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Deep Neural Network Hardware Deployment Optimization via Advanced Active Learning

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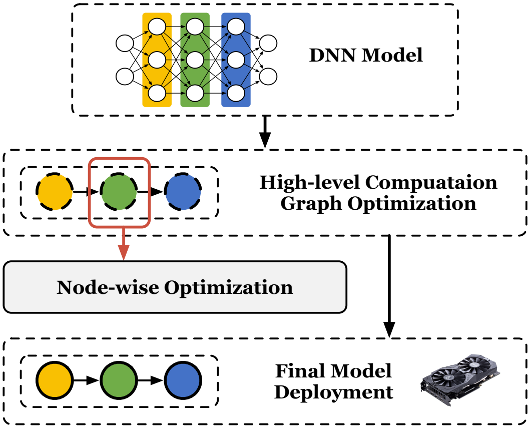
Background

Hardware deployment of deep neural networks



- General deployment framework.
- Support various hardware platforms and DNN models.
- A DNN model is represented as a graph.
- Layer-wise (node-wise) optimization, to determine the deployment configuration for each layer.
- The final model deployment configuration is the combination of the layers.

Background – Some Definitions

Deployment configuration

All of the deployment settings (*e.g.*, thread binding, tensor decomposition, *etc.*) to be determined are encoded as a feature vector, denoted as $\boldsymbol{x}$.

GFLOPS

Giga floating operations per second (GFLOPS) measures the number of floating-point operations conducted by the hardware per second.

Latency

Latency computes end-to-end model inference time and intuitively reflects the performance of model deployment.

Objective

Find the optimal $\boldsymbol{x}$, which has the best deployment performance, from the design space $\mathcal{D}$.

Background – Traditional active learning optimization

Initialization

- Randomly sample some configurations from the design space.
- Initialize an evaluation model (*e.g.*, XGBoost).

Iterative optimization

- Iteratively select a configruation according to the evaluation model and searching strategy
- Compile and deploy the configuration.
- Update the evaluation model.
- Stop until convergence.

Background

Current status

- Usually more than millions of candidate configurations in the design space.
- Slow compilation and depolyment processes.

Unsolved problems

- **Initialization** with underabundant information
- **Un-scalability** of the optimization process
- **Inaccuracy** of evaluation functions

Our Solution

Targets

- Improve data **diversity**.
- Improve model **scalability**.
- Improve model **accuracy**.

Proposed methods

- Batch Transductive Experimental Design
- Bootstrap-guided Adaptive Optimization

Initialization – Transductive Experimental Design (TED)

Maximize the intra-set diversity

$$x = \arg\max_{v \in \mathcal{V}} \frac{\|K_v\|^2}{k(v, v) + \mu}$$

- K: Euclidean distance matrix
- K_v is v's corresponding column in K
- $k(v, v)$ is v's diagonal entry in K, μ is a coefficient
- Iteratively select the configuration point which has the largest distance to other configurations
- The selected points are the **initialization set** for the evaluation model

Initialization – Batch TED

Batch method

- Computing distance matrix is very slow, even impossible.
- Sample a batch of sets from the design space and compute the distance matrix for each set.

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Algorithm 2 Batch Transductive Experimental Design – **BTED**$(\mathcal{V}, \mu, M, m, B)$

Require: $(\mathcal{V}, \mu, M, m, B)$, where $\mathcal{V}$ is the un-sampled configuration set, μ is the normalization coefficient, B is the batch size, M is the number of randomly sampled points and m is the number of points to be sampled as the initial set.

Ensure: Newly sampled configuration set $\mathcal{X}$.

1: **for** $b = 1 \rightarrow B$ **do**
2:     Randomly sample a set $\mathcal{V}_b$ from $\mathcal{V}$, with $|\mathcal{V}_b| = M$;
3:     $\tilde{\mathcal{X}}_b \leftarrow$ **TED**$(\mathcal{V}_b, \mu, m)$;
4: **end for**
5: Temporal union set $\tilde{\mathcal{X}}_U = \tilde{\mathcal{X}}_1 \cup \tilde{\mathcal{X}}_2 \cup \cdots \cup \tilde{\mathcal{X}}_B$;
6: $\mathcal{X} \leftarrow$ **TED**$(\tilde{\mathcal{X}}_U, \mu, m)$; **return** Newly sampled configuration set $\mathcal{X}$;

Initialization – Batch TED

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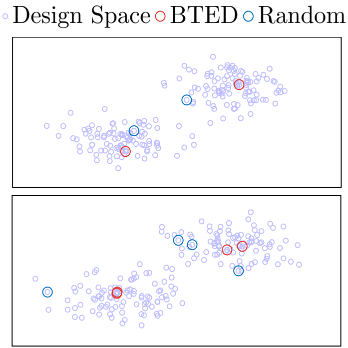
```
for b = 1 → B do
    Randomly sample a set V_b from V, with |V_b| = M;
    X̃_b ← TED(V_b, μ, m);
end for
Temporal union set X̃_U = X̃_1 ∪ X̃_2 ∪ ··· ∪ X̃_B;
X ← TED(X̃_U, μ, m); return Newly sampled configuration set X;
```

- **for** $b = 1 \rightarrow B$ **do**
  - Randomly sample a set $\mathcal{V}_b$ from $\mathcal{V}$, with $|\mathcal{V}_b| = M$;
  - $\tilde{\mathcal{X}}_b \leftarrow$ **TED**$(\mathcal{V}_b, \mu, m)$;
- **end for**
- Temporal union set $\tilde{\mathcal{X}}_U = \tilde{\mathcal{X}}_1 \cup \tilde{\mathcal{X}}_2 \cup \cdots \cup \tilde{\mathcal{X}}_B$;
- $\mathcal{X} \leftarrow$ **TED**$(\tilde{\mathcal{X}}_U, \mu, m)$; **return** Newly sampled configuration set $\mathcal{X}$;

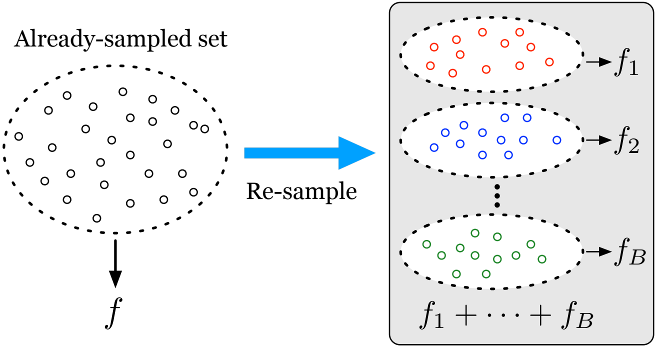
- Example



Iterative Opt. – Bootstrap-guided Adaptive Opt. (BAO)

Bootstrap re-sampling

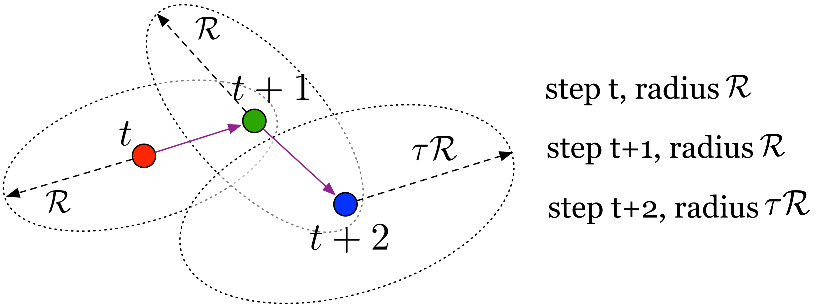
- Randomly re-sample a batch of sub-sets from the already-sampled configuration set.
- Build new evaluation functions for each of these re-sampled sub-sets.
- The final evaluation function is built as the summation of the evaluation functions of these re-sampled sub-sets.



Iterative Opt. – Bootstrap-guided Adaptive Opt. (BAO)

Adaptive Sampling

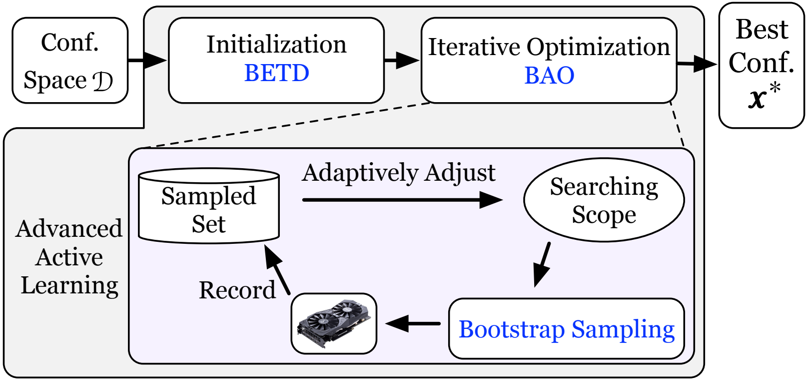
- Adjust the searching space (neighborhood of the previously-sampled point) adaptively in each optimization step.
- If the relative performance improvement is satisfying, we will keep the size of the searching space.
- Otherwise, we will enlarge the searching space.



Our Framework

Advanced active learning

- Batch transductive experimental design
- Bootstrap-guided adaptive optimization



Experimental Settings

Platform

- Intel(R) Xeon(R) E5-2680 v4 CPU@ 2.40GHz
- NVIDIA GeForce GTX 1080Ti GPU, CUDA 9.0.176

Benchmark

AlexNet, ResNet-18, VGG-16, MobileNet-v1, and SqueezeNet-v1.1

Criterion

- Inference latency
- Giga floating operations per second (GFLOPS)

Baseline

- AutoTVM

Convergence

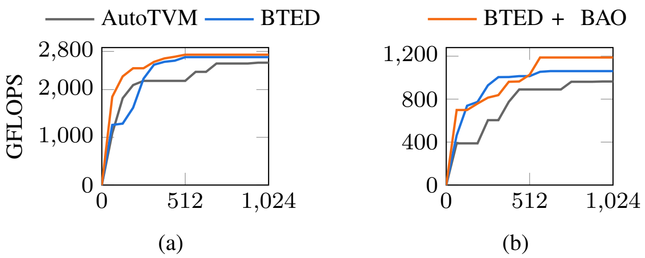


Fig. 4 Convergence trends of GFLOPs for the first 2 layers of MobileNet-v1, (a) the first layer, (b) the second layer.

Sampled Configurations and GFLOPS

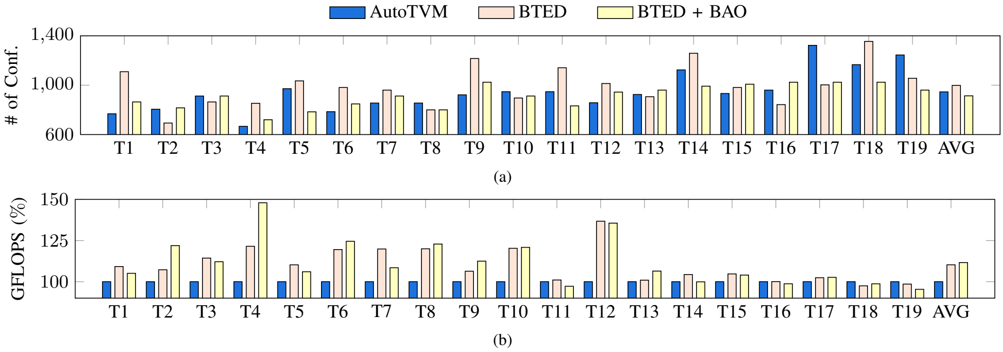


Fig. 5 The number of sampled configurations and GFLOPS values of MobileNet-v1. AVG represents the average results of the 19 tasks.

Results

Table: Comparisons of End-to-end Model Inference Latency and Variance

Model	AutoTVM		BTED				BTED + BAO			
	Latency (ms)	Variance	Latency (ms)	Δ (%)	Variance	Δ (%)	Latency (ms)	Δ (%)	Variance	Δ (%)
`AlexNet`	1.3639	0.1738	1.3373	- 1.95	0.2246	+29.23	1.3304	**- 2.46**	0.0711	**-59.09**
`ResNet-18`	1.8323	0.4651	1.7935	- 2.12	0.4487	- 3.53	1.7519	**- 4.39**	0.3848	**-17.27**
`VGG-16`	6.5176	2.3834	5.6808	-12.84	0.6574	-72.42	5.6183	**-13.80**	0.3617	**-84.82**
`MobileNet-v1`	1.0597	0.9290	0.8738	-17.54	0.5398	-41.89	0.7621	**-28.08**	0.0674	**-92.74**
`SqueezeNet-v1.1`	0.8697	1.1208	0.7436	-14.50	0.5533	-50.63	0.6920	**-20.43**	0.1709	**-84.75**
Average	2.3286	1.0144	2.0858	- 9.79	0.4848	-27.85	**2.0309**	**-13.83**	**0.2112**	**-67.74**

Thank You