nn-Meter: Towards Accurate Latency Prediction of Deep-Learning Model Inference on Diverse Edge Devices

MobiSys' 22

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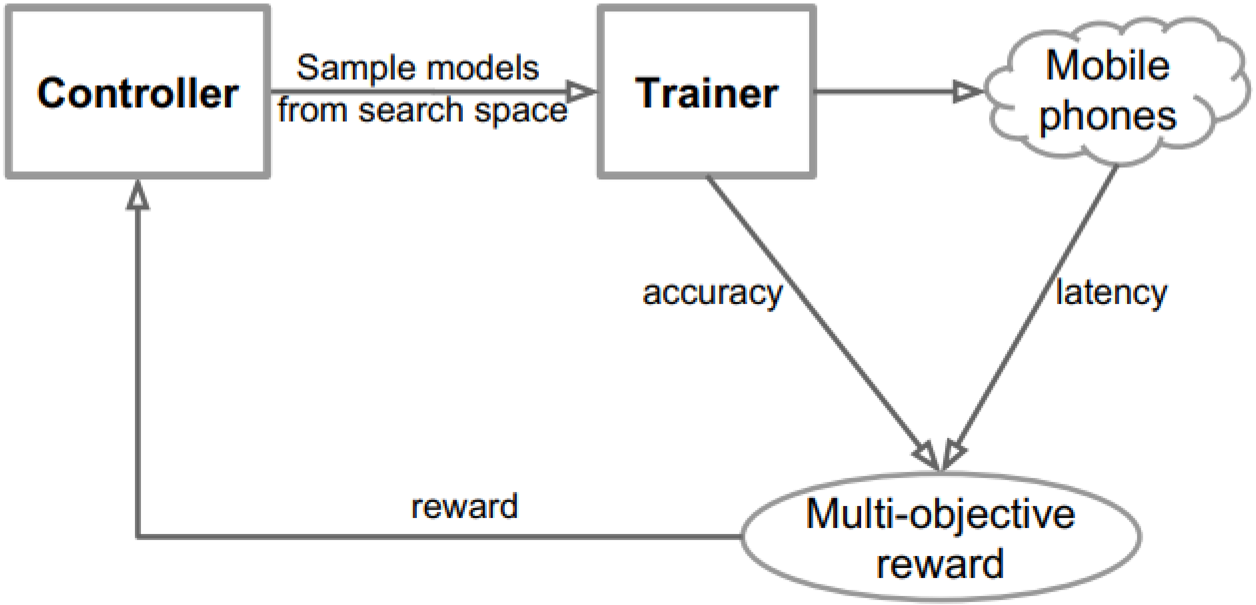
Introduction

To design a model with both high accuracy and efficiency, **model compression** and **neural architecture search** consider the inference latency of DNN models as the hard design constraint.



MnasNet-CVPR’19

Introduction

The engineering effort is tremendous for diverse edge devices and different inference frameworks.

Edge Devices

CPU

GPU

VPU

Inference frameworks (backend)

TensorFlow Lite

TensorRT

OpenVINO

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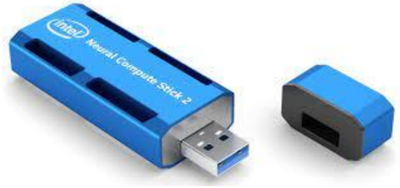

VPU

Inference frameworks (backend)

TensorFlow Lite

TensorRT

OpenVINO™

… …

TNN

… …

Introduction

Some approaches just used theoretical metrics.

FLOPs

FLOPs+MAC

Some approaches build operator-wise lookup table.

```
Conv-input:224x224x3-output:112x112x32:
  count: 982
  mean: 4.083755600814664
  var: 0.2502372872758427
Conv_1-input:7x7x320-output:7x7x1280:
  count: 982
  mean: 3.088623217922607
  var: 0.19174675835259503
Logits-input:7x7x1280-output:1000:
  count: 982
  mean: 0.3096415478615071
  var: 0.05583766681628091
expanded_conv-input:112x112x16-output:56x56x24-expand:3-kernel:3-stride:2-idskip:0:
  count: 164
  mean: 6.240567073170731
  var: 0.07330791484716055
expanded_conv-input:112x112x16-output:56x56x24-expand:3-kernel:5-stride:2-idskip:0:
  count: 159
  mean: 7.519106918238994
  var: 0.09288016159302682
expanded_conv-input:112x112x16-output:56x56x24-expand:3-kernel:7-stride:2-idskip:0:
  count: 161
  mean: 9.143757763975156
  var: 0.10378775382215095
expanded_conv-input:112x112x16-output:56x56x24-expand:6-kernel:3-stride:2-idskip:0:
  count: 173
  mean: 16.766225433526014
  var: 0.5075419297470916
expanded_conv-input:112x112x16-output:56x56x24-expand:6-kernel:5-stride:2-idskip:0:
  count: 161
  mean: 18.941260869565216
  var: 0.3943272992116978
```

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```

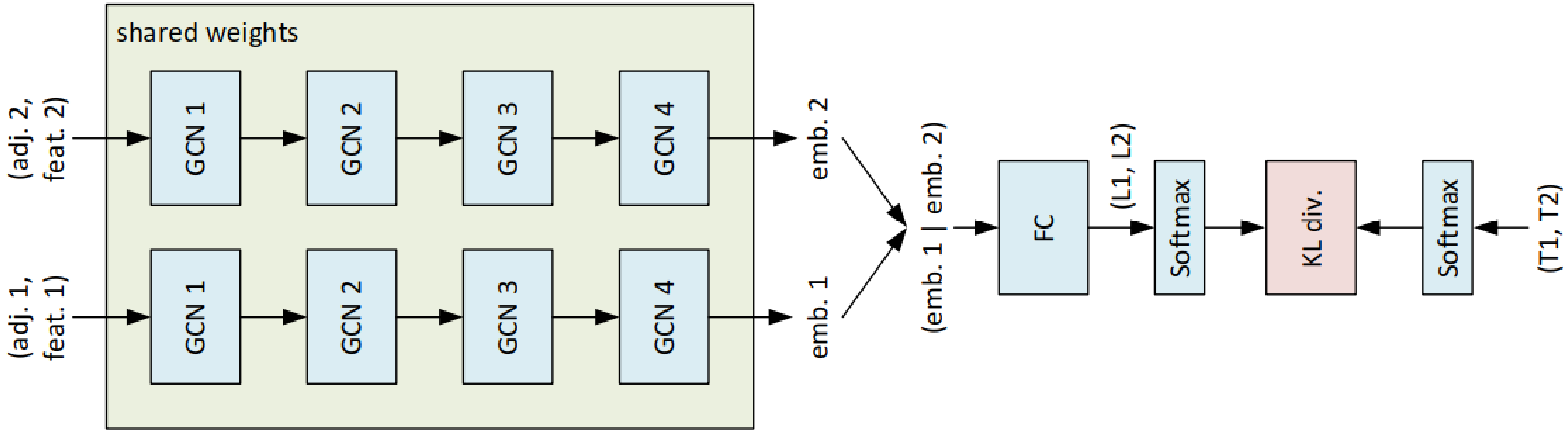
Problem:

They do not consider the model latency differences caused by **runtime optimizations** of model graphs.

Introduction

The state-of-the-art BRP-NAS uses graph convolutional networks to predict latency of the NASBench201 dataset on various devices. **It captures the runtime optimizations by learning the representation of model graphs and corresponding latency.**

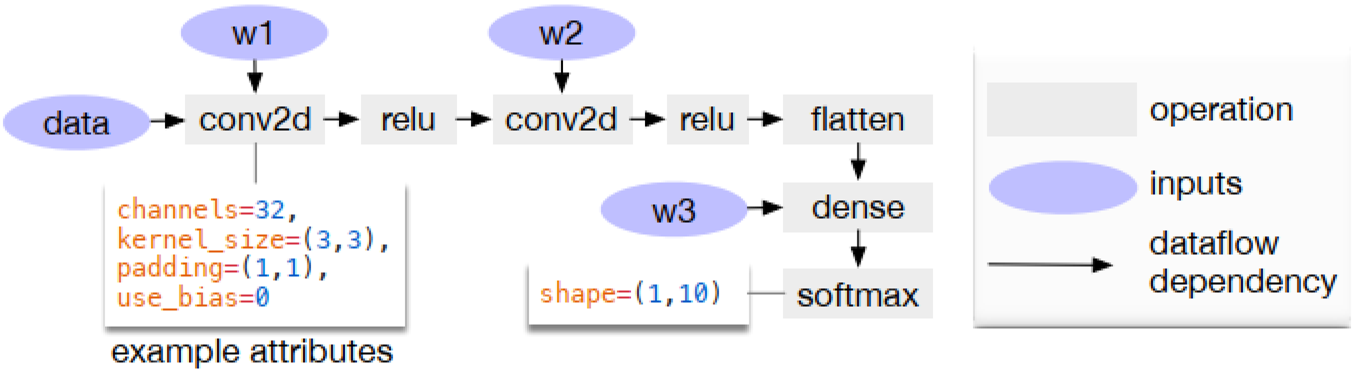
But it heavily depends on the tested model structures and may not work for many unseen model structures.



BRP-NAS-NIPS’20

Introduction

Neural network graph



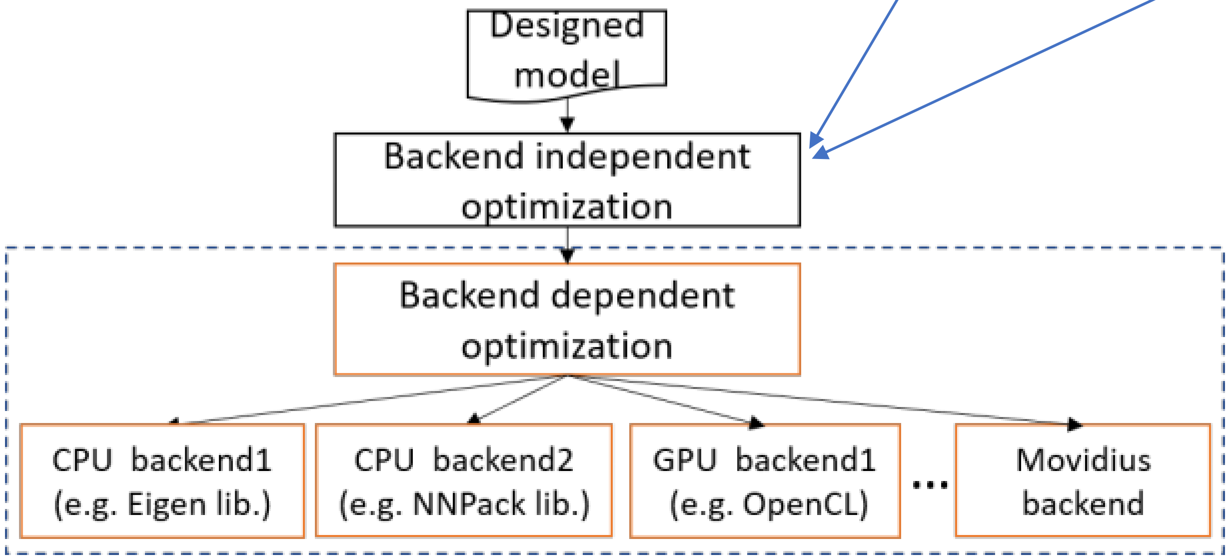
Introduction

Graph optimization

constant folding

$add(c1, add(x, c2))$ -> $add(x, c1 + c2)$

common expression elimination



operator fusion

Figure 1: Graph optimizations of framework.

Introduction

Operator fusion

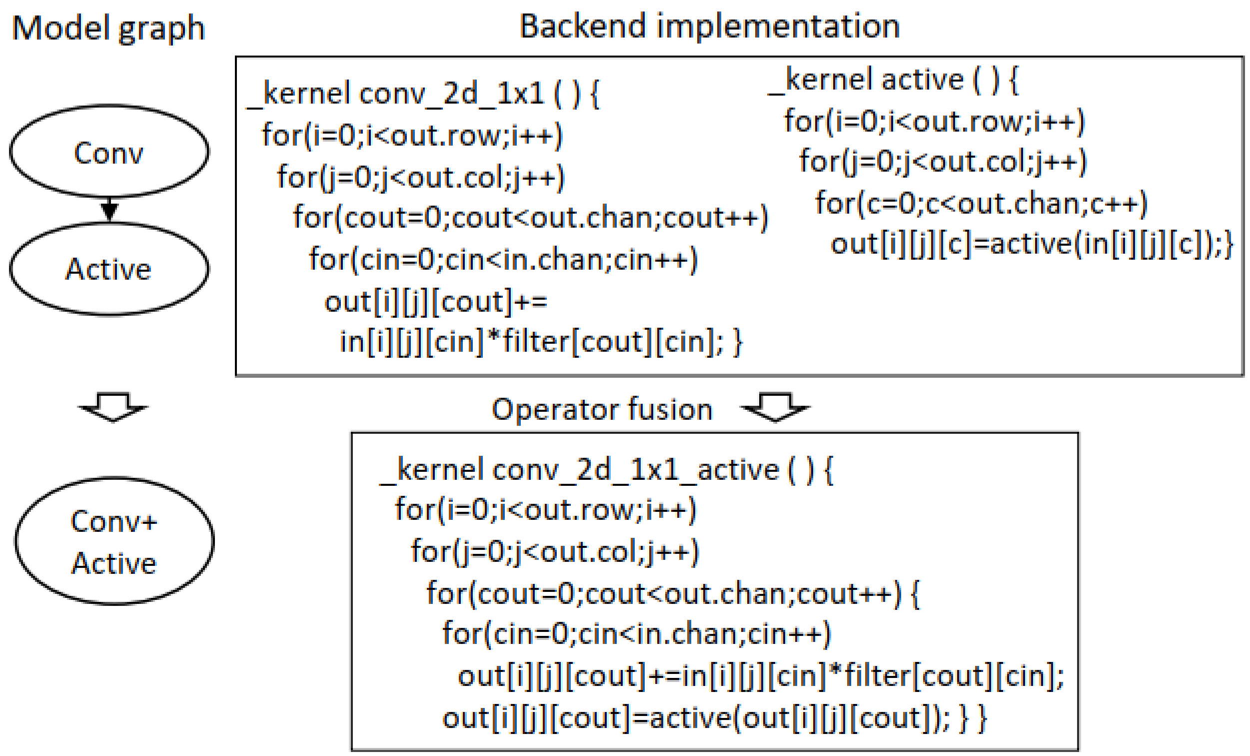
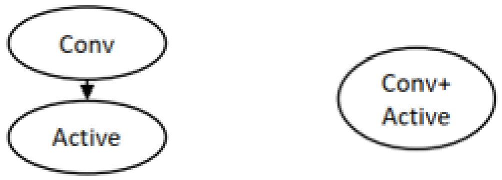


Figure 2: Kernel implementation for operator fusion("+" is used to represent fusion in this paper).

Introduction

Kernel-level prediction



	Model	Operator sum		Kernel sum	
	Latency	Latency	Error	Latency	Error
CPU	45.57ms	51.23ms	12.42%	45.41ms	0.35%
GPU	10.18ms	12.31ms	20.92%	9.91ms	2.65%
VPU	22.64ms	33.86ms	49.56%	23.18ms	2.38%

Table 1: MobileNetv2 latency.

System Overview

nn-Meter

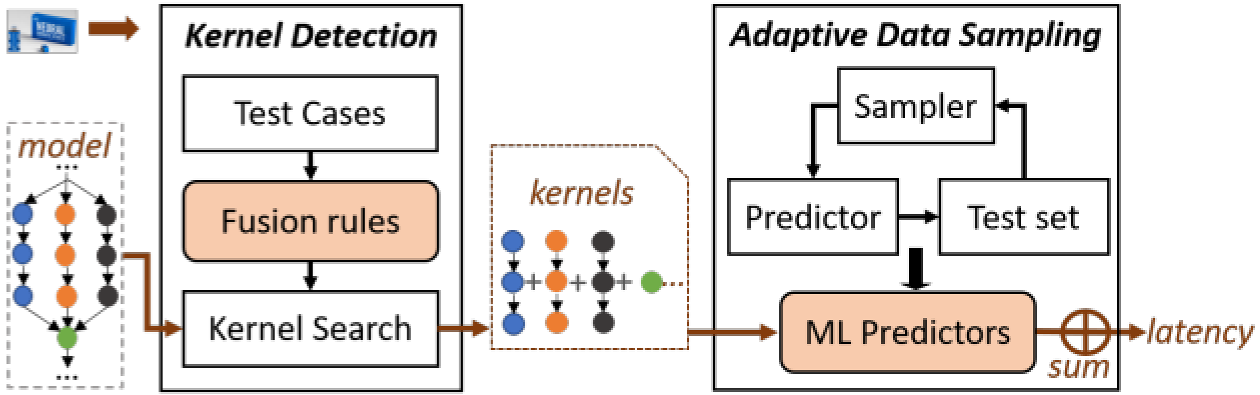


Figure 3: System architecture of nn-Meter. It offline detects fusion rules and builds ML predictors of kernels.

System Overview

Benchmark dataset collection

Model variants	avg FLOPs (M)	Latency(ms) Mobile CPU min - max	Mobile GPU min - max	Intel VPU min - max
AlexNets	973	7.1 - 494.4	0.4 - 81.7	2.1 - 47.3
VGGs	28422	178.4 - 10289	20.1 - 1278	25.6 - 1467
DenseNets	1794	109.6 - 431.6	26.7 - 69.5	26.4 - 70.7
ResNets	4151	35.9 - 1921.7	7.3 - 329.5	10.7 - 145.5
SqueezNets	1597	42.7 - 524.9	7.5 - 72.2	6.9 - 57.3
GoogleNets	1475	115.5 - 274.6	23.0 - 49.0	12.2 - 24.4
MobileNetv1s	547	27.5 - 140.0	5.5 - 28.8	8.9 - 37.0
MobileNetv2s	392	15.6 - 211.0	3.5 - 37.0	11.3 - 86.1
MobileNetv3s	176	10.4 - 78.4	4.3 - 18.6	17.4 - 70.8
ShuffleNetv2s	307	22.2 - 84.3	-	20.9 - 44.2
MnasNets	327	25.6 - 99.3	5.8 - 24.1	19.8 - 60.9
ProxylessNass	532	34.5 - 195.9	7.9 - 72.2	18.0 - 77.8
NASBench201	97.5	5.6 - 27.9	1.8 - 8.3	2.3 - 6.4

Table 2: The FLOPs and latency of each model variants in our proposed dataset. It covers a wide spectrum.

Key1-Kernel Detection

Test case design

operator type and **operator connection**

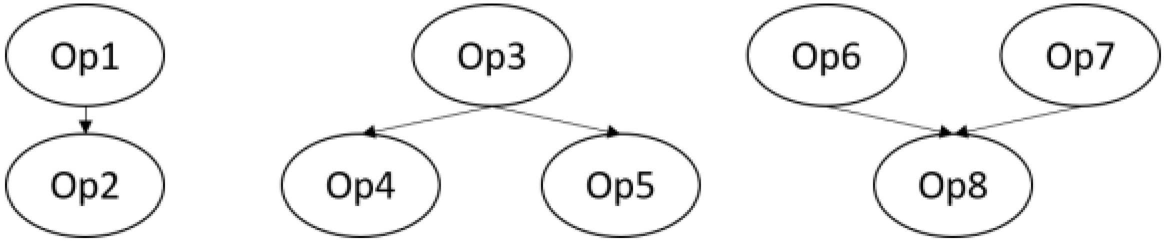
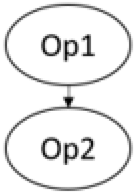


Figure 4: Operator connections: (a) single inbound and outbound; (b) multiple outbounds; (c) multiple inbounds.

Key1-Kernel Detection

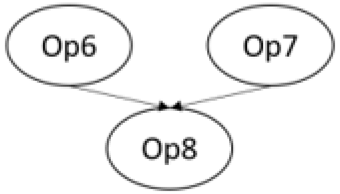
Test case design

How to find fusion rules in black-box backend?



$$T_{Op1} + T_{Op2} - T_{(Op1,Op2)} > \alpha * \min(T_{Op1}, T_{Op2})$$

Pick the closest time cost as the real time among:



$$T_{Op6} + T_{Op7} + T_{Op8}, T_{Op6+Op8} + T_{Op7}, T_{Op6} + T_{Op7+Op8}$$

Key1-Kernel Detection

Example-pool_relu

Backend	T_{pool} (μs)	T_{relu} (μs)	$T_{(pool,relu)}$ $(T_{pool} + T_{relu})$	Rule
VPU	13	26	16 (39)	“pool_relu":True
GPU	5.08	3.50	6.00 (8.60)	“pool_relu":True
CPU	23.60	0.81	24.48 (24.42)	“pool_relu":False

Table 3: A fusion detection example (pool, relu).

Key1-Kernel Detection

Algorithm 1 Kernel searching

Input: G a CNN model graph; R a set of fusion rules for a backend;
Output: Updated G with fused operators

function FUSE(O_{pred}, O_{succ})
  $O \leftarrow$ add a new operator in G as $O_{pred} + O_{succ}$
  $O.in \leftarrow O_{pred}.in \cup O_{succ}.in - O_{pred}$
  $O.out \leftarrow O_{pred}.out \cup O_{succ}.out - O_{succ}$
  $O.type \leftarrow O_{pred}.type$
  remove O_{pred}, O_{succ} from G
  return O
end function
function DFSTRAVERSE(O_{pred})
  for $O_{succ} \in O_{pred}.out$ **do**
    if $Rule_{fuse}(O_{pred}.type, O_{succ}.type)$
      and (len($O_{pred}.out$)==1 or $Rule_{multiout}()$)
      and (len($O_{succ}.in$)==1 or $Rule_{multiin}()$) **then**
        $O_{next} \leftarrow$ FUSE(O_{pred}, O_{succ})
    else
        $O_{next} \leftarrow O_{succ}$
    end if
    DFSTRAVERSE(O_{next})
  end for
end function
▷ Initial traverse input is the root of G
DFSTRAVERSE(O_{root})

Key1-Kernel Detection

Example-ResNet18

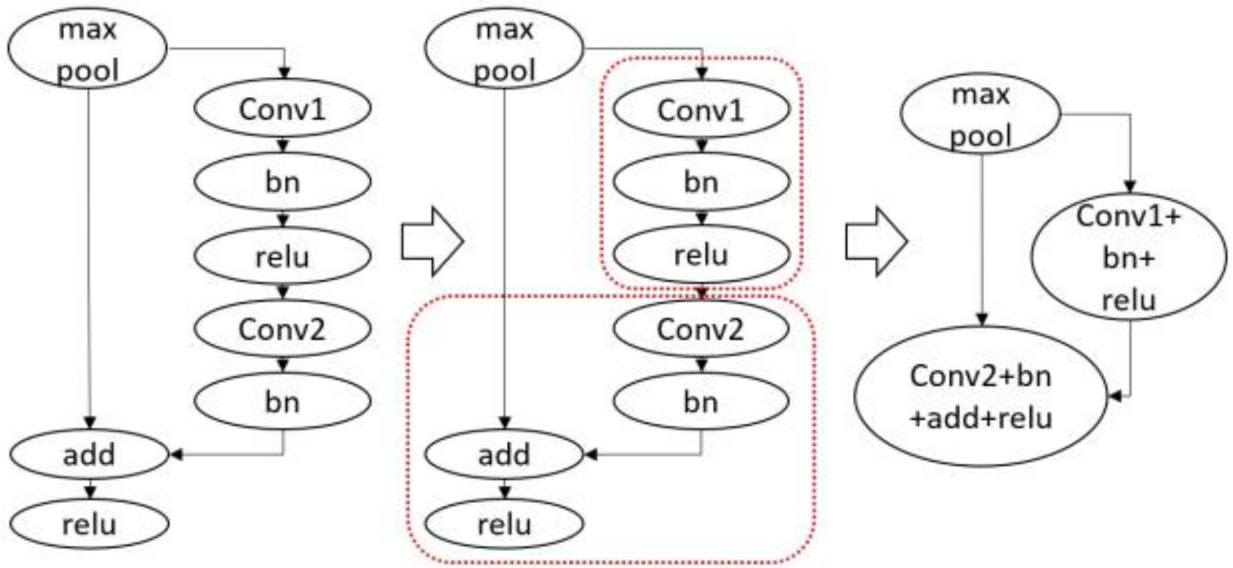


Figure 5: A kernel search example on a subgraph of ResNet18 model. The found kernels are {maxpool, Conv+bn+relu, Conv+bn+add+relu}.

Key1-Kernel Detection

Example-ResNet18

VPU		GPU		CPU	
kernel	#	kernel	#	kernel	#
Conv+bn+relu	9	Conv+bn+relu	9	Conv+bn+relu	9
maxpool	1	maxpool	1	maxpool	1
Conv+bn	11	Conv+bn+add+relu	8	Conv+bn	11
add+relu	8	Conv+bn	3	add+relu	8
avgpool	1	avgpool	1	avgpool	1
FC	1	FC	1	FC	1

Table 4: Found kernels for ResNet18.

Key2-Latency Prediction

Kernel characterization

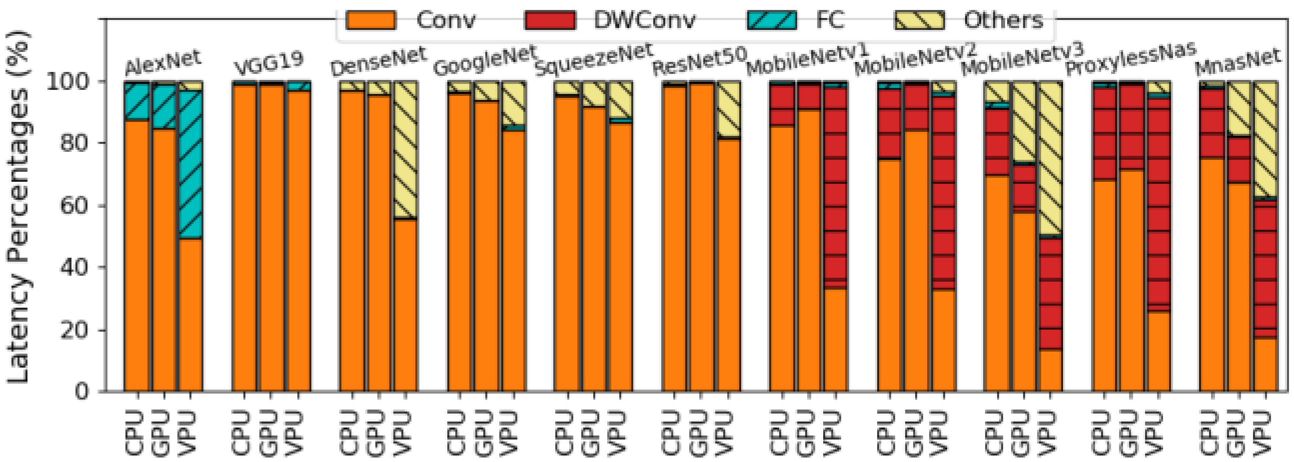


Figure 6: Model latency percentage breakdown. Conv and DWConv are the latency-dominating kernels.

Conv and DWConv dominate the latency

Key2-Latency Prediction

Kernel characterization

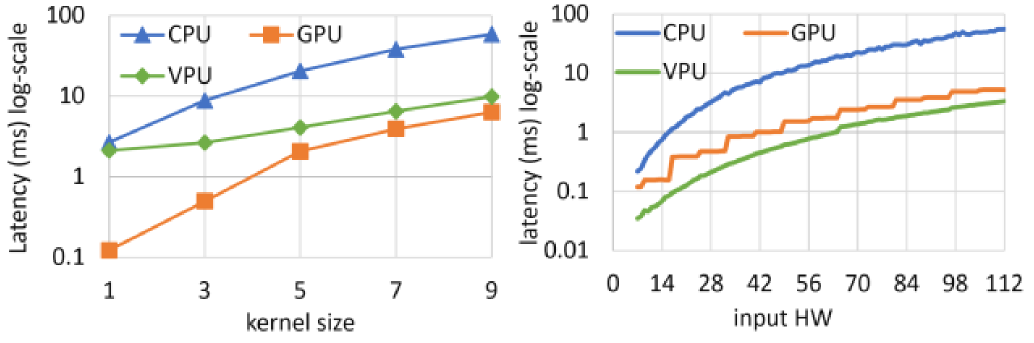
Dimension	Sample space
input HW	224, 112, 56, 32, 28, 27, 14, 13, 8, 7, 1
kernel size K	1, 3, 5, 7, 9
stride S	1, 2, 4
C_{cin}	range(3, 2160)
C_{out}	range(16, 2048)

Table 5: Sample space of Conv+bn+relu. It contains $\approx$ 0.7 billion configurations.

Large sample space of Conv

Key2-Latency Prediction

Kernel characterization



(a) Kernel Size (b) Input HW

Figure 7: Conv+bn+relu with (a): different kernel sizes (HW=224, C_{in}=3, C_{out}=32, S=1); (b): different input heights/widths. (C_{in}=C_{out}=64, K=3, S=1)

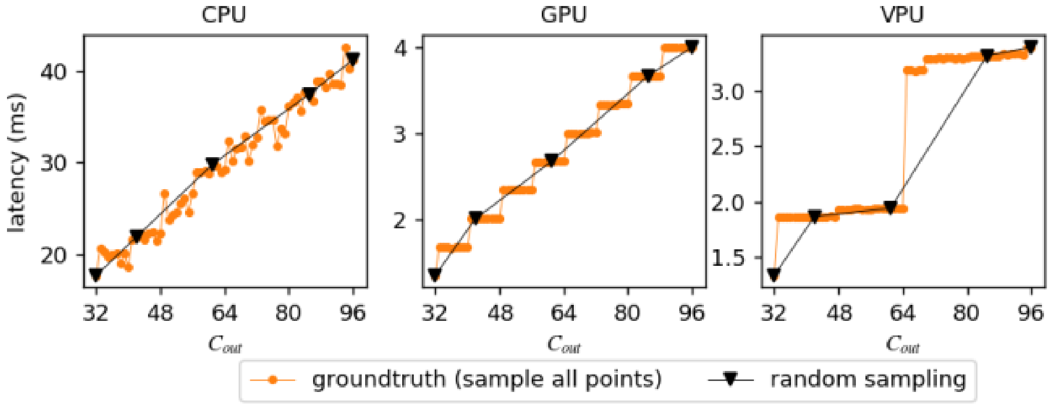


Figure 8: Latency of Conv+bn+relu with different output channel numbers. The groundtruth with sampling all channel numbers shows a staircase pattern on VPU and GPU. (HW=112, C_{in}=32, K=3, S=1)

Non-linear latency pattern

Random sampling misses hardware-crucial data

Key2-Latency Prediction

Algorithm 2 Adaptive Data Sampling Algorithm

Input: P prior possibility distribution from existing model zoo;
N initial data to sample from P; TD initial Test set;
M, number of data to sample for fine-grained sampling
e, the error threshold for regression model performance;
Output: all the sampled data (X,Y)

function FINEGRAINEDSAMPLE(X, M)
    for $x \in X$ **do**
        $D \leftarrow$ sample M data, we fix the (HW, K, S), channel numbers are randomly sampled from range $(0.4C_o, 1.2C_o)$
        $X_{new} \leftarrow X_{new}+D$
    end for
    $Y_{new} \leftarrow$ MEASURELATENCYONDEVICE(X_{new})
    return (X_{new}, Y_{new})
end function

▷ initialize N data from prior distribution to measure
$(X,Y) \leftarrow$ sample N data from distribution P
$f \leftarrow$ Construct regression model with (X_{train}, Y_{train})
$TD \leftarrow TD + (X_{test}, Y_{test})$
$e(f) \leftarrow$ test f on TD
▷ perform fine-grained sampling for inaccurate data
while $e(f) > e$ **do**
    $X^* \leftarrow$ select data with large predict error from TD
    $(X_i, Y_i) \leftarrow$ FINEGRAINEDSAMPLE(X^*, M)
    $(X, Y) \leftarrow (X, Y) + (X_i, Y_i)$
    update regression model f with (X_{train}, Y_{train})
    $TD \leftarrow TD + (X_{test}, Y_{test})$
    $e(f) \leftarrow$ test f on TD
end while

Key2-Latency Prediction

Collected data

Kernel	Features	# Collected Data CPU	GPU	VPU
Conv+bn+relu	HW, C_{in}, C_{out}, K S, FLOPs, params	15824	14040	39968
DWConv+bn+relu	$HW, C_{in}, K, S,$ FLOPs, params	4255	5054	7509
FC	C_{in}, C_{out} FLOPs, params	2000	3700	7065
maxpool	HW, C_{in}, K, S	1200	1366	1264
avgpool	HW, C_{in}, K, S	2575	1523	2179
SE	HW, C_{in}, ratio	2000	2000	2000
hswish	HW, C_{in}	1567	1567	1533
channelshuffle	HW, C_{in}	1000	-	1000
bn+relu	HW, C_{in}	2307	2000	-
add+relu	HW, C_{in}	2000	2000	2262
concat	$HW, C_{in1}, C_{in2},$ C_{in3}, C_{in4}	7674	8513	-

Table 6: Main kernels, features and valid data.

train:val:test 7:2:1

Key2-Latency Prediction

Predictor

Random Forests Regression

Use **NNI** to auto-tune hyper-parameters.

Measure latency:

- TFLite backend CPU: Using TFLite benchmark tool.
- TFLite backend GPU: A self-implemented profiler.
- OpenVINO backend VPU: OpenVINO toolkit.

Experiments

Setup

	Device	Processor	Framework
CPU	Pixel4	CortexA76 CPU	TFLite v2.1
GPU	Xiaomi Mi9	Adreno 640 GPU	TFLite v2.1
VPU	Intel NCS2	MyriadX VPU	OpenVINO2019R2[17]

Table 7: Evaluated edge devices.

Experiments

End-to-end prediction evaluation

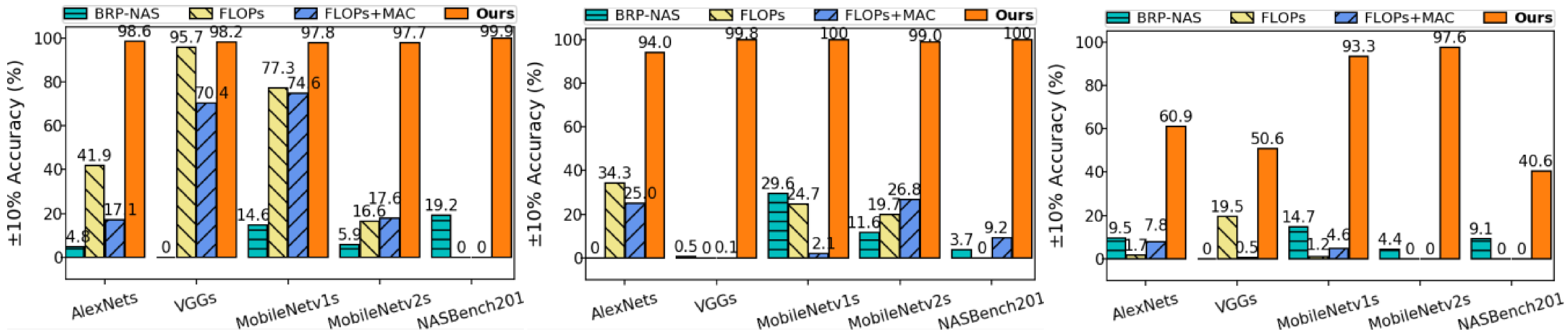


Figure 9: Compared to baseline predictors, nn-Meter achieves much higher ±10% accuracy on unseen models.

Experiments

End-to-end prediction evaluation

Model variants	Mobile CPU RMSE (ms)	Mobile CPU RMSPE (%)	Mobile CPU ±5% Acc.	Mobile CPU ±10% Acc.	Mobile GPU RMSE (ms)	Mobile GPU RMSPE (%)	Mobile GPU ±5% Acc.	Mobile GPU ±10% Acc.	Intel VPU RMSE (ms)	Intel VPU RMSPE (%)	Intel VPU ±5% Acc.	Intel VPU ±10% Acc.
AlexNets	4.02	3.90	81.0%	98.6%	0.93	5.32	72.0%	94.0%	1.17	10.74	23.4%	60.9%
VGGs	185.71	4.84	66.1%	98.2%	12.74	2.97	91.8%	99.8%	85.35	22.25	27.1%	50.6%
DenseNets	7.10	2.76	93.1%	99.9%	1.99	4.52	68.55%	99.9%	2.83	5.89	75.6%	86.3%
GoogleNets	5.69	3.27	85.9%	100%	0.44	1.35	100%	100%	0.94	5.86	39.7%	98.4%
SqueezeNets	7.19	3.59	84.5%	99.9%	1.17	3.85	81.9%	97.9%	1.93	7.08	66.1%	88.5%
ResNets	26.87	4.41	72.3%	98.1%	2.58	3.16	88.8%	99.9%	3.39	7.42	37.9%	84.2%
MobileNetv1s	3.71	4.98	63.8%	97.8%	0.37	2.56	96.9%	100%	1.21	5.90	54.2%	93.3%
MobileNetv2s	3.25	4.84	67.6%	97.7%	0.54	3.93	80.0%	99.0%	1.29	4.26	78.3%	97.6%
MobileNetv3s	2.03	4.34	73.8%	99.0%	0.40	4.02	84.4%	100%	2.47	5.72	47.6%	98.5%
ShuffleNetv2s	2.48	5.01	61.6%	98.3%	-	-	-	-	1.91	6.37	45.6%	91.3%
MnasNets	3.19	5.54	50.9%	99.2%	0.25	1.86	100%	100%	1.76	4.34	77.3%	97.7%
ProxylessNass	3.18	3.44	84.6%	100%	0.61	3.28	95.6%	98.9%	1.97	5.05	65.6%	96.9%
NASBench201	0.44	3.51	82.4%	99.9%	0.12	3.80	75.9%	100%	0.90	18.20	19.3%	40.6%

Table 8: End-to-end latency prediction for 26,000 models on mobile CPU, GPU and Intel VPU.

Experiments

Kernel prediction evaluation

Kernel	CPU		GPU		VPU	
	RMSE (ms)	±10% Acc.	RMSE (ms)	±10% Acc.	RMSE (ms)	±10% Acc.
Conv+bn+relu	6.24	89.1%	6.77	82.0%	18.74	67.9%
DWConv+bn+relu	0.21	97.4%	0.10	98.7%	0.28	89.4%
FC	0.64	94.3%	0.07	96.2%	0.12	93.9%
maxpool	0.12	89.6%	0.06	97.1%	0.21	89.7%
avgpool	1.94	99.0%	0.01	99.7%	0.26	95.4%
SE	0.45	87.1%	0.39	99.8%	0.44	99.0%
hswish	0.16	98.1%	0.01	100%	0.02	100%
channelshuffle	0.14	99.5%	-	-	0.35	100%
bn+relu	0.85	80.7%	0.01	100%	-	-
add+relu	0.10	93.7%	0.003	98.3%	0.02	98.9%
concat	0.09	89.3%	0.42	77.1%	-	-

Table 9: Performance for main kernel predictors.

Experiments

VPU study

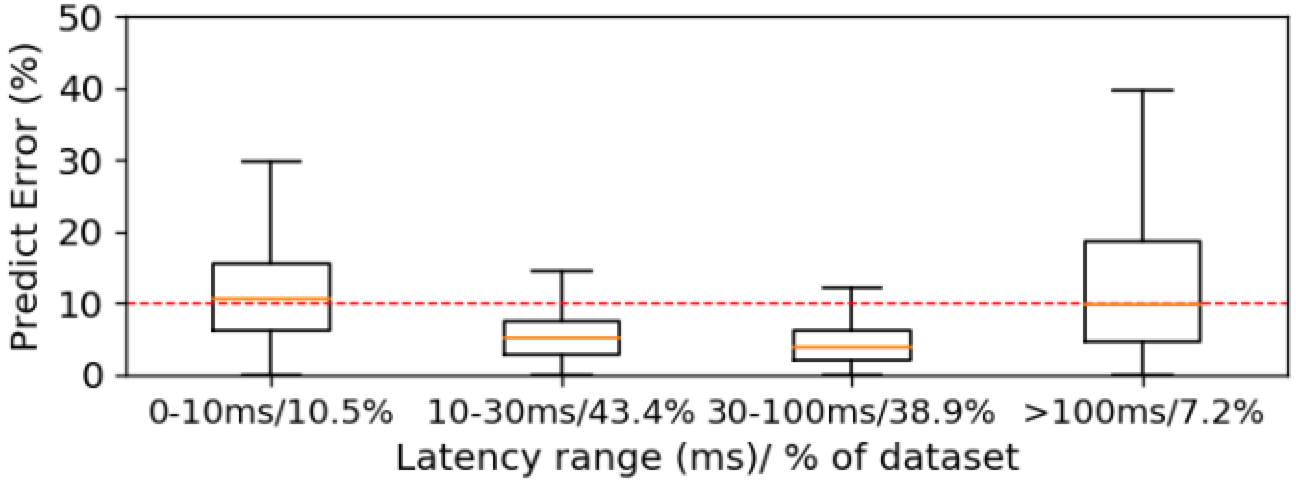
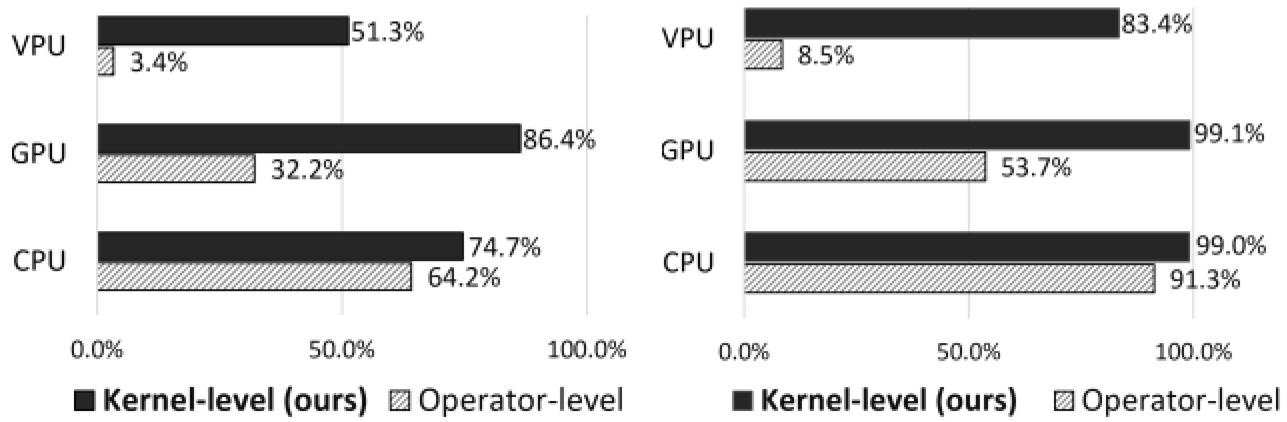


Figure 10: Prediction errors on the VPU. X-axis label: latency range/group size percentages of the dataset.

Experiments

Kernel-level prediction



(a) ±5% accuracy (b) ±10% accuracy

Figure 11: Operator-level approach achieves much lower ±5% and ±10% accuracy on three devices.

Experiments

Sampling performance

Device	Random Sampling		Adaptive Sampling	
	RMSE	±10% Acc.	RMSE	±10% Acc.
CPU	25.47 ms	21.92%	10.13 ms	71.78%
GPU	1.67 ms	48.70%	1.19 ms	75.34%
VPU	7.87 ms	23.98%	7.58 ms	54.33%

Table 10: Under the same amount of sampled data, we achieve better performance than random sampling.

Experiments

Generalization performance

Models (measure on Adreno630)	Adreno640 predictor rmse (ms)	rmspe (%)	±5% Acc.	±10% Acc.	Adreno630 predictor rmse (ms)	rmspe (%)	±5% Acc.	±10% Acc.
AlexNets	8.02	25.40	0.6%	2.3%	0.87	3.61	86.5%	97.9%
VGGs	154.50	24.85	0%	0%	19.47	3.10	89.5%	99.9%
DenseNets	4.44	7.80	18.4%	84.0%	2.41	4.58	67.1%	100%
GoogleNets	6.71	17.03	0%	0%	1.45	3.75	95.8%	100%
SqueezeNets	8.02	19.21	0.4%	3.0%	1.14	3.30	87.3%	100%
ResNets	33.82	21.36	1.3%	11.0%	2.52	2.65	93.4%	100%
MobileNetv1s	0.28	1.92	98.3%	100%	0.23	1.68	99.7%	100%
MobileNetv2s	0.85	5.43	55.6%	97.2%	0.41	3.42	85.7%	99.5%
MobileNetv3s	0.87	8.25	5.2%	87.5%	0.56	6.14	31.5%	99.6%
MnasNets	0.74	5.45	42.2%	99.8%	0.31	2.26	99.9%	100%
ProxylessNass	0.86	4.33	71.5%	100%	0.21	1.11	100%	100%
NASBench201	0.77	14.94	3.2%	17.5%	0.36	6.22	48.1%	90.6%

Table 11: Two different latency predictors for model inference on the Adreno GPU 630.

Experiments

System overhead

	CPU	GPU	VPU
total measure time	2.5 *days*	1 *day*	4.4 *days*

Table 12: Time cost of nn-Meter.

Conclusion

Advantages:

- Kernel detector is a nice idea to detect optimized kernels in black-box frameworks.
- Predictor introduces an adaptive random sampling method to achieve good trade-off between accuracy and complexity.

Disadvantages:

- Only support CNN currently.
- Retrain needed for new version of backends or networks.
- No consideration of dynamic environment.
- No detailed consideration of heterogenous computing.
- No modeling for power consumption.
- Black-box model based predictor.
- No applicable experiments on SOTA NAS or model compression to evaluate its performance.

Thank You !

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