TPU-MLIR Quick Start

Release 1.10

SOPHGO

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Release Record

Version	Release date	Explanation
v1.6.0	2024.02.23	Added PyPI release form; Supports user-defined Global operators; Support for the CV186X processor platform
v1.5.0	2023.11.03	Enhanced Global Layer support for multicore parallelism;
v1.4.0	2023.09.27	System dependencies upgraded to Ubuntu 22.04; Supported BM1684 Winograd
v1.3.0	2023.07.27	Add the function to manually specify operations computing with floating-point; Add the list of supported front-end framework operators; Add a comparison between NNTC and TPU-MLIR quantization methods.
v1.2.0	2023.06.14	Adjusted the mixed quantization example
v1.1.0	2023.05.26	Added using Tensor Computing Processor for post-processing
v1.0.0	2023.04.10	Support for PyTorch, added section introducing the conversion to PyTorch models
v0.8.0	2023.02.28	Added using Tensor Computing Processor for pre-processing
v0.6.0	2022.11.05	Support mix precision
v0.5.0	2022.10.20	Support test model_zoo models
v0.4.0	2022.09.20	Support convert caffe model
v0.3.0	2022.08.24	Support TFLite. Add the chapter on TFLite model conversion.
v0.2.0	2022.08.02	Add the chapter on test samples in running SDK.
v0.1.0	2022.07.29	Initial release, supporting `resnet/mobilenet/vgg/ssd/yolov5s` and using yolov5s as the use case.

CHAPTER 1

TPU-MLIR Introduction

TPU-MLIR is the Tensor Computing Processor compiler project for Depp Learning processors. This project provides a complete toolchain, which can convert pre-trained neural networks under different frameworks into binary files `bmodel` that can be efficiently run on tensor computing processors. The code has been open-sourced to github: https://github.com/sophgo/tpu-mlir .

The overall architecture of TPU-MLIR is shown in the figure (TPU-MLIR overall architecture).

The current directly supported frameworks are pytorch, onnx, tflite and caffe. Models from other frameworks need to be converted to onnx models. The method of converting models from other frameworks to onnx can be found on the onnx official website: https://github.com/onnx/tutorials.

To convert a model, firstly you need to execute it in the specified docker. With the required environment, conversion work can be done in two steps, converting the original model to mlir file by `model_transform` and converting the mlir file to bmodel/cvimodel by `model_deploy`. To obtain an INT8 model, you need to call `run_calibration` to generate a quantization table and pass it to `model_deploy`. This article mainly introduces the process of this model conversion.

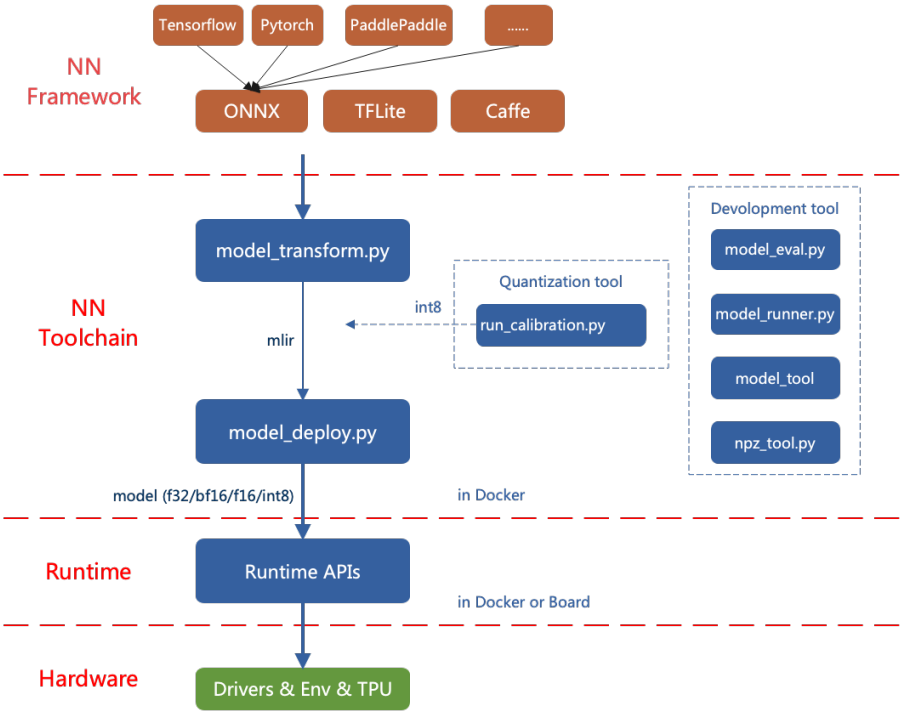

Fig. 1.1: TPU-MLIR overall architecture

CHAPTER 2

Environment Setup

First check whether the current system environment meets ubuntu 22.04 and python 3.10. If not, please proceed to the next section Basic Environment Configuration; if satisfied, jump directly to Install tpu_mlir.

2.1 Basic Environment Configuration

If you do not meet the above system environment, you need to use Docker, download the required image file from DockerHub https://hub.docker.com/r/sophgo/tpuc_dev, or use the following command to pull the image directly:

```
$ docker pull sophgo/tpuc_dev:v3.2
```

If the pulling fails, you can download the required image file from the official website development materials https://developer.sophgo.com/site/index/material/86/all.html, or use the following command to download and load the image:

```
$ wget https://sophon-file.sophon.cn/sophon-prod-s3/drive/24/06/14/12/sophgo-tpuc_dev-v3.2_
↪191a433358ad.tar.gz
$ docker load -i sophgo-tpuc_dev-v3.2_191a433358ad.tar.gz
```

If you are using docker for the first time, you can execute the following commands to install and configure it (only for the first time):

```
$ sudo apt install docker.io
$ sudo systemctl start docker
$ sudo systemctl enable docker
$ sudo groupadd docker
```

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```
$ sudo usermod -aG docker $USER
$ newgrp docker
```

If you download the image file, make sure the image file is in the current directory, and then create a container in the current directory as follows:

```
$ docker run --privileged --name myname -v $PWD:/workspace -it sophgo/tpuc_dev:v3.2
```

where myname is the name of the container, which can be customized; $PWD is the current directory, synchronized with the container' s /workspace directory.

Subsequent chapters assume that the user is already in the /workspace directory inside docker.

2.2 Install tpu_mlir

Currently supported 2 methods to install, which are online and offline installation.

Online installation

Download and install directly from pypi, the latest version will be installed by default:

```
$ pip install tpu_mlir
```

Offline installation

Download tpu_mlir-*-py3-none-any.whl from Assets on Github, then install with pip:

```
$ pip install tpu_mlir-*-py3-none-any.whl
```

2.3 Install the dependency of tpu_mlir

tpu_mlir requires different dependencies when processing models of different frameworks, Both the online and offline installation methods require additional dependencies to be installed.

Online installation

For model files generated by onnx or torch when online installation, use the following command to install additional dependency environments:

```
# install onnx dependency
$ pip install tpu_mlir[onnx]
# install torch dependency
$ pip install tpu_mlir[torch]
```

There are 5 config currently supported:

```
onnx, torch, tensorflow, caffe, paddle
```

You can install multiple dependency config in one command, or use all to install all dependencies:

```
# install onnx, torch, caffe dependency at the same time
$ pip install tpu_mlir[onnx,torch,caffe]
# install all dependency
$ pip install tpu_mlir[all]
```

Offline installation

Similarly, the offline installation method allows you to install additional dependencies using the following command:

```
# install onnx dependency
$ pip install tpu_mlir-*-py3-none-any.whl[onnx]
# install all dependency
$ pip install tpu_mlir-*-py3-none-any.whl[all]
```


CHAPTER 3

Compile the ONNX model

This chapter takes yolov5s.onnx as an example to introduce how to compile and transfer an onnx model to run on the BM1684X platform.

The model is from the official website of yolov5: https://github.com/ultralytics/yolov5/releases/download/v6.0/yolov5s.onnx

This chapter requires the tpu_mlir python package.

platform	file name	info
cv183x/cv182x/cv181x/cv180x	xxx.cvimodel	please refer to the CV18xx Guidance
Other	xxx.bmodel	please refer to the following

3.1 Install tpu_mlir

Go to the Docker container and execute the following command to install tpu_mlir:

```
$ pip install tpu_mlir[onnx]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[onnx]
```

3.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a model_yolov5s directory, and put both model files and image files into the model_yolov5s directory.

The operation is as follows:

```
$ mkdir model_yolov5s && cd model_yolov5s
$ wget https://github.com/ultralytics/yolov5/releases/download/v6.0/yolov5s.onnx
$ cp -rf tpu_mlir_resource/dataset/COCO2017 .
$ cp -rf tpu_mlir_resource/image .
$ mkdir workspace && cd workspace
```

3.3 ONNX to MLIR

If the input is image, we need to know the preprocessing of the model before transferring it. If the model uses preprocessed npz files as input, no preprocessing needs to be considered. The preprocessing process is formulated as follows (x represents the input):

$$y = (x - mean) \times scale$$

The image of the official yolov5 is rgb. Each value will be multiplied by 1/255, respectively corresponding to 0.0,0.0,0.0 and 0.0039216,0.0039216,0.0039216 when it is converted into mean and scale.

The model conversion command is as follows:

```
$ model_transform \
    --model_name yolov5s \
    --model_def ../yolov5s.onnx \
    --input_shapes [[1,3,640,640]] \
    --mean 0.0,0.0,0.0 \
    --scale 0.0039216,0.0039216,0.0039216 \
    --keep_aspect_ratio \
    --pixel_format rgb \
    --output_names 350,498,646 \
    --test_input ../image/dog.jpg \
    --test_result yolov5s_top_outputs.npz \
    --mlir yolov5s.mlir
```

The main parameters of model_transform are described as follows (for a complete introduction, please refer to the user interface chapter of the TPU-MLIR Technical Reference Manual):

Table 3.1: Function of model_transform parameters

Name	Required?	Explanation
model_name	Y	Model name
model_def	Y	Model definition file (e.g., .onnx , .tflite or .prototxt files)
input_shapes	N	Shape of the inputs, such as [[1,3,640,640]] (a two-dimensional array), which can support multiple inputs
input_types	N	Type of the inputs, such int32; separate by ',' for multi inputs; float32 as default
resize_dims	N	The size of the original image to be adjusted to. If not specified, it will be resized to the input size of the model
keep_aspect_ratio	N	Whether to maintain the aspect ratio when resize. False by default. It will pad 0 to the insufficient part when setting
mean	N	The mean of each channel of the image. The default is 0.0,0.0,0.0
scale	N	The scale of each channel of the image. The default is 1.0,1.0,1.0
pixel_format	N	Image type, can be rgb, bgr, gray or rgbd. The default is bgr
channel_format	N	Channel type, can be nhwc or nchw for image input, otherwise it is none. The default is nchw
output_names	N	The names of the output. Use the output of the model if not specified, otherwise use the specified names as the output
test_input	N	The input file for validation, which can be an image, npy or npz. No validation will be carried out if it is not specified
test_result	N	Output file to save validation result
excepts	N	Names of network layers that need to be excluded from validation. Separated by comma
mlir	Y	The output mlir file name (including path)

After converting to an mlir file, a ${model_name}_in_f32.npz file will be generated, which is the input file for the subsequent models.

3.4 MLIR to F16 bmodel

To convert the mlir file to the f16 bmodel, we need to run:

```
$ model_deploy \
  --mlir yolov5s.mlir \
  --quantize F16 \
  --processor bm1684x \
  --test_input yolov5s_in_f32.npz \
  --test_reference yolov5s_top_outputs.npz \
  --tolerance 0.99,0.99 \
  --model yolov5s_1684x_f16.bmodel
```

The main parameters of model_deploy are as follows (for a complete introduction, please refer to the user interface chapter of the TPU-MLIR Technical Reference Manual):

Table 3.2: Function of model_deploy parameters

Name	Required?	Explanation
mlir	Y	Mlir file
quantize	Y	Quantization type (F32/F16/BF16/INT8)
processor	Y	The platform that the model will use. Support bm1690/bm1688/bm1684x/bm1684/cv186x/cv183x/cv182x/cv181x/cv1
calibration_table	N	The calibration table path. Required when it is INT8 quantization
tolerance	N	Tolerance for the minimum similarity between MLIR quantized and MLIR fp32 inference results
test_input	N	The input file for validation, which can be an image, npy or npz. No validation will be carried out if it is not specified
test_reference	N	Reference data for validating mlir tolerance (in npz format). It is the result of each operator
compare_all	N	Compare all tensors, if set.
excepts	N	Names of network layers that need to be excluded from validation. Separated by comma
op_divide	N	cv183x/cv182x/cv181x/cv180x only, Try to split the larger op into multiple smaller op to achieve the purpose of ion memory saving, suitable for a few specific models
model	Y	Name of output model file (including path)
num_core	N	When the target is selected as bm1688, it is used to select the number of tpu cores for parallel computing, and the default setting is 1 tpu core
skip_validation	N	Skip bmodel correctness verification to boost deployment efficiency; bmodel verification is on by default

After compilation, a file named yolov5s_1684x_f16.bmodel is generated.

3.5 MLIR to INT8 bmodel

3.5.1 Calibration table generation

Before converting to the INT8 model, you need to run calibration to get the calibration table. The number of input data is about 100 to 1000 according to the situation.

Then use the calibration table to generate a symmetric or asymmetric bmodel. It is generally not recommended to use the asymmetric one if the symmetric one already meets the requirements, because the performance of the asymmetric model will be slightly worse than the symmetric model.

Here is an example of the existing 100 images from COCO2017 to perform calibration:

```
$ run_calibration yolov5s.mlir \
    --dataset ../COCO2017 \
    --input_num 100 \
    -o yolov5s_cali_table
```

After running the command above, a file named yolov5s_cali_table will be generated, which is used as the input file for subsequent compilation of the INT8 model.

3.5.2 Compile to INT8 symmetric quantized model

Execute the following command to convert to the INT8 symmetric quantized model:

```
$ model_deploy \
    --mlir yolov5s.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_cali_table \
    --processor bm1684x \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --model yolov5s_1684x_int8_sym.bmodel
```

After compilation, a file named yolov5s_1684x_int8_sym.bmodel is generated.

3.6 Effect comparison

In tpu_mlir package, there are yolov5 use cases written in python, using the detect_yolov5 command to detect objects in images.

This command corresponds to the source code path {package/path/to/tpu_mlir}/python/samples/detect_yolov5.py.

It can be learned how the model is used by reading the code. Firstly, preprocess to get the model' s input, then do inference to get the output, and finally do post-processing.

Use the following codes to validate the inference results of onnx/f16/int8 respectively.

The onnx model is run as follows to get dog_onnx.jpg:

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model ../yolov5s.onnx \
   --output dog_onnx.jpg
```

The f16 bmodel is run as follows to get dog_f16.jpg :

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model yolov5s_1684x_f16.bmodel \
   --output dog_f16.jpg
```

The int8 symmetric bmodel is run as follows to get dog_int8_sym.jpg:

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model yolov5s_1684x_int8_sym.bmodel \
   --output dog_int8_sym.jpg
```

The result images are compared as shown in the figure (Comparison of TPU-MLIR for YOLOv5s' compilation effect).

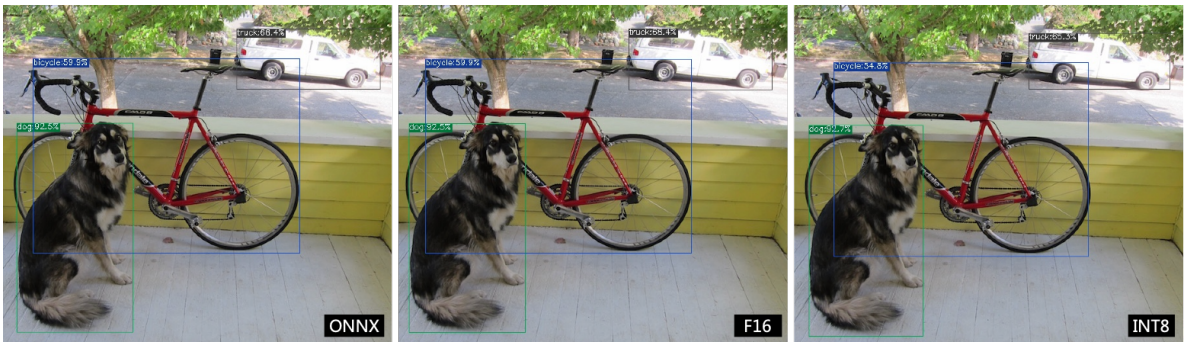

Fig. 3.1: Comparison of TPU-MLIR for YOLOv5s' compilation effect

Due to different operating environments, the final performance will be somewhat different from Fig. 3.1.

3.7 Model performance test

The following operations need to be performed outside of Docker,

3.7.1 Install the libsophon

Please refer to the **libsophon** manual to install **libsophon**.

3.7.2 Check the performance of BModel

After installing **libsophon**, you can use **bmrt_test** to test the accuracy and performance of the **bmodel**. You can choose a suitable model by estimating the maximum fps of the model based on the output of **bmrt_test**.

```
# Test the bmodel compiled above
# --bmodel parameter followed by bmodel file,

$ cd path/to/model_yolov5s/workspace
$ bmrt_test --bmodel yolov5s_1684x_f16.bmodel
$ bmrt_test --bmodel yolov5s_1684x_int8_sym.bmodel
```

Take the output of the last command as an example (the log is partially truncated here):

```
[BMRT][load_bmodel:983] INFO:pre net num: 0, load net num: 1
[BMRT][show_net_info:1358] INFO: ##########################
[BMRT][show_net_info:1359] INFO: NetName: yolov5s, Index=0
[BMRT][show_net_info:1361] INFO: ---- stage 0 ----
[BMRT][show_net_info:1369] INFO:   Input 0) 'images' shape=[ 1 3 640 640 ] dtype=FLOAT32
[BMRT][show_net_info:1378] INFO:   Output 0) '350_Transpose_f32' shape=[ 1 3 80 80 85 ] ...
[BMRT][show_net_info:1378] INFO:   Output 1) '498_Transpose_f32' shape=[ 1 3 40 40 85 ] ...
[BMRT][show_net_info:1378] INFO:   Output 2) '646_Transpose_f32' shape=[ 1 3 20 20 85 ] ...
[BMRT][show_net_info:1381] INFO: ##########################
[BMRT][bmrt_test:770] INFO:==> running network #0, name: yolov5s, loop: 0
[BMRT][bmrt_test:834] INFO:reading input #0, bytesize=4915200
[BMRT][print_array:702] INFO:  --> input_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ...
[BMRT][bmrt_test:982] INFO:reading output #0, bytesize=6528000
[BMRT][print_array:702] INFO:  --> output ref_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0...
[BMRT][bmrt_test:982] INFO:reading output #1, bytesize=1632000
[BMRT][print_array:702] INFO:  --> output ref_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0...
[BMRT][bmrt_test:982] INFO:reading output #2, bytesize=408000
[BMRT][print_array:702] INFO:  --> output ref_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0...
[BMRT][bmrt_test:1014] INFO:net[yolov5s] stage[0], launch total time is 4122 us (npu 4009 us,F
↪normal 113 us)
[BMRT][bmrt_test:1017] INFO:+++ The network[yolov5s] stage[0] output_data +++
[BMRT][print_array:702] INFO:output data #0 shape: [1 3 80 80 85 ] < 0.301003    ...
[BMRT][print_array:702] INFO:output data #1 shape: [1 3 40 40 85 ] < 0 0.228689  ...
[BMRT][print_array:702] INFO:output data #2 shape: [1 3 20 20 85 ] < 1.00135     ...
[BMRT][bmrt_test:1058] INFO:load input time(s): 0.008914
```

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```
25 [BMRT][bmrt_test:1059] INFO:calculate  time(s): 0.004132
26 [BMRT][bmrt_test:1060] INFO:get output time(s): 0.012603
27 [BMRT][bmrt_test:1061] INFO:compare    time(s): 0.006514
```

The following information can be learned from the output above:

1. Lines 05-08: the input and output information of bmodel
2. Line 19: running time on the Tensor Computing Processor, of which the processor takes 4009us and the non-accelerated part takes 113us. The time of the latter mainly refers to the waiting time of calling at HOST
3. Line 24: the time to load data into the NPU' s DDR
4. Line 25: the total time of Line 19
5. Line 26: the output data retrieval time

CHAPTER 4

Compile the Torch Model

This chapter takes yolov5s.pt as an example to introduce how to compile and transfer an pytorch model to run on the BM1684X platform.

This chapter requires the tpu_mlir python package.

4.1 Install tpu_mlir

Go to the Docker container and execute the following command to install tpu_mlir:

```
$ pip install tpu_mlir[torch]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[torch]
```

4.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a model_yolov5s_pt directory, and put both model files and image files into the model_yolov5s_pt directory.

The operation is as follows:

```
$ mkdir model_yolov5s_pt && cd model_yolov5s_pt
$ wget -O yolov5s.pt "https://github.com/sophgo/tpu-mlir/raw/master/regression/model/yolov5s.
↪pt"
$ cp -rf tpu_mlir_resource/dataset/COCO2017 .
$ cp -rf tpu_mlir_resource/image .
$ mkdir workspace && cd workspace
```

4.3 TORCH to MLIR

The model in this example has a RGB input with mean and scale of 0.0,0.0,0.0 and 0.0039216, 0.0039216,0.0039216 respectively.

The model conversion command:

```
$ model_transform \
   --model_name yolov5s_pt \
   --model_def ../yolov5s.pt \
   --input_shapes [[1,3,640,640]] \
   --mean 0.0,0.0,0.0 \
   --scale 0.0039216,0.0039216,0.0039216 \
   --keep_aspect_ratio \
   --pixel_format rgb \
   --test_input ../image/dog.jpg \
   --test_result yolov5s_pt_top_outputs.npz \
   --mlir yolov5s_pt.mlir
```

After converting to mlir file, a ${model_name}_in_f32.npz file will be generated, which is the input file of the model. It is worth noting that we only support static models, and the model needs to call torch.jit.trace() to generate a static model before compilation.

4.4 MLIR to F16 bmodel

Convert the mlir file to the bmodel of f16, the operation method is as follows:

```
$ model_deploy \
   --mlir yolov5s_pt.mlir \
   --quantize F16 \
   --processor bm1684x \
   --test_input yolov5s_pt_in_f32.npz \
   --test_reference yolov5s_pt_top_outputs.npz \
   --tolerance 0.99,0.99 \
   --model yolov5s_pt_1684x_f16.bmodel
```

After comiplation, a file named yolov5s_pt_1684x_f16.bmodel will be generated.

4.5 MLIR to INT8 bmodel

4.5.1 Calibration table generation

Before converting to the INT8 model, you need to run calibration to get the calibration table. Here is an example of the existing 100 images from COCO2017 to perform calibration:

```
$ run_calibration yolov5s_pt.mlir \
    --dataset ../COCO2017 \
    --input_num 100 \
    -o yolov5s_pt_cali_table
```

After running the command above, a file named yolov5s_pt_cali_table will be generated, which is used as the input file for subsequent compilation of the INT8 model.

4.5.2 Compile to INT8 symmetric quantized model

Execute the following command to convert to the INT8 symmetric quantized model:

```
$ model_deploy \
    --mlir yolov5s_pt.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_pt_cali_table \
    --processor bm1684x \
    --test_input yolov5s_pt_in_f32.npz \
    --test_reference yolov5s_pt_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --model yolov5s_pt_1684x_int8_sym.bmodel
```

After compilation, a file named yolov5s_pt_1684x_int8_sym.bmodel will be generated.

4.6 Effect comparison

Use the command detect_yolov5 path to perform object detection on the image.

Use the following codes to verify the execution results of pytorch/ f16/ int8 respectively.

The pytorch model is run as follows to get dog_torch.jpg:

```
$ detect_yolov5 \
    --input ../image/dog.jpg \
    --model ../yolov5s.pt \
    --output dog_torch.jpg
```

The f16 bmodel is run as follows to get dog_f16.jpg :

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model yolov5s_pt_1684x_f16.bmodel \
   --output dog_f16.jpg
```

The int8 asymmetric bmodel is run as follows to get dog_int8_sym.jpg :

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model yolov5s_pt_1684x_int8_sym.bmodel \
   --output dog_int8_sym.jpg
```

The result images are compared as shown in the figure (Comparison of TPU-MLIR for YOLOv5s compilation effect).

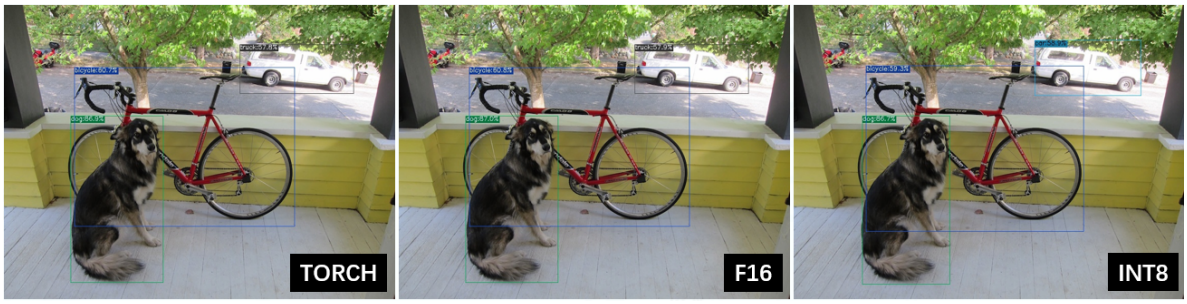

Fig. 4.1: Comparison of TPU-MLIR for YOLOv5s compilation effect

Due to different operating environments, the final performance will be somewhat different from Fig. 4.1.

CHAPTER 5

Compile the Caffe model

This chapter takes mobilenet_v2_deploy.prototxt and mobilenet_v2.caffemodel as examples to introduce how to compile and transfer a caffe model to run on the BM1684X platform.

This chapter requires the tpu_mlir python package.

5.1 Install tpu_mlir

Go to the Docker container and execute the following command to install tpu_mlir:

```
$ pip install tpu_mlir[caffe]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[caffe]
```

5.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a mobilenet_v2 directory, and put both model files and image files into the mobilenet_v2 directory.

The operation is as follows:

```
$ mkdir mobilenet_v2 && cd mobilenet_v2
$ wget https://raw.githubusercontent.com/shicai/MobileNet-Caffe/master/mobilenet_v2_deploy.
↪prototxt
$ wget https://github.com/shicai/MobileNet-Caffe/raw/master/mobilenet_v2.caffemodel
$ cp -rf tpu_mlir_resource/dataset/ILSVRC2012 .
$ cp -rf tpu_mlir_resource/image .
$ mkdir workspace && cd workspace
```

5.3 Caffe to MLIR

The model in this example has a BGR input with mean and scale of 103.94, 116.78, 123.68 and 0.017, 0.017, 0.017 respectively.

The model conversion command:

```
$ model_transform \
   --model_name mobilenet_v2 \
   --model_def ../mobilenet_v2_deploy.prototxt \
   --model_data ../mobilenet_v2.caffemodel \
   --input_shapes [[1,3,224,224]] \
   --resize_dims=256,256 \
   --mean 103.94,116.78,123.68 \
   --scale 0.017,0.017,0.017 \
   --pixel_format bgr \
   --test_input ../image/cat.jpg \
   --test_result mobilenet_v2_top_outputs.npz \
   --mlir mobilenet_v2.mlir
```

After converting to mlir file, a ${model_name}_in_f32.npz file will be generated, which is the input file of the model.

5.4 MLIR to F32 bmodel

Convert the mlir file to the bmodel of f32, the operation method is as follows:

```
$ model_deploy \
   --mlir mobilenet_v2.mlir \
   --quantize F32 \
   --processor bm1684x \
   --test_input mobilenet_v2_in_f32.npz \
   --test_reference mobilenet_v2_top_outputs.npz \
   --tolerance 0.99,0.99 \
   --model mobilenet_v2_1684x_f32.bmodel
```

After compilation, a file named mobilenet_v2_1684x_f32.bmodel is generated.

5.5 MLIR to INT8 bmodel

5.5.1 Calibration table generation

Before converting to the INT8 model, you need to run calibration to get the calibration table. The number of input data is about 100 to 1000 according to the situation.

Then use the calibration table to generate a symmetric or asymmetric bmodel. It is generally not recommended to use the asymmetric one if the symmetric one already meets the requirements, because the performance of the asymmetric model will be slightly worse than the symmetric model.

Here is an example of the existing 100 images from ILSVRC2012 to perform calibration:

```
$ run_calibration mobilenet_v2.mlir \
    --dataset ../ILSVRC2012 \
    --input_num 100 \
    -o mobilenet_v2_cali_table
```

After running the command above, a file named mobilenet_v2_cali_table will be generated, which is used as the input file for subsequent compilation of the INT8 model.

5.5.2 Compile to INT8 symmetric quantized model

Execute the following command to convert to the INT8 symmetric quantized model:

```
$ model_deploy \
    --mlir mobilenet_v2.mlir \
    --quantize INT8 \
    --calibration_table mobilenet_v2_cali_table \
    --processor bm1684x \
    --test_input mobilenet_v2_in_f32.npz \
    --test_reference mobilenet_v2_top_outputs.npz \
    --tolerance 0.96,0.70 \
    --model mobilenet_v2_1684x_int8_sym.bmodel
```

After compilation, a file named mobilenet_v2_1684x_int8_sym.bmodel is generated.

CHAPTER 6

Compile the TFLite model

This chapter takes the lite-model_mobilebert_int8_1.tflite model as an example to introduce how to compile and transfer a TFLite model to run on the BM1684X platform.

This chapter requires the tpu_mlir python package.

6.1 Install tpu_mlir

Go to the Docker container and execute the following command to install tpu_mlir:

```
$ pip install tpu_mlir[tensorflow]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[tensorflow]
```

6.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a mobilebert_tf directory, note that it is the same level as tpu-mlir, and put the test image file into the mobilebert_tf directory.

The operation is as follows:

```
$ mkdir mobilebert_tf && cd mobilebert_tf
$ wget -O lite-model_mobilebert_int8_1.tflite https://storage.googleapis.com/tfhub-lite-models/
↪iree/lite-model/mobilebert/int8/1.tflite
$ cp -rf tpu_mlir_resource/npz_input/squad_data.npz .
$ mkdir workspace && cd workspace
```

6.3 TFLite to MLIR

The model conversion command:

```
$ model_transform \
   --model_name mobilebert_tf \
   --mlir mobilebert_tf.mlir \
   --model_def ../lite-model_mobilebert_int8_1.tflite \
   --test_input ../squad_data.npz \
   --test_result mobilebert_tf_top_outputs.npz \
   --input_shapes [[1,384],[1,384],[1,384]] \
   --channel_format none
```

After converting to mlir file, a **mobilebert_tf_in_f32.npz** file will be generated, which is the input file of the model.

6.4 MLIR to bmodel

This model is a tflite asymmetric quantized model, which can be converted into a bmodel according to the following parameters:

```
$ model_deploy \
   --mlir mobilebert_tf.mlir \
   --quantize INT8 \
   --processor bm1684x \
   --test_input mobilebert_tf_in_f32.npz \
   --test_reference mobilebert_tf_top_outputs.npz \
   --model mobilebert_tf_bm1684x_int8.bmodel
```

Once compiled, a file named **mobilebert_tf_bm1684x_int8.bmodel** is generated.

CHAPTER 7

Quantization and optimization

In deploying neuron network, the accuracy and throughput (inference speed) are critical targets. To achieve high accuracy and high speed, for some networks, mix precision inference is essential.

The mixed-precision method of TPU-MLIR is searching layers in neural network that are not suitable for low-bit quantization to generate a quantize table, which is used to specify these layers to use higher-bit quantization in the model_deploy stage. This chapter will first introduce the current full int8 symmetric quantization of TPU-MLIR, and then explain how to use the existing quantize table automatic generation tools in TPU-MLIR.

7.1 TPU-MLIR Full Int8 Symmetric Quantization

TPU-MLIR adopts full int8 symmetric quantization by default, where full int8 means that all operators, except for those that the compiler defaults to floating-point operations (such as layernorm), are quantized to int8. This section introduces how to use the TPU-MLIR full int8 symmetric quantization tool.

After generating the corresponding MLIR file for the model using the model_transform command as instructed in the previous tutorial, if you want to perform int8 symmetric quantization on the model, you also need to generate a calibration table cali_table using the run_calibration command. How to use the parameters of the run_calibration command for different types of models to ensure the generated quantized model has good accuracy will be provided in detailed guidance below.

7.1.1 run_calibration Process Introduction

The quantization part of the following figure (:ref:calibration) shows the overall process of the current `run_calibration` , which includes the automatic mixed-precision module `search_qtable` , the automatic calibration method selection module `search_threshold` , cross-layer weight equalization module `weight_equalization`, and bias correction module `bias_correction`, etc. In the following sections, we will provide the usage details of the above methods based on actual situations.

7.1.2 run_calibration Parameter Introduction

The table below provides an introduction to the parameters of the `run_calibration` command.

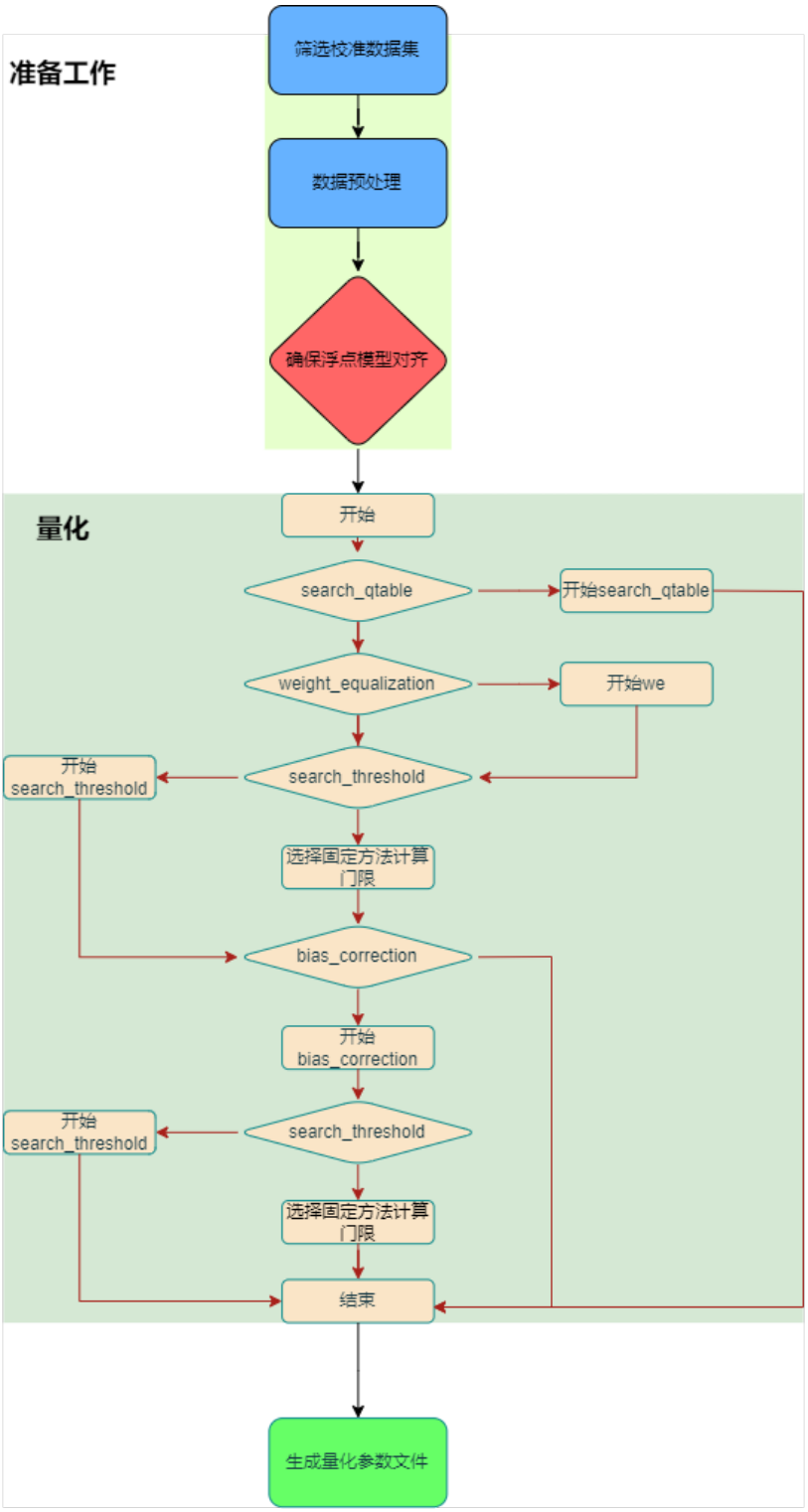

Fig. 7.1: run_calibration process

Table 7.1: run_calibration.py parameter

parameter	description
mlir_file	mlir file
we	open weight_equalization
bc	open bias_correction
dataset	calibration dataset
data_list	sample list
input_num	number of calibration sample
inference_num	the number of images required for the inference process with search_qtable and search_threshold is set to 30 by default
bc_inference_num	the number of images required for the inference process with bias correction is set to 30 by default
tune_list	the list of sample used for tuning
tune_num	the number of images for tuning
histogram_bin_num	specify the number of histogram bins for KLD calculation, default is 2048
expected_cos	expect the similarity between the mixed-precision model output of search_qtable and the floating-point model output, with a value range of [0,1], default is 0.99
min_layer_cos	the lower bound of similarity between the quantized output and the floating-point output of the layer in bias_correction; compensation is required for the layer when it falls below this threshold, with a value range of [0,1], default is 0.99
max_float_layers	set the number of floating-point layers for search_qtable, default is 5
chip	chip type, default is bm1684x
cali_method	select the calibration mode; if this parameter is not added, the default is KLD calibration. "use_percentile9999" uses the 99.99 percentile as the threshold. "use_max" uses the absolute maximum value as the threshold. "use_torch_observer_for_cali" uses torch's observer for calibration. "use_mse" uses octav for calibration.
fp_type	search_qtable floating-point layer data type
post_process	post-processing path
global_compare_layers	specify the global contrastive layers, for example, layer1,layer2 or layer1:0.3,layer2:0.7.
search	specify the search type, which includes search_qtable, search_threshold, and false. The default is false, which means search is not enabled
transformer	whether it is a transformer model, in search_qtable, if it is a transformer model, a specific acceleration strategy can be assigned, default is False
quantize_method_list	the calibration method used for searching in search_qtable, default is MSE, with selectable range being MSE, KL, MAX, Percentile9999
benchmark_method	specify the similarity calculation method of search_threshold, with the default being cosine similarity (cos)
quantize_table	the mixed-precision quantization table from search_qtable
o	cali_table output path
debug_cmd	debug command
debug_log	log output level

7.1.3 The Use of run_calibration Parameters Introduction

Based on the user' s needs and their understanding of the model itself and quantization, we have provided targeted ways to use the run_calibration parameters in different situations.

Table 7.2: applicable scenarios for run_calibration parameter

scenario	description	quantization speed	calibration method	recommended method
case1	initial model quantization	insensitive	unclear	search_threshold
case2	initial model quantization	/	clear	cali_method directly selects the corresponding calibration method
case3	initial model quantization	sensitive	unclear	the cali_method selects a fixed calibration method; for details on choosing a specific calibration method, refer to the subsequent sections
case4	after model quantization, the accuracy on the bm1684 chip does not meet the requirements	/	/	open we and bc methods

case 1: When you perform the initial quantization on your model, which is the first time you use the run_calibration command, you may not be clear about the calibration method that is best suited for your current model and you may not be sensitive to the quantization speed. In this case, it is recommended to use the search_threshold method. This method can automatically select the calibration method that is most suitable for your current model and output the calibration table cali_table generated by this method to the output path you specify. It will also generate a log file Search_Threshold, which records the quantization information for different calibration methods. The specific operation is as follows:

```
$ run_calibration mlir.file \
   --dataset data_path \
   --input_num 100 \
   --chip bm1684x \
   --search search_threshold \
   --inference_num 30 \
   -o cali_table
```

Notes:1.At this point, it is necessary to select the chip parameter, which corresponds to the chip platform on which the model is intended to be deployed. The current default is bm1684x. 2. inference_num corresponds to the number of inference data required for the search_threshold process (this data will be extracted from the dataset you provide). The

larger the inference_num, the more accurate the search_threshold result, but the longer the quantization time required. Here, the default for inference_num is set to 30, which can be customized according to the actual situation.

case2: When quantizing your model for the first time, you already know which calibration method is suitable for the model. At this point, you can directly choose a fixed calibration method based on the cali_method parameter. The specific operation is as follows:

```
$ run_calibration mlir.file \
   --dataset data_path \
   --input_num 100 \
   --cali_method use_mse \
   -o cali_table
```

Notes:1.when the cali_method parameter is not added, the default KLD calibration method will be used. 2.currently, the cali_method supports five options, including use_mse, use_max, use_percentile9999, use_aciq_gauss and use_aciq_laplace.

case3: When you are sensitive to quantization time and wish to generate the calibration table cali_table as quickly as possible, but you are unsure how to choose a calibration method, it is recommended to select a fixed calibration method based on the cali_method parameter. In comparison to the quantization speed of TPU-MLIR V1.8, the V1.9 version shows a 100% speed improvement for individual calibration methods, resulting in an average time reduction of around 50%. The acceleration effect is significant. In the V1.9 version, use_mse is the fastest calibration method on average. When selecting a calibration method, you can consider the following empirical conclusions:

1.For non-transformer models without attention structure, use_mse is a suitable calibration method. Here is a specific operation guide:

```
$ run_calibration mlir.file \
   --dataset data_path \
   --input_num 100 \
   --cali_method use_mse \
   -o cali_table
```

You can also choose the default KLD calibration method. Here is a specific operation guide:

```
$ run_calibration mlir.file \
   --dataset data_path \
   --input_num 100 \
   -o cali_table
```

If neither of the above two methods meets the accuracy requirements, you may need to consider adopting a mixed precision strategy or a hybrid threshold method. More detailed information on these approaches can be found in the subsequent section.

2.When your model is a transformer model that includes an attention structure, you can choose the use_mse calibration method. If the use_mse calibration method does not produce satisfactory results, you can then consider trying the use_max calibration method. Here is a specific operation guide:

```
$ run_calibration mlir.file \
   --dataset data_path \
   --input_num 100 \
   --cali_method use_max \
   -o cali_table
```

If the use_max method also fails to meet the requirements, at this point, you may need to adopt a mixed precision strategy. You can then try the mixed precision methods that will be introduced later.

Apart from the overall selection rules mentioned above, here are some specific details for choosing calibration methods:1.If your model is a YOLO series object detection model, it is recommended to use the default KLD calibration method.2.If your model is a multi-output classification model, it is also recommended to use the default KLD calibration method.

case4: When your model is deployed on the bm1684 chip and the full int8 quantized model obtained through the methods mentioned above has poor accuracy, you can try enabling cross-layer weight equalization (we) and bias correction (bc). To do this, simply add the we and bc parameters to the original command. If you have used search_threshold for searching, the operations for adding we and bc are as follows:

```
$ run_calibration mlir.file \
   --we \
   --bc \
   --dataset data_path \
   --input_num 100 \
   --chip bm1684 \
   --search search_threshold \
   --inference_num 30 \
   --bc_inference_num 100 \
   -o cali_table
```

If you choose a fixed calibration method using cali_method , for example, using use_mse , to add the we and bc methods, the specific operation is as follows:

```
$ run_calibration mlir.file \
   --we \
   --bc \
   --dataset data_path \
   --input_num 100 \
   --chip bm1684 \
   --cali_method use_mse \
   --bc_inference_num 100 \
   -o cali_table
```

If you are using the default KLD calibration method, simply remove the cali_method parameter.

Notes:1.Make sure to specify the chip parameter as bm1684. 2.The bc_inference_num parameter is the number of data samples required when using the bc quantization method (these samples will be extracted from the dataset you provide), so the number of images should not

be too few. 3.The we and bc methods can be used independently. If you choose only the we method, simply omit the bc parameter in the operation.

7.2 Overview of TPU-MLIR Mixed Precision Quantization

Currently, TPU-MLIR provides four mixed precision quantization methods: search_qtable , run_qtable , run_sensitive_layer and fp_forward. Among these, search_qtable is an optimized version of run_qtable and run_sensitive_layer. Compared to run_qtable , search_qtable offers better effectiveness and typically achieves superior quantization results, albeit at a slightly slower speed. In contrast to run_sensitive_layer, search_qtable is faster and supports more customizable parameters. The following section will provide detailed introductions to these four mixed precision tools.

7.3 1. search_qtable

search_qtable is a mixed precision feature integrated into run_calibration. When full int8 quantization precision does not meet the requirements, mixed precision method are needed, meaning that some operators are set to perform floating-point operations. This section takes mobilenet-v2 as example to introduce how to use search_qtable.

This section requires the tpu_mlir python package.

7.3.1 Install tpu_mlir

```
$ pip install tpu_mlir[all]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[all]
```

7.3.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a mobilenet-v2 directory, and put both model files and image files into the mobilenet-v2 directory.

The operation is as follows:

```
1 $ mkdir mobilenet-v2 && cd mobilenet-v2
2 $ wget https://github.com/sophgo/tpu-mlir/releases/download/v1.4-beta.0/mobilenet_v2.pt
```

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```
$ cp -rf tpu_mlir_resource/dataset/ILSVRC2012 .
$ mkdir workspace && cd workspace
```

7.3.3 Accuracy test of float anf int8 models

Step 1: To F32 mlir

```
$ model_transform \
    --model_name mobilenet_v2 \
    --model_def ../mobilenet_v2.pt \
    --input_shapes [[1,3,224,224]] \
    --resize_dims 256,256 \
    --mean 123.675,116.28,103.53 \
    --scale 0.0171,0.0175,0.0174 \
    --pixel_format rgb \
    --mlir mobilenet_v2.mlir
```

Step 2: Gen calibartion table

Here, we use the use_mse method for calibration.

```
$ run_calibration.py mobilenet_v2.mlir \
    --dataset ../ILSVRC2012 \
    --input_num 100 \
    --cali_method use_mse \
    -o mobilenet_v2_cali_table
```

Step 3: To F32 bmodel

```
$ model_deploy \
    --mlir mobilenet_v2.mlir \
    --quantize F32 \
    --processor bm1684 \
    --model mobilenet_v2_1684_f32.bmodel
```

Step 4: To INT8 model

```
$ model_deploy \
    --mlir mobilenet_v2.mlir \
    --quantize INT8 \
    --processor bm1684 \
    --calibration_table mobilenet_v2_cali_table \
    --model mobilenet_v2_bm1684_int8_sym.bmodel
```


Step 5: Accuracy test

classify_mobilenet_v2 is a python program, to run mobilenet-v2 model.

Test the fp32 model:

```
$ classify_mobilenet_v2.py \
   --model_def mobilenet_v2_bm1684_f32.bmodel \
   --input ../ILSVRC2012/n02090379_7346.JPEG \
   --output mobilenet_v2_fp32_bmodel.JPEG \
   --category_file ../ILSVRC2012/synset_words.txt
```

The classification information is displayed on the output image. The right label sleeping bag ranks first.

Test the INT8 model:

```
$ classify_mobilenet_v2.py \
   --model_def mobilenet_v2_bm1684_int8_sym.bmodel \
   --input ../ILSVRC2012/n02090379_7346.JPEG \
   --output mobilenet_v2_INT8_sym_bmodel.JPEG \
   --category_file ../ILSVRC2012/synset_words.txt
```

The classification information is displayed on the output image. The right label sleeping bag ranks second.

7.3.4 To Mix Precision Model

After int8 conversion, do these commands as beflow.

Step 1: Execute the search_qtable command

The search_qtable feature is currently integrated into the run_calibration process. Therefore, to use it, you only need to add the relevant parameters to the run_calibration command. The parameters related to search_qtable in run_calibration are explained as follows:

Fig. 7.2: Execution Performance of classify_mobilenet_v2 in FP32

Fig. 7.3: Execution Performance of classify_mobilenet_v2 in INT8

Table 7.3: search_qtable parameters

Name	Required?	Explanation
(None)	Y	mlir file
dataset	N	Directory of input samples. Images, npz or npy files are placed in this directory
data_list	N	The sample list (cannot be used together with "dataset")
chip	Y	The platform that the model will use. Support bm1690, bm1688, bm1684x, bm1684, cv186x, cv183x, cv182x, cv181x, cv180x
fp_type	N	Specifies the type of float used for mixing precision. Support auto,F16,F32,BF16. Default is auto, indicating that it is automatically selected by program
input_num	N	The number of samples used for calibration
inference_num	N	The number of samples used for inference, default 30
max_float_layers	N	The number of layers set to float, default 5
tune_list	N	The sample list for tune threshold
tune_num	N	The number of samples for tune threshold, default 5
post_process	N	The user defined prost process program path, default None
expected_cos	N	Specify the minimum cos value for the expected final output layer of the network. The default is 0.99
debug_cmd	N	Specifies a debug command string for development. It is empty by default
global_compare_layers	N	global compare layers, for example: layer1,layer2 or layer1:0.3,layer2:0.7
search	Yes	Specify the search type, which includes search_qtable, search_threshold, or false. You need to select search_qtable
transformer	N	Is it a transformer model? In search_qtable, if it is a transformer model, a specific acceleration strategy can be assigned. The default is False
quantize_method_list	N	the calibration method used for searching in search_qtable, default is MSE, with selectable range being MSE, KL, MAX, Percentile9999
quantize_table	Yes	qtable output path
calibration_table	Yes	cali_table output path

search_qtable supports user defined post process programs post_process_func.py. It can be placed in the current project directory or in another location, if it is placed in another location, you need to specify the full path of the file in the post_process . The post process function must be named PostProcess , the input data is the output of the network and the output data is the post-processing result. Create the post_process_func.py file with the following sample contents:

```
def PostProcess(data):
    print("in post process")
    return data
```

search_qtable can customize the calibration method with mixed thresholds, controlled by the parameter quantize_method_list. By default, only the MSE calibration method is used for the search. If you want to use a mixed search with KLD and MSE, set the parameter quantize_method_list to KL,MSE. search_qtable has an acceleration strategy for transformer models. If the model is a transformer model with an attention structure, you can set the parameter transformer to True. Use search_qtable to search for layers with significant loss. Note that it is recommended to use bad cases for the search.

In this example, 100 images are used for quantization, 30 images are used for inference, and a mixed search using KLD and MSE calibration methods is performed. Execute the command as follows:

```
$ run_calibration.py mobilenet_v2.mlir \
    --dataset ../ILSVRC2012 \
    --input_num 100 \
    --inference_num 30 \
    --expected_cos 0.99 \
    --quantize_method_list KL,MSE \
    --search search_qtable \
    --transformer False \
    --chip bm1684 \
    --post_process post_process_func.py \
    --quantize_table mobilenet_v2_qtable \
    --calibration_table mobilenet_v2_cali_table \
```

The final output after execution is printed as follows:

```
the layer input3.1 is 0 sensitive layer, loss is 0.004858517758037473, type is top.Conv
the layer input5.1 is 1 sensitive layer, loss is 0.002798812150635266, type is top.Scale
the layer input11.1 is 2 sensitive layer, loss is 0.0015642610676610547, type is top.Conv
the layer input13.1 is 3 sensitive layer, loss is 0.0009357141882855302, type is top.Scale
the layer input6.1 is 4 sensitive layer, loss is 0.0009211346574943269, type is top.Conv
the layer input2.1 is 5 sensitive layer, loss is 0.0007767164275293004, type is top.Scale
the layer input0.1 is 6 sensitive layer, loss is 0.0006842551513905892, type is top.Conv
the layer input128.1 is 7 sensitive layer, loss is 0.0003780628201499603, type is top.Conv
......
run result:
int8 outputs_cos:0.986809 old
mix model outputs_cos:0.993372
Output mix quantization table to mobilenet_v2_qtable
total time:667.644282579422
success search qtable
```

Above, int8 outputs_cos represents the cosine similarity between network outputs of int8 model and float model; mix model outputs_cos represents the cosine similarity between network outputs of mix model and float model; total time represents the search time is 667 seconds. In addition, this program generates a quantization table mobilenet_v2_qtable, the

context is as below:

```
# op_name  quantize_mode
input3.1 F32
input5.1 F32
input11.1 F32
input13.1 F32
input6.1 F32
```

In the table, the first column represents the corresponding layer, and the second column represents the type. Supported types are F32/F16/BF16/INT8. search_qtable will determine the number of mixed precision layers in the qtable based on the user-defined expected_cos parameter value. For example, if the expected_cos parameter value is equal to 0.99, the number of mixed precision layers in the qtable corresponds to the minimum number of mixed precision layers required to achieve that level of model output comparison. Of course, the number of mixed precision layers in the table will be limitted based on the number of model operators. If the minimum number of mixed precision layers exceeds the limitation, only the limited quantity of mixed precision layers will be taken. Additionally, a log file Search_Qtable will be generated with the following content:

```
INFO:root:quantize_method_list =['KL', 'MSE']
INFO:root:run float mode: mobilenet_v2.mlir
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:all_int8_cos=0.9868090914371674
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:layer name check pass !
INFO:root:all layer number: 117
INFO:root:all layer number no float: 116
INFO:root:transformer model: False, all search layer number: 116
INFO:root:Global metrics layer is : None
INFO:root:start to handle layer: input0.1, type: top.Conv
INFO:root:adjust layer input0.1 th, with method KL, and threshlod 9.442267236793155
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:outputs_cos_los = 0.0006842551513905892
INFO:root:adjust layer input0.1 th, with method MSE, and threshlod 9.7417731
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:outputs_cos_los = 0.0007242344141149548
INFO:root:layer input0.1, layer type is top.Conv, best_th = 9.442267236793155, best_method =F
↪KL, best_cos_loss = 0.0006842551513905892
.....
```

The log file first provides the custom parameters, including the calibration method used for the mixed threshold quantize_method_list, the number of ops to be searched all search layer number and whether it is a transformer model or not. Then, it records the threshold obtained for each op under the given calibration methods (in this case, MSE and KL) and provides the loss of similarity (1 - cosine similarity) between the mixed-precision model using only the corresponding threshold for that operation in int8 computation and the original float model. It also includes the loss information of each operation output on the screen side and the cosine similarity between the final mixed-precision model and the original float model. Users can use the qtable output by the program, or modify the qtable based on the loss information, and then

generate the mixed-precision model. After Search_Qtable is finished, the optimal threshold will be updated to a new quantization table new_cali_table.txt , stored in the current project directory, which needs to be called when generating the mixed-precision model.

Step 2: Gen mix precision model

```
$ model_deploy \
   --mlir mobilenet_v2.mlir \
   --quantize INT8 \
   --processor bm1684 \
   --calibration_table new_cali_table.txt \
   --quantize_table mobilenet_v2_qtable \
   --model mobilenet_v2_bm1684_int8_mix.bmodel
```

Step 3: Test accuracy of mix model

```
$ classify_mobilenet_v2 \
   --model_def mobilenet_v2_bm1684_int8_mix.bmodel \
   --input ../ILSVRC2012/n02090379_7346.JPEG \
   --output mobilenet_v2_INT8_mix_bmodel_1.JPEG \
   --category_file ../ILSVRC2012/synset_words.txt
```

The classification information is displayed on the output image. The right label sleeping bag ranks first.

7.4 2. run_qtable

This section takes yolov3 tiny as examples to introduce how to use run_qtable for mix precision.

This section requires the tpu_mlir python package.

7.4.1 Install tpu_mlir

```
$ pip install tpu_mlir[all]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[all]
```

Fig. 7.4: Execution Performance of classify_mobilenet_v2 in the Mixed Precision Model

7.4.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a yolov3_tiny directory, and put both model files and image files into the yolov3_tiny directory.

The operation is as follows:

```
$ mkdir yolov3_tiny && cd yolov3_tiny
$ wget https://media.githubusercontent.com/media/onnx/models/main/validated/vision/object_
↪detection_segmentation/tiny-yolov3/model/tiny-yolov3-11.onnx
$ cp -rf tpu_mlir_resource/dataset/COCO2017 .
$ mkdir workspace && cd workspace
```

Note that if tiny-yolov3-11.onnx fails to download with wget, please download it by other means and put it into yolov3_tiny directory.

7.4.3 Verify onnx

detect_yolov3 is a python program, to run yolov3_tiny model.

The operation is as follows:

```
$ detect_yolov3 \
    --model ../tiny-yolov3-11.onnx \
    --input ../COCO2017/000000366711.jpg \
    --output yolov3_onnx.jpg
```

The print result as follows:

```
person:60.7%
orange:77.5%
```

And get result image yolov3_onnx.jpg, as below (yolov3_tiny ONNX):

7.4.4 To INT8 symmetric model

Step 1: To F32 mlir

```
$ model_transform \
   --model_name yolov3_tiny \
   --model_def ../tiny-yolov3-11.onnx \
   --input_shapes [[1,3,416,416]] \
```

(continues on next page)

Fig. 7.5: yolov3_tiny ONNX

(continued from previous page)

```
    --scale 0.0039216,0.0039216,0.0039216 \
    --pixel_format rgb \
    --keep_aspect_ratio \
    --pad_value 128 \
    --output_names=convolution_output1,convolution_output \
    --mlir yolov3_tiny.mlir
```

Step 2: Gen calibartion table

```
$ run_calibration yolov3_tiny.mlir \
    --dataset ../COCO2017 \
    --input_num 100 \
    -o yolov3_cali_table
```

Step 3: To model

```
$ model_deploy \
    --mlir yolov3_tiny.mlir \
    --quantize INT8 \
    --calibration_table yolov3_cali_table \
    --processor bm1684x \
    --model yolov3_int8.bmodel
```

Step 4: Run model

```
$ detect_yolov3 \
     --model yolov3_int8.bmodel \
     --input ../COCO2017/000000366711.jpg \
     --output yolov3_int8.jpg
```

The print result as follows, indicates that one target is detected:

```
orange:72.9.0%
```

And get image yolov3_int8.jpg, as below (yolov3_tiny int8 symmetric):

It can be seen that the int8 symmetric quantization model performs poorly compared to the original model on this image and only detects one target.

Fig. 7.6: yolov3_tiny int8 symmetric

7.4.5 To Mix Precision Model

After int8 conversion, do these commands as beflow.

Step 1: Gen quantization table

Use `run_qtable` to gen qtable, parameters as below:

Table 7.4: run_qtable parameters

Name	Required?	Explanation
(None)	Y	mlir file
dataset	N	Directory of input samples. Images, npz or npy files are placed in this directory
data_list	N	The sample list (cannot be used together with "dataset")
calibration_table	Y	Name of calibration table file
processor	Y	The platform that the model will use. Support bm1690, bm1688, bm1684x, bm1684, cv186x, cv183x, cv182x, cv181x, cv180x.
fp_type	N	Specifies the type of float used for mixing precision. Support auto,F16,F32,BF16. Default is auto, indicating that it is automatically selected by program
input_num	N	The number of sample, default 10
expected_cos	N	Specify the minimum cos value for the expected final output layer of the network. The default is 0.99. The smaller the value, the more layers may be set to floating-point
min_layer_cos	N	Specify the minimum cos expected per layer, below which an attempt is made to set the fp32 calculation. The default is 0.99
debug_cmd	N	Specifies a debug command string for development. It is empty by default
o	Y	output quantization table
global_compare_layers	N	global compare layers, for example: `layer1,layer2` or `layer1:0.3,layer2:0.7`
loss_table	N	Specify the name of the file that holds the loss values for all layers quantized to floating point type, default is `full_loss_table.txt`

In this example, the default calibration of 10 images is used, you need install Graphviz first:

```
$ sudo apt-get install graphviz
```

Then use following command:

```
$ run_qtable yolov3_tiny.mlir \
    --dataset ../COCO2017 \
    --calibration_table yolov3_cali_table \
    --min_layer_cos 0.999 \
    --expected_cos 0.9999 \
    --processor bm1684x \
    -o yolov3_qtable
```

If the default 0.99 is used in --min_layer_cos, the program detects that the original int8 model already meets the cos of 0.99 and simply stops searching. The final output after execution is printed as follows:

```
int8 outputs_cos:0.999115 old
mix model outputs_cos:0.999517
Output mix quantization table to yolov3_qtable
total time:44 second
```

Above, int8 outputs_cos represents the cos similarity between original network output of int8 model and fp32; mix model outputs_cos represents the cos similarity of network output after mixing precision is used in some layers; total time represents the search time of 44 seconds. In addition, get quantization table yolov3_qtable, context as below:

```
# op_name   quantize_mode
model_1/leaky_re_lu_2/LeakyRelu:0_pooling0_MaxPool F16
convolution_output10_Conv F16
model_1/leaky_re_lu_3/LeakyRelu:0_LeakyRelu F16
model_1/leaky_re_lu_3/LeakyRelu:0_pooling0_MaxPool F16
model_1/leaky_re_lu_4/LeakyRelu:0_LeakyRelu F16
model_1/leaky_re_lu_4/LeakyRelu:0_pooling0_MaxPool F16
model_1/leaky_re_lu_5/LeakyRelu:0_LeakyRelu F16
model_1/leaky_re_lu_5/LeakyRelu:0_pooling0_MaxPool F16
model_1/concatenate_1/concat:0_Concat F16
```

In the table, first col is layer name, second is quantization type. Also full_loss_table.txt is generated, context as blow:

```
# platform: bm1684x  mix_mode: F16
###
No.0   : Layer: model_1/leaky_re_lu_3/LeakyRelu:0_LeakyRelu            Cos: 0.994022
No.1   : Layer: model_1/leaky_re_lu_5/LeakyRelu:0_LeakyRelu            Cos: 0.997445
No.2   : Layer: model_1/leaky_re_lu_2/LeakyRelu:0_LeakyRelu            Cos: 0.997487
No.3   : Layer: model_1/leaky_re_lu_4/LeakyRelu:0_LeakyRelu            Cos: 0.997978
No.4   : Layer: model_1/leaky_re_lu_2/LeakyRelu:0_pooling0_MaxPool     Cos: 0.998159
No.5   : Layer: convolution_output11_Conv                              Cos: 0.998307
No.6   : Layer: model_1/leaky_re_lu_1/LeakyRelu:0_LeakyRelu            Cos: 0.999249
No.7   : Layer: convolution_output9_Conv                               Cos: 0.999292
No.8   : Layer: convolution_output8_Conv                               Cos: 0.999427
No.9   : Layer: model_1/leaky_re_lu_1/LeakyRelu:0_pooling0_MaxPool     Cos: 0.999580
No.10  : Layer: convolution_output12_Conv                              Cos: 1.000004
```

This table is arranged smoothly according to the cos from small to large, indicating the

cos calculated by this Layer after the precursor layer of this layer has been changed to the corresponding floating-point mode. If the cos is still smaller than the previous parameter min_layer_cos, this layer and its immediate successor layer will be set to floating-point calculation。 run_qtable calculates the output cos of the whole network every time the neighboring two layers are set to floating point. If the cos is larger than the specified expected_cos, the search is withdrawn. Therefore, if you set a larger expected_cos value, you will try to set more layers to floating point。

Step 2: Gen mix precision model

```
$ model_deploy \
   --mlir yolov3_tiny.mlir \
   --quantize INT8 \
   --quantize_table yolov3_qtable \
   --calibration_table yolov3_cali_table \
   --processor bm1684x \
   --model yolov3_mix.bmodel
```

Step 3: run mix precision model

```
$ detect_yolov3 \
    --model yolov3_mix.bmodel \
    --input ../COCO2017/000000366711.jpg \
    --output yolov3_mix.jpg
```

The print result as follows:

```
person:63.9%
orange:72.9%
```

And get image yolov3_mix.jpg , as below (yolov3_tiny mix):

It can be seen that targets that cannot be detected in int8 model can be detected again with the use of mixing precision.

7.5 3. run_sensitive_layer

This section takes mobilenet-v2 as example to introduce how to use sensitive layer search.

This section requires the tpu_mlir python package.

Fig. 7.7: yolov3_tiny mix

7.5.1 Install tpu_mlir

```
$ pip install tpu_mlir[all]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[all]
```

7.5.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a mobilenet-v2 directory, and put both model files and image files into the mobilenet-v2 directory.

The operation is as follows:

```
$ mkdir mobilenet-v2 && cd mobilenet-v2
$ wget https://github.com/sophgo/tpu-mlir/releases/download/v1.4-beta.0/mobilenet_v2.pt
$ cp -rf tpu_mlir_resource/dataset/ILSVRC2012 .
$ mkdir workspace && cd workspace
```

7.5.3 Accuracy test of float anf int8 models

Step 1: To F32 mlir

```
$ model_transform \
    --model_name mobilenet_v2 \
    --model_def ../mobilenet_v2.pt \
    --input_shapes [[1,3,224,224]] \
    --resize_dims 256,256 \
    --mean 123.675,116.28,103.53 \
    --scale 0.0171,0.0175,0.0174 \
    --pixel_format rgb \
    --mlir mobilenet_v2.mlir
```

Step 2: Gen calibartion table

```
$ run_calibration mobilenet_v2.mlir \
    --dataset ../ILSVRC2012 \
    --input_num 100 \
    -o mobilenet_v2_cali_table
```

Step 3: To F32 bmodel

```
$ model_deploy \
    --mlir mobilenet_v2.mlir \
    --quantize F32 \
    --processor bm1684 \
    --model mobilenet_v2_1684_f32.bmodel
```

Step 4: To INT8 model

```
$ model_deploy \
    --mlir mobilenet_v2.mlir \
    --quantize INT8 \
    --processor bm1684 \
    --calibration_table mobilenet_v2_cali_table \
    --model mobilenet_v2_bm1684_int8_sym.bmodel
```

Step 5: Accuracy test

classify_mobilenet_v2 is a python program, to run mobilenet-v2 model.

Test the fp32 model:

```
$ classify_mobilenet_v2 \
    --model_def mobilenet_v2_bm1684_f32.bmodel \
    --input ../ILSVRC2012/n01440764_9572.JPEG \
    --output mobilenet_v2_fp32_bmodel.JPEG \
    --category_file ../ILSVRC2012/synset_words.txt
```

The classification information is displayed on the output image. The right label tench, Tinca tinca ranks first.

```
Top-5
n01440764 tench, Tinca tinca
n02536864 coho, cohoe, coho salmon, blue jack, silver salmon, Oncorhynchus kisutch
n02422106 hartebeest
n02749479 assault rifle, assault gun
n02916936 bulletproof vest
```

Test the INT8 model:

```
$ classify_mobilenet_v2 \
    --model_def mobilenet_v2_bm1684_int8_sym.bmodel \
    --input ../ILSVRC2012/n01440764_9572.JPEG \
    --output mobilenet_v2_INT8_sym_bmodel.JPEG \
    --category_file ../ILSVRC2012/synset_words.txt
```

The right label tench, Tinca tinca ranks first.

```
Top-5
n01440764 tench, Tinca tinca
n02749479 assault 日 file, assau
n02536864 coho, cohoe, coho
n02916936 bulletproof vest
n04336792 stretcher
```

7.5.4 To Mix Precision Model

After int8 conversion, do these commands as beflow.

Step 1: Search sensitive layers

Use run_sensitive_layer and bad cases to search sensitive layers, parameters as below:

Table 7.5: run_sensitive_layer parameters

Name	Required?	Explanation
(None)	Y	mlir file
dataset	N	Directory of input samples. Images, npz or npy files are placed in this directory
data_list	N	The sample list (cannot be used together with "dataset")
calibration_table	Y	Name of calibration table file
processor	Y	The platform that the model will use. Support bm1690, bm1688, bm1684x, bm1684, cv186x, cv183x, cv182x, cv181x, cv180x.
fp_type	N	Specifies the type of float used for mixing precision. Support auto,F16,F32,BF16. Default is auto, indicating that it is automatically selected by program
input_num	N	The number of samples used for calibration, default 10
inference_num	N	The number of samples used for inference, default 10
max_float_layers	N	The number of layers set to float, default 5
tune_list	N	The sample list for tune threshold
tune_num	N	The number of samples for tune threshold, default 5
histogram_bin_num	N	The number of bins used in kld calibration, default 2048
post_process	N	The user defined prost process program path, default None
expected_cos	N	Specify the minimum cos value for the expected final output layer of the network. The default is 0.99. The smaller the value, the more layers may be set to floating-point
debug_cmd	N	Specifies a debug command string for development. It is empty by default
o	Y	output quantization table
global_compare_layers	N	global compare layers, for example: layer1,layer2 or layer1:0.3,layer2:0.7
fp_type	N	float type of mix precision

Sensitive layer program supports user defined post process programs post_process_func.py. It can be placed in the current project directory or in another location, if it is placed in another location, you need to specify the full path of the file in the post_process . The post process function must be named PostProcess , the input data is the output of the network and the output data is the post-processing result. Create the post_process_func.py file with the following sample contents:

```
def PostProcess(data):
    print("in post process")
    return data
```

In this example, 100 images are used for calibration and 30 images are used for inference, and

the command is as follows:

The operation is as follows:

```
$ run_sensitive_layer mobilenet_v2.mlir \
    --dataset ../ILSVRC2012 \
    --input_num 100 \
    --inference_num 30 \
    --calibration_table mobilenet_v2_cali_table \
    --processor bm1684 \
    --post_process post_process_func.py \
    -o mobilenet_v2_qtable
```

The final output after execution is printed as follows:

```
the layer input3.1 is 0 sensitive layer, loss is 0.008808857469573828, type is top.Conv
the layer input11.1 is 1 sensitive layer, loss is 0.0016958347875666302, type is top.Conv
the layer input128.1 is 2 sensitive layer, loss is 0.0015641432811860367, type is top.Conv
the layer input130.1 is 3 sensitive layer, loss is 0.0014325751094084183, type is top.Scale
the layer input127.1 is 4 sensitive layer, loss is 0.0011817314259702227, type is top.Add
the layer input13.1 is 5 sensitive layer, loss is 0.001018420214596527, type is top.Scale
the layer 787 is 6 sensitive layer, loss is 0.0008603856180608993, type is top.Scale
the layer input2.1 is 7 sensitive layer, loss is 0.0007558935451825732, type is top.Scale
the layer input119.1 is 8 sensitive layer, loss is 0.000727441637624282, type is top.Add
the layer input0.1 is 9 sensitive layer, loss is 0.0007138056757098887, type is top.Conv
the layer input110.1 is 10 sensitive layer, loss is 0.000662179506136229, type is top.Conv
......
run result:
int8 outputs_cos:0.978847 old
mix model outputs_cos:0.989741
Output mix quantization table to mobilenet_v2_qtable
total time:402.15848112106323
success sensitive layer search
```

Above, int8 outputs_cos represents the cosine similarity between network outputs of int8 model and float model; mix model outputs_cos represents the cosine similarity between network outputs of mix model and float model; total time represents the search time is 402 seconds. In addition, this program generates a quantization table mobilenet_v2_qtable, the context is as below:

```
# op_name   quantize_mode
input3.1 F32
input11.1 F32
input128.1 F32
input130.1 F32
input127.1 F32
```

The first column in the table is layer name, and the second one is quantization type. Also a log file named SensitiveLayerSearch is generated, its context is as blow:

```
1 INFO:root:start to handle layer: input3.1, type: top.Conv
2 INFO:root:adjust layer input3.1 th, with method MAX, and threshlod 5.5119305
```

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```
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:outputs_cos_los = 0.014830573787862011
INFO:root:adjust layer input3.1 th, with method Percentile9999, and threshlod 4.1202815
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:outputs_cos_los = 0.011843443367980822
INFO:root:adjust layer input3.1 th, with method KL, and threshlod 2.6186381997094728
INFO:root:run int8 mode: mobilenet_v2.mlir
INFO:root:outputs_cos_los = 0.008808857469573828
INFO:root:layer input3.1, layer type is top.Conv, best_th = 2.6186381997094728, best_method =F
↪KL, best_cos_loss = 0.008808857469573828
```

The log file records the threshold obtained for each operation under different quantization methods (MAX/Percentile9999/KL) and provides the loss of similarity (1 - cosine similarity) between the mixed-precision model using only the corresponding threshold for that operation in int8 computation and the original float model. It also includes the loss information of each operation output on the screen side and the cosine similarity between the final mixed-precision model and the original float model. Users can use the qtable output by the program, or modify the qtable based on the loss information, and then generate the mixed-precision model. After the search for sensitive layers is finished, the optimal threshold will be updated to a new quantization table 'new_cali_table.txt', stored in the current project directory, which needs to be called when generating the mixed-precision model. In this case, based on the output loss information, it was observed that the loss of input3.1 is much higher than that of other operations, which can be set to FP32 only in the qtable.

Step 2: Gen mix precision model

```
$ model_deploy \
  --mlir mobilenet_v2.mlir \
  --quantize INT8 \
  --processor bm1684 \
  --calibration_table new_cali_table.txt \
  --quantize_table mobilenet_v2_qtable \
  --model mobilenet_v2_bm1684_int8_mix.bmodel
```

Step 3: Test accuracy of mix model

```
$ classify_mobilenet_v2 \
  --model_def mobilenet_v2_bm1684_mix.bmodel \
  --input ../ILSVRC2012/n01440764_9572.JPEG \
  --output mobilenet_v2_INT8_sym_bmodel.JPEG \
  --category_file ../ILSVRC2012/synset_words.txt
```

The classification results are as follows. The right label tench, Tinca tinca ranks first again.


```
Top-5
n01440764 tench, Tinca tinca
n02749479 assault rifle, assault gun
n02916936 bulletproof vest
n02536864 coho, cohoe, coho salmon, blue jack, silver salmon, Oncorhynchus kisutch
n04090263 rifle
```

7.6 4. fp_forward

For specific neural networks, some layers may not be suitable for quantization due to significant differences in data distribution. The "Local Non-Quantization" allows you to add certain layers before, after, or between other layers to a mixed-precision table. These layers will not be quantized when generating a mixed-precision model.

In this section, we will continue using the example of the YOLOv5s network mentioned in Chapter 3 and demonstrate how to use the Local Non-Quantization to quickly generate a mix-precision model.

The process of generating FP32 and INT8 models is the same as in Chapter 3. Here, we focus on generating mix-precision model and the accuracy testing.

For YOLO series models, the last three convolutional layers often have significantly different data distributions, and adding them manually to the mixed-precision table can improve accuracy. With the Local Non-Quantization feature, you can search for the corresponding layers from the Top MLIR file generated by model_transform and quickly add them to the mixed-precision table using the following command:

```
$ fp_forward \
   yolov5s.mlir \
   --quantize INT8 \
   --processor bm1684x \
   --fpfwd_outputs 474_Conv,326_Conv,622_Conv\
   -o yolov5s_qtable
```

Opening the file "yolov5s_qtable" will reveal that the relevant layers have been added to the qtable.

Generating the Mixed-Precision Model

```
$ model_deploy \
   --mlir yolov5s.mlir \
   --quantize INT8 \
   --calibration_table yolov5s_cali_table \
   --quantize_table yolov5s_qtable \
   --processor bm1684x \
   --test_input yolov5s_in_f32.npz \
   --test_reference yolov5s_top_outputs.npz \
   --tolerance 0.85,0.45 \
   --model yolov5s_1684x_mix.bmodel
```

Validating the Accuracy of FP32 and Mixed-Precision Models In the model-zoo, there is a program called "yolo" used for accuracy validation of object detection models. You can use the "harness" field in the mlir.config.yaml file to invoke "yolo" as follows:

Modify the relevant fields as follows:

```
$ dataset:
    imagedir: $(coco2017_val_set)
    anno: $(coco2017_anno)/instances_val2017.json

harness:
    type: yolo
    args:
        - name: FP32
        bmodel: $(workdir)/$(name)_bm1684_f32.bmodel
        - name: INT8
        bmodel: $(workdir)/$(name)_bm1684_int8_sym.bmodel
        - name: mix
        bmodel: $(workdir)/$(name)_bm1684_mix.bmodel
```

Switch to the top-level directory of model-zoo and use tpu_perf.precision_benchmark for accuracy testing, as shown in the following command: .. code-block:: shell

    $ python3 -m tpu_perf.precision_benchmark yolov5s_path –mlir –target BM1684X –devices 0

The accuracy test results will be stored in output/yolo.csv:

mAP for the FP32 model: mAP for the mixed-precision model using the default mixed-precision table:

Performance Testing

mAP for the mixed-precision model using the manually added mixed-precision table:

Parameter Description

Table 7.6: fp_forward parameters

Name	Required?	Explanation
(None)	Y	mlir file
processor	Y	The platform that the model will use. Support bm1690, bm1688, bm1684x, bm1684, cv186x, cv183x, cv182x, cv181x, cv180x.
fpfwd_inputs	N	Specify layers (including this layer) to skip quantization before them. Multiple inputs are separated by commas.
fpfwd_outputs	N	Specify layers (including this layer) to skip quantization after them. Multiple inputs are separated by commas.
fpfwd_blocks	N	Specify the start and end layers between which quantization will be skipped. Start and end layers are separated by colon, and multiple blocks are separated by space.
fp_type	N	Specifies the type of float used for mixing precision. Support auto,F16,F32,BF16. Default is auto, indicating that it is automatically selected by program
o	Y	output quantization table

CHAPTER 8

Use Tensor Computing Processor for Preprocessing

At present, the two main series of processors supported by TPU-MLIR are BM168x (except BM1684) and CV18xx. Both of them support common image preprocessing fusion. The developer can pass the preprocessing arguments during the compilation process, and the compiler will directly insert the corresponding preprocessing operators into the generated model. The generated bmodel or cvimodel can directly use the unpreprocessed image as input and use TPU to do the preprocessing.

Table 8.1: Supported Preprocessing Type

Preprocessing Type	BM168x	CV18xx
Crop	True	True
Normalization	True	True
NHWC to NCHW	True	True
BGR/ RGB Conversion	True	True

The image cropping will first adjust the image to the size specified by the "–resize_dims" argument of the `model_transform` tool, and then crop it to the size of the model input. The normalization supports directly converting unpreprocessed image data.

To integrate preprocessing into the model, you need to speficy the "–fuse_preprocess" argument when using the `model_deploy` tool, and the `test_input` should be an image of the original format (i.e., jpg, jpeg and png format). There will be a preprocessed npz file of input named `${model_name}_in_ori.npz` generated. In addition, there is a "–customization_format" argument to specify the original image format input to the model. The supported image formats are described as follows:

Table 8.2: Types of customization_format and Description

customization_format	Description	BM168x	CV18xx
None	same with model format, do nothing, as default	True	True
RGB_PLANAR	rgb color order and nchw tensor format	True	True
RGB_PACKED	rgb color order and nhwc tensor format	True	True
BGR_PLANAR	bgr color order and nchw tensor format	True	True
BGR_PACKED	bgr color order and nhwc tensor format	True	True
GRAYSCALE	one color channel only and nchw tensor format	True	True
YUV420_PLANAR	yuv420 planner format, from vpss input	False	True
YUV_NV21	NV21 format of yuv420, from vpss input	False	True
YUV_NV12	NV12 format of yuv420, from vpss input	False	True
RGBA_PLANAR	rgba format and nchw tensor format	False	True

The "YUV*" type format is the special input format of CV18xx series processors. When the order of the color channels in the customization_format is different from the model input, a channel conversion operation will be performed. If the customization_format argument is not specified, the corresponding customization_format will be automatically set according to the pixel_format and channel_format arguments defined when using the model_transform tool.

8.1 Model Deployment Example

Take the mobilenet_v2 model as an example, use the model_transform tool to generate the original mlir, and the run_calibration tool to generate the calibration table (refer to the chapter "Compiling the Caffe Model" for more details).

8.1.1 Deploy to BM168x

The command to generate the preprocess-fused symmetric INT8 quantized bmodel model is as follows:

```
$ model_deploy \
  --mlir mobilenet_v2.mlir \
  --quantize INT8 \
  --calibration_table mobilenet_v2_cali_table \
  --processor bm1684x \
  --test_input ../image/cat.jpg \
  --test_reference mobilenet_v2_top_outputs.npz \
  --tolerance 0.96,0.70 \
  --fuse_preprocess \
  --model mobilenet_v2_bm1684x_int8_sym_fuse_preprocess.bmodel
```

8.1.2 Deploy to CV18xx

The command to generate the preprocess-fused symmetric INT8 quantized cvimodel model are as follows:

```
$ model_deploy \
   --mlir mobilenet_v2.mlir \
   --quantize INT8 \
   --calibration_table mobilenet_v2_cali_table \
   --processor cv183x \
   --test_input ../image/cat.jpg \
   --test_reference mobilenet_v2_top_outputs.npz \
   --tolerance 0.96,0.70 \
   --fuse_preprocess \
   --customization_format RGB_PLANAR \
   --model mobilenet_v2_cv183x_int8_sym_fuse_preprocess.cvimodel
```

vpss input

When the input data comes from the video post-processing module VPSS provided by CV18xx (for details on how to use VPSS for preprocessing, please refer to "CV18xx Media Software Development Reference"), data alignment is required (e.g., 32-bit aligned width), fuse_preprocess and aligned_input need to be set at the same time. The command to generate the preprocessed-fused cvimodel model is as follows:

```
$ model_deploy \
   --mlir mobilenet_v2.mlir \
   --quantize INT8 \
   --calibration_table mobilenet_v2_cali_table \
   --processor cv183x \
   --test_input ../image/cat.jpg \
   --test_reference mobilenet_v2_top_outputs.npz \
   --tolerance 0.96,0.70 \
   --fuse_preprocess \
   --customization_format RGB_PLANAR \
   --aligned_input \
   --model mobilenet_v2_cv183x_int8_sym_fuse_preprocess_aligned.cvimodel
```

In the above command, aligned_input specifies the alignment that the model input needs to do.

Note that with vpss as input, runtime can use CVI_NN_SetTensorPhysicalAddr to reduce memory data copy.

CHAPTER 9

Use Tensor Computing Processor for Postprocessing

Currently, TPU-MLIR supports integrating the post-processing of YOLO series and SSD network models into the model. The processors currently supporting this function include BM1684X, BM1688, CV186X and BM1690. This chapter will take the conversion of YOLOv5s to F16 model as an example to introduce how this function is used.

This chapter requires the tpu_mlir python package.

9.1 Install tpu_mlir

Go to the Docker container and execute the following command to install tpu_mlir:

```
$ pip install tpu_mlir[onnx]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[onnx]
```

9.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a model_yolov5s directory, and put both model files and image files into the model_yolov5s directory.

The operation is as follows:

```
$ mkdir yolov5s_onnx && cd yolov5s_onnx
$ wget https://github.com/ultralytics/yolov5/releases/download/v6.0/yolov5s.onnx
$ cp -rf tpu_mlir_resource/dataset/COCO2017 .
$ cp -rf tpu_mlir_resource/image .
$ mkdir workspace && cd workspace
```

9.3 ONNX to MLIR

The model conversion command is as follows:

```
$ model_transform \
    --model_name yolov5s \
    --model_def ../yolov5s.onnx \
    --input_shapes [[1,3,640,640]] \
    --mean 0.0,0.0,0.0 \
    --scale 0.0039216,0.0039216,0.0039216 \
    --keep_aspect_ratio \
    --pixel_format rgb \
    --output_names 326,474,622 \
    --add_postprocess yolov5 \
    --test_input ../image/dog.jpg \
    --test_result yolov5s_top_outputs.npz \
    --mlir yolov5s.mlir
```

There are two points to note here. The first is that the --add_postprocess argument needs to be included in the command. The second is that the specified --output_names should correspond to the final convolution operation.

The generated yolov5s.mlir file finally has a top.YoloDetection inserted at the end as follows:

```
%260 = "top.Weight"() : () -> tensor<255x512x1x1xf32> loc(#loc261)
%261 = "top.Weight"() : () -> tensor<255xf32> loc(#loc262)
%262 = "top.Conv"(%253, %260, %261) {dilations = [1, 1], do_relu = false, group = 1 : i64,F
↪kernel_shape = [1, 1], pads = [0, 0, 0, 0], relu_limit = -1.000000e+00 : f64, strides = [1, 1]} :F
↪(tensor<1x512x6x32xf32>, tensor<255x512x1x1xf32>, tensor<255xf32>) -> tensor
↪<1x255x6x32xf32> loc(#loc263)
%263 = "top.YoloDetection"(%256, %259, %262) {anchors = [10, 13, 16, 30, 33, 23, 30, 61, 62, 45,
↪ 59, 119, 116, 90, 156, 198, 373, 326], class_num = 80 : i64, keep_topk = 200 : i64, net_input_
↪h = 640 : i64, net_input_w = 640 : i64, nms_threshold = 5.000000e-01 : f64, num_boxes = 3F
↪: i64, obj_threshold = 0.69999999999999996 : f64, version = "yolov5"} : (tensor
↪<1x255x24x128xf32>, tensor<1x255x12x64xf32>, tensor<1x255x6x32xf32>) -> tensor
↪<1x1x200x7xf32> loc(#loc264)
return %263 : tensor<1x1x200x7xf32> loc(#loc)
```

Here you can see that top.YoloDetection includes parameters such as anchors, num_boxes, and so on. If the post-processing is not standard YOLO, and needs to be changed to other parameters, these parameters in the MLIR file can be directly modified. Also, the output has been changed to one, with the shape of 1x1x200x7, where 200 represents the maximum number

of detection boxes. When there are multiple batches, its value will change to batchx200. The 7 elements respectively represent [batch_number, class_id, score, center_x, center_y, width, height]. The coordinates are relative to the width and length of the model input, it' s 640x640 in this example, with the following values:

```
[0., 16., 0.924488, 184.21094, 401.21973, 149.66412, 268.50336 ]
```

9.4 MLIR to Bmodel

To convert the MLIR file to an F16 bmodel, proceed as follows:

```
$ model_deploy \
   --mlir yolov5s.mlir \
   --quantize F16 \
   --processor bm1684x \
   --fuse_preprocess \
   --test_input yolov5s_in_f32.npz \
   --test_reference yolov5s_top_outputs.npz \
   --model yolov5s_1684x_f16.bmodel
```

Here, the --fuse_preprocess parameter is added in order to integrate the preprocessing into the model as well. In this way, the converted model is a model that includes post-processing. The model information can be viewed with model_tool as follows:

```
$ model_tool --info yolov5s_1684x_f16.bmodel
```

```
bmodel version: B.2.2
processor: BM1684X
create time: Wed Jan  3 07:29:14 2024

kernel_module name: libbm1684x_kernel_module.so
kernel_module size: 2677600
==========================================
net 0: [yolov5]  static
------------
stage 0:
subnet number: 2
input: images_raw, [1, 3, 640, 640], uint8, scale: 1, zero_point: 0
output: yolo_post, [1, 1, 200, 7], float32, scale: 1, zero_point: 0

device mem size: 31238060 (coeff: 14757888, instruct: 124844, runtime: 16355328)
host mem size: 0 (coeff: 0, runtime: 0)
```

Here, [1, 1, 200, 7] is the maximum shape, and the actual output varies depending on the number of detected boxes.

9.5 Bmodel Verification

In tpu_mlir package, there are yolov5 use cases written in python, using the detect_yolov5 command to detect objects in images. This command corresponds to the source code path {package/path/to/tpu_mlir}/python/samples/detect_yolov5.py. It is used for object detection in images. By reading this code, you can understand how the final output result is transformed into bounding boxes.

The command execution is as follows:

```
$ detect_yolov5 \
    --input ../image/dog.jpg \
    --model yolov5s_1684x_f16.bmodel \
    --net_input_dims 640,640 \
    --fuse_preprocess \
    --fuse_postprocess \
    --output dog_out.jpg
```

CHAPTER 10

Appendix.01: Reference for converting model to ONNX format

This chapter provides a reference for how to convert PyTorch, TensorFlow and PaddlePaddle models to ONNX format. You can also refer to the model conversion tutorial provided by ONNX official repository: https://github.com/onnx/tutorials. All the operations in this chapter are carried out in the Docker container. For the specific environment configuration method, please refer to the content of Chapter 2.

10.1 PyTorch model to ONNX

This section takes a self-built simple PyTorch model as an example to perform onnx conversion.

10.1.1 Step 0: Create a working directory

Create and enter the torch_model directory using the command line.

```
$ mkdir torch_model
$ cd torch_model
```

10.1.2 Step 1: Build and save the model

Create a script named simple_net.py in this directory and run it. The specific content of the script is as follows:

```
#!/usr/bin/env python3
import torch

# Build a simple nn model
class SimpleModel(torch.nn.Module):

  def __init__(self):
    super(SimpleModel, self).__init__()
    self.m1 = torch.nn.Conv2d(3, 8, 3, 1, 0)
    self.m2 = torch.nn.Conv2d(8, 8, 3, 1, 1)

  def forward(self, x):
    y0 = self.m1(x)
    y1 = self.m2(y0)
    y2 = y0 + y1
    return y2

# Create a SimpleModel and save its weight in the current directory
model = SimpleModel()
torch.save(model.state_dict(), "weight.pth")
```

The run command as follows:

```
$ python simple_net.py
```

After running the script, we will get a weight.pth weight file in the current directory.

10.1.3 Step 2: Export ONNX model

Create another script named export_onnx.py in the same directory and run it. The specific content of the script is as follows:

```
#!/usr/bin/env python3
import torch
from simple_net import SimpleModel

# Load the pretrained model and export it as onnx
model = SimpleModel()
model.eval()
checkpoint = torch.load("weight.pth", map_location="cpu")
model.load_state_dict(checkpoint)

# Prepare input tensor
input = torch.randn(1, 3, 16, 16, requires_grad=True)

```

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```
# Export the torch model as onnx
torch.onnx.export(model,
                  input,
                  'model.onnx', # name of the exported onnx model
                  opset_version=13,
                  export_params=True,
                  do_constant_folding=True)
```

After running the script, we can get the onnx model named **model.onnx** in the current directory.

10.2 TensorFlow model to ONNX

In this section, we use the **mobilenet_v1_0.25_224** model provided in the TensorFlow official repository as a conversion example.

10.2.1 Step 0: Create a working directory

Create and enter the tf_model directory using the command line.

```
$ mkdir tf_model
$ cd tf_model
```

10.2.2 Step 1: Prepare and convert the model

Download the model with the following commands and use the **tf2onnx** tool to export it as an ONNX model:

```
$ wget -nc http://download.tensorflow.org/models/mobilenet_v1_2018_08_02/mobilenet_v1_0.
↪25_224.tgz
# tar to get "*.pb" model def file
$ tar xzf mobilenet_v1_0.25_224.tgz
$ python -m tf2onnx.convert --graphdef mobilenet_v1_0.25_224_frozen.pb \
    --output mnet_25.onnx --inputs input:0 \
    --inputs-as-nchw input:0 \
    --outputs MobilenetV1/Predictions/Reshape_1:0
```

After running all commands, we can get the onnx model named **mnet_25.onnx** in the current directory.

10.3 PaddlePaddle model to ONNX

This section uses the SqueezeNet1_1 model provided in the official PaddlePaddle repository as a conversion example. This section requires additional installation of openssl-1.1.1o (ubuntu 22.04 provides openssl-3.0.2 by default).

10.3.1 Step 0: Install openssl-1.1.1o

```
wget http://nz2.archive.ubuntu.com/ubuntu/pool/main/o/openssl/libssl1.1_1.1.1f-1ubuntu2.19_amd64.deb
sudo dpkg -i libssl1.1_1.1.1f-1ubuntu2.19_amd64.deb
```

If the link is expired, check http://nz2.archive.ubuntu.com/ubuntu/pool/main/o/openssl/?C=M;O=D for a valid one.

10.3.2 Step 1: Create a working directory

Create and enter the pp_model directory using the command line.

```
$ mkdir pp_model
$ cd pp_model
```

10.3.3 Step 2: Prepare the model

Download the model with the following commands:

```
$ wget https://bj.bcebos.com/paddlehub/fastdeploy/SqueezeNet1_1_infer.tgz
$ tar xzf SqueezeNet1_1_infer.tgz
$ cd SqueezeNet1_1_infer
```

In addition, use the paddle_infer_shape.py script from the PaddlePaddle project to perform shape inference on the model. The input shape is set to [1,3,224,224] in NCHW format here:

```
$ wget https://raw.githubusercontent.com/jiangjiajun/PaddleUtils/main/paddle/paddle_infer_shape.py
$ python paddle_infer_shape.py  --model_dir . \
                        --model_filename inference.pdmodel \
                        --params_filename inference.pdiparams \
                        --save_dir new_model \
                        --input_shape_dict="{'inputs':[1,3,224,224]}"
```

After running all commands, we will be in the SqueezeNet1_1_infer directory, and the new_model directory will be generated in that directory.

10.3.4 Step 3: Convert the model

Install the paddle2onnx tool through the following commands, and use this tool to convert the PaddlePaddle model to the ONNX format:

```
$ pip install paddle2onnx
$ paddle2onnx  --model_dir new_model \
        --model_filename inference.pdmodel \
        --params_filename inference.pdiparams \
        --opset_version 13 \
        --save_file squeezenet1_1.onnx
```

After running all the above commands we will get an onnx model named squeezenet1_1.onnx .

CHAPTER 11

Appendix.02: CV18xx Guidance

CV18xx series processor currently supports ONNX and Caffe models but not TFLite models. In terms of quantization, CV18xx supports BF16 and symmetric INT8 format. This chapter takes the CV183X as an example to introduce the compilation and runtime sample of the CV18xx series processor.

11.1 Compile yolov5 model

11.1.1 Install tpu_mlir

Go to the Docker container and execute the following command to install tpu_mlir:

```
$ pip install tpu_mlir[all]
# or
$ pip install tpu_mlir-*-py3-none-any.whl[all]
```

11.1.2 Prepare working directory

Please download tpu-mlir-resource.tar from Assets and unzip it, and rename the folder to tpu_mlir_resource :

```
$ tar -xvf tpu-mlir-resource.tar
$ mv regression/ tpu-mlir-resource/
```

Create a model_yolov5s directory, and put both model files and image files into the model_yolov5s directory.

The operation is as follows:

```
$ mkdir model_yolov5s && cd model_yolov5s
$ wget https://github.com/ultralytics/yolov5/releases/download/v6.0/yolov5s.onnx
$ cp -rf tpu_mlir_resource/dataset/COCO2017 .
$ cp -rf tpu_mlir_resource/image .
$ mkdir workspace && cd workspace
```

11.1.3 ONNX to MLIR

If the input is an image, we need to learn the preprocessing of the model before conversion. If the model uses the preprocessed npz file as input, there is no need to consider preprocessing. The preprocessing process is expressed as follows (x stands for input):

$$y = (x - mean) \times scale$$

The input of yolov5 on the official website is rgb image, each value of it will be multiplied by 1/255, and converted into mean and scale corresponding to 0.0,0.0,0.0 and 0.0039216,0.0039216,0.0039216.

The model conversion command is as follows:

```
$ model_transform \
   --model_name yolov5s \
   --model_def ../yolov5s.onnx \
   --input_shapes [[1,3,640,640]] \
   --mean 0.0,0.0,0.0 \
   --scale 0.0039216,0.0039216,0.0039216 \
   --keep_aspect_ratio \
   --pixel_format rgb \
   --output_names 326,474,622 \
   --test_input ../image/dog.jpg \
   --test_result yolov5s_top_outputs.npz \
   --mlir yolov5s.mlir
```

For the argument description of model_transform, refer to the section The main parameters of model_transform .

11.1.4 MLIR to BF16 Model

Convert the mlir file to the cvimodel of bf16, the operation is as follows:

```
$ model_deploy \
   --mlir yolov5s.mlir \
   --quantize BF16 \
   --processor cv183x \
   --test_input yolov5s_in_f32.npz \
   --test_reference yolov5s_top_outputs.npz \
   --model yolov5s_cv183x_bf16.cvimodel
```

For the argument description of model_deploy, refer to the section The main parameters of model_deploy .

11.1.5 MLIR to INT8 Model

Before converting to the INT8 model, you need to do calibration to get the calibration table. The number of input data depends on the situation but is normally around 100 to 1000. Then use the calibration table to generate INT8 symmetric cvimodel.

Here we use the 100 images from COCO2017 as an example to perform calibration:

```
$ run_calibration yolov5s.mlir \
    --dataset ../COCO2017 \
    --input_num 100 \
    -o yolov5s_cali_table
```

After the operation is completed, a file named ${model_name}_cali_table will be generated, which is used as the input of the following compilation work.

To convert to symmetric INT8 cvimodel model, execute the following command:

```
$ model_deploy \
    --mlir yolov5s.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_cali_table \
    --processor cv183x \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --model yolov5s_cv183x_int8_sym.cvimodel
```

After compiling, a file named ${model_name}_cv183x_int8_sym.cvimodel will be generated.

11.1.6 Result Comparison

The onnx model is run as follows to get dog_onnx.jpg:

```
$ detect_yolov5 \
    --input ../image/dog.jpg \
    --model ../yolov5s.onnx \
    --output dog_onnx.jpg
```

The FP32 mlir model is run as follows to get dog_mlir.jpg:

```
$ detect_yolov5 \
    --input ../image/dog.jpg \
    --model yolov5s.mlir \
    --output dog_mlir.jpg
```

The BF16 cvimodel is run as follows to get dog_bf16.jpg:

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model yolov5s_cv183x_bf16.cvimodel \
   --output dog_bf16.jpg
```

The INT8 cvimodel is run as follows to get dog_int8.jpg:

```
$ detect_yolov5 \
   --input ../image/dog.jpg \
   --model yolov5s_cv183x_int8_sym.cvimodel \
   --output dog_int8.jpg
```

The comparison of the four images is shown in Fig. 11.1, due to the different operating environments, the final effect and accuracy will be slightly different from Fig. 11.1.

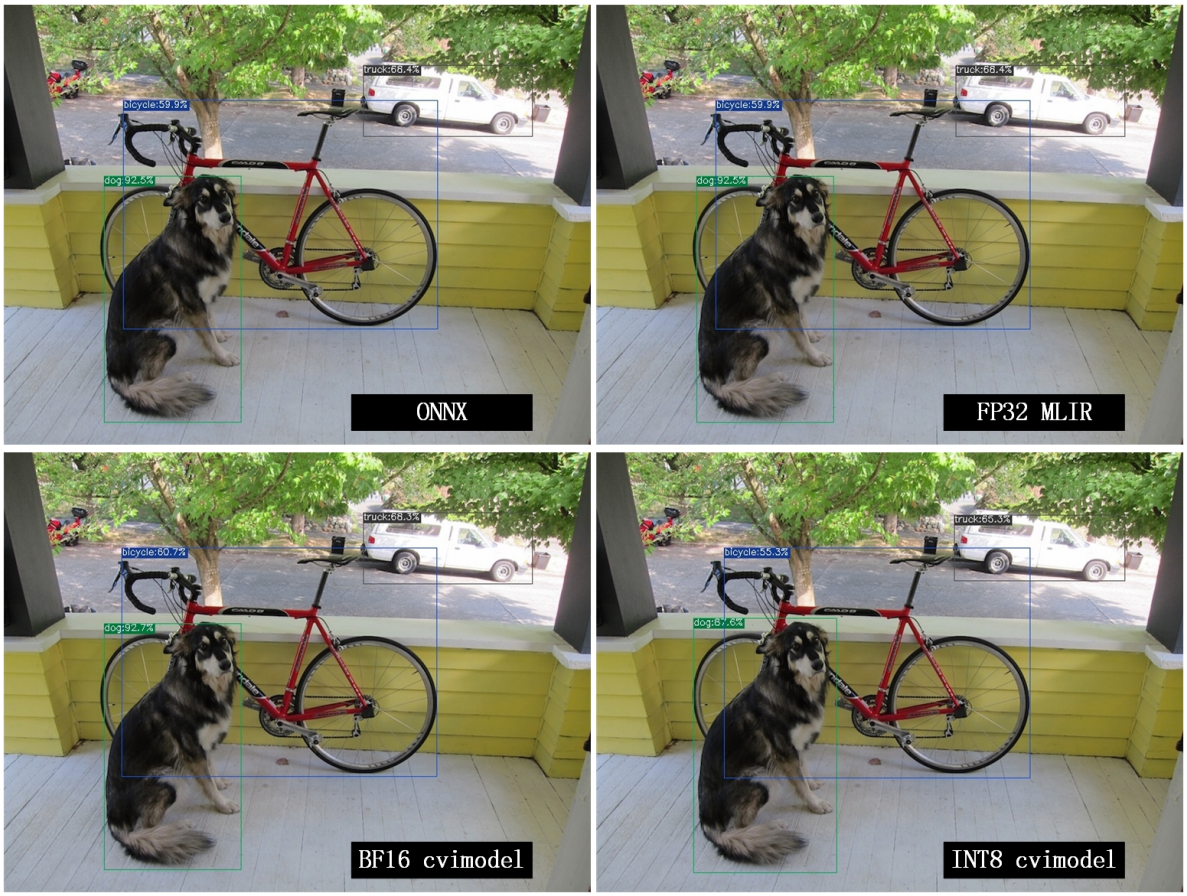

Fig. 11.1: Comparing the results of different models

The above tutorial introduces the process of TPU-MLIR deploying the ONNX model to the CV18xx series processors. For the conversion process of the Caffe model, please refer to the chapter “Compiling the Caffe Model” . You only need to replace the processors name with the specific CV18xx processors.

11.2 Merge cvimodel Files

For the same model, independent cvimodel files can be generated according to the input batch size and resolution(different H and W). However, in order to save storage, you can merge these related cvimodel files into one cvimodel file and share its weight part. The steps are as follows:

11.2.1 Step 0: generate the cvimodel for batch 1

Please refer to the previous section to create a new workspace directory and convert yolov5s to the mlir fp32 model by model_transform

---

Attention :

1.Use the same workspace directory for the cvimodels that need to be merged, and do not share the workspace with other cvimodes that do not need to be merged.

2.In Step 0, Step 1, –merge_weight is required

```
$ model_transform \
   --model_name yolov5s \
   --model_def ../yolov5s.onnx \
   --input_shapes [[1,3,640,640]] \
   --mean 0.0,0.0,0.0 \
   --scale 0.0039216,0.0039216,0.0039216 \
   --keep_aspect_ratio \
   --pixel_format rgb \
   --output_names 326,474,622 \
   --test_input ../image/dog.jpg \
   --test_result yolov5s_top_outputs.npz \
   --mlir yolov5s_bs1.mlir
```

Use the yolov5s_cali_table generated in preceding sections, or generate calibration table by run_calibration.

```
# Add --merge_weight
 $ model_deploy \
    --mlir yolov5s_bs1.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_cali_table \
    --processor cv183x \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --merge_weight \
    --model yolov5s_cv183x_int8_sym_bs1.cvimodel
```


11.2.2 Step 1: generate the cvimodel for batch 2

Generate mlir fp32 file in the same workspace:

```
$ model_transform \
   --model_name yolov5s \
   --model_def ../yolov5s.onnx \
   --input_shapes [[2,3,640,640]] \
   --mean 0.0,0.0,0.0 \
   --scale 0.0039216,0.0039216,0.0039216 \
   --keep_aspect_ratio \
   --pixel_format rgb \
   --output_names 326,474,622 \
   --test_input ../image/dog.jpg \
   --test_result yolov5s_top_outputs.npz \
   --mlir yolov5s_bs2.mlir
```

```
# Add --merge_weight
 $ model_deploy \
    --mlir yolov5s_bs2.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_cali_table \
    --processor cv183x \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --merge_weight \
    --model yolov5s_cv183x_int8_sym_bs2.cvimodel
```

11.2.3 Step 2: merge the cvimodel of batch 1 and batch 2

Use model_tool to mrege two cvimodel files:

```
model_tool \
  --combine \
    yolov5s_cv183x_int8_sym_bs1.cvimodel \
    yolov5s_cv183x_int8_sym_bs2.cvimodel \
    -o yolov5s_cv183x_int8_sym_bs1_bs2.cvimodel
```

11.2.4 Step 3: use the cvimodel through the runtime interface

Use model_tool to check the program id of bs1 and bs2.:

```
model_tool --info yolov5s_cv183x_int8_sym_bs1_bs2.cvimodel
```

At runtime, you can run different batch program in the following ways:

```
CVI_MODEL_HANDEL bs1_handle;
CVI_RC ret = CVI_NN_RegisterModel("yolov5s_cv183x_int8_sym_bs1_bs2.cvimodel", &bs1_
↪handle);
assert(ret == CVI_RC_SUCCESS);
// choice batch 1 program
CVI_NN_SetConfig(bs1_handle, OPTION_PROGRAM_INDEX, 0);
CVI_NN_GetInputOutputTensors(bs1_handle, ...);
....


CVI_MODEL_HANDLE bs2_handle;
// Reuse loaded cvimodel
CVI_RC ret = CVI_NN_CloneModel(bs1_handle, &bs2_handle);
assert(ret == CVI_RC_SUCCESS);
// choice batch 2 program
CVI_NN_SetConfig(bs2_handle, OPTION_PROGRAM_INDEX, 1);
CVI_NN_GetInputOutputTensors(bs2_handle, ...);
...

// clean up bs1_handle and bs2_handle
CVI_NN_CleanupModel(bs1_handle);
CVI_NN_CleanupModel(bs2_handle);
```

11.2.5 Overview:

Using the above command, you can merge either the same models or different models

The main steps are:

1. When generating a cvimodel through model_deploy, add the –merge_weight parameter.
2. The work directory of the model to be merged must be the same, and do not clean up any intermediate files before merging the models(Reuse the previous model' s weight is implemented through the intermediate file _weight_map.csv).
3. Use model_tool to merge cvimodels.

11.3 Compile and Run the Runtime Sample

This part introduces how to compile and run the runtime samples, include how to cross-compile samples for EVB board and how to compile and run samples in docker. The following 4 samples are included:

- Sample-1 : classifier (mobilenet_v2)
- Sample-2 : classifier_bf16 (mobilenet_v2)
- Sample-3 : classifier fused preprocess (mobilenet_v2)
- Sample-4 : classifier multiple batch (mobilenet_v2)

11.3.1 1) Run the provided pre-build samples

The following files are required:

- cvitek_tpu_sdk_[cv183x|cv182x|cv182x_uclibc|cv181x_glibc32|cv181x_musl_riscv64_rvv|cv180x_n
- cvimodel_samples_[cv183x|cv182x|cv181x|cv180x].tar.gz

Select the required files according to the processor type and load them into the EVB file system. Execute them on the Linux console of EVB. Here, we take CV183x as an example.

Unzip the model file (delivered in cvimodel format) and the TPU_SDK used by samples. Enter into the samples directory to execute the test. The process is as follows:

```
#env
tar zxf cvimodel_samples_cv183x.tar.gz
export MODEL_PATH=$PWD/cvimodel_samples
tar zxf cvitek_tpu_sdk_cv183x.tar.gz
export TPU_ROOT=$PWD/cvitek_tpu_sdk
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh
# get cvimodel info
cd samples
./bin/cvi_sample_model_info $MODEL_PATH/mobilenet_v2.cvimodel

#####################################
# sample-1 : classifier
#####################################
./bin/cvi_sample_classifier \
    $MODEL_PATH/mobilenet_v2.cvimodel \
    ./data/cat.jpg \
    ./data/synset_words.txt

# TOP_K[5]:
#  0.326172, idx 282, n02123159 tiger cat
#  0.326172, idx 285, n02124075 Egyptian cat
#  0.099609, idx 281, n02123045 tabby, tabby cat
#  0.071777, idx 287, n02127052 lynx, catamount
#  0.041504, idx 331, n02326432 hare

#####################################
# sample-2 : classifier_bf16
#####################################
./bin/cvi_sample_classifier_bf16 \
    $MODEL_PATH/mobilenet_v2_bf16.cvimodel \
    ./data/cat.jpg \
    ./data/synset_words.txt

# TOP_K[5]:
#  0.314453, idx 285, n02124075 Egyptian cat
#  0.040039, idx 331, n02326432 hare
#  0.018677, idx 330, n02325366 wood rabbit, cottontail, cottontail rabbit
#  0.010986, idx 463, n02909870 bucket, pail
#  0.010986, idx 852, n04409515 tennis ball
```

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```
##############################################
# sample-3 : classifier fused preprocess
##############################################
./bin/cvi_sample_classifier_fused_preprocess \
    $MODEL_PATH/mobilenet_v2_fused_preprocess.cvimodel \
    ./data/cat.jpg \
    ./data/synset_words.txt

# TOP_K[5]:
#  0.326172, idx 282, n02123159 tiger cat
#  0.326172, idx 285, n02124075 Egyptian cat
#  0.099609, idx 281, n02123045 tabby, tabby cat
#  0.071777, idx 287, n02127052 lynx, catamount
#  0.041504, idx 331, n02326432 hare

##############################################
# sample-4 : classifier multiple batch
##############################################
./bin/cvi_sample_classifier_multi_batch \
    $MODEL_PATH/mobilenet_v2_bs1_bs4.cvimodel \
    ./data/cat.jpg \
    ./data/synset_words.txt

# TOP_K[5]:
#  0.326172, idx 282, n02123159 tiger cat
#  0.326172, idx 285, n02124075 Egyptian cat
#  0.099609, idx 281, n02123045 tabby, tabby cat
#  0.071777, idx 287, n02127052 lynx, catamount
#  0.041504, idx 331, n02326432 hare
```

At the same time, the script is provided as a reference, and the execution effect is the same as that of direct operation, as follows:

```
./run_classifier.sh
./run_classifier_bf16.sh
./run_classifier_fused_preprocess.sh
./run_classifier_multi_batch.sh
```

There are more samples can be refered in the cvitek_tpu_sdk/samples/samples_extra:

```
./bin/cvi_sample_detector_yolo_v3_fused_preprocess \
    $MODEL_PATH/yolo_v3_416_fused_preprocess_with_detection.cvimodel \
    ./data/dog.jpg \
    yolo_v3_out.jpg

./bin/cvi_sample_detector_yolo_v5_fused_preprocess \
    $MODEL_PATH/yolov5s_fused_preprocess.cvimodel \
    ./data/dog.jpg \
```

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```
    yolo_v5_out.jpg

./bin/cvi_sample_detector_yolox_s \
    $MODEL_PATH/yolox_s.cvimodel \
    ./data/dog.jpg \
    yolox_s_out.jpg

./bin/cvi_sample_alphapose_fused_preprocess \
    $MODEL_PATH/yolo_v3_416_fused_preprocess_with_detection.cvimodel \
    $MODEL_PATH/alphapose_fused_preprocess.cvimodel \
    ./data/pose_demo_2.jpg \
    alphapose_out.jpg

./bin/cvi_sample_fd_fr_fused_preprocess \
    $MODEL_PATH/retinaface_mnet25_600_fused_preprocess_with_detection.cvimodel \
    $MODEL_PATH/arcface_res50_fused_preprocess.cvimodel \
    ./data/obama1.jpg \
    ./data/obama2.jpg
```

11.3.2 2) Cross-compile samples

The source code is given in the released packages. You can cross-compile the samples' source code in the docker environment and run them on EVB board according to the following instructions.

The following files are required in this part:

- cvitek_tpu_sdk_[cv183x|cv182x|cv182x_uclibc|cv181x_glibc32|cv181x_musl_riscv64_rvv|cv180x_n
- cvitek_tpu_samples.tar.gz

aarch 64-bit (such as cv183x aarch64-bit platform)

Prepare TPU sdk:

```
tar zxf host-tools.tar.gz
tar zxf cvitek_tpu_sdk_cv183x.tar.gz
export PATH=$PWD/host-tools/gcc/gcc-linaro-6.3.1-2017.05-x86_64_aarch64-linux-gnu/bin:
↪$PATH
export TPU_SDK_PATH=$PWD/cvitek_tpu_sdk
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh && cd ..
```

Compile samples and install them into "install_samples" directory:

```
tar zxf cvitek_tpu_samples.tar.gz
cd cvitek_tpu_samples
mkdir build_soc
cd build_soc
```

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```
cmake -G Ninja \
   -DCMAKE_BUILD_TYPE=RELEASE \
   -DCMAKE_C_FLAGS_RELEASE=-O3 \
   -DCMAKE_CXX_FLAGS_RELEASE=-O3 \
   -DCMAKE_TOOLCHAIN_FILE=$TPU_SDK_PATH/cmake/toolchain-aarch64-linux.cmake \
   -DTPU_SDK_PATH=$TPU_SDK_PATH \
   -DOPENCV_PATH=$TPU_SDK_PATH/opencv \
   -DCMAKE_INSTALL_PREFIX=../install_samples \
   ..
cmake --build . --target install
```

arm 32-bit (such as 32-bit cv183x/cv182x platform)

Prepare TPU sdk:

```
tar zxf host-tools.tar.gz
tar zxf cvitek_tpu_sdk_cv182x.tar.gz
export TPU_SDK_PATH=$PWD/cvitek_tpu_sdk
export PATH=$PWD/host-tools/gcc/gcc-linaro-6.3.1-2017.05-x86_64_arm-linux-gnueabihf/bin:
↪$PATH
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh && cd ..
```

If docker version < 1.7, please update 32-bit system library(just once):

```
dpkg --add-architecture i386
apt-get update
apt-get install libc6:i386 libncurses5:i386 libstdc++6:i386
```

Compile samples and install them into install_samples directory:

```
tar zxf cvitek_tpu_samples.tar.gz
cd cvitek_tpu_samples
mkdir build_soc
cd build_soc
cmake -G Ninja \
   -DCMAKE_BUILD_TYPE=RELEASE \
   -DCMAKE_C_FLAGS_RELEASE=-O3 \
   -DCMAKE_CXX_FLAGS_RELEASE=-O3 \
   -DCMAKE_TOOLCHAIN_FILE=$TPU_SDK_PATH/cmake/toolchain-linux-gnueabihf.
↪cmake \
   -DTPU_SDK_PATH=$TPU_SDK_PATH \
   -DOPENCV_PATH=$TPU_SDK_PATH/opencv \
   -DCMAKE_INSTALL_PREFIX=../install_samples \
   ..
cmake --build . --target install
```


uclibc 32-bit platform (such as cv182x uclibc platform)

Prepare TPU sdk:

```
tar zxf host-tools.tar.gz
tar zxf cvitek_tpu_sdk_cv182x_uclibc.tar.gz
export TPU_SDK_PATH=$PWD/cvitek_tpu_sdk
export PATH=$PWD/host-tools/gcc/arm-cvitek-linux-uclibcgnueabihf/bin:$PATH
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh && cd ..
```

If docker version < 1.7, please update 32-bit system library(just once):

```
dpkg --add-architecture i386
apt-get update
apt-get install libc6:i386 libncurses5:i386 libstdc++6:i386
```

Compile samples and install them into install_samples directory:

```
tar zxf cvitek_tpu_samples.tar.gz
cd cvitek_tpu_samples
mkdir build_soc
cd build_soc
cmake -G Ninja \
    -DCMAKE_BUILD_TYPE=RELEASE \
    -DCMAKE_C_FLAGS_RELEASE=-O3 \
    -DCMAKE_CXX_FLAGS_RELEASE=-O3 \
    -DCMAKE_TOOLCHAIN_FILE=$TPU_SDK_PATH/cmake/toolchain-linux-uclibc.cmake \
    -DTPU_SDK_PATH=$TPU_SDK_PATH \
    -DOPENCV_PATH=$TPU_SDK_PATH/opencv \
    -DCMAKE_INSTALL_PREFIX=../install_samples \
    ..
cmake --build . --target install
```

riscv 64-bit musl platform (such as cv180x/cv181x riscv 64-bit musl platform)

Prepare TPU sdk:

```
tar zxf host-tools.tar.gz
tar zxf cvitek_tpu_sdk_cv181x_musl_riscv64_rvv.tar.gz
export TPU_SDK_PATH=$PWD/cvitek_tpu_sdk
export PATH=$PWD/host-tools/gcc/riscv64-linux-musl-x86_64/bin:$PATH
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh && cd ..
```

Compile samples and install them into install_samples directory:

```
tar zxf cvitek_tpu_samples.tar.gz
cd cvitek_tpu_samples
mkdir build_soc
cd build_soc
cmake -G Ninja \
```

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```
  -DCMAKE_BUILD_TYPE=RELEASE \
  -DCMAKE_C_FLAGS_RELEASE=-O3 \
  -DCMAKE_CXX_FLAGS_RELEASE=-O3 \
  -DCMAKE_TOOLCHAIN_FILE=$TPU_SDK_PATH/cmake/toolchain-riscv64-linux-musl-
↪x86_64.cmake \
  -DTPU_SDK_PATH=$TPU_SDK_PATH \
  -DOPENCV_PATH=$TPU_SDK_PATH/opencv \
  -DCMAKE_INSTALL_PREFIX=../install_samples \
  ..
cmake --build . --target install
```

riscv 64-bit glibc platform(such as cv180x/cv181x 64-bit glibc platform)

Prepare TPU sdk:

```
tar zxf host-tools.tar.gz
tar zxf cvitek_tpu_sdk_cv181x_glibc_riscv64.tar.gz
export TPU_SDK_PATH=$PWD/cvitek_tpu_sdk
export PATH=$PWD/host-tools/gcc/riscv64-linux-x86_64/bin:$PATH
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh && cd ..
```

Compile samples and install them into install_samples directory:

```
tar zxf cvitek_tpu_samples.tar.gz
cd cvitek_tpu_samples
mkdir build_soc
cd build_soc
cmake -G Ninja \
  -DCMAKE_BUILD_TYPE=RELEASE \
  -DCMAKE_C_FLAGS_RELEASE=-O3 \
  -DCMAKE_CXX_FLAGS_RELEASE=-O3 \
  -DCMAKE_TOOLCHAIN_FILE=$TPU_SDK_PATH/cmake/toolchain-riscv64-linux-x86_64.
↪cmake \
  -DTPU_SDK_PATH=$TPU_SDK_PATH \
  -DOPENCV_PATH=$TPU_SDK_PATH/opencv \
  -DCMAKE_INSTALL_PREFIX=../install_samples \
  ..
cmake --build . --target install
```

11.3.3 3) Run samples in docker environment

The following files are required:

- cvitek_tpu_sdk_x86_64.tar.gz
- cvimodel_samples_[cv183x|cv182x|cv181x|cv180x].tar.gz
- cvitek_tpu_samples.tar.gz

Prepare TPU sdk:

```
tar zxf cvitek_tpu_sdk_x86_64.tar.gz
export TPU_SDK_PATH=$PWD/cvitek_tpu_sdk
cd cvitek_tpu_sdk && source ./envs_tpu_sdk.sh && cd ..
```

Compile samples and install them into install_samples directory:

```
tar zxf cvitek_tpu_samples.tar.gz
cd cvitek_tpu_samples
mkdir build
cd build
cmake -G Ninja \
  -DCMAKE_BUILD_TYPE=RELEASE \
  -DCMAKE_C_FLAGS_RELEASE=-O3 \
  -DCMAKE_CXX_FLAGS_RELEASE=-O3 \
  -DTPU_SDK_PATH=$TPU_SDK_PATH \
  -DCNPY_PATH=$TPU_SDK_PATH/cnpy \
  -DOPENCV_PATH=$TPU_SDK_PATH/opencv \
  -DCMAKE_INSTALL_PREFIX=../install_samples \
  ..
cmake --build . --target install
```

Run samples:

```
# envs
tar zxf cvimodel_samples_cv183x.tar.gz
export MODEL_PATH=$PWD/cvimodel_samples
source cvitek_mlir/cvitek_envs.sh

# get cvimodel info
cd ../install_samples
./bin/cvi_sample_model_info $MODEL_PATH/mobilenet_v2.cvimodel
```

Other samples are samely to the instructions of running on EVB board.

11.4 FAQ

11.4.1 Model transformation FAQ

1 Related to model transformation

1.1 Whether pytorch,tensorflow, etc. can be converted directly to cvimodel?

pytorch: Supports the .pt model statically via jit.trace(torch_model.eval(), inputs).save('model_name.pt').

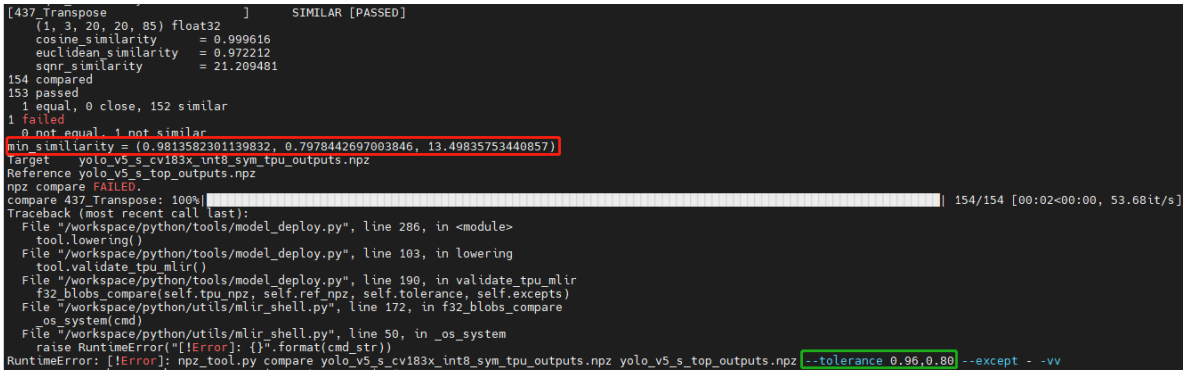
tensorflow / others: It is not supported yet and can be supported indirectly through onnx.

1.2 An error occurs when model_transform is executed

model_transform This command convert the onnx,caffe model into the fp32 mlir. The high probability of error here is that there are unsupported operators or incompatible operator attributes, which can be fed back to the tpu team to solve.

1.3 An error occurs when model_deploy is executed

model_deploy This command quantizes fp32 mlir to int8/bf16mlir, and then converts int8/bf16mlir to cvimodel. In the process of conversion, two similarity comparisons will be involved: one is the quantitative comparison between fp32 mlir and int8/bf16mlir, and the other is the similarity comparison between int8/bf16mlir and the final converted cvimodel. If the similarity comparison fails, the following err will occur:



Solution: The tolerance parameter is incorrect. During the model conversion process, similarity will be calculated for the output of int8/bf16 mlir and fp32 mlir, and tolerance is to limit the minimum value of similarity. If the calculated minimum value of similarity is lower than the corresponding preset tolerance value, the program will stop execution. Consider making adjustments to tolerance. (If the minimum similarity value is too low, please report it to the tpu team.)

1.4 What is the difference between the **pixel_format** parameter of **model_transform** and the **customization_format** parameter of **model_deploy**?

Channel_order is the input image type of the original model (only gray/rgb planar/bgr planar is supported),customization_format is the input image type of cvimodel, which is determined by the customer and must be used together with fuse_preprocess. (If the input is a YUV image obtained through VPSS or VI, set customization_format to YUV format.) If pixel_format is inconsistent with customization_format,cvimodel will automatically converts the input to the type specified by pixel_format.

1.5 Whether the multi-input model is supported and how to preprocess it?

Models with multiple input images using different preprocessing methods are not supported.

2 Related to model quantization

2.1 run run_calibration raise KeyError: 'images'

Please check that the path of the data set is correct.

2.2 How to deal with multiple input problems by running quantization?

When running run_calibration, you can store multiple inputs using .npz, or using the –data_list argument, and the multiple inputs in each row of the data_list are separated by "," .

2.3 Is the input preprocessed when quantization is performed?

Yes, according to the preprocessing parameters stored in the mlir file, the quantization process is preprocessed by loading the preprocessing parameters.

2.4 The program is killed by the system or the memory allocation fails when run calibration

It is necessary to check whether the memory of the host is enough, and the common model requires about 8G memory. If memory is insufficient, try adding the following parameters when running run_calibration to reduce memory requirements.

```
--tune_num 2                    # default is 5
```

2.5 Does the calibration table support manual modification?

Supported, but it is not recommended.

3 Others

3.1 Does the converted model support encryption?

Not supported for now.

3.2 What is the difference in inference speed between bf16 model and int8 model?

The theoretical difference is about 3-4 times, and there will be differences for different models, which need to be verified in practice.

3.3 Is dynamic shape supported?

Cvimodel does not support dynamic shape. If several shapes are fixed, independent cvimodel files can be generated through the form of shared weights. See Merge cvimodel Files for details.

11.4.2 Model performance evaluation FAQ

1 Evaluation process

First converted to bf16 model, through the model_tool --info xxxx.cvimodel command to obtain the ION memory and the storage space required by the model , and then execute model_runner on the EVB board to evaluate the performance, and then evaluate the accuracy in the business scenario according to the provided sample. After the accuracy of the model output meets the expectation, the same evaluation is performed on the int8 model.

2 After quantization, the accuracy does not match the original model, how to debug?

2.1 Ensure --test_input, --test_reference, --compare_all , --tolerance parameters are set up correctly.

2.2 Compare the results of the original model and the bf16 model. If the error is large, check whether the pre-processing and post-processing are correct.

2.3 If int8 model accuracy is poor:

1) Verify that the data set used by run_calibration is the validation set used when training the model;
2) A business scenario data set (typically 100-1000 images) can be added for run_calibration.

2.4 Confirm the input type of cvimodel:

1) If the --fuse_preprocess argument is specified, the input type of cvimodel is uint8;
2) If --quant_input is specified,in general,bf16_cvimoel input type is fp32,int8_cvimodel input type is int8;
3) The input type can also be obtained with model_tool --info xxx.cvimodel

3 bf16 model speed is relatively slow,int8 model accuracy does not meet expectations how to do?

Try using a mixed-precision quantization method. See mix precision for details.

11.4.3 Common problems of model deployment

1 The The CVI_NN_Forward interface encounters an error after being invoked for many times or is stuck for a long time

There may be driver or hardware issues that need to be reported to the tpu team for resolution.

2 Is the model preprocessing slow?

2.1 Add the --fuse_preprocess parameter when running model_deploy, which will put the preprocessing inside the Tensor Computing Processor for processing.

2.2 If the image is obtained from vpss or vi, you can use --fuse_preprocess, --aligned_input when converting to the model. Then use an interface such as CVI_NN_SetTensorPhysicalAddr to set the input tensor address directly to the physical address of the image, reducing the data copy time.

3 Are floating-point and fixed-point results the same when comparing the inference results of docker and evb ?

Fixed point has no difference, floating point has difference, but the difference can be ignored.

4 Support multi-model inference parallel?

Multithreading is supported, but models are inferred on Tensor Computing Processor in serial.

5 Fill input tensor related interface

CVI_NN_SetTensorPtr : Set the virtual address of input tensor, and the original tensor memory will not be freed. Inference **copies data** from a user-set virtual address to the original tensor memory.

CVI_NN_SetTensorPhysicalAddr : Set the physical address of input tensor, and the original tensor memory will be freed. Inference directly reads data from the newly set physical address, **data copy is not required** . A Frame obtained from VPSS can call this interface by passing in the Frame' s first address. Note that model_deploy must be set --fused_preprocess and --aligned_input .

CVI_NN_SetTensorWithVideoFrame : Fill the Input Tensor with the VideoFrame structure. Note The address of VideoFrame is a physical address. If the model is fused preprocess and aligned_input, it is equivalent to CVI_NN_SetTensorPhysicalAddr, otherwise the VideoFrame data will be copied to the Input Tensor.

CVI_NN_SetTensorWithAlignedFrames : Support multi-batch, similar to CVI_NN_SetTensorWithVideoFrame .

CVI_NN_FeedTensorWithFrames : similar to CVI_NN_SetTensorWithVideoFrame .

6 How is ion memory allocated after model loading

6.1 Calling CVI_NN_RegisterModel allocates ion memory for weight and cmdbuf (you can see the weight and cmdbuf sizes by using model_tool).

6.2 Calling CVI_NN_GetInputOutputTensors allocates ion memory for tensor(including private_gmem, shared_gmem, io_mem).

6.3 Calling CVI_NN_CloneModel can share weight and cmdbuf memory.

6.4 Other interfaces do not apply for ion memory.

6.5 Shared_gmem of different models can be shared (including multithreading), so initializing shared_gmem of the largest model first will saves ion memory.

7 The model inference time becomes longer after loading the business program

Generally, after services are loaded, the tdma_exe_ms becomes longer, but the tiu_exe_ms remains unchanged. This is because tdma_exe_ms takes time to carry data in memory. If the memory bandwidth is insufficient, the tdma time will increase.

suggestion:

1) vpss/venc optimize chn and reduce resolution
2) Reduces memory copy
3) Fill input tensor by using copy-free mode

11.4.4 Others

1 In the cv182x/cv181x/cv180x on-board environment, the taz:invalid option –z decompression fails

Decompress the sdk in other linux environments and then use it on the board. windows does not support soft links. Therefore, decompressing the SDK in Windows may cause the soft links to fail and an error may be reported

2 If tensorflow model is pb form of saved_model, how to convert it to pb form of frozen_model

```
import tensorflow as tf
from tensorflow.keras.applications.mobilenet_v2 import MobileNetV2
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input, decode_
↪predictions
import numpy as np
import tf2onnx
import onnxruntime as rt

img_path = "./cat.jpg"
# pb model and variables should in model dir
pb_file_path = "your model dir"
img = image.load_img(img_path, target_size=(224, 224))
x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)
# Or set your preprocess here
x = preprocess_input(x)

model = tf.keras.models.load_model(pb_file_path)
preds = model.predict(x)

# different model input shape and name will differently
spec = (tf.TensorSpec((1, 224, 224, 3), tf.float32, name="input"), )
output_path = model.name + ".onnx"

model_proto, _ = tf2onnx.convert.from_keras(model, input_signature=spec,F
↪opset=13, output_path=output_path)
```

CHAPTER 12

Appendix.03: BM168x Guidance

BM168x series processor currently supports ONNX, pytorch, Caffe and TFLite models. This chapter takes the BM1684x processor as an example to introduce merging bmodel files of the BM168x series processors.

12.1 Merge bmodel Files

For the same model, independent bmodel files can be generated according to the input batch size and resolution(different H and W). However, in order to save storage, you can merge these related bmodel files into one bmodel file and share its weight part. The steps are as follows:

12.1.1 Step 0: generate the bmodel for batch 1

Please refer to the previous section to create a new workspace directory and convert yolov5s to the mlir fp32 model by model_transform

---

Attention :

1.Use the same workspace directory for the bmodels that need to be merged, and do not share the workspace with other bmodes that do not need to be merged.

2.In Step 0, Step 1, –merge_weight is required

```
$ model_transform \
   --model_name yolov5s \
   --model_def ../yolov5s.onnx \
   --input_shapes [[1,3,640,640]] \
   --mean 0.0,0.0,0.0 \
   --scale 0.0039216,0.0039216,0.0039216 \
   --keep_aspect_ratio \
   --pixel_format rgb \
   --output_names 350,498,646 \
   --test_input ../image/dog.jpg \
   --test_result yolov5s_top_outputs.npz \
   --mlir yolov5s_bs1.mlir
```

Use the yolov5s_cali_table generated in preceding sections, or generate calibration table by run_calibration.

```
# Add --merge_weight
 $ model_deploy \
    --mlir yolov5s_bs1.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_cali_table \
    --processor bm1684x \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --merge_weight \
    --model yolov5s_bm1684x_int8_sym_bs1.bmodel
```

12.1.2 Step 1: generate the bmodel for batch 2

Generate mlir fp32 file in the same workspace:

```
$ model_transform \
   --model_name yolov5s \
   --model_def ../yolov5s.onnx \
   --input_shapes [[2,3,640,640]] \
   --mean 0.0,0.0,0.0 \
   --scale 0.0039216,0.0039216,0.0039216 \
   --keep_aspect_ratio \
   --pixel_format rgb \
   --output_names 350,498,646 \
   --test_input ../image/dog.jpg \
   --test_result yolov5s_top_outputs.npz \
   --mlir yolov5s_bs2.mlir
```

```
# Add --merge_weight
 $ model_deploy \
    --mlir yolov5s_bs2.mlir \
    --quantize INT8 \
```

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```
    --calibration_table yolov5s_cali_table \
    --processor bm1684x \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --merge_weight \
    --model yolov5s_bm1684x_int8_sym_bs2.bmodel
```

12.1.3 Step 2: merge the bmodel of batch 1 and batch 2

Use model_tool to mrege two bmodel files:

```
model_tool \
  --combine \
    yolov5s_bm1684x_int8_sym_bs1.bmodel \
    yolov5s_bm1684x_int8_sym_bs2.bmodel \
    -o yolov5s_bm1684x_int8_sym_bs1_bs2.bmodel
```

12.1.4 Overview:

Using the above command, you can merge either the same models or different models

The main steps are:

1. When generating a bmodel through model_deploy, add the –merge_weight parameter.
2. The work directory of the model to be merged must be the same, and do not clean up any intermediate files before merging the models(Reuse the previous model' s weight is implemented through the intermediate file _weight_map.csv).
3. Use model_tool to merge bmodels.

CHAPTER 13

Appendix.04: Model-zoo test

13.1 Configure the system environment

If you are using Docker for the first time, use the methods in Environment Setup to install and configure Docker. At the same time, git-lfs will be used in this chapter. If you use git-lfs for the first time, you need execute the following commands for installation and configuration in the user' s own system (not in Docker container).

```
$ curl -s https://packagecloud.io/install/repositories/github/git-lfs/script.deb.sh | sudo bash
$ sudo apt-get install git-lfs
```

13.2 Get the model-zoo model

In your working directory, get the model-zoo test package from the SDK package provided by SOPHGO, then create and set up model-zoo as follows:

```
$ mkdir -p model-zoo
$ tar -xvf path/to/model-zoo_<date>.tar.bz2 --strip-components=1 -C model-zoo
```

The directory structure of model-zoo is as follows:

```
├─── config.yaml
├─── requirements.txt
├─── dataset
├─── harness
├─── output
└─── ...
```

- config.yaml: contains generic configuration: dataset directory, model root directory, etc., as well as some reused parameters and commands
- requirements.txt: contains python dependencies for model-zoo.
- dataset: directory contains the datasets of the models in modelzoo, which will be called by tpu_perf as plugins.
- output: directory will be used to store the compiled output bmodel and some intermediate data.
- The other directories contain information and configuration for each model. The directory corresponding to each model has a config.yaml file, which configures the model' s name, path and FLOPs, dataset production parameters, and the model' s quantization compilation commands.

13.3 Prepare the runtime environment

Install the dependencies needed to run model-zoo on your system (outside of the Docker container):

```
# for ubuntu operating system
$ sudo apt install build-essential
$ sudo apt install python3-dev
$ sudo apt install -y libgl1
# for centos operating system
$ sudo yum install make automake gcc gcc-c++ kernel-devel
$ sudo yum install python-devel
$ sudo yum install mesa-libGL
# accuracy tests require the following operations to be performed, performance tests can be
↪performed without, it is recommended to use Anaconda to create a virtual environment of
↪python 3.7 or above
$ cd path/to/model-zoo
$ pip3 install -r requirements.txt
```

In addition, tpu hardware needs to be invoked for performance and accuracy tests, so please install the runtime environment for the TPU hardware.

13.4 Configure SOC device

Note: If your device is a PCIE board, you can skip this section directly.

The performance test only depends on the runtime environment for the TPU hardware, so after packaging models, compiled in the toolchain compilation environment, and model-zoo, the performance test can be carried out in the SOC environment by tpu_perf. However, the complete model-zoo as well as compiled output contents may not be fully copied to the SOC since the storage on the SOC device is limited. Here is a method to run tests on SOC devices through linux nfs remote file system mounts.

First, install the nfs service on the toolchain environment server "host system" :

```
$ sudo apt install nfs-kernel-server
```

Add the following content to /etc/exports (configure the shared directory):

```
/the/absolute/path/of/model-zoo *(rw,sync,no_subtree_check,no_root_squash)
```

Where * means that everyone can access the shared directory. Moreover, it can be configured to be accessible by a specific network segment or IP, such as:

```
/the/absolute/path/of/model-zoo 192.168.43.0/24(rw,sync,no_subtree_check,no_root_squash)
```

Then execute the following command to make the configuration take effect:

```
$ sudo exportfs -a
$ sudo systemctl restart nfs-kernel-server
```

In addition, you need to add read permissions to the images in the dataset directory:

```
$ chmod -R +r path/to/model-zoo/dataset
```

Install the client on the SOC device and mount the shared directory:

```
$ mkdir model-zoo
$ sudo apt-get install -y nfs-common
$ sudo mount -t nfs <IP>:/path/to/model-zoo ./model-zoo
```

In this way, the test directory is accessible in the SOC environment. The rest of the SOC test operation is basically the same as that of PCIE. Please refer to the following content for operation. The difference in command execution position and operating environment has been explained in the execution place.

13.5 Prepare dataset

13.5.1 ImageNet

Download ImageNet 2012 Dataset 。

After unzipping, move the data under Data/CLS_LOC/val to a directory like model-zoo:

```
$ cd path/to/sophon/model-zoo
$ mv path/to/imagenet-object-localization-challenge/Data/CLS_LOC/val dataset/ILSVRC2012/
↪ILSVRC2012_img_val
# It is also possible to map the dataset directory to dataset/ILSVRC2012/ILSVRC2012_img_val
↪through the soft link ln -s
```

13.5.2 COCO (optional)

If the precision test uses the coco dataset (networks trained with coco such as yolo), please download and unzip it as follows:

```
$ cd path/to/model-zoo/dataset/COCO2017/
$ wget http://images.cocodataset.org/annotations/annotations_trainval2017.zip
$ wget http://images.cocodataset.org/zips/val2017.zip
$ unzip annotations_trainval2017.zip
$ unzip val2017.zip
```

13.5.3 Vid4 (optional)

If you need precision test on BasicVSR, please download and unzip the Vid4 dataset as follows:

```
$ pip3 install gdown
$ cd path/to/model-zoo/dataset/basicvsr/
$ gdown https://drive.google.com/open?id=1ZuvNNLgR85TV_whJoHM7uVb-XW1y70DW --fuzzy
$ unzip -o Vid4.zip -d eval
```

13.6 Prepare the toolchain compilation environment

It is recommended to use the toolchain software in a docker environment, see Base environment configuration to install Docker. and execute the following commands in your working directory (the directory which model-zoo is located) to create a Docker container:

```
$ docker pull sophgo/tpuc_dev:v3.2
$ docker run --rm --name myname -v $PWD:/workspace -it sophgo/tpuc_dev:v3.2
```

The --rm parameter ensures that the container is automatically removed after exiting. If you want to keep the container after it exits, simply remove this parameter.

After running the command, it will be in a Docker container. You can the latest tpu-mlir wheel installation package from the SDK package provided by SOPHGO, such as tpu_mlir-*-py3-none-any.whl. Install tpu_mlir in the Docker container:

```
$ pip install tpu_mlir-*-py3-none-any.whl[all]
```

13.7 Install tpu-perf tool

Get the latest **tpu-perf** wheel installer from the SDK package provided by SOPHGO. For example, **tpu_perf-x.x.x-py3-none-manylinux2014_x86_64.whl** .

You need to install **tpu-perf** both inside and outside of Docker:

```
# go to Docker and install tpu-perf
$ pip3 install path/to/tpu_perf-x.x.x-py3-none-manylinux2014_x86_64.whl
```

13.8 Model performance and accuracy testing process

13.8.1 Compile the model

The model compilation process needs to be done within Docker, where **tpu_mlir** and **tpu_perf** need to be installed as described above.

confg.yaml in **model-zoo** configures the test content of the SDK. For example, the configuration file for resnet18 is **model-zoo/vision/classification/resnet18-v2/config.yaml** .

Execute the following command to compile the **resnet18-v2** model:

```
$ cd ../model-zoo
$ python3 -m tpu_perf.build --target BM1684X --mlir vision/classification/resnet18-v2
```

where the **--target** is used to specify the processor model, which currently supports **BM1684** , **BM1684X** , **BM1688** , **BM1690** and **CV186X** .

Execute the following command to compile all test samples:

```
$ cd ../model-zoo
$ python3 -m tpu_perf.build --target BM1684X --mlir -l full_cases.txt
```

The following models are compiled (Due to continuous additions of models in the model-zoo, only a partial list of models is provided here):

```
* efficientnet-lite4
* mobilenet_v2
* resnet18
* resnet50_v2
* shufflenet_v2
* squeezenet1.0
* vgg16
* yolov5s
* ...
```

After the command is finished, you will see the newly generated **output** folder. This compilation result can be used for performance and accuracy testing without recompilation. But

you need modify the properties of the output folder to make it accessible to systems outside of Docker:

```
$ chmod -R a+rw output
```

13.8.2 Performance test

Running the test needs to be done in an environment outside Docker, it is assumed that you have installed and configured the runtime environment for the TPU hardware, so you can exit the Docker environment:

```
$ exit
```

PCIE board

Run the following commands under the PCIE board to test the performance of the generated bmodel :

```
$ pip3 install path/to/tpu_perf-x.x.x-py3-none-manylinux2014_x86_64.whl
$ cd model-zoo
$ python3 -m tpu_perf.run --target BM1684X --mlir -l full_cases.txt
```

where the --target is used to specify the processor model, which currently supports BM1684 , BM1684X , BM1688 , BM1690 and CV186X .

Note: If multiple SOPHGO accelerator cards are installed on the host, you can specify the running device of tpu_perf by adding --devices id when using tpu_perf. Such as:

```
$ python3 -m tpu_perf.run --target BM1684X --devices 2 --mlir -l full_cases.txt
```

SOC device

The SOC device uses the following steps to test the performance of the generated bmodel.

Get the latest tpu-perf wheel installer from the SDK package provided by SOPHGO. For example, tpu_perf-x.x.x-py3-none-manylinux2014_aarch64.whl, then transfer the file to the SOC device and execute the following operations:

```
$ pip3 install path/to/tpu_perf-x.x.x-py3-none-manylinux2014_aarch64.whl
$ cd model-zoo
$ python3 -m tpu_perf.run --target BM1684X --mlir -l full_cases.txt
```

Output results

After that, performance data is available in output/stats.csv, in which the running time, computing resource utilization, and bandwidth utilization of the relevant models are recorded. The performance test results for resnet18-v2 as follows:

```
name,prec,shape,gops,time(ms),mac_utilization,ddr_utilization,processor_usage
resnet18-v2,FP32,1x3x224x224,3.636,6.800,26.73%,10.83%,3.00%
```

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```
resnet18-v2,FP16,1x3x224x224,3.636,1.231,18.46%,29.65%,2.00%
resnet18-v2,INT8,1x3x224x224,3.636,0.552,20.59%,33.20%,3.00%
resnet18-v2,FP32,4x3x224x224,14.542,26.023,27.94%,3.30%,3.00%
resnet18-v2,FP16,4x3x224x224,14.542,3.278,27.73%,13.01%,2.00%
resnet18-v2,INT8,4x3x224x224,14.542,1.353,33.59%,15.46%,2.00%
```

13.8.3 Precision test

Running the test needs to be done in an environment outside Docker, it is assumed that you have installed and configured the runtime environment for the TPU hardware, so you can exit the Docker environment:

```
$ exit
```

Run the following commands under the PCIE board to test the precision of the generated bmodel :

```
$ pip3 install path/to/tpu_perf-x.x.x-py3-none-manylinux2014_x86_64.whl
$ cd model-zoo
$ python3 -m tpu_perf.precision_benchmark --target BM1684X --mlir -l full_cases.txt
```

where the --target is used to specify the processor model, which currently supports BM1684 , BM1684X , BM1688 , BM1690 and CV186X .

Note: If multiple SOPHGO accelerator cards are installed on the host, you can specify the running device of tpu_perf by adding --devices id when using tpu_perf. Such as:

```
$ python3 -m tpu_perf.precision_benchmark --target BM1684X --devices 2 --mlir -l full_cases.txt
```

Specific parameter descriptions can be obtained with the following commands:

```
$ python3 -m tpu_perf.precision_benchmark --help
```

The output precision data is available in output/topk.csv . The precision results for resnet18-v2:

```
name,top1,top5
resnet18-v2-FP32,69.68%,89.23%
resnet18-v2-INT8,69.26%,89.08%
```

CHAPTER 14

Appendix.05: TPU Profile Tool Guidance

This chapter mainly introduces how to use Profile data and Tensor Computing Processor Profile tools to visualize the complete running process of the model to facilitate model performance analysis.

14.1 Compile Bmodel

TPU Profile is a tool for converting Profile data into visual web pages. First, generate bmodel. The following uses the yolov5s model in the tpu-mlir project to demonstrate.

Since Profile data will save some layer information during compilation into bmodel, causing the size of bmodel to increase, it is turned off by default. The way to open it is to call model_deploy with the --debug option. If this option is not turned on at compile time, some data will be missing when the data obtained by turning on Profile at runtime is visualized. The command to generate a bmodel within Docker is as follows:

```
# generate top mlir
$ model_transform \
    --model_name yolov5s \
    --model_def ../yolov5s.onnx \
    --input_shapes [[1,3,640,640]] \
    --mean 0.0,0.0,0.0 \
    --scale 0.0039216,0.0039216,0.0039216 \
    --keep_aspect_ratio \
    --pixel_format rgb \
    --output_names 350,498,646 \
    --test_input ../image/dog.jpg \
    --test_result yolov5s_top_outputs.npz \
    --mlir yolov5s.mlir
```

```
# convert top mlir to fp16 precision bmodel
$ model_deploy \
   --mlir yolov5s.mlir \
   --quantize F16 \
   --processor bm1684x \
   --test_input yolov5s_in_f32.npz \
   --test_reference yolov5s_top_outputs.npz \
   --model yolov5s_1684x_f16.bmodel \
   --debug
```

Through the above commands, yolov5s.onnx is compiled into yolov5s_bm1684x_f16.bmodel , and the --debug parameter will record the profile data.

14.2 Generate Raw Profile Data

Copy the generated yolov5s_bm1684x_f16.bmodel to the running environment with libsophon. In the same compilation process, the Profile function at runtime is turned off by default to prevent additional time consumption when saving and transmitting profiles. When you need to enable the profile function, set the environment variable BMRUNTIME_ENABLE_PROFILE=1 before running the compiled application. Then use the model testing tool bmrt_test provided in libsophon to run bmodel and generate profile data. Execute the following command outside of Docker:

```
export BMRUNTIME_ENABLE_PROFILE=1
bmrt_test --bmodel yolov5s_1684x_f16.bmodel
```

The following is the log output after opening Profile:

After the run completes, the bmprofile_data-1 folder is generated in the current directory, which contains all Profile data.

14.3 Visualize Profile Data

Copy the bmprofile_data-1 directory back to the tpu-mlir project environment inside Docker. Tpu-mlir provides the tpu_profile script to convert the generated profile data into a web page file for visualization. Execute the following command inside Docker:

```
# Convert the original profile data in the bmprofile_data_0 directory into a web
# page and place it in the bmprofile_out directory
# If there is a graphical interface, the browser will be opened directly and the
# results will be seen directly.
tpu_profile bmprofile_data-1 bmprofile_out
ls bmprofile_out
# echarts.min.js  profile_data.js  result.html
```

Open bmprofile_out/result.html with a browser to see the profile chart. In addition, there are other uses of this tool, which can be viewed through the command as follows:

```
[BMRT][load_bmodel:1084] INFO:Loading bmodel from [yolov5s_1684x_f16.bmodel]. Thanks for your patience...
[BMRT][load_bmodel:1023] INFO:pre net num: 0, load net num: 1
[BMRT][show_net_info:1520] INFO: ########################
[BMRT][show_net_info:1521] INFO: NetName: yolov5s, Index=0
[BMRT][show_net_info:1523] INFO: ---- stage 0 ----
[BMRT][show_net_info:1532] INFO:   Input 0) 'images' shape=[ 1 3 640 640 ] dtype=FLOAT32 scale=1 zero_point=0
[BMRT][show_net_info:1542] INFO:   Output 0) '350_Transpose_f32' shape=[ 1 3 80 80 85 ] dtype=FLOAT32 scale=1 zero_point=0
[BMRT][show_net_info:1542] INFO:   Output 1) '498_Transpose_f32' shape=[ 1 3 40 40 85 ] dtype=FLOAT32 scale=1 zero_point=0
[BMRT][show_net_info:1542] INFO:   Output 2) '646_Transpose_f32' shape=[ 1 3 20 20 85 ] dtype=FLOAT32 scale=1 zero_point=0
[BMRT][show_net_info:1545] INFO: ########################
[BMRT][bmrt_test:782] INFO:==> running network #0, name: yolov5s, loop: 0
[BMRT][bmrt_test:868] INFO:reading input #0, bytesize=4915200
[BMRT][print_array:706] INFO:  --> input_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ... > len=1228800
[BMRT][write_block:295] INFO:write_block: type=1, len=36
[BMRT][write_block:295] INFO:write_block: type=8, len=44
[BMRT][end:76] INFO:bdc record_num=1838, max_record_num=1048576
[BMRT][write_block:295] INFO:write_block: type=3, len=58816
[BMRT][end:89] INFO:gdma record_num=196, max_record_num=1048576
[BMRT][write_block:295] INFO:write_block: type=4, len=37632
[BMRT][write_block:295] INFO:write_block: type=5, len=256
[BMRT][write_block:295] INFO:write_block: type=6, len=1072
[BMRT][print_note:94] INFO:*****************************************************************
[BMRT][print_note:95] INFO:* PROFILE MODE due to BMRUNTIME_ENABLE_PROFILE=1
[BMRT][print_note:96] INFO:* Note: BMRuntime will collect time data during running
[BMRT][print_note:97] INFO:*       that will cost extra time.
[BMRT][print_note:98] INFO:* Close PROFILE Mode by "unset BMRUNTIME_ENABLE_PROFILE"
[BMRT][print_note:99] INFO:*****************************************************************
[BMRT][bmrt_test:1005] INFO:reading output #0, bytesize=6528000
[BMRT][print_array:706] INFO:  --> output ref_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ... > len=1632000
[BMRT][bmrt_test:1005] INFO:reading output #1, bytesize=1632000
[BMRT][print_array:706] INFO:  --> output ref_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ... > len=408000
[BMRT][bmrt_test:1005] INFO:reading output #2, bytesize=408000
[BMRT][print_array:706] INFO:  --> output ref_data: < 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 ... > len=102000
[BMRT][bmrt_test:1039] INFO:net[yolov5s] stage[0], launch total time is 375609 us (npu 5650 us, cpu 369959 us)
[BMRT][bmrt_test:1042] INFO:+++ The network[yolov5s] stage[0] output_data +++
[BMRT][print_array:706] INFO:output data #0 shape: [1 3 80 80 85 ] < 0.30957 -0.289551 0.0744629 -0.203003 -11.9375 -1.54297 -5.25391 -3.05859 -5.39453 -5.64844
95 -6.26172 ... > len=1632000
[BMRT][print_array:706] INFO:output data #1 shape: [1 3 40 40 85 ] < -0.0398254 0.253174 -0.383057 -0.520996 -11.0391 -1.3125 -5.11328 -3.32031 -5.46484 -5.97656
812 -6.29688 ... > len=408000
[BMRT][print_array:706] INFO:output data #2 shape: [1 3 20 20 85 ] < 0.713379 0.654297 -0.534668 -0.241577 -9.82031 -1.23047 -5.77344 -3.35547 -5.92578 -5.12109
44 -6.63672 ... > len=102000
[BMRT][bmrt_test:1083] INFO:load input time(s): 0.003650
[BMRT][bmrt_test:1084] INFO:calculate  time(s): 0.375613
[BMRT][bmrt_test:1085] INFO:get output time(s): 0.003838
[BMRT][bmrt_test:1086] INFO:compare    time(s): 0.000827
```

The saved profile data information

Profile Mode Tips to avoid misuse during formal deploying

CPU Time is not accuracy on Profile Mode

Fig. 14.1: The log output after opening Profile

```
tpu_profile --help
```

For more analysis instructions on using Profile tools, please refer to https://tpumlir.org/zh-cn/2023/09/18/analyse-tpu-performance-with-tpu-profile.html

CHAPTER 15

Appendix.06: TDB Guidance

This chapter mainly introduces the use of the Tensor Debugger(TDB) tool. TDB provides a debugging window similar to pdb and gdb interfaces, which can be used to debug the BModel running process, including adding breakpoints, single-step execution, viewing memory data, data comparison, and other functions.

This tool currently supports BM1684, BM1684X, and BM1688.

15.1 Preparatory work

Environment configuration

First you need to refer to Environment Setup chapter to complete the environment configuration, enter the Docker container of TPU-MLIR, and install tpu_mlir in it.

If you have completed the environment configuration, you can ignore this step.

Generate bmodel

Before using TDB, you need to generate the bmodel file through TPU-MLIR, refer to Compile the ONNX model chapter to generate the bmodel file from the model.

You need to use the following two commands:

```
# Convert the ONNX model to top_mlir
$ model_transform
# Convert top_mlir to bmodel
$ model_deploy
```

Here, the `model_deploy` command needs to add `--debug` and `--compare_all` arguments to save the `tpu_output.npz` file and keep the intermediate data.

When the bmodel is built, a directory with the compilation.bmodel and final.mlir files is automatically generated, this directory is called the Context directory.

15.2 Start TDB

```
$ tdb [-h]
      [--inputs [INPUTS]]
      [--ref_data [REF_DATA ...]]
      [--plugins [PLUGINS]]
      [--ddr_size [DDR_SIZE]] [-v]
      [context_dir]
```

The main parameters of the tdb command are described as follows:

Table 15.1: Function of tdb parameters

Name	Required?	Explanation
context_dir	Y	The directory where the bmodel file resides, which is the current directory by default
-h, –help	N	Display help information
–inputs	N	Specify input data for the bmodel file
–ref_data	N	Specify reference data for the bmodel file
–plugins	N	Add extra plugins
–ddr_size	N	Specify the ddr_size of the cmodel
-v, –verbose	N	Use the progress bar

Example of starting TDB:

```
$ tdb
# equivalent to
$ tdb ./
```

15.3 TDB command summary

After entering TDB, press tab twice to get the command prompt. The display looks like this:

```
(tdb)
EOF         continue    enable      n           print       r           skip        w
b           delete      help        next        py          reload      start       watch
break       disable     info        p           q           run         static-check
c           display     list        plugin      quit        s           status
```

After entering TDB, the following commands can be used:

Table 15.2: TDB command summary

Command	Explanation
s/start	Load the bmodel and initialize it
r/run	Execute from the beginning to the end, the run instruction contains the initialization function
b/break	Add breakpoints in final.mlir
delete	Delete breakpoint
n/next	Execute the next instruction, you can use `n [num]` to execute more than one instruction
c/continue	Continue the instruction until the break point or the end of the run
info	Print breakpoint information or instructions in different formats
p/print	Print the current instruction or the data corresponding to the instruction
w/watch	Monitors a certain input/output of the current or previous atomic instruction and returns a prompt when the data at its address changes
q/quit	Quit TDB
py [py_cmd]	Execute python commands in TDB, integrated with pdb' s code completion function

Where `num` represents number; `py_cmd` denotes the python command.

15.4 TDB usage process

```
# start TDB in context directory
$ cd path/to/context_dir
$ tdb
# initialize
$ s
# execute line by line
$ n
# add breakpoint
$ b
# keep running
$ c
# continue debugging
$ info/p/w
# quit
$ q
```


15.5 TDB function description

15.5.1 next feature

```
# execute line by line use next
(tdb) n
# execute multiple instructions
(tdb) n [num]
# execute 3 instructions
(tdb) n 3
```

The instruction displayed after the `n` command is the next unexecuted instruction.

15.5.2 breakpoint feature

Breakpoint feature include viewing breakpoints, adding/removing breakpoints, and turning breakpoints on/off. Here' s how to use it:

Table 15.3: breakpoint feature

Command	Explanation	Example
info b/break	View breakpoint information	info b; info break
b/break	Add breakpoint	b 1
enable	Enable breakpoint	enable 1; enable 1,2
disable	Disable breakpoint	disable 1; disable 1,2
delete	Delete breakpoint	delete 1

Currently supported breakpoint types are as follows:

value-id

The Operation prefix in final.mlir corresponding to bmodel, for example:

```
%140 = "tpu.Load"(%6) {do_bcast = false ···
```

where %140 and %6 are value-id , adding this type of breakpoint example is as follows:

```
(tdb) b %140
(tdb) b %6
```

op-name

The Operation name in final.mlir , in the above example, tpu.Load is the Op name, add this type of breakpoint example is as follows:

```
(tdb) b tpu.Load
```

cmd-id

The cmd-id of asm which is resolved. In the above example, D1 and B0 are cmd-id . The example of adding this type of breakpoint is as follows:

```
(tdb) b D2
(tdb) b B4
```

15.5.3 info feature

The info feature can print breakpoint information or instructions in different formats as follows:

info b

View breakpoint information.

```
(tdb) info b
index     type enable     text hit
    1  dialect      y tpu.load   0
    2     addr      y       R0   3
    3   cmd-id      y       D1   0
    4 value-id      y       %7   0
```

info asm

Show the current asm instruction.

```
(tdb) info asm
%R0, %B15 = "arith.add"(%R13, %C1.0, %D3) {round_mode = 0} : (memref<1x32x54x160xf32,F
↪strides: [8640, 8640, 160, 1]>, f32, none) -> (memref<1x32x54x160xf32, strides: [8640, 8640, 160,
↪ 1]>, none)
```

info mlir

Show the Operation in final.mlir that corresponds to the current instruction.

```
(tdb) info mlir
%137 = "tpu.Active"(%134) {ginfo = #tpu.lg<out_addr = 212992, out_size = 35456, buffer_
↪addr = 0, buffer_size = 71040, eu_align = true, n_idx = [0], n_slice = [1], c_idx = [0], c_
↪slice = [32], d_idx = [0], d_slice = [1], h_idx = [0, 53, 107, 161, 215, 267], h_slice = [54, 55, 55,
↪ 55, 53, 53], w_idx = [0, 159], w_slice = [160, 161], id = 6, stage = 1, group_type = 0>, mode F
↪= #tpu<active_mode SILU>} : (tensor<1x32x320x320xf32>) -> tensor<1x32x320x320xf32>F
↪loc(#loc19)
```

info reg

Show the value of each field after the current command has been parsed.

```
(tdb) info reg
{'cmd_short': 1, 'cmd_id': 15, 'cmd_id_dep': 3, 'tsk_typ': 3, 'tsk_eu_typ': 2, 'opd0_const': 0,
↪'opd1_const': 1, 'opd2_const': 0, 'tsk_opd_num': 2, 'cmd_id_en': 1, 'pwr_step': 0, 'intr_en': 0,
```

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```
↪ 'res0_prec': 2, 'opd0_prec': 2, 'opd1_prec': 2, 'opd2_prec': 0, 'opd0_sign': 1, 'opd1_sign': 1,
↪'res0_str': 0, 'opd0_str': 0, 'opd1_str': 0, 'opd2_n_str': 0, 'rsvd0': 0, 'res0_n': 1, 'res0_c': 32,
↪'res0_h': 54, 'res0_w': 160, 'res0_addr': 0, 'opd0_addr': 212992, 'opd1_addr': 1065353216,
↪'opd2_addr': 0, 'res0_n_str': 0, 'res0_c_str': 0, 'opd0_n_str': 0, 'opd0_c_str': 0, 'opd1_n_str
↪': 0, 'opd1_c_str': 0, 'res0_h_str': 0, 'res0_w_str': 0, 'opd0_h_str': 0, 'opd2_sign': 0, 'rsvd1': 0,
↪ 'opd0_w_str': 0, 'opd1_h_str': 0, 'opd1_w_str': 0, 'rsvd2': 0}
```

info loc

Show the corresponding Operation information of tensor_location.json in the Context directory.

```
(tdb) info loc
{'core_id': 0,
'file_line': 27,
'loc_index': 4,
'opcode': 'tpu.Active',
'operands': [@163840({name=122_Conv, layout=eu_align, slice=[0:1, 0:32, 0:1, 0:54, 0:160], mlir_
↪type=tensor<1x32x320x320xf32>, memory_type=<1x32x54x160xf32>})],
'results': [@212992({name=124_Mul, layout=eu_align, slice=[0:1, 0:32, 0:1, 0:54, 0:160], mlir_
↪type=tensor<1x32x320x320xf32>, memory_type=<1x32x54x160xf32>})],
'slice_all': False,
'subnet_id': 0,
'tiu_dma_id_after': [17, 3],
'tiu_dma_id_before': [1, 3]}
```

15.5.4 print feature

The print feature not only prints the current asm instruction, but also the input and output data of the instruction, the method of use is as follows:

Table 15.4: print feature

Command	Explanation	Example
p op	Show upcoming commands	p op
p pre/next	Show the previous or next instruction	p pre; p next
p in	Show the input data for the next unexecuted instruction	p in; p in 0
p out	Show the output data of the previous executed instruction	p out; p out 0

15.5.5 watchpoint feature

The watchpoint feature can monitor the input/output data of an instruction and return an alert when the data of a monitored variable changes, the method of use is as follows:

w

Show the currently added watchpoints, see the following example:

```
(tdb) w
index    cmd_type cmd_id core_id enabled                                                value
    1 CMDType.dma      2       0       y %G0: memref<1x32x3x36xf32, strides: [3456, 108, 36, 1]>
```

w in

Adds one of the inputs for the next pending instruction as a watchpoint, see the following example:

```
(tdb) n
%R15.2688, %D2 = "dma.tensor"(%G0, %B0) {decompress = False} : (memref<1x32x3x36xf32,F
↪strides: [3456, 108, 36, 1]>, none) -> (memref<1x32x3x36xf32, strides: [108, 108, 36, 1]>, none)
(tdb) w in 0
(tdb) w
index    cmd_type cmd_id core_id enabled                                                value
    1 CMDType.dma      2       0       y %G0: memref<1x32x3x36xf32, strides: [3456, 108, 36, 1]>
```

as you can see, w in 0 adds the first input %G0 of the next pending instruction as watchpoint.

w out

Adds one of the outputs of the last executed instruction as a watchpoint, see the following example:

```
(tdb) w out 0
(tdb) w
index    cmd_type cmd_id core_id enabled                                                  value
    1 CMDType.dma      2       0       y       %G0: memref<1x32x3x36xf32, strides: [3456, 108, 36,F
↪1]>
    2 CMDType.dma      1       0       y %R0: memref<1x3x110x322xf32, strides: [35424, 35424, 322,
↪ 1]>
```

p w idx old/now

Prints the value of the added watchpoint, as shown in the following example:

Where idx is the index of the watchpoint returned using the w command, old means to view the data when the watchpoint was originally added, and now means to view the current data of the watchpoint.

The old/now can be omitted and the default is now, which means view the current data of the watchpoint.


```
(tdb) w
index    cmd_type cmd_id core_id enabled                                                value
   1 CMDType.dma      2       0       y       %G0: memref<1x32x3x36xf32, strides: [3456, 108, 36,F
↪1]>
   2 CMDType.dma      1       0       y %R0: memref<1x3x110x322xf32, strides: [35424, 35424, 322,
↪ 1]>
(tdb) p w 1
(tdb) p w 1 old
```

w delete [idx]

Deletes the added watchpoint, as shown in the following example:

When idx is entered, the corresponding watchpoint will be deleted; when idx is not entered, all watchpoints will be deleted.

```
(tdb) w
index    cmd_type cmd_id core_id enabled                                                value
   1 CMDType.dma      2       0       y       %G0: memref<1x32x3x36xf32, strides: [3456, 108, 36,F
↪1]>
   2 CMDType.dma      1       0       y %R0: memref<1x3x110x322xf32, strides: [35424, 35424, 322,
↪ 1]>
   3 CMDType.tiu     11       0      y %R13: memref<1x32x54x160xsi16, strides: [8640, 8640, 160,
↪ 1]>
(tdb) w delete 1
(tdb) w
index    cmd_type cmd_id core_id enabled                                                value
   2 CMDType.dma      1       0       y %R0: memref<1x3x110x322xf32, strides: [35424, 35424, 322,
↪ 1]>
   3 CMDType.tiu     11       0      y %R13: memref<1x32x54x160xsi16, strides: [8640, 8640, 160,
↪ 1]>
(tdb) w delete
(tdb) w
index cmd_type cmd_id core_id enabled value
```

15.5.6 py feature

The py feature can execute python commands directly in the TDB environment, the method of use is as follows:

```
(tdb) py a = 2
(tdb) py b = a + 2
(tdb) py print(b)
4
```

15.6 BModel Disassembler

BModel Disassembler can disassemble the bmodel file to get the assembly code of atomic instruction in MLIR format, which is asm instruction. They are used to analyze the final runtime instruction of the model.

When you use it, you need to enter the Context directory first, and the method of use is as follows:

```
$ bmodel_dis [-h] [--format {mlir,reg,bits,bin,reg-set}] bmodels [bmodels ...]
```

where --format can specify the output format, which default use mlir format, bmodels means the bmodel file to be parsed. Example usage is as follows:

```
$ bmodel_dis compilation.bmodel
$ bmodel_dis --format reg compilation.bmodel
```

The output can be saved to a file as follows:

```
$ bmodel_dis compilation.bmodel > dis_bmodel.mlir
$ bmodel_dis --format reg compilation.bmodel > dis_reg.json
```

15.7 BModel Checker

BModel Checker is used to find errors (codegen errors) in a bmodel, if during model_deploy you find that the generated bmodel cannot be aligned with the tpu' s reference data, you can use this tool to locate the error.BModel for BM1684, BM1684X, BM1688 processors is currently supported.

When generating a bmodel file, the model_deploy command needs to add the --debug and -compare_all parameters, which are used to save the tpu_output.npz file and retain intermediate data.

The usage is as follows:

```
$ bmodel_checker [-h]
                 [--tolerance TOLERANCE]
                 [--report REPORT] [--fail_fast]
                 [--quiet] [--no_interactive]
                 [--dump_mode {failed,all,never}]
                 context_dir reference_data
```

The main parameters of bmodel_checker are described as follows:

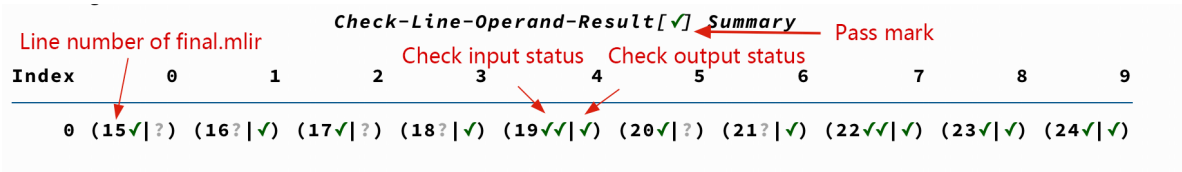
Table 15.5: Function of bmodel_checker parameters

Name	Required?	Explanation
context_dir	Y	bmodel file directory
reference_data	Y	tpu_output.npz file location
quiet	N	The execution progress bar is not displayed
fail_fast	N	Stop at the first error
dump_mode	N	Specifies the data to be downloaded by the dump command, the default value is failed, it can also be all or never
tolerance	N	Specify comparison tolerances, default is "0.99,0.90"
report	N	Save the wrong data to file, default is failed_bmodel_outputs.npz
no_interactive	N	After running bmodel_checker, it exits TDB mode directly

To use bmodel_checker you need to enter the Context directory, as shown in the following example:

```
$ bmodel_checker ./ ../yolov5s_bm1684x_f32_tpu_outputs.npz
$ bmodel_checker ./ ../yolov5s_bm1684x_f32_tpu_outputs.npz --fail_fast
$ bmodel_checker ./ ../yolov5s_bm1684x_f32_tpu_outputs.npz --tolerance 0.99,0.90
```

After executing the bmodel_checker command, the checker report is output and the error outputs are saved to the failed_bmodel_outputs.npz file, which is described below:



where the "check" means pass, which the data is checked and its similarity conforms to cos > 0.99, eul > 0.9 (This is the default threshold, which can be modified by the tolerance parameter); The "cross" means an error, which the data does not reach the required similarity; The "question mark" means an unknown, which the reference data is not found and the correctness of the data cannot be determined. A complete checker report of a yolov5s model is shown below:

After outputting the check report, it automatically enters the interactive mode. The interactive mode provides a detailed view of the errors and also allows you to quickly jump between lines, as shown in the following example of a cswin_tiny model.

check summary

The check report can be reprinted by using the check summary command:

It is worth noting that you can aggregate inputs and outputs with the same line numbers using the check summary reduce command.


(tdb) check summary
(21√|?) (22?|?) (23?|?) (24???|√) (27√|√) (25?|?) (26?|?) (28√??|√) (21√|?) (31√|√) (29?|?) (30?|?) (33√??|√) (32√|√) (36√|√) (34?|?) (35?|?) (37√??|√)
(39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√)
(28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√)
(36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√)
(40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√)
(33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√)
(38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√)
(21√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (21√|?) (31√|√) (33√??|√) (32√|√) (36√|√)
(37√??|√) (39√|√) (38√|√) (24???|√) (40√|√) (27√|√) (28√??|√) (54√|?) (31√|√) (33√??|√) (32√|√) (36√|√) (37√??|√) (56?|?) (39√|√) (38√|√) (55?|?)
(58???|√) (57√|?) (40√|√) (60√|√) (59√|?) (63?√|√) (61?|?) (62?|?) (64???|√) (66√|√) (65?|?) (68√√|√) (67?|?) (69√??|√) (72√|√) (70?|?) (71?|?) (73√??|√)
(54√|?) (76√|√) (74?|?) (75?|?) (78√??|√) (77√|√) (79√|√) (58???|√) (80√|√) (57√|?) (60√|√) (59√|?) (63?√|√) (64???|√) (66√|√) (68√√|√) (69√??|√) (72√|√)
(73√??|√) (54√|?) (76√|√) (78√??|√) (77√|√) (79√|√) (58???|√) (80√|√) (57√|?) (60√|√) (59√|?) (63?√|√) (64???|√) (66√|√) (68√√|√) (69√??|√) (72√|√)
(73√??|√) (76√|√) (78√??|√) (77√|√) (79√|√) (160?|?) (80√|√) (158√|?) (159?|?) (161???|√) (164√|√) (162?|?) (163?|?) (165√??|√) (166√|√) (169?√|√)
(167?|?) (168?|?) (170√??|√) (173√|√) (171?|?) (172?|?) (175√??|√) (174√|?) (177√|√) (176?|?) (179√√|√) (178?|?) (180???|√) (183√|√) (181?|?) (182?|?)
(184√√|√) (185√??|√) (188√|√) (186?|?) (187?|?) (189√??|√) (192√|√) (190?|?) (191?|?) (193√??|√) (196√|√) (194?|?) (195?|?) (198√??|√) (197?|?) (200√|√)
(199?|?) (201√??|√) (204√|√) (202?|?) (203?|?) (205√√|√) (207√??|√) (206?|?) (209√|√) (208?|?) (210√??|√) (213√|√) (211?|?) (212?|?) (214√√|√) (216√??|√)
(215?|?) (218√|√) (217?|?) (219√??|√) (222√|√) (220?|?) (221?|?) (223√√|√) (224√??|√) (227√|√) (225?|?) (226?|?) (228√√|√) (230√??|√) (229?|?) (232√|√)
(231?|?) (234√??|√) (233?|?) (236√|√) (235?|?) (239√??|√) (237?|?) (238?|?) (241√|√) (240?|?) (242√??|√) (244√|√) (243?|?) (246√??|√) (245?|?) (248√|√)
(247?|?) (249√√|√) (252√??|√) (250?|?) (251?|?) (253√|√) (254√√|√) (256√??|√) (255?|?) (258√|√) (257?|?) (261√??|√) (259?|?) (260?|?) (262√|√) (263√|√)
(264√|√) (265√|√) (266√√√√|√) (268√??|√) (267?|?) (270√|√) (269?|?) (272√??|√) (271?|?) (274√|√) (273?|?) (275√|√) (276√√|√) (278√??|√) (277√|√) (281√|√)
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check data

(tdb) check data [file-line]

where file-line is the line number in the checker report, which corresponds to the line number of final.mlir . This command gives a description of all the input and output data of the command corresponding to file-line, an example is shown below:

```
(tdb) check data 291
```

291	loc_index	owner	value name	value type	compare	index
0	205	tpu.Add	/stage2.0/attns.1/MatMul_1_output_0_MatMul	operand	√	0
1	205	tpu.Add	/stage2.0/attns.1/Transpose_7_output_0_Transpose	operand	√	1
2	205	tpu.Add	/stage2.0/attns.1/Add_output_0_Add	result	x	2

(tdb) check data [file-line] [index]

Where index is the index of the data output by the check data [file-line] command. This command gives detailed information about the corresponding index data, and an example of comparing the correct data is shown below:

```
(tdb) check data 291 0
```

value-Info

opcode	tpu.Add
core_id	0
value	{ "address": 687195987968, "layout": "continuous", "memory_type": "<14x2x56x32xsi8>", "name": "/stage2.0/attns.1/MatMul_1_output_0_MatMul", "reshape": "", "slice": "[...]", "type": "tensor<14x2x56x32x!quant.uniform<i8:f32, 0.033072317322834645>, 687195987968 : i64>" }
tiu_dma_id (before codegen)	[7959, 553]
tiu_dma_id (after codegen)	[7971, 565]
compare	√
value type	operand

An example of comparison error data is shown below:

CHAPTER 16

Appendix.07: Supported Operations

16.1 List of operators currently supported by TPU-MLIR

Table 16.1: A

Onnx	Pytorch	Caffe	TOP
Abs	aten::abs	AbsVal	top.Abs
Acos	aten::acos	ArgMax	top.AdaptiveAvgPool
Add	aten::adaptive_avg_pool1		top.Add
And	aten::adaptive_avg_pool2		top.AddConst
ArgMax	aten::add		top.Arange
ArgMin	aten::addmm		top.Arccos
Atan	aten::arange		top.Arctanh
Atanh	aten::argmax		top.Arg
AveragePool	aten::argmin		top.Attention
	aten::atan		top.AvgPool
	aten::atanh		
	aten::avg_pool1d		
	aten::avg_pool2d		
	aten::avg_pool3d		

Table 16.2: B

Onnx	Pytorch	Caffe	TOP
BatchNormalization	aten::baddbmm	BatchNorm	top.BatchNorm
	aten::batch_norm	BN	top.BatchNormBwd
	aten::bmm		top.BatchNormTrain
			top.BinaryConstShift
			top.BinaryShift

Table 16.3: C

Onnx	Pytorch	Caffe	TOP
Cast	aten::cat	Concat	top.Cast
Ceil	aten::ceil	ContinuationIndicator	top.Ceil
Clip	aten::channel_shuffle	Convolution	top.Clip
Concat	aten::chunk	ConvolutionDepthwise	top.Compare
Constant	aten::clamp	Crop	top.CompareConst
ConstantOfShape	aten::constant_pad_nd		top.Concat
Conv	aten::contiguous		top.ConstantFill
ConvTranspose	aten::_convolution		top.Conv
Cos	aten::_convolution_mode		top.ConvBwd_Weight
CumSum	aten::copy		top.Copy
	aten::cos		top.Cos
	aten::cosh		top.Cosh
	aten::cumsum		top.Csc
			top.CumSum
			top.Custom

Table 16.4: D

Onnx	Pytorch	Caffe	TOP
DepthToSpace	aten::detach	Deconvolution	top.Deconv
DequantizeLinear	aten::div	DetectionOutput	top.DeformConv2D
Div	aten::dot	Dropout	top.DepackRaw
Dropout	aten::dropout	DummyData	top.Depth2Space
			top.DequantInt
			top.DequantizeLinear
			top.DetectionOutput
			top.Div
			top.DivConst
			top.DtypeCast

Table 16.5: E

Onnx	Pytorch	Caffe	TOP
Einsum	aten::elu	Eltwise	top.Einsum
Elu	aten::embedding	Embed	top.Elu
Equal	aten::empty		top.EmbDenseBwd
Erf	aten::eq		top.Erf
Exp	aten::erf		top.Exp
Expand	aten::exp		top.Expand
	aten::expand		
	aten::expand_as		

Table 16.6: F

Onnx	Pytorch	Caffe	TOP
Flatten	aten::flatten	Flatten	top.Flatten
Floor	aten::flip	FrcnDetection	top.Floor
	aten::floor		top.FrcnDetection
	aten::floor_divide		
	aten::frobenius_norm		

Table 16.7: G

Onnx	Pytorch	Caffe	TOP
Gather	aten::gather		top.GELU
GatherElements	aten::ge		top.GRU
GatherND	aten::gelu		top.Gather
GELU	aten::grid_sampler		top.GatherElements
Gemm	aten::group_norm		top.GatherND
GlobalAveragePool	aten::gru		top.GridSampler
GlobalMaxPool	aten::gt		top.GroupNorm
Greater			top.GroupNormTrain
GreaterOrEqual			
GridSample			
GroupNormaliza-tion			
GRU			

Table 16.8: H

Onnx	Pytorch	Caffe	TOP
HardSigmoid	aten::hardsigmoid		top.HardSigmoid
HardSwish	aten::hardswish		top.HardSwish
	aten::hardtanh		

Table 16.9: I

Onnx	Pytorch	Caffe	TOP
Identity	aten::index	ImageData	top.If
If	aten::index_put_	InnerProduct	top.IndexPut
InstanceNormalization	aten::index_put	Input	top.Input
	aten::index_select	Interp	top.InstanceNorm
	aten::instance_norm		top.Interp

Table 16.10: L

Onnx	Pytorch	Caffe	TOP
LayerNormalization	aten::layer_norm	LRN	top.LRN
LeakyRelu	aten::le	LSTM	top.LSTM
Less	aten::leaky_relu	Lstm	top.LayerNorm
LessOrEqual	aten::linalg_norm		top.LayerNormBwd
Log	aten::linear		top.LayerNormTrain
LogSoftmax	aten::log		top.LeakyRelu
Loop	aten::log2		top.List
LRN	aten::log_sigmoid		top.Log
LSTM	aten::log_softmax		top.LogB
	aten::lstm		top.LogicalAnd
	aten::lt		top.Loop
			top.Lut

Table 16.11: M

Onnx	Pytorch	Caffe	TOP
MatMul	aten::masked_fill	MatMul	top.MaskedFill
Max	aten::matmul	Mish	top.MatMul
MaxPool	aten::max		top.MatchTemplate
Min	aten::max_pool1d		top.Max
Mul	aten::max_pool2d		top.MaxConst
	aten::max_pool3d		top.MaxPool
	aten::mean		top.MaxPoolWithMask
	aten::meshgrid		top.MaxUnpool
	aten::min		top.MeanRstd
	aten::mish		top.MeanStdScale
	aten::mm		top.MeshGrid
	aten::mul		top.Min
	aten::mv		top.MinConst
			top.Mish
			top.Mul
			top.MulConst

Table 16.12: N

Onnx	Pytorch	Caffe	TOP
Neg	aten::ne	Normalize	top.Nms
NonMaxSuppression	aten::neg		top.NonZero
NonZero	aten::new_full		top.None
Not	aten::new_ones		top.Normalize
	aten::new_zeros		
	aten::nonzero		

Table 16.13: O

Onnx	Pytorch	Caffe	TOP
OneHot	aten::ones		
	aten::ones_like		

Table 16.14: P

Onnx	Pytorch	Caffe	TOP
Pad	aten::pad	Padding	top.PRelu
PixelNormalization	aten::permute	Permute	top.Pack
Pow	aten::pixel_shuffle	Pooling	top.Pad
PRelu	aten::pixel_unshuffle	Power	top.Permute
	aten::pow	PReLU	top.PixelNorm
	aten::prelu	PriorBox	top.PoolMask
		Proposal	top.Pow
			top.Pow2
			top.Preprocess
			top.PriorBox
			top.Proposal

Table 16.15: Q

Onnx	Pytorch	Caffe	TOP
QuantizeLinear			top.QuantizeLinear

Table 16.16: R

Onnx	Pytorch	Caffe	TOP
Range	aten::reflection_pad1d	ReLU	top.RMSNorm
Reciprocal	aten::reflection_pad2d	ReLU6	top.ROIPooling
ReduceL1	aten::relu	Reorg	top.Range
ReduceL2	aten::remainder	Reshape	top.Reciprocal
ReduceMax	aten::repeat	RetinaFaceDetection	top.Reduce
ReduceMean	aten::replication_pad1d	Reverse	top.Relu
ReduceMin	aten::replication_pad2d	ROIPooling	top.Remainder
ReduceProd	aten::reshape		top.Repeat
ReduceSum	aten::roll		top.RequantFp
Relu	aten::rsqrt		top.RequantInt
Reshape	aten::rsub		top.Reshape
Resize			top.RetinaFaceDetection
RoiAlign			top.Reverse
Round			top.RoiAlign
			top.Round
			top.Rsqrt

Table 16.17: S

Onnx	Pytorch	Caffe	TOP
ScatterElements	aten::scatter	Scale	top.Scale
ScatterND	aten::select	ShuffleChannel	top.ScaleLut
Shape	aten::sigmoid	Sigmoid	top.ScatterElements
Sigmoid	aten::sign	Silence	top.ScatterND
Sign	aten::silu	Slice	top.Shape
Sin	aten::sin	Softmax	top.ShuffleChannel
Slice	aten::sinh	Split	top.SiLU
Softmax	aten::size		top.Sigmoid
Softplus	aten::slice		top.Sign
SpaceToDepth	aten::softmax		top.Sin
Split	aten::softplus		top.Sinh
Sqrt	aten::sort		top.Size
Squeeze	aten::split		top.Slice
Sub	aten::split_with_sizes		top.SliceAxis
Sum	aten::sqrt		top.Softmax
	aten::squeeze		top.SoftmaxBwd
	aten::stack		top.Softplus
	aten::sub		top.Softsign
	aten::sum		top.Sort
			top.Split
			top.Sqrt
			top.Squeeze
			top.StridedSlice
			top.Sub
			top.SubConst
			top.SwapChannel
			top.SwapDimInner

Table 16.18: T

Onnx	Pytorch	Caffe	TOP
Tanh	aten::t	TanH	top.Tan
Tile	aten::tan	Tile	top.Tanh
TopK	aten::tanh		top.Tile
Transpose	aten::tile		top.TopK
Trilu	aten::to		top.Transpose
	aten::topk		top.Trilu
	aten::transpose		top.Tuple
	aten::type_as		

Table 16.19: U

Onnx	Pytorch	Caffe	TOP
Unsqueeze	aten::unbind	Upsample	top.UnTuple
Upsample	aten::unsqueeze		top.Unpack
	aten::upsample_bilinear2d		top.Unsqueeze
	aten::upsample_linear1d		top.Upsample
	aten::upsample_nearest1d		
	aten::upsample_nearest2d		
	aten::upsample_nearest3d		

Table 16.20: V

Onnx	Pytorch	Caffe	TOP
	aten::view		top.Variance
			top.View

Table 16.21: W

Onnx	Pytorch	Caffe	TOP
Where	aten::where		top.Weight
			top.WeightReorder
			top.Where

Table 16.22: Y

Onnx	Pytorch	Caffe	TOP
		YoloDetection	top.Yield
			top.YoloDetection
			top.Yuv2rgbFormula

Table 16.23: Z

Onnx	Pytorch	Caffe	TOP
	aten::zeros		
	aten::zeros_like		