automatic generation based on scheduling languages: Halide [7], TVM [5], etc.
  - Search-based compilation and auto-tuning: Stock[8], OpenTuner[2], etc.
  - Polyhedral compilation models: Tiramisu [3], TensorComprehensions [10], etc.
  - ...
- This paper (2nd generation auto tuner. 1st: AutoTVM [5]) influenced subsequent works:
  - MetaSchedule [9] (3rd generation auto tuner. Introduced modularity based on DSL)
  - ML2Tuner [4] (Potential 4th generation auto tuner. Multi-level machine learning-guided)
  - LoopTune [6] (Potential 4th generation auto tuner. Based on reinforcement learning)
  - ...

Impact & Possible Impact

- Impact:
  - This paper was accepted by OSDI 2020 [12]
  - This paper has been cited 578 times
  - Ansor integrated into Apache TVM as AutoScheduler [11]
- Possible Impact:
  - Other areas of compilation may be inspired to explore automated high-performance program generation, such as traditional compilers
  - Other areas that rely on manual templates may be inspired to move towards automation, such as system configuration
  - Application deployment may involve increasing automation optimization

Possible Discussion Questions

- How to achieve an automatic high-performance program search framework for traditional compilers (C++, Java, Rust)? What are the challenges?
- How to extend Ansor to support distributed environments? How to train a learned cost model suitable for distributed cluster environments at a low cost?
- How to extend Ansor to be aware of hardware features? How to make the learned cost model become accurate faster by utilizing hardware information?
- How to extend Ansor to support multi-objective optimization? (Not only throughput, but also memory consumption, program size, etc)
- Is it possible that random annotations and evolutionary search could introduce subtle, hard-to-detect errors in tensor programs?

Thanks

Thank you for listening

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