TPU-MLIR Technical Reference Manual

Release 6.1.6

SOPHGO

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Technical Support

Address

Building 1, Zhongguancun Integrated Circuit Design Park (ICPARK), No. 9 Fenghao East Road, Haidian District, Beijing

Postcode

100094

URL

https://www.sophgo.com/

Email

sales@sophgo.com

Tel

+86-10-57590723
+86-10-57590724

Release Record

Version	Release date	Explanation
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 a 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 the processors. The code has been open-sourced to github: https://github.com/sophgo/tpu-mlir .

The overall architecture of TPU-MLIR is as follows:

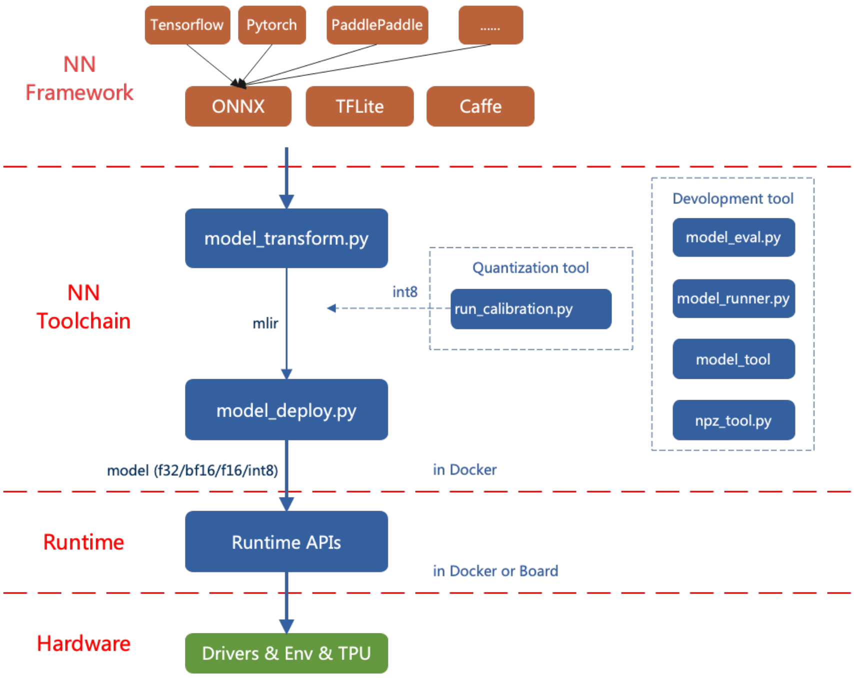

Fig. 1.1: TPU-MLIR overall architecture

The current directly supported frameworks are onnx, caffe and tflite. 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.py` and converting the mlir file to bmodel by `model_deploy.py`. To obtain an INT8 model, you need to call `run_calibration.py` to generate a quantization table and pass it to `model_deploy.py`.

This article presents the implementation details to guide future development.

CHAPTER 2

Environment Setup

This chapter describes the development environment configuration. The code is compiled and run in docker.

2.1 Code Download

Github link: https://github.com/sophgo/tpu-mlir

After cloning this code, it needs to be compiled in docker. For specific steps, please refer to the following.

2.2 Docker Configuration

TPU-MLIR is developed in the Docker environment, and it can be compiled and run after Docker is configured.

Download the required image from DockerHub https://hub.docker.com/r/sophgo/tpuc_dev :

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

Make sure the installation package 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
# "myname" is just an example, you can use any name you want
```

Note that the path of the TPU-MLIR project in docker should be /workspace/tpu-mlir

2.3 ModelZoo (Optional)

TPU-MLIR comes with the yolov5s model. If you want to run other models, you need to download them from ModelZoo. The path is as follows:

https://github.com/sophgo/model-zoo

After downloading, put it in the same directory as tpu-mlir. The path in docker should be /workspace/model-zoo

2.4 Compilation

In the docker container, the code is compiled as follows:

```
$ cd tpu-mlir
$ source ./envsetup.sh
$ ./build.sh
```

Regression validation:

```
# This project contains the yolov5s.onnx model, which can be used directly for validation
$ pushd regression
$ python run_model.py yolov5s
$ popd
```

You can validate more networks with model-zoo, but the whole regression takes a long time:

```
# The running time is very long, so it is not necessary
$ pushd regression
$ ./run_all.sh
$ popd
```

CHAPTER 3

User Interface

This chapter introduces the user interface.

3.1 Introduction

The basic procedure is transforming the model into a mlir file with **model_transform.py**, and then transforming the mlir into the corresponding model with **model_deploy.py**. Calibration is required if you need to get the INT8 model. The general process is shown in the figure (User interface 1).

Other complex cases such as image input with preprocessing and multiple inputs are also supported, as shown in the figure (User interface 2).

TFLite model conversion is also supported, with the following command:

```
# TFLite conversion example
$ model_transform.py \
    --model_name resnet50_tf \
    --model_def  ../resnet50_int8.tflite \
    --input_shapes [[1,3,224,224]] \
    --mean 103.939,116.779,123.68 \
    --scale 1.0,1.0,1.0 \
    --pixel_format bgr \
    --test_input ../image/dog.jpg \
    --test_result resnet50_tf_top_outputs.npz \
    --mlir resnet50_tf.mlir
$ model_deploy.py \
   --mlir resnet50_tf.mlir \
   --quantize INT8 \
```

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```
    --processor bm1684x \
    --test_input resnet50_tf_in_f32.npz \
    --test_reference resnet50_tf_top_outputs.npz \
    --tolerance 0.95,0.85 \
    --model resnet50_tf_1684x.bmodel
```

Supporting the conversion of Caffe models, the commands are as follows:

```
# Caffe conversion example
$ model_transform.py \
    --model_name resnet18_cf \
    --model_def ../resnet18.prototxt \
    --model_data ../resnet18.caffemodel \
    --input_shapes [[1,3,224,224]] \
    --mean 104,117,123 \
    --scale 1.0,1.0,1.0 \
    --pixel_format bgr \
    --test_input ../image/dog.jpg \
    --test_result resnet50_cf_top_outputs.npz \
    --mlir resnet50_cf.mlir
# The call of model_deploy is consistent with onnx
# ......
```

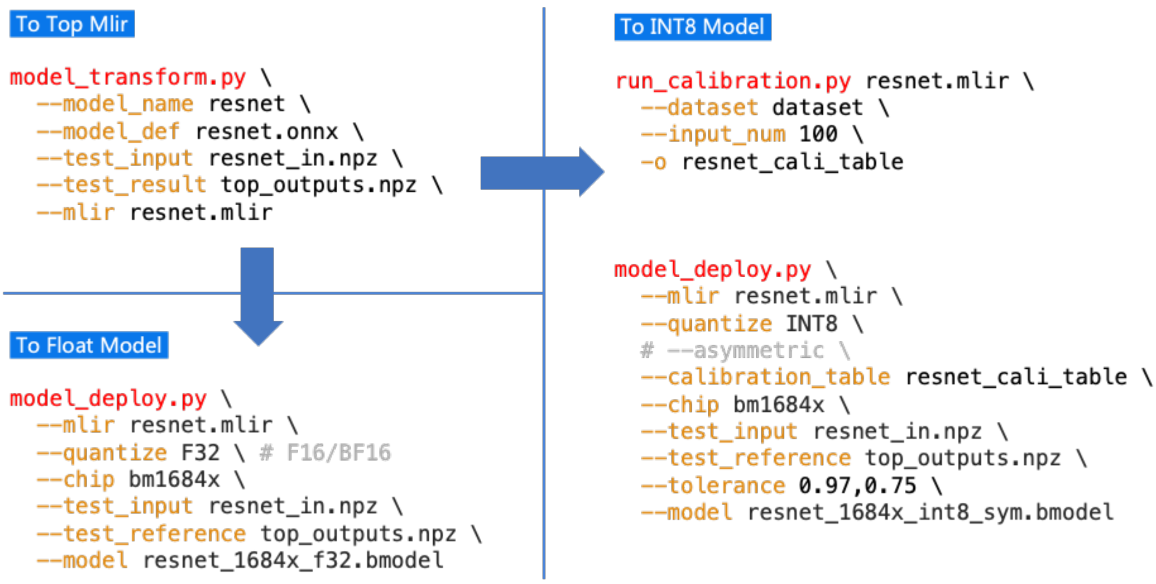

Fig. 3.1: User interface 1

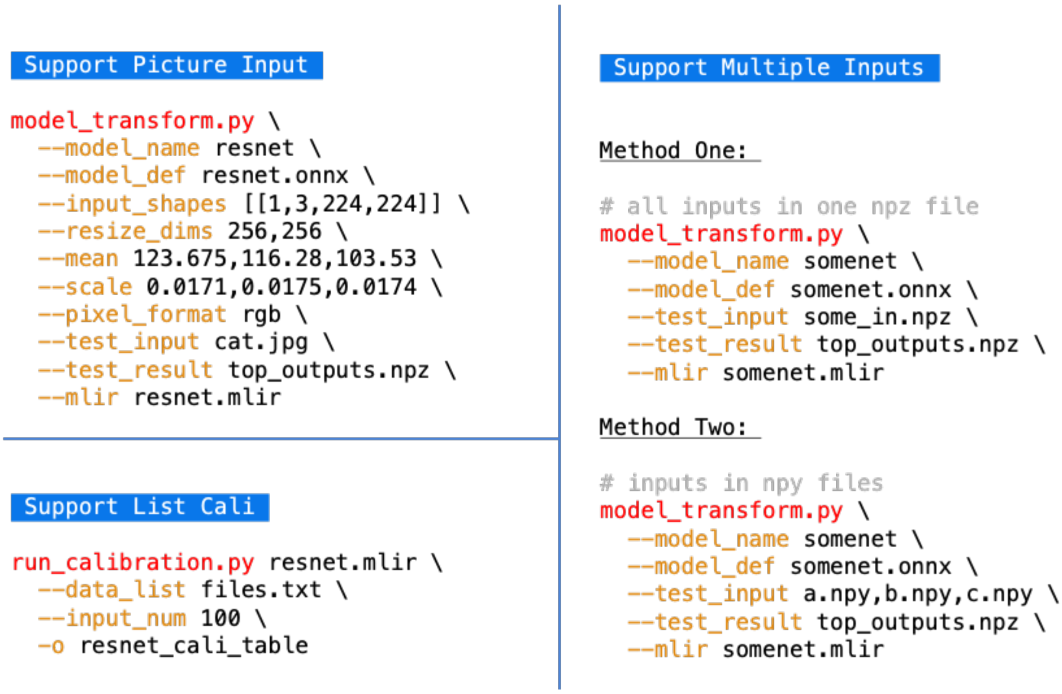

Fig. 3.2: User interface 2

3.2 model_transform.py

Used to convert various neural network models into MLIR files, the supported parameters are shown below:

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)
model_data	N	Specify the model weight file, required when it is caffe model (corresponding to the ‘.caffemodel’ file)
input_shapes	N	The shape of the input, 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
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
add_postprocess	N	add postprocess op into bmodel, set the type of post handle op such as yolov3/yolov3_tiny/yolov5/ssd
test_input	N	The input file for verification, which can be an image, npy or npz. No verification will be carried out if it is not specified
test_result	N	Output file to save verification result
excepts	N	Names of network layers that need to be excluded from verification. Separated by comma
onnx_sim	N	option for onnx-sim, currently only support ‘skip_fuse_bn’ args
mlir	Y	The output mlir file name (including path)
debug	N	If open debug, immediate model file will keep; or will remove after conversion done
tolerance	N	Minimum similarity tolerance to model transform

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.

3.3 run_calibration.py

Use a small number of samples for calibration to get the quantization table of the network (i.e., the threshold/min/max of each layer of op).

Supported parameters:

Table 3.2: Function of run_calibration 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")
input_num	N	The number of input for calibration. Use all samples if it is 0
tune_num	N	The number of fine-tuning samples. 10 by default
tune_list	N	Tune list file contain all input for tune
histogram_bin_num	N	The number of histogram bins. 2048 by default
o	Y	Name of output calibration table file
debug_cmd	N	debug cmd

A sample calibration table is as follows:

```
# genetated time: 2022-08-11 10:00:59.743675
# histogram number: 2048
# sample number: 100
# tune number: 5
###
# op_name    threshold    min    max
images 1.0000080 0.0000000 1.0000080
122_Conv 56.4281803 -102.5830231 97.6811752
124_Mul 38.1586478 -0.2784646 97.6811752
125_Conv 56.1447888 -143.7053833 122.0844193
127_Mul 116.7435987 -0.2784646 122.0844193
128_Conv 16.4931355 -87.9204330 7.2770605
130_Mul 7.2720342 -0.2784646 7.2720342
......
```

It is divided into 4 columns: the first column is the name of the Tensor; the second column is the threshold (for symmetric quantization); The third and fourth columns are min/max, used for asymmetric quantization.

3.4 run_qtable.py

Use **run_qtable.py** to generate a mixed precision quantization table. The relevant parameters are described as follows:

Supported parameters:

Table 3.3: Function of run_qtable.py 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	N	The quantization table path
chip	Y	The platform that the model will use. Support bm1688/bm1684x/bm1684/cv186x/cv183x/cv182x/cv181x/cv180x
input_num	N	The number of input for calibration. Use all samples if it is 10
expected_cos	N	Expected net output cos
global_compare_laye	N	Global compare layers, for example: layer1,layer2 or layer1:0.3,layer2:0.7
fp_type	N	The precision type, default auto
base_quantize_table	N	Base quantize table
loss_table	N	The output loss table, default full_loss_table.txt
o	N	Output mixed precision quantization table

A sample mixed precision quantization table is as follows:

```
# genetated time: 2022-11-09 21:35:47.981562
# sample number: 3
# all int8 loss: -39.03119206428528
# chip: bm1684x  mix_mode: F32
###
# op_name   quantize_mode
conv2_1/linear/bn F32
conv2_2/dwise/bn  F32
conv6_1/linear/bn F32
```

It is divided into 2 columns: the first column corresponds to the name of the layer, and the second column corresponds to the quantization mode.

At the same time, a loss table will be generated, the default is **full_loss_table.txt**, the sample is as follows:

```
# genetated time: 2022-11-09 22:30:31.912270
# sample number: 3
```

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```
# all int8 loss: -39.03119206428528
# chip: bm1684x  mix_mode: F32
###
No.0 : Layer: conv2_1/linear/bn Loss: -36.14866065979004
No.1 : Layer: conv2_2/dwise/bn  Loss: -37.15774385134379
No.2 : Layer: conv6_1/linear/bn Loss: -38.44639046986898
No.3 : Layer: conv6_2/expand/bn Loss: -39.7430411974589
No.4 : Layer: conv1/bn          Loss: -40.067259073257446
No.5 : Layer: conv4_4/dwise/bn  Loss: -40.183939139048256
No.6 : Layer: conv3_1/expand/bn Loss: -40.1949667930603
No.7 : Layer: conv6_3/expand/bn Loss: -40.61786969502767
No.8 : Layer: conv3_1/linear/bn Loss: -40.9286363919576
No.9 : Layer: conv6_3/linear/bn Loss: -40.97952524820963
No.10: Layer: block_6_1         Loss: -40.987406969070435
No.11: Layer: conv4_3/dwise/bn  Loss: -41.18325670560201
No.12: Layer: conv6_3/dwise/bn  Loss: -41.193763415018715
No.13: Layer: conv4_2/dwise/bn  Loss: -41.2243926525116
......
```

It represents the loss of the output obtained after the corresponding Layer is changed to floating point calculation.

3.5 model_deploy.py

Convert the mlir file into the corresponding model, the parameters are as follows:

Table 3.4: Function of model_deploy parameters

Name	Required?	Explanation
mlir	Y	Mlir file
quantize	Y	Quantization type (F32/F16/BF16/INT8)
quant_input	N	Strip input type cast in bmodel, need outside type conversion
quant_input_list	N	choose index to strip cast, such as 1,3 means first & third input`s cast
quant_output	N	Strip output type cast in bmodel, need outside type conversion
quant_output_list	N	Choose index to strip cast, such as 1,3 means first & third output`s cast
chip	Y	The platform that the model will use. Support bm1688/bm1684x/bm1684/cv186x/cv183x/cv182x/cv181x/cv180x.
calibration_table	N	The quantization table path. Required when it is INT8 quantization
ignore_f16_overflow	N	Operators with F16 overflow risk are still implemented according to F16; otherwise, F32 will be implemented by default, such as LayerNorm
tolerance	N	Tolerance for the minimum similarity between MLIR quantized and MLIR fp32 inference results
test_input	N	The input file for verification, which can be an image, npy or npz. No verification will be carried out if it is not specified
test_reference	N	Reference data for verifying mlir tolerance (in npz format). It is the result of each operator
excepts	N	Names of network layers that need to be excluded from verification. 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)
debug	N	to keep all intermediate files for debug
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
asymmetric	N	Do INT8 asymmetric quantization
dynamic	N	Do compile dynamic
includeWeight	N	Include weight in tosa.mlir
customization_format	N	Pixel format of input frame to the model
compare_all	N	Decide if compare all tensors when lowering
num_device	N	The number of devices to run for distributed computation
num_core	N	The number of Tensor Computing Processor cores used for parallel computation
skip_verification	N	Skip checking the correctness of bmodel
merge_weight	N	Merge weights into one weight binary with previous generated cvimodel
model_version	N	If need old version cvimodel, set the verion, such as 1.2
q_group_size	N	Group size for per-group quant, only used in W4A16 quant mode

3.6 Other Tools

3.6.1 model_runner.py

Model inference. mlir/pytorch/onnx/tflie/bmodel/prototxt supported.

Example:

```
$ model_runner.py \
  --input sample_in_f32.npz \
  --model sample.bmodel \
  --output sample_output.npz
```

Supported parameters:

Table 3.5: Function of model_runner parameters

Name	Required?	Explanation
input	Y	Input npz file
model	Y	Model file (mlir/pytorch/onnx/tflie/bmodel/prototxt)
dump_all_tensors	N	Export all the results, including intermediate ones, when specified

3.6.2 npz_tool.py

npz will be widely used in TPU-MLIR project for saving input and output results, etc. npz_tool.py is used to process npz files.

Example:

```
# Check the output data in sample_out.npz
$ npz_tool.py dump sample_out.npz output
```

Supported functions:

Table 3.6: npz_tool functions

Function	Description
dump	Get all tensor information of npz
compare	Compare difference of two npz files
to_dat	Export npz as dat file, contiguous binary storage

3.6.3 visual.py

visual.py is an visualized network/tensor compare application with interface in web browser, if accuracy of quantized network is not as good as expected, this tool can be used to investigate the accuracy in every layer.

Example:

```
# use TCP port 9999 in this example
$ visual.py \
  --f32_mlir netname.mlir \
  --quant_mlir netname_int8_sym_tpu.mlir \
  --input top_input_f32.npz --port 9999
```

Supported functions:

Table 3.7: visual functions

Function	Description
f32_mlir	fp32 mlir file
quant_mlir	quantized mlir file
input	test input data for networks, can be in jpeg or npz format.
port	TCP port used for UI, default port is 10000, the port should be mapped when starting docker
host	Host ip, default:0.0.0.0
manual_run	if net will be automaticall inferenced when UI is opened, default is false for auto inference

Notice: --debug flag should be opened during model_deploy.py to save intermediate files for visual.py. More details refer to (visual tool introduction)

3.6.4 gen_rand_input.py

During model transform, if you do not want to prepare additional test data (test_input), you can use this tool to generate random input data to facilitate model verification.

The basic procedure is transforming the model into a mlir file with model_transform.py. This step does not perform model verification. And then use gen_rand_input.py to read the mlir file generated in the previous step and generate random test data for model verification. Finally, use model_transform.py again to do the complete model transformation and verification.

Example:

```
# To MLIR
$ model_transform.py \
    --model_name yolov5s \
    --model_def ../regression/model/yolov5s.onnx \
```

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```
    --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 \
    --mlir yolov5s.mlir

# Generate dummy input. Here is a pseudo test picture.
$ python gen_rand_input.py
    --mlir yolov5s.mlir \
    --img --output yolov5s_fake_img.png

# Verification
$ model_transform.py \
    --model_name yolov5s  \
    --model_def ../regression/model/yolov5s.onnx \
    --input_shapes [[1,3,640,640]] \
    --mean 0.0,0.0,0.0 \
    --scale 0.0039216,0.0039216,0.0039216 \
    --test_input yolov5s_fake_img.png    \
    --test_result yolov5s_top_outputs.npz \
    --keep_aspect_ratio    --pixel_format rgb \
    --output_names 350,498,646 \
    --mlir yolov5s.mlir
```

For more detailed usage, please refer to the following:

```
# Value ranges can be specified for multiple inputs.
$ python gen_rand_input.py \
  --mlir ernie.mlir \
  --ranges [[0,300],[0,0]] \
  --output ern.npz

# Type can be specified for the input.
$ python gen_rand_input.py \
  --mlir resnet.mlir \
  --ranges [[0,300]] \
  --input_types si32 \
  --output resnet.npz

# Generate random image
$ python gen_rand_input.py
    --mlir yolov5s.mlir \
    --img --output yolov5s_fake_img.png
```

Supported functions:

Table 3.8: gen_rand_input functions

Name	Required?	Explanation
mlir	Y	The input mlir file name (including path)
img	N	Used for CV tasks to generate random images, otherwise generate npz files. The default image value range is [0,255], the data type is 'uint8', and cannot be changed.
ranges	N	Set the value ranges of the model inputs, expressed in list form, such as [[0,300],[0,0]]. If you want to generate a picture, you do not need to specify the value range, the default is [0,255]. In other cases, value ranges need to be specified.
input_types	N	Set the model input types, such as 'si32,f32'. 'si32' and 'f32' types are supported. False by default, and it will be read from mlir. If you generate an image, you do not need to specify the data type, the default is 'uint8'.
output	Y	The names of the output.

Notice: CV-related models usually perform a series of preprocessing on the input image. To ensure that the model is verificated correctly, you need to use '–img' to generate a random image as input. Random npz files cannot be used as input. It is worth noting that random input may cause model correctness verification to fail, especially NLP-related models, so it is recommended to give priority to using real test data.

CHAPTER 4

Overall Design

4.1 Layered

TPU-MLIR treats the compilation process of the network model in two layers.

Top Dialect
: Hardware-independent layer, including graph optimization, quantization and inference, etc.

Tpu Dialect
: Hardware-related layer, including weight reordering, operator slicing, address assignment, inference, etc.

The overall flow is shown in the (TPU-MLIR overall process) diagram, where the model is gradually converted into final instructions by Passes. Here is a detailed description of what functions each Pass does in the Top layer and the Tpu layer. The following chapters will explain the key points of each Pass in detail.

4.2 Top Pass

shape-infer
: Do shape inference, and constant folder

canonicalize
: Graph optimization related to specific OP, such as merging relu into conv, shape merge, etc.

extra-optimize
: Do extra patterns, such as get FLOPs, remove unuse output, etc.

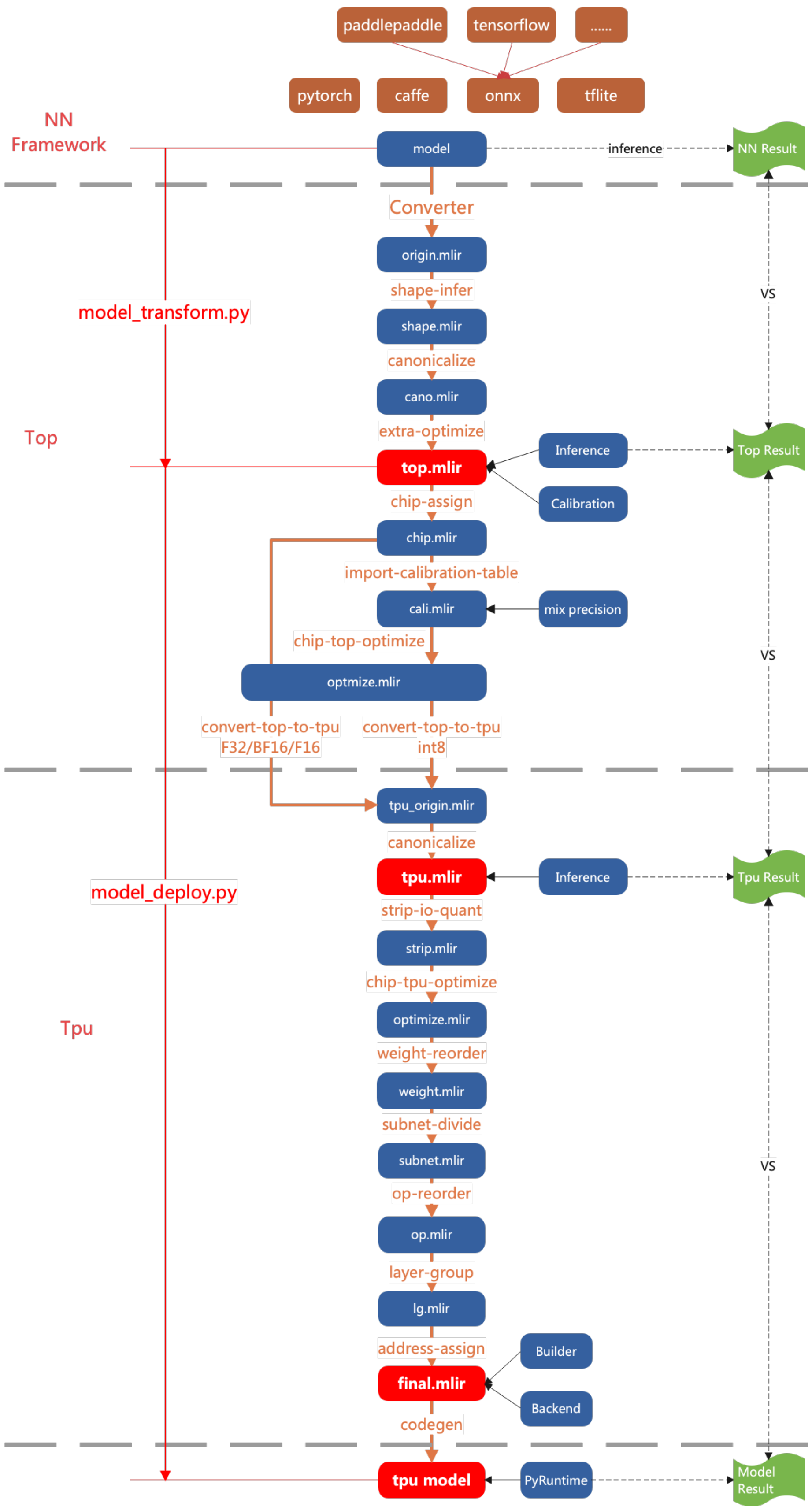


Fig. 4.1: TPU-MLIR overall process

processor-assign
Assign processor, such as bm1684x, cv183x, etc; and adjust top mlir by processor, for example, make all cv18xx input types as F32.

import-calibration-table
Import calibration table, assign min and max for all ops, for quantization later.

processor-top-optimize
Do top ops optimization by processor.

convert-top-to-tpu
Lower top ops to tpu ops; if for mode F32/F16/BF16, top op normally convert to tpu op directly; if INT8, quantization is needed.

4.3 Tpu Pass

canonicalize
Graph optimization related to specific OP, such as merging of consecutive Requants, etc.

strip-io-quant
Input and output types will be quantized if true; or be F32

processor-tpu-optimize
Do tpu ops optimization by processor.

weight-reorder
Reorder the weights of individual OP based on processor characteristics, such as filter and bias for convolution.

subnet-divide
Divide the network into various subnets based on the processor type. If the Tensor Competing Processor can compute all operators, then it forms a single subnet.

op-reorder
Reorder op to make sure ops are close to their users.

layer-group
Slice the network so that as many OPs as possible are computed consecutively in the local mem.

address-assign
Assign addresses to the OPs that need global mem.

codegen
Use Builder module to generate the final model in flatbuffers format.

4.4 Other Passes

There are some optional passes, not in the diagram, used for special functions.

fuse-preprocess

Fuse image preprocess to model.

add-postprocess

add postprocess to model, only support ssd/yolov3/yolov5.

CHAPTER 5

Front-end Conversion

This chapter takes the onnx model as an example to introduce the front-end conversion process of models/operators in this project.

5.1 Main Work

The front-end is mainly responsible for transforming the original model into a Top (hardware-independent) mlir model (without the Canonicalize part, so the generated file is named "*_origin.mlir"). This process creates and adds the corresponding operators (Op) based on the original model and the input arguments when running model_transform.py. The transformed model and weights will be saved in mlir and npz file respectively.

5.2 Workflow

1. Prereq: definition of the Top layer operator in TopOps.td.
2. Input: input the original onnx model and arguments (preprocessing arguments mainly).
3. Initialize OnnxConverter (load_onnx_model + initMLIRImporter).
   - load_onnx_model part is mainly to refine the model, intercept the model according to the output_names in arguments, and extract the relevant information from the refined model.
   - The init_MLIRImporter part generates the initial mlir text.
4. generate_mlir

- Create the input op, the model intermediate nodes op and the return op in turn and add them to the mlir text (if the op has tensors, additional weight op will be created).

5. Output

   - Save the simplified model as a "*_opt.onnx" file
   - Generate a ".prototxt" file to save the model information except the weights
   - Convert the generated text to str and save it as a ".mlir" file
   - Save model weights (tensors) in ".npz" file

The workflow of the front-end conversion is shown in the figure (Front-end conversion workflow).

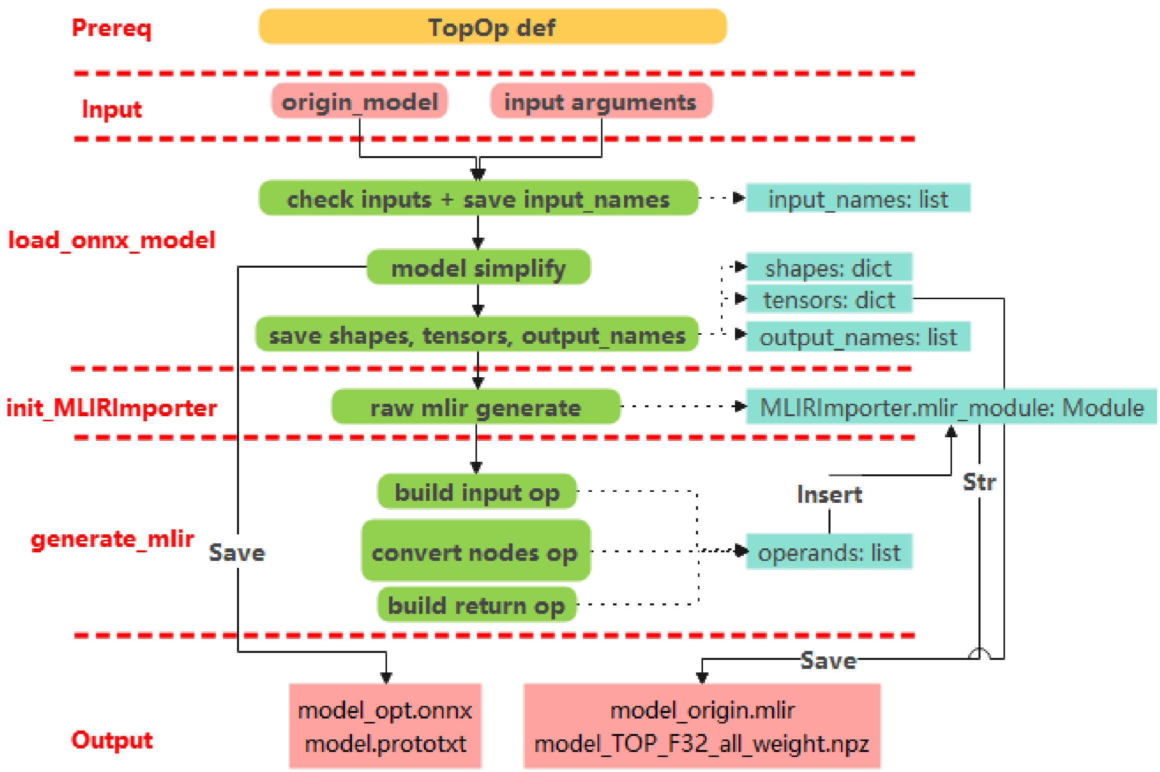


Fig. 5.1: Front-end conversion workflow

Additional Notes:

- Build input op requires:
  1. input_names.
  2. index for each input.
  3. preprocessing arguments (if the input is an image).
- Convert nodes op requires:

1. former ops.
2. the output_shape from shapes.
3. attrs extracted from the onnx node. Attrs are set by MLIRImporter according to definition in TopOps.td.

- Build return op requires:

  output ops according to output_names.

- Insertion operation is performed for each op conversion or creation. The operator is inserted into the mlir text so that the final generated text can one-to-one correspond with the original onnx model.

5.3 Example

This section takes the Conv onnx operator as an example for Top mlir conversion. The original model is shown in the figure (Conv onnx model).

The conversion process:

1. Conv op definition

   Define the Top.Conv operator in TopOps.td. The definition is shown in the figure (Top.Conv definition).

2. Initialize OnnxConverter

   load_onnx_model:

   - Since this example uses the simplest model, the resulting Conv_opt.onnx model is the same as the original one.
   - input_names for saving input name "input" of Conv op.
   - The weight and bias of the Conv op are stored in tensors.
   - shapes saves input_shape and output_shape of conv op.
   - output_names holds the output name of the Conv op "output".

   init_MLIRImporter:

   The initial mlir text MLIRImporter.mlir_module is generated based on model name, input shape and output shape from shapes, as shown in the figure (Initial mlir text).

3. generate_mlir

   - build input op, the generated Top.inputOp will be inserted into MLIRImporter.mlir_module.
   - call convert_conv_op(), which calls MLIRImporter.create_conv_op to create a ConvOp, and the create function takes the following arguments.

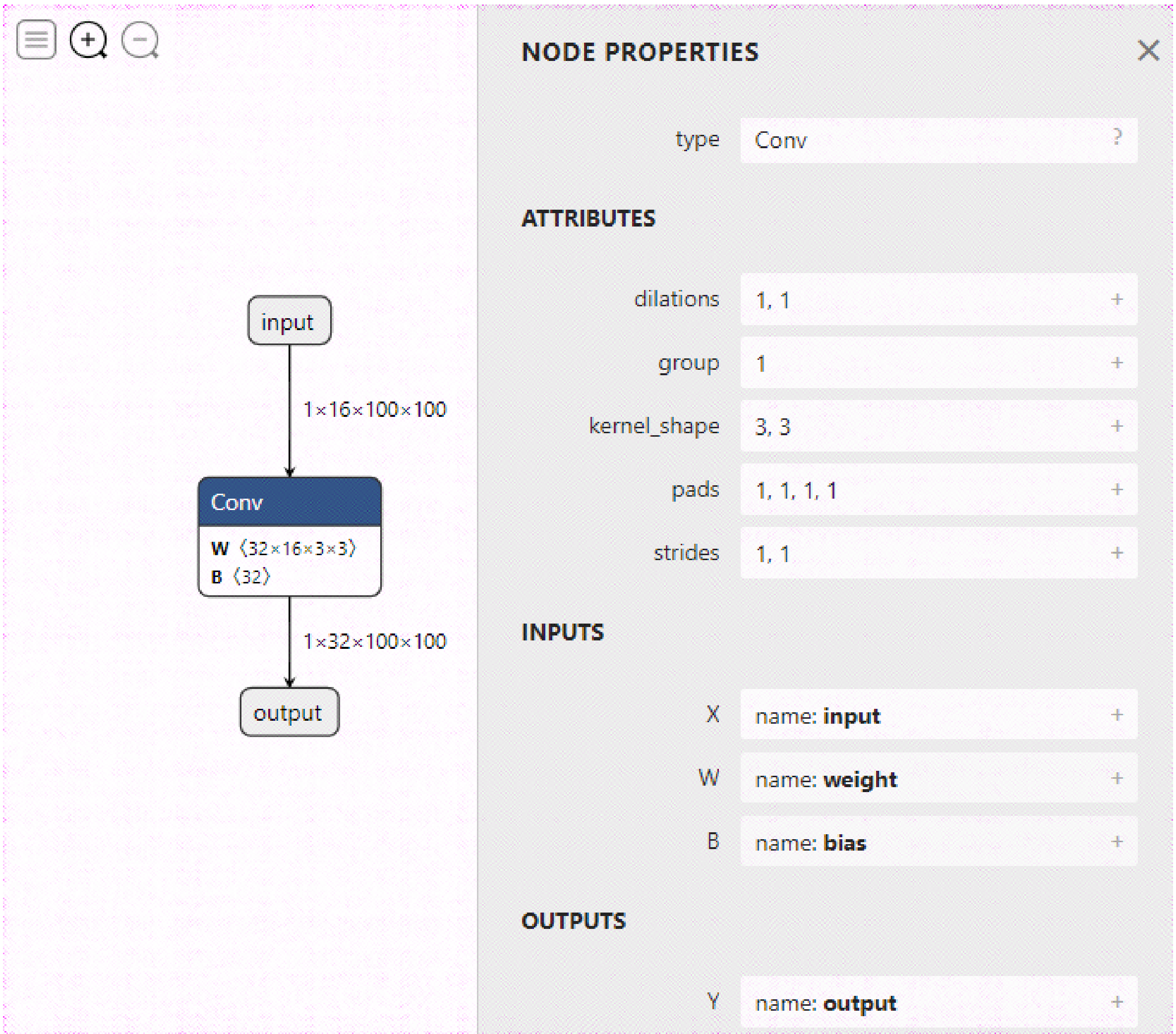


Fig. 5.2: Conv onnx model

include > tpu_mlir > Dialect > Top > IR > TopOps.td

```
def Top_ConvOp: Top_Op<"Conv", [SupportFuseRelu]> {
  let summary = "Convolution operator";

  let description = [{
    In the simplest case, the output value of the layer with input size
    .......
  }];

  let arguments = (ins
    AnyTensor:$input,
    AnyTensor:$filter,
    AnyTensorOrNone:$bias,
    I64ArrayAttr:$kernel_shape,
    I64ArrayAttr:$strides,
    I64ArrayAttr:$pads, // top,left,bottom,right
    DefaultValuedAttr<I64Attr, "1">:$group,
    OptionalAttr<I64ArrayAttr>:$dilations,
    OptionalAttr<I64ArrayAttr>:$inserts,
    DefaultValuedAttr<BoolAttr, "false">:$do_relu,
    OptionalAttr<F64Attr>:$upper_limit,
    StrAttr:$name
  );

  let results = (outs AnyTensor:$output);
  let extraClassDeclaration = [{
    void parseParam(int64_t &n, int64_t &ic, int64_t &ih, int64_t &iw, int64_t &oc,
                    int64_t &oh, int64_t &ow, int64_t &g, int64_t &kh, int64_t &kw, int64_t &
                    ins_h,
                    int64_t &ins_w, int64_t &sh, int64_t &sw, int64_t &pt, int64_t &pb,
                    int64_t &pl,
                    int64_t &pr, int64_t &dh, int64_t &dw, bool &is_dw, bool &with_bias, bool &
                    do_relu,
                    float &relu_upper_limit);
  }];
}
```

Fig. 5.3: Top.Conv definition

```
module attributes {module.chip = "ALL", module.name = "Conv2d", module.state = "TOP_F
32", module.weight_file = "conv2d_top_f32_all_weight.npz"} {
  func.func @main(%arg0: tensor<1x16x100x100xf32>) -> tensor<1x32x100x100xf32> {
    %0 = "top.None"() : () -> none
  }
}
```

Fig. 5.4: Initial mlir text

1) inputOp: from (Conv onnx model), we can see that inputs of the Conv operator contain input, weight and bias. inputOp has been created, and the op of weight and bias will be created by getWeightOp().

2) output_shape: use onnx_node.name to get the output shape of the Conv operator from `shapes`.

3) Attributes: get attributes such as (Conv onnx model) from the onnx Conv operator.

   The attributes of the Top.Conv operator are set according to the definition in (Top.Conv definition). Top.ConvOp will be inserted into the MLIR text after it is created.

- Get the output op from `operands` based on `output_names` to create return_op and insert it into the mlir text. Up to this point, the generated mlir text is shown (Complete mlir text).

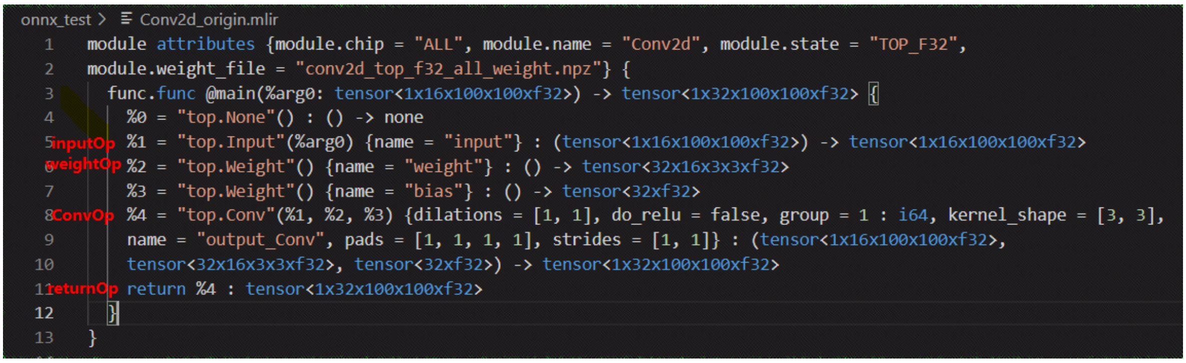


Fig. 5.5: Complete mlir text

4. Output

   Save the mlir text as Conv_origin.mlir and the weights in the `tensors` as Conv_TOP_F32_all_weight.npz.

CHAPTER 6

Quantization

The theory of quantization is based on: Quantization and Training of Neural Networks for Efficient Integer-Arithmetic-Only Inference

Paper link: https://arxiv.org/abs/1712.05877

This chapter introduces the quantization design of TPU-MLIR, focusing on the application of the paper in practical quantization.

6.1 Basic Concepts

INT8 quantization is divided into symmetric and asymmetric quantization. Symmetric quantization is a special case of asymmetric quantization, and usually, the performance of the former will be better than the latter, while the accuracy is in contrast.

6.1.1 Asymmetric Quantization

As shown in the figure (Asymmetric quantization), asymmetric quantization is actually the fixed-pointing of values in the range [min,max] to the interval [-128, 127] or [0, 255].

The quantization formula from int8 to float is:

$$
\begin{aligned}
r &= S(q - Z) \\
S &= \frac{max - min}{qmax - qmin} \\
Z &= Round(-\frac{min}{S} + qmin)
\end{aligned}
$$

where r is the real value of type float and q is the quantized value of type INT8 or UINT8.

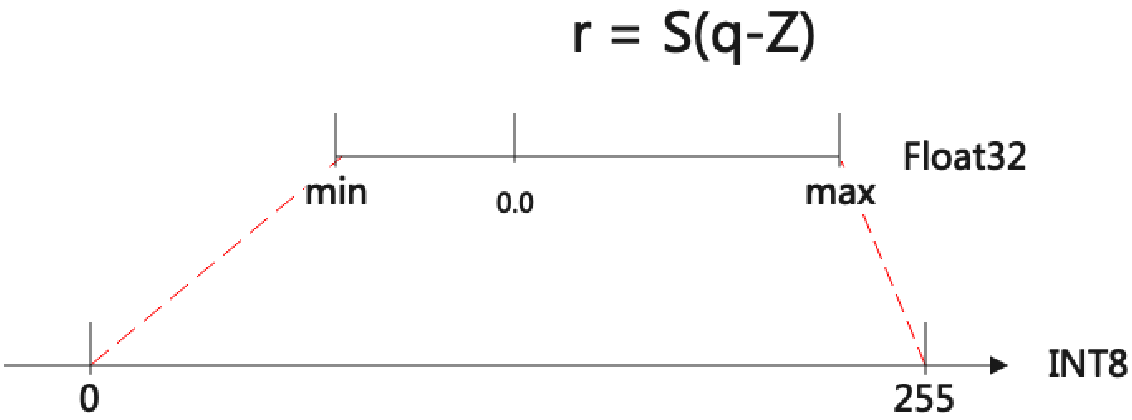


Fig. 6.1: Asymmetric quantization

S denotes scale, which is float; Z is zeropoint, which is of type INT8.

When quantized to INT8, qmax=127,qmin=-128, and for UINT8, qmax=255,qmin=0.

The quantization formula from float to INT8 is:

$$q = \frac{r}{S} + Z$$

6.1.2 Symmetric Quantization

Symmetric quantization is a special case of asymmetric quantization when Z=0. The formula is:

$$i8\_value = f32\_value \times \frac{128}{threshold}$$
$$f32\_value = i8\_value \times \frac{threshold}{128}$$

The range of Tensor is [-threshold, threshold].

For activation, usually $S = threshold/128$.

For weight, usually $S = threshold/127$.

In the case of UINT8, the Tensor range is [0, threshold], at this time $S = threshold/255.0$.

6.2 Scale Conversion

The formula in the paper:

$$M = 2^{-n} M_0, wheretherangeof M_0 is[0.5, 1], andnisanon - negativenumber$$

In other words, it is the floating point Scale, which can be converted to Multiplier and rshift:

$$Scale = \frac{Multiplier}{2^{rshift}}$$

For example:

$$\begin{aligned}
& y = x \times 0.1234 \\
& => y = x \times 0.9872 \times 2^{-3} \\
& => y = x \times (0.9872 \times 2^{31}) \times 2^{-34} \\
& => y = x \times \frac{2119995857}{1 \ll 34} \\
& => y = (x \times 2119995857) \gg 34
\end{aligned}$$

The higher the number of bits supported by Multiplier, the closer to Scale it will be, but that leads to worse performance. Therefore, generally, the hardware will use a 32-bit or 8-bit Multiplier.

6.3 Quantization derivation

We can use quantization formulas and derive quantization for different OPs to get their corresponding INT8 calculations.

Both symmetric and asymmetric are used for Activation, and for weights generally only symmetric quantization is used.

6.3.1 Convolution

The abbreviation of Convolution: $Y = X_{(n,ic,ih,iw)} \times W_{(oc,ic,kh,kw)} + B_{(1,oc,1,1)}$.

Substitute it into the int8 quantization formula, the derivation is as follows:

$$\begin{aligned}
float: & \quad Y = X \times W + B \\
step0 & \quad => S_y(q_y - Z_y) = S_x(q_x - Z_x) \times S_w q_w + B \\
step1 & \quad => q_y - Z_y = S_1(q_x - Z_x) \times q_w + B_1 \\
step2 & \quad => q_y - Z_y = S_1 q_x \times q_w + B_2 \\
step3 & \quad => q_y = S_3(q_x \times q_w + B_3) + Z_y \\
step4 & \quad => q_y = (q_x \times q_w + b_{i32}) * M_{i32} >> rshift_{i8} + Z_y
\end{aligned}$$

In particular, for asymmetric quantization, Pad is filled with Zx.

In the symmetric case, Pad is filled with 0 (both Zx and Zy are 0).

In PerAxis (or PerChannal) quantization, each OC of Filter will be quantized, and the derivation formula will remain unchanged, but there will be OC Multiplier and rshift.

6.3.2 InnerProduct

Expression and derivation are the same as (Convolution).

6.3.3 Add

The expression for addition is: $Y = A + B$

Substitute it into the int8 quantization formula, the derivation is as follows:

$$\begin{aligned}
float: &\quad Y = A + B \\
step0 &\quad => S_y(q_y - Z_y) = S_a(q_a - Z_a) + S_b(q_b - Z_b) \\
step1(Symmetric) &\quad => q_y = (q_a * M_a + q_b * M_b)_{i16} >> rshift_{i8} \\
step1(Asymmetric) &\quad => q_y = requant(dequant(q_a) + dequant(q_b))
\end{aligned}$$

The way to implement Add with Tensor Computing Processor is related to specific processor instructions.

The symmetric method here is to use INT16 as the intermediate buffer.

The asymmetric method is to first de-quantize into the float, do the addition and then requantize into INT8.

6.3.4 AvgPool

The expression of average pooling can be abbreviated as: $Y_i = \frac{\sum_{j=0}^{k}(X_j)}{k}, k = kh \times kw$.

Substitute it into the int8 quantization formula, the derivation is as follows:

$$
\begin{aligned}
float: \quad & Y_i = \frac{\sum_{j=0}^{k}(X_j)}{k} \\
step0: \quad & => S_y(y_i - Z_y) = \frac{S_x \sum_{j=0}^{k}(x_j - Z_x)}{k} \\
step1: \quad & => y_i = \frac{S_x}{S_y k}\sum_{j=0}^{k}(x_j - Z_x) + Z_y \\
step2: \quad & => y_i = \frac{S_x}{S_y k}\sum_{j=0}^{k}(x_j) - (Z_y - \frac{S_x}{S_y}Z_x) \\
step3: \quad & => y_i = (Scale_{f32}\sum_{j=0}^{k}(x_j) - Offset_{f32})_{i8} \\
& Scale_{f32} = \frac{S_x}{S_y k}, Offset_{f32} = Z_y - \frac{S_x}{S_y}Z_x
\end{aligned}
$$

6.3.5 LeakyReLU

The expression of LeakyReLU can be abbreviated as: $Y = \begin{cases} X, if X \geq 0 \\ \alpha X, if X < 0 \end{cases}$

Substitute it into the int8 quantization formula, the derivation is as follows:

$$
\begin{aligned}
float: \quad & Y = \begin{cases} X, if\ X \geq 0 \\ \alpha X, if\ X < 0 \end{cases} \\
step0: \quad & => S_y(q_y - Z_y) = \begin{cases} S_x(q_x - Z_x), if\ q_x \geq 0 \\ \alpha S_x(q_x - Z_x), if\ q_x < 0 \end{cases} \\
step1: \quad & => q_y = \begin{cases} \frac{S_x}{S_y}(q_x - Z_x) + Z_y, if\ q_x \geq 0 \\ \alpha\frac{S_x}{S_y}(q_x - Z_x) + Z_y, if\ q_x < 0 \end{cases}
\end{aligned}
$$

In INT8 symmetric quantization: $S_y = \frac{threshold_y}{128}, S_x = \frac{threshold_x}{128}$. In INT8 asymmetric quantization: $S_y = \frac{max_y - min_y}{255}, S_x = \frac{max_x - min_x}{255}$. After BackwardCalibration, $max_y = max_x, min_y = min_x, threshold_y = threshold_x$, so Sx/Sy = 1.

$$
\begin{aligned}
step2: \quad & => q_y = \begin{cases} (q_x - Z_x) + Z_y, if\ q_x \geq 0 \\ \alpha(q_x - Z_x) + Z_y, if\ q_x < 0 \end{cases} \\
step3: \quad & => q_y = \begin{cases} q_x - Z_x + Z_y, if\ q_x \geq 0 \\ M_{i8} >> rshift_{i8}(q_x - Z_x) + Z_y, if\ q_x < 0 \end{cases}
\end{aligned}
$$

In the symmetric case, both Zx and Zy are 0.

6.3.6 Pad

The expression of Pad can be abbreviated as: $Y = \begin{cases} X,\ origin\ location \\ value,\ padded\ location \end{cases}$

Substitute it into the int8 quantization formula, the derivation is as follows:

$$
\begin{aligned}
float: \quad & Y = \begin{cases} X,\ origin\ location \\ value,\ padded\ location \end{cases} \\
step0: \quad & => S_y(q_y - Z_y) = \begin{cases} S_x(q_x - Z_x),\ origin\ location \\ value,\ padded\ location \end{cases} \\
step1: \quad & => q_y = \begin{cases} \frac{S_x}{S_y}(q_x - Z_x) + Z_y,\ origin\ location \\ \frac{value}{S_y} + Z_y,\ padded\ location \end{cases}
\end{aligned}
$$

After BackwardCalibration, $max_y = max_x, min_y = min_x, threshold_y = threshold_x$, so Sx/Sy = 1。

$$
step2: \quad => q_y = \begin{cases} (q_x - Z_x) + Z_y,\ origin\ location \\ \frac{value}{S_y} + Z_y,\ padded\ location \end{cases}
$$

In the symmetric case, both Zx and Zy are 0, so the padded value is round(value/Sy). When asymmetric quantization, the padded value is round(value/Sy + Zy)。

6.3.7 PReLU

The expression of PReLU can be abbreviated as: $Y_i = \begin{cases} X_i, if\ X_i \geq 0 \\ \alpha_i X_i, if\ X_i < 0 \end{cases}$

Substitute it into the int8 quantization formula, the derivation is as follows:

$$
\begin{aligned}
float: \quad & Y_i = \begin{cases} X_i, if\ X_i \geq 0 \\ \alpha_i X_i, if\ X_i < 0 \end{cases} \\
step0: \quad & => S_y(y_i - Z_y) = \begin{cases} S_x(x_i - Z_x), if\ x_i \geq 0 \\ S_\alpha q_{\alpha_i} S_x(x_i - Z_x), if\ x_i < 0 \end{cases} \\
step1: \quad & => y_i = \begin{cases} \frac{S_x}{S_y}(x_i - Z_x) + Z_y, if\ x_i \geq 0 \\ S_\alpha q_{\alpha_i} \frac{S_x}{S_y}(x_i - Z_x) + Z_y, if\ x_i < 0 \end{cases}
\end{aligned}
$$

After BackwardCalibration, $max_y = max_x, min_y = min_x, threshold_y = threshold_x$, so Sx/Sy = 1。

$$
\begin{aligned}
step2: \quad & => y_i = \begin{cases} (x_i - Z_x) + Z_y, if\ x_i \geq 0 \\ S_\alpha q_{\alpha_i}(x_i - Z_x) + Z_y, if\ x_i < 0 \end{cases} \\
step3: \quad & => y_i = \begin{cases} (x_i - Z_x) + Z_y, if\ x_i \geq 0 \\ q_{\alpha_i} * M_{i8}(x_i - Z_x) >> rshift_{i8} + Z_y, if\ x_i < 0 \end{cases}
\end{aligned}
$$

There are oc Multipliers and 1 rshift. When symmetric quantization, Zx and Zy are both 0.

CHAPTER 7

Calibration

7.1 General introduction

Calibration is the use of real scene data to tune the proper quantization parameters. Why do we need calibration? When we perform asymmetric quantization of the activation, we need to know the overall dynamic range, i.e., the minmax value, in advance. When applying symmetric quantization to activations, we need to use a suitable quantization threshold algorithm to calculate the quantization threshold based on the overall data distribution of the activation. However, the general trained model does not have the activation statistics. Therefore, both of them need to inference on a miniature sub-training set to collect the output activation of each layer. Then aggregate them to obtain the overall minmax and histogram of the data point distribution. The appropriate symmetric quantization threshold is obtained based on algorithms such as KLD. Finally, the auto-tune algorithm will be enabled to tune the quantization threshold of the input activation of a certain int8 layer by making use of the Euclidean distance between the output activation of int8 and fp32 layers. The above processes are integrated together and executed in unison. The optimized threshold and min/max values for each op are saved in a text file for quantization parameters. Int8 quantization can be achieved by using this text file in `model_deploy.py`. The overall process is shown in the figure (Overall process of quantization).

The following figure (Example of quantization parameters file) shows the final output of the calibration quantization parameters file

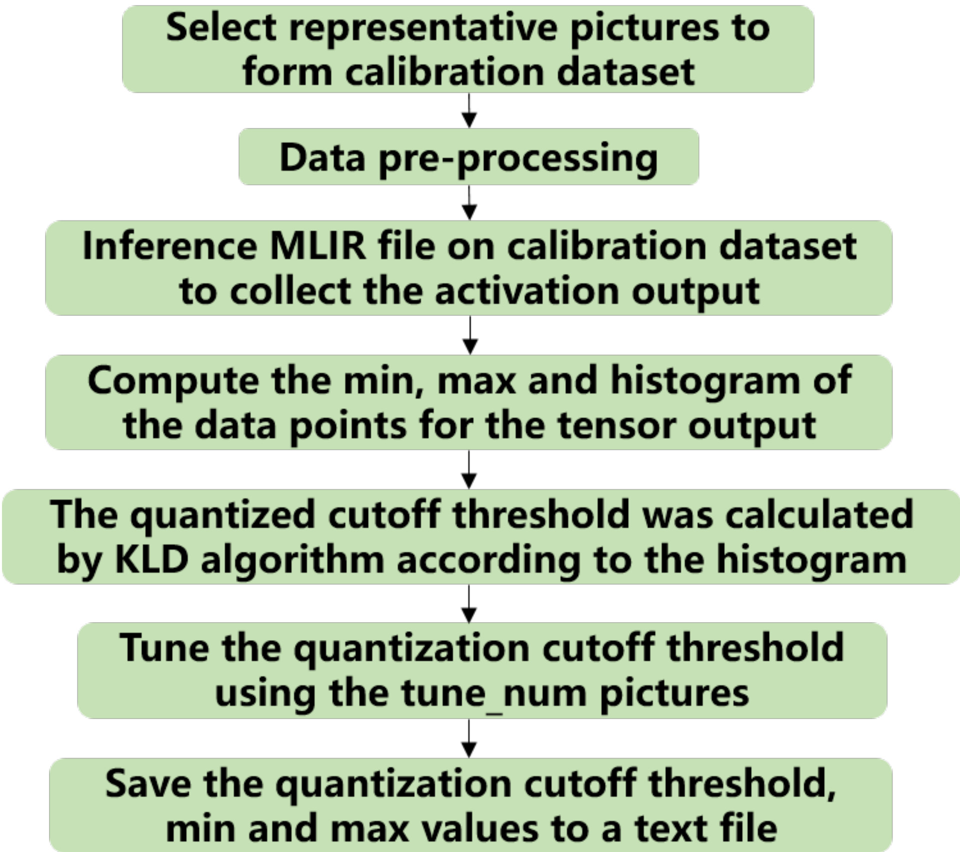


Fig. 7.1: Overall process of quantization

```
# genetated time: 2022-08-11 10:00:59.743675
# histogram number: 2048
# sample number: 100
# tune number: 5
###
# op_name    threshold    min    max
images 1.0000080 0.0000000 1.0000080
122_Conv 56.4281803 -102.5830231 97.6811752
124_Mul 38.1586478 -0.2784646 97.6811752
125_Conv 56.1447888 -143.7053833 122.0844193
127_Mul 116.7435987 -0.2784646 122.0844193
128_Conv 16.4931355 -87.9204330 7.2770605
130_Mul 7.2720342 -0.2784646 7.2720342
131_Conv 51.5455152 -56.4878578 26.2175255
133_Mul 22.2855371 -0.2784646 26.2175255
134_Conv 19.6111164 -28.0139256 21.4674854
136_Mul 20.8639418 -0.2784646 21.4674854
137_Add 20.5015809 -0.5569289 21.8679256
138_Conv 14.7106976 -87.1445465 32.7312393
```

Fig. 7.2: Example of quantization parameters file

7.2 Calibration data screening and preprocessing

7.2.1 Screening Principles

Selecting about 100 to 200 images covering each typical scene style in the training set for calibration. Using a approach similar to training data cleaning to exclude some anomalous samples.

7.2.2 Input format and preprocessing

Table 7.1: Input format

Format	Description
Original Image	For CNN-like vision networks, image input is supported. Image preprocessing arguments must be the same as in training step when generating the mlir file by model_transform.py.
npz or npy file	For cases where non-image inputs or image preprocessing types are not supported at the moment, it is recommended to write an additional script to save the preprocessed input data into npz/npy files (npz file saves multiple tensors in the dictionary, and npy file only contains one tensor). run_calibration.py supports direct input of npz/npy files.

There is no need to specify the preprocessing parameters for the above two formats when calling run_calibration.py to call the mlir file for inference.

Table 7.2: Methods of speciying parameters

Method	Description
–dataset	For single-input networks, place images or preprocessed input npy/npz files (no order required). For multi-input networks, place the pre-processed npz files of each sample.
–data_list	Place the path of the image, npz or npy file of each sample (one sample per line) in a text file. If the network has more than one input file, separate them by commas (note that the npz file should have only 1 input path).

```
/data/cali_100pics/n01440764_9572.JPEG
/data/cali_100pics/n01531178_12753.JPEG
/data/cali_100pics/n01537544_17475.JPEG
/data/cali_100pics/n01608432_4202.JPEG
/data/cali_100pics/n01608432_4203.JPEG
```

Fig. 7.3: Example of data_list required format

7.3 Algorithm Implementation

7.3.1 KLD Algorithm

The KLD algorithm implemented by tpu-mlir refers to the implementation of tensorRT. In essence, it cuts off some high-order outliers (the intercepted position is fixed at 128 bin, 256bin ··· until 2048 bin) from the waveform of abs (fp32_tensor) (represented by the histogram of 2048 fp32 bins) to get the fp32 reference probability distribution P. This fp32 waveform is expressed in terms of 128 ranks of int8 type. By merging multiple adjacent bins (e.g., 256 bins are 2 adjacent fp32 bins) into 1 rank of int8 values, calculating the distribution probability, and then expanding bins to ensure the same length as P, the probability distribution Q of the quantized int8 values can be got. The KL divergences of P and Q are calculated for the interception positions of 128bin, 256bin, ···, and 2048 bin, respectively in each loop until the interception with the smallest divergence is found. Interception here means the probability distribution of fp32 can be best simulated with the 128 quantization levels of int8. Therefore, it is most appropriate to set the quantization threshold here. The pseudo-code for the implementation of the KLD algorithm is shown below:

```
the pseudocode of computing int8 quantize threshold by kld:
    Prepare fp32 histogram H with 2048 bins
    compute the absmax of fp32 value

    for i in range(128,2048,128):
      Outliers_num=sum(bin[i], bin[i+1],···, bin[2047])
      Fp32_distribution=[bin[0], bin[1],···, bin[i-1]+Outliers_num]
      Fp32_distribution/= sum(Fp32_distribution)

      int8_distribution = quantize [bin[0], bin[1],···, bin[i]] into 128 quant level
      expand int8_distribution to i bins
      int8_distribution /= sum(int8_distribution)
      kld[i] = KLD(Fp32_distribution, int8_distribution)
    end for

    find i which kld[i] is minimal
    int8 quantize threshold = (i + 0.5)*fp32 absmax/2048
```

7.3.2 Auto-tune Algorithm

From the actual performance of the KLD algorithm, its candidate threshold is relatively coarse and does not take into account the characteristics of different scenarios, such as object detection and key point detection, in which tensor outliers may be more important to the performance. In these cases, a larger quantization threshold is required to avoid saturation which will affect the expression of distribution features. In addition, the KLD algorithm calculates the quantization threshold based on the similarity between the quantized int8 and the fp32 probability distribution, while there are other methods to evaluate the waveform similarity such as Euclidean distance, cos similarity, etc. These metrics evaluate the tensor numerical distribution similarity directly without the need for a coarse interception threshold, which most of the time has better performance. Therefore, with the basis of efficient KLD quantization threshold, tpu-mlir proposes the auto-tune algorithm to fine-tune these activations quantization thresholds based on Euclidean distance metric, which ensures a better accuracy performance of its int8 quantization.

Implementation: firstly, uniformly pseudo-quantize layers with weights in the network, i.e., quantize their weights from fp32 to int8, and then de-quantize to fp32 for introducing quantization error. After that, tune the input activation quantization threshold of op one by one (i.e., uniformly select 10 candidates among the initial KLD quantization threshold and maximum absolute values of activations. Use these candidates to quantize fp32 reference activation values for introducing quantization error. Input op for fp32 calculation, calculating the Euclidean distance between the output and the fp32 reference activations. The candidate with a minimum Euclidean distance will be selected as the tuning threshold). For the case where the output of one op is connected to multiple subsequent ones, the quantization thresholds are calculated for the multiple branches according to the above method, and then the larger one is taken. For instance, the output of layer1 will be adjusted for layer2 and layer3 respectively as shown in the figure (Implementation of auto-tune).

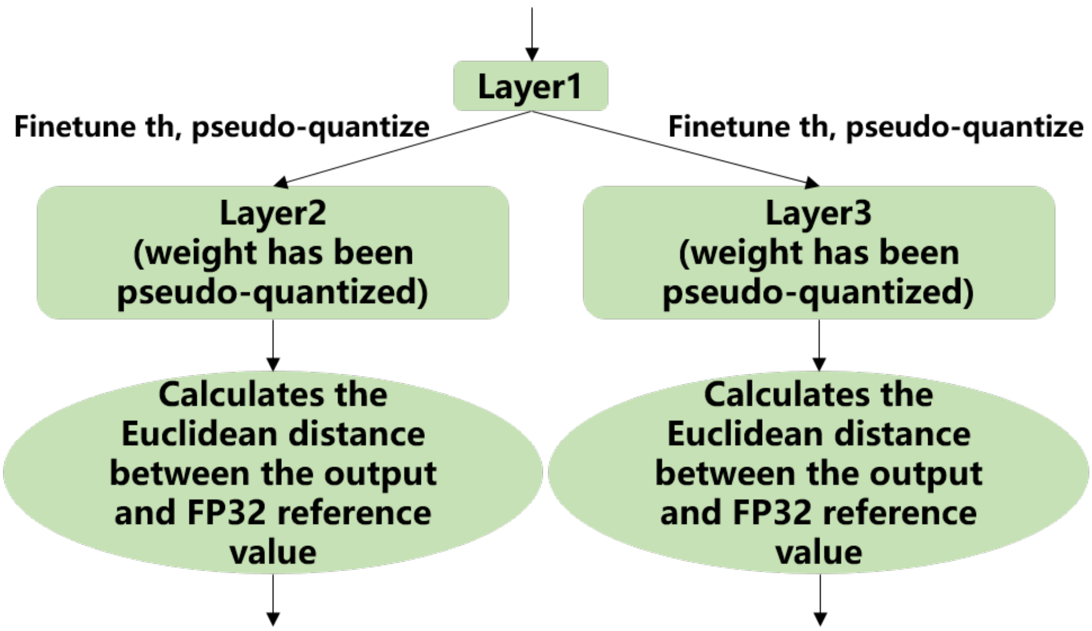


Fig. 7.4: Implementation of auto-tune

7.4 Example: yolov5s calibration

In the docker environment of tpu-mlir, execute **source envsetup.sh** in the tpu-mlir directory to initialize the environment, then enter any new directory and execute the following command to complete the calibration process for yolov5s.

```
$ model_transform.py \
  --model_name yolov5s \
  --model_def ${REGRESSION_PATH}/model/yolov5s.onnx \
  --input_shapes [[1,3,640,640]] \
  --keep_aspect_ratio \ #keep_aspect_ratio、mean、scale、pixel_format are preprocessing arguments
  --mean 0.0,0.0,0.0 \
  --scale 0.0039216,0.0039216,0.0039216 \
  --pixel_format rgb \
  --output_names 350,498,646 \
  --test_input ${REGRESSION_PATH}/image/dog.jpg \
  --test_result yolov5s_top_outputs.npz \
  --mlir yolov5s.mlir
```

Table 7.3: The arguments of model_transform.py

Argument	Description
model_name	Model name
–model_def	Model definition file (.onnx,.pt,.tflite or .prototxt)
–model_data	Specify the model weight file, required when it is caffe model (corresponding to the ‘.caffemodel’ file)
–input_shapes	The shape of the input, such as [[1,3,640,640]] (a two-dimensional array), which can support multiple inputs
–resize_dims	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	Whether to maintain the aspect ratio when resize. False by default. It will pad 0 to the insufficient part when setting
–mean	The mean of each channel of the image. The default is 0.0,0.0,0.0
–scale	The scale of each channel of the image. The default is 1.0,1.0,1.0
–pixel_format	Image type, can be rgb, bgr, gray or rgbd
–output_names	The names of the output. Use the output of the model if not specified, otherwise use the specified names as the output
–test_input	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	Output file to save validation result
–excepts	Names of network layers that need to be excluded from validation. Separated by comma
–debug	if open debug, immediate model file will keep; or will remove after conversion done
–mlir	The output mlir file name (including path)

```
$ run_calibration.py yolov5s.mlir \
  --dataset $REGRESSION_PATH/dataset/COCO2017 \
  --input_num 100 \
  --tune_num 10 \
  -o yolov5s_cali_table
```

Table 7.4: The arguments of run_calibration.py

Argument	Description
mlir_file	mlir file
–dataset	dataset for calibration
–data_list	Input list file contain all input
–input_num	num of images for calibration
–tune_list	Tune list file contain all input for tune
–tune_num	num of images for tune
– histogram_bin_nun	Specify histogram bin numer for kld calculate
-o	output threshold table
–debug_cmd	debug command to specify calibration mode; "percentile9999" initialize the threshold via percentile function, "use_max" specifies the maximum of absolute value to be the threshold, "use_torch_observer_for_cali" adopts Torch observer for calibration.

The result is shown in the following figure (yolov5s_cali calibration result).

7.5 visual tool introduction

visual.py is an visualized net/tensor compare tool with UI in web browser. When quantized net encounters great accuracy decrease, this tool can be used to investigate the accuracy loss layer by layer. This tool is started in docker as an server listening to TCP port 10000 (default), and by input localhost:10000 in url of browser in host computer, the tool UI will be displayed in it, the port must be mapped to host in advance when starting the docker, and the tool must be start in the same directory where the mlir files located, start command is as following:

```
root@80ab6476536b:/workspace/code/tpu-mlir/doc/developer_manual/tmp1# run_calibration.py yolov5s.mlir \
>   --dataset $REGRESSION_PATH/dataset/COCO2017 \
>   --input_num 10 \
>   --tune_num 2 \
>   -o yolov5s_cali_table
SOPHGO Toolchain v0.3.10-g3630539-20220816
2022/08/17 17:18:16 - INFO :
  load_config Preprocess args :
        resize_dims           : [640, 640]
        keep_aspect_ratio     : True
        pad_value             : 0
        pad_type              : center
        input_dims            : [640, 640]
        -------------------------
        mean                  : [0.0, 0.0, 0.0]
        scale                 : [0.0039216, 0.0039216, 0.0039216]
        -------------------------
        pixel_format          : rgb
        channel_format        : nchw

mem info before _activations_generator_and_find_minmax:total mem is 32802952, used mem is 7537492
inference and find Min Max *000000281447.jpg: 100%|
mem info after _activations_generator_and_find_minmax:total mem is 32802952, used mem is 7794272
calculate histogram..
mem info before calc_thresholds:total mem is 32802952, used mem is 7793756
calc_thresholds: 000000281447.jpg: 100%|
mem info after calc_thresholds:total mem is 32802952, used mem is 7785728
[2048] threshold: images: 100%|
mem info after find_threshold:total mem is 32802952, used mem is 7786352
start fake_quant_weight
tune op: 646_Transpose: 100%|
root@80ab6476536b:/workspace/code/tpu-mlir/doc/developer_manual/tmp1# ll
total 573036
drwxr-xr-x 3 root root      4096 Aug 17 17:23 ./
drwxrwxr-x 7 1003 1003      4096 Aug 17 17:15 ../
drwxr-xr-x 2 root root      4096 Aug 17 17:19 tmpdata/
-rw-r--r-- 1 root root     38065 Aug 17 17:17 yolov5s.mlir
-rw-r--r-- 1 root root      6233 Aug 17 17:23 yolov5s_cali_table
-rw-r--r-- 1 root root   4915466 Aug 17 17:17 yolov5s_in_f32.npz
-rw-r--r-- 1 root root  28931068 Aug 17 17:17 yolov5s_opt.onnx
-rw-r--r-- 1 root root    126202 Aug 17 17:17 yolov5s_opt.onnx.prototxt
-rw-r--r-- 1 root root     50069 Aug 17 17:17 yolov5s_origin.mlir
```

Fig. 7.5: yolov5s_cali calibration result

```
sophgo@3cc464b1891d:/workspace/regression/mlir_deploy.1$ visual.py --f32_mlir transformed.mlir --quant_mlir openpose_bm1684x_int8_asym_tpu.mlir --input
openpose_in_f32.npz --port 9999
Dash is running on http://0.0.0.0:9999/

 * Serving Flask app 'visual'
 * Debug mode: off
-------------------------------------------
f32 mlir is  :transformed.mlir
quant mlir is:openpose_bm1684x_int8_asym_tpu.mlir
input is     :openpose_in_f32.npz
-------------------------------------------
```

Table 7.5: visual tool parameters

Param	Description
–port	the TCP port used to listen to browser as server, default value is 10000
–f32_mlir	the float mlir net to compare to, this file is produced by model_transform, and usually with the name of netname.mlir, it is the base float32 mlir net.
–quant_mlir	the quantized mlir net to compare with float net, this file is generated in model_deploy, usually with netname_int8_sym_tpu.mlir, _final.mlir to generate bmodel can't be used here.
–input	input data to run the float net and quantized net for data compare, can be image or npy/npz file, can be the test_input when graph_transform
–manual_run	if run the nets when browser connected to server, default is true, if set false, only the net structure will be displayed

Open browser in host computer and input localhost:9999, the tool UI will be displayed. The float and quantized net will automatically inference to get output of every layer, if the nets are huge, it would took a long time to wait! UI is as following:

Areas of the UI is marked with light blue rectangle for reference, dark green comments on the areas, includeing:

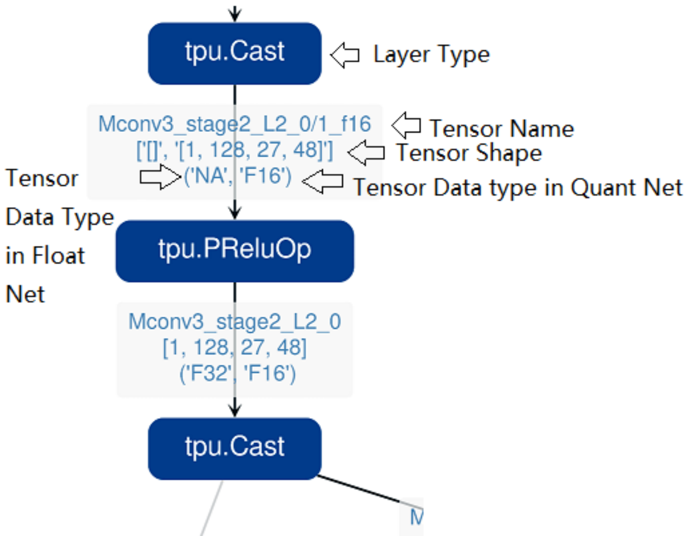
1. working directory and net file indication
2. accuracy summary area
3. layer information area

4. graph display area
5. tensor data compare figure area
6. infomation summary and tensor distribution area (by switching tabs)

With scroll wheel over graph display area, the displayed net graph can be zoomed in and out, and hover or click on the nodes (layer), the attributes of it will be displayed in the layer information card, by clicking on the edges (tensor), the compare of tensor data in float and quantized net is displayed in tensor data compare figure, and by clicking on the dot in accuracy summary or information list cells, the layer/tensor will be located in graph display area.

Notice: the net graph is displayed according to quantized net, and there may be difference in it comparing to float net, some layer/tensor may not exist in float net, but the data is copied from quantized net for compare, so the accuracy may seem perfect, but in fact, it should be ignored. Typical layer is Cast layer in quantized net, in following picture, the non-exist tensor data type will be NA. Notice: without –debug parameter in deployment of the net, some essential intermediate files needed by visual tool would have been deleted by default, please re-deploy with –debug parameter.

information displayed on edge (tensor) is illustrated as following:



CHAPTER 8

Lowering

Lowering lowers the Top layer OP to the Tpu layer OP, it supports types of F32/F16/BF16/INT8 symmetric/INT8 asymmetric.

When converting to INT8, it involves the quantization algorithm. For different processors, the quantization algorithm is different. For example, some support per-channel and some do not. Some support 32-bit Multiplier and some only support 8-bit, etc.

Therefore, lowering converts op from the hardware-independent layer (TOP), to the hardware-related layer (TPU).

8.1 Basic Process

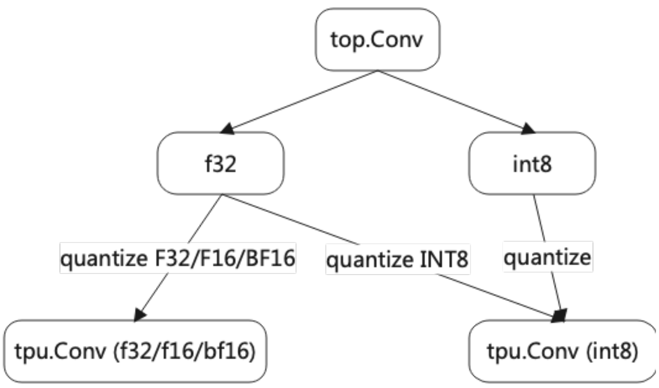


Fig. 8.1: Lowering process

The process of lowering is shown in the figure (Lowering process).

- Top op can be divided into f32 and int8. The former is the case of most networks and the latter is the case of quantized networks such as tflite.
- f32 op can be directly converted to f32/f16/bf16 tpu layer operator. If it is to be converted to int8, the type should be calibrated_type.
- int8 op can only be directly converted to tpu layer int8 op.

8.2 Mixed precision

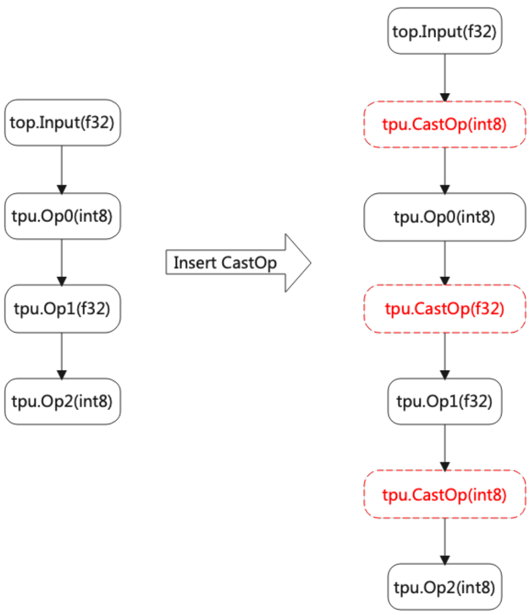


Fig. 8.2: Mixed precision

When the type is not the same between OPs, CastOp is inserted as shown in the figure (Mixed precision).

It is assumed that the type of output is the same as the input. Otherwise, special treatment is needed. For example, no matter what the type of embedding output is, the input is of type uint.

CHAPTER 9

SubNet

CHAPTER 10

LayerGroup

10.1 Basic Concepts

The memory in a Tensor Computing Processor can be categorized into global memory (GMEM) and local memory (LMEM).

Usually the global memory is very large (e.g., 4GB) while the local memory is quite limited (e.g., 16MB).

In general, the amount of data and computation of neural network model is very large, so the OP of each layer usually needs to be sliced and put into local memory for operation, and then the result is saved to global memory.

LayerGroup enables as many OPs as possible to be executed in local memory after being sliced, so that it can avoid too many copy operations between local and global memory.

Problem to be solved:

How to keep Layer data in the limited local memory for computing, instead of repeatedly making copies between local and global memory.

Basic idea:

Slicing the N and H of activation, make the operation of each layer always in local memory, as shown in the figure (Network slicing example).

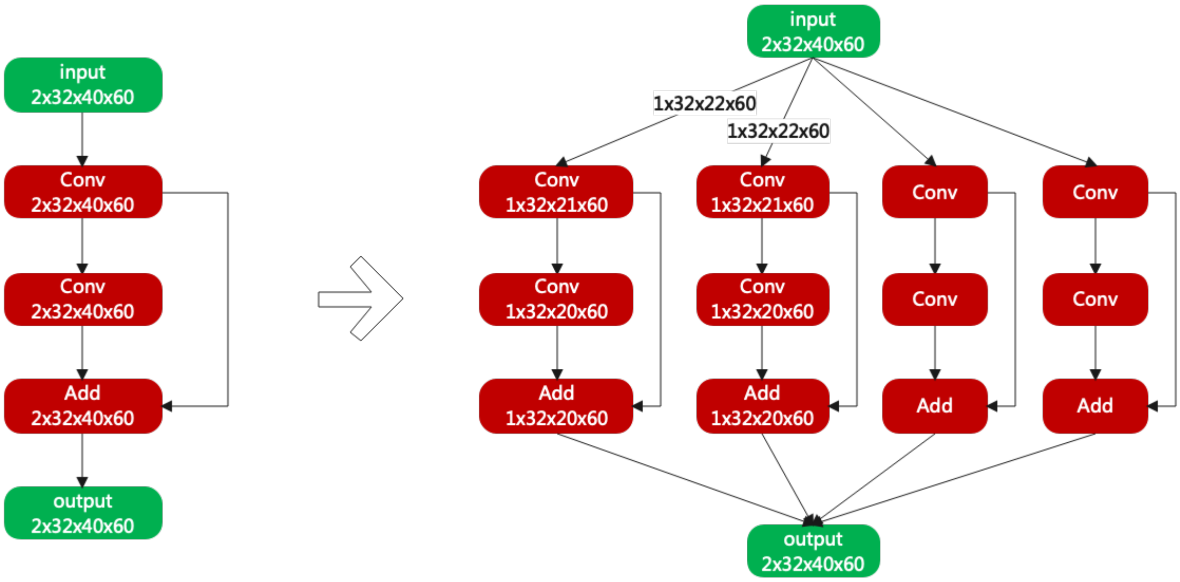


Fig. 10.1: Network slicing example

10.2 BackwardH

When slicing along the axis of H, the input and output H of most layers are consistent. But for Conv, Pool, etc., additional calculations are needed.

Take Conv for example, as shown in the figure (Convolutional BackwardH example).

10.3 Dividing the Mem Cycle

How to divide the group? First of all, list the lmem needed for each layer, which can be broadly classified into three categories:

1. Activation Tensor, which is used to save the input and output results, and is released directly after there is no user.
2. Weight, used to save the weights, released when there is no slice. Otherwise, always resides in the lmem.
3. Buffer, used for Layer operation to save intermediate results, released after use.

Then configure the ids in a breadth-first manner, for example, as shown in the figure (LMEM's ID assignment).

Then configure the period as shown in (TimeStep assignment).

Details of configuring period are as follows:

- [T2,T7], which means that lmem should be requested at the beginning of T2 and released at the end of T7.

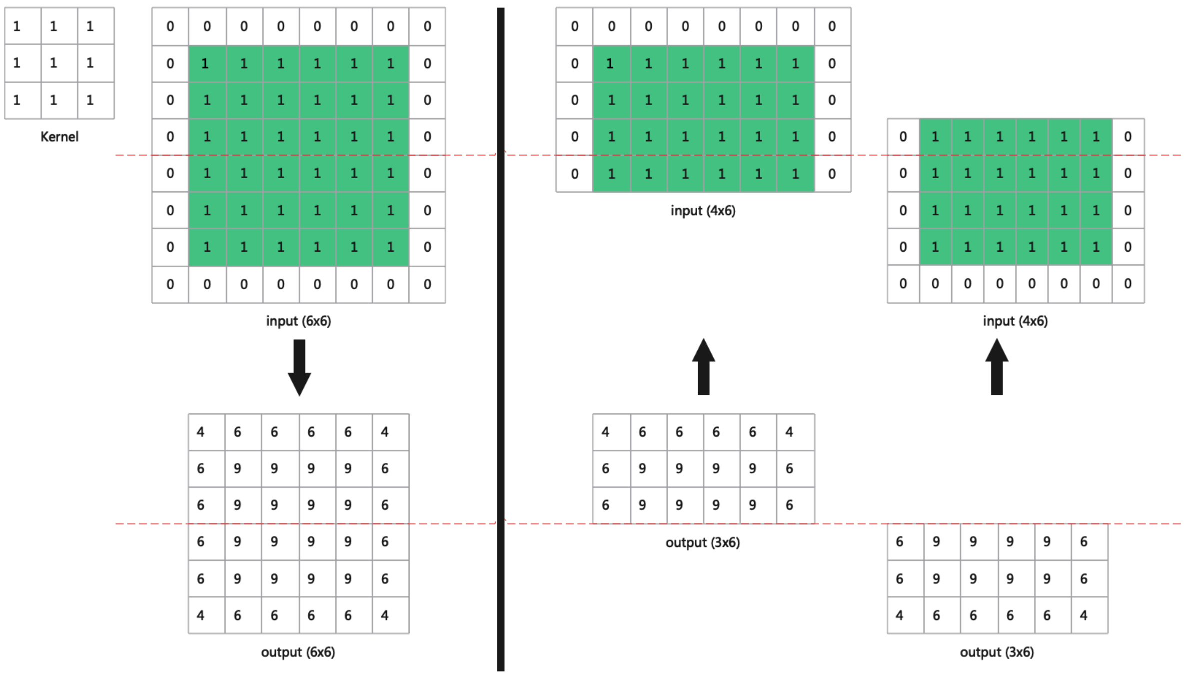


Fig. 10.2: Convolutional BackwardH example

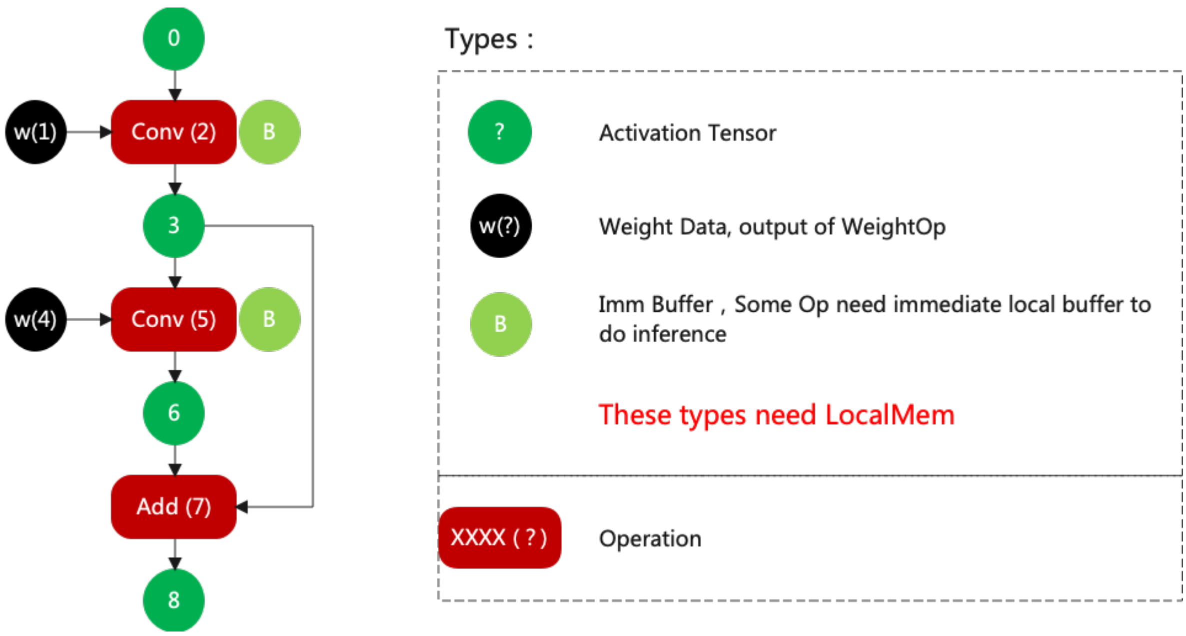


Fig. 10.3: LMEM’s ID assignment

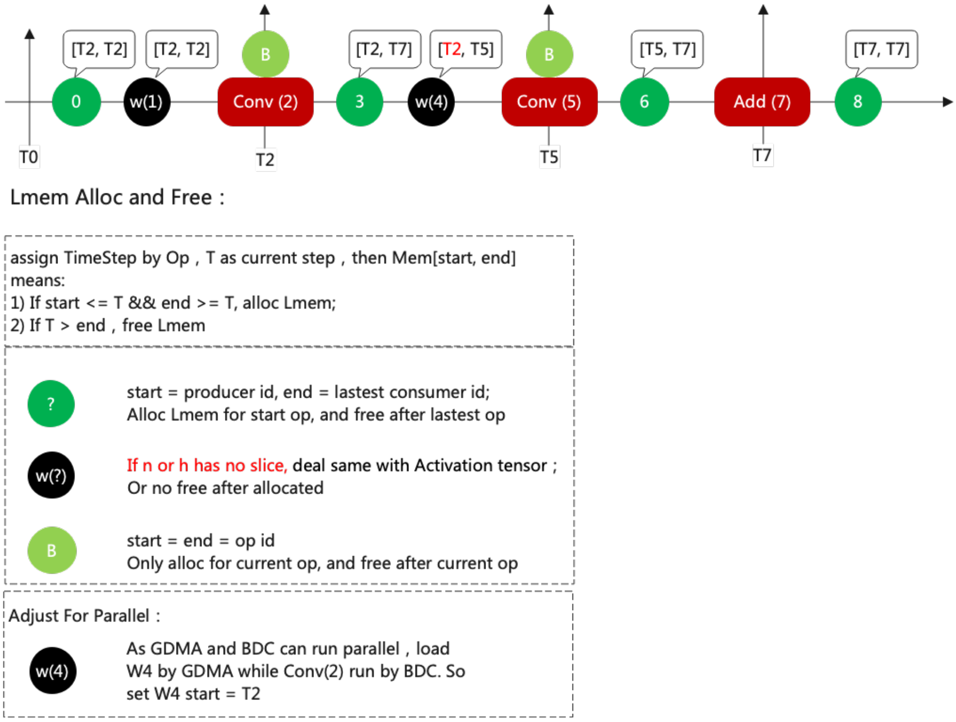


Fig. 10.4: TimeStep assignment

- The original period of w4 should be [T5,T5], but it is corrected to [T2,T5], because w4 can be loaded at the same time when T2 does the convolution operation.
- When N or H is sliced, weight does not need to be reloaded and its end point will be corrected to positive infinity.

10.4 LMEM Allocation

When the slice exists in N or H, weight is resident in LMEM so that each slice can use it.

At this point weight will be allocated first, as shown in the figure (Allocation in the case of slice)

When there is no slice, weight and activation are handled the same way, and released when not in use.

The allocation process at this point is shown in the figure (Allocation in the case of no slice).

Then the LMEM allocation problem can be converted into a problem of how to place these squares (note that these squares can only be moved left and right, not up and down).

In addition, LMEM allocation is better not to cross the bank.

The current strategy is to allocate them in order of op, giving priority to those with long timestep, followed by those with large LMEM.

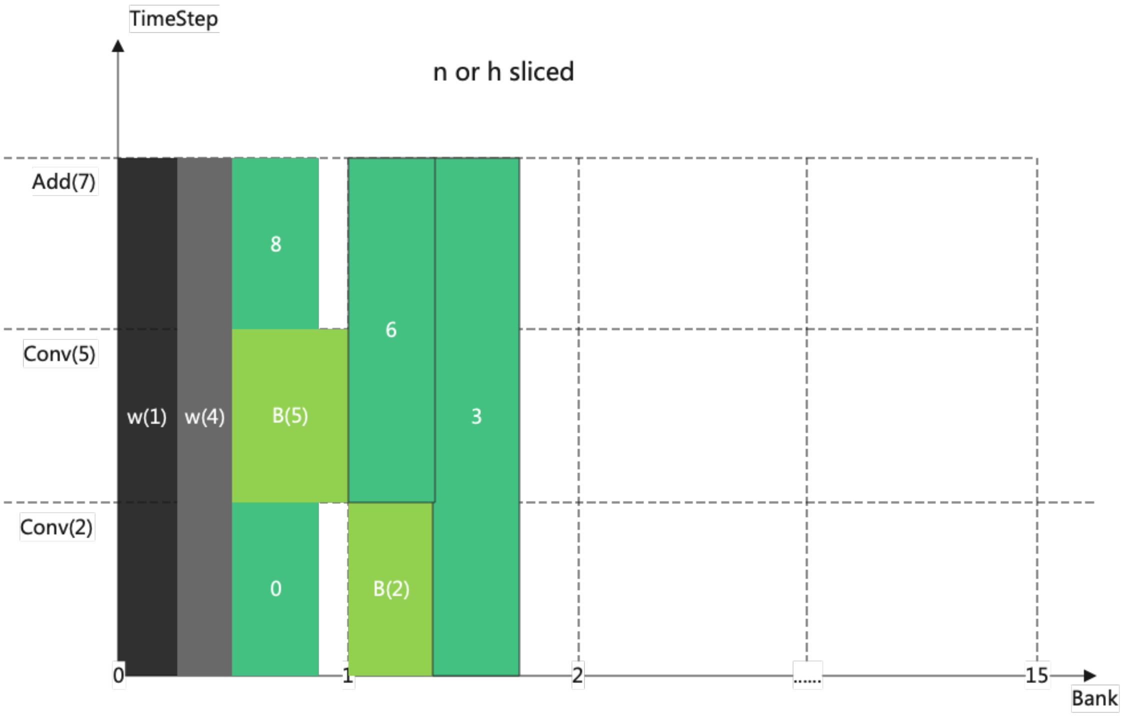


Fig. 10.5: Allocation in the case of slice

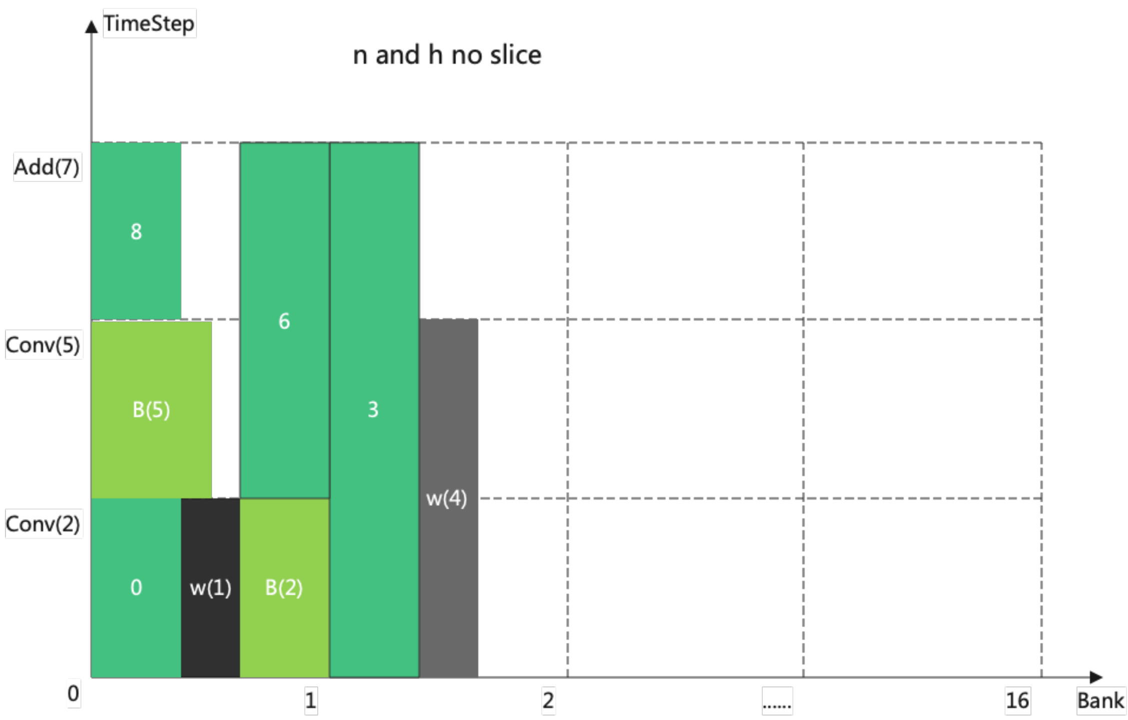


Fig. 10.6: Allocation in the case of no slice

10.5 Divide the optimal Group

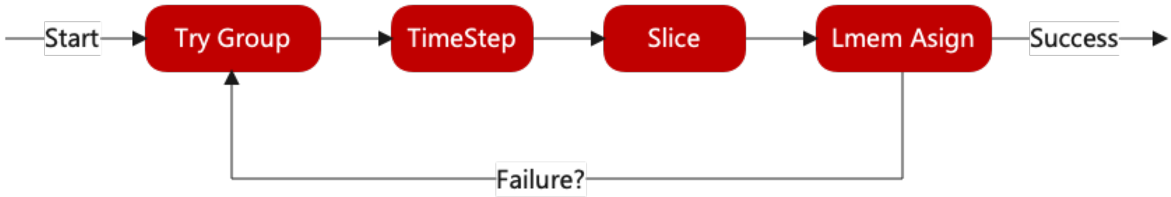


Fig. 10.7: Group process

At present, the group is divided from the tail to the head. N will be sliced first till the smallest unit, then H when it is needed.

When the network is very deep, because Conv, Pool and other operators have duplicate computation parts, too much H slice leads to too many duplicate parts.

In order to avoid too much duplication, it is considered as failed when the input of layer after backward has duplicated part of h_slice > h/2.

Example: if the input has h = 100, and it is sliced into two inputs, h[0, 80) and h[20, 100), then the duplicate part is 60. It is considered as failed. The repeated part is 40 when two inputs are h[0, 60) and h[20, 100), which is considered as success.

CHAPTER 11

GMEM Allocation

11.1 1. Purpose

In order to save global memory space and reuse memory space to the greatest extent, GMEM will be allocated to weight tensor first, and then allocated to all global neuron tensors according to their life cycle. In addition, allocated GMEM will be reused during the allocation process.

> **Note:** global neuron tensor definition: the tensor that needs to be saved in GMEM after the Op operation. If it is a LayerGroup op, only the input/output tensor is considered as global neuron tensor.

11.2 1. Principle

11.2.1 2.1. GMEM allocation in weight tensor

Iterate through all WeightOp and allocate GMEM sequentially with 4K alignment. Address space will keep accumulating.

11.2.2 2.2. GMEM allocation in global neuron tensors

Maximize the reuse of memory space. Allocate GMEM to all global neuron tensors according to their life cycle, and reuse the allocated GMEM during the allocation process.

a. **Introduction of data structure:**

The corresponding tensor, address, size, ref_cnt (how many OPs are using this tensor) are recorded in rec_tbl at each allocation. The tensor and address are recorded in the auxiliary data structures hold_edges,in_using_addr respectively.

```
//Value, offset, size, ref_cnt
using gmem_entry = std::tuple<mlir::Value, int64_t, int64_t, int64_t>;
std::vector<gmem_entry> rec_tbl;
std::vector<mlir::Value> hold_edges;
std::set<int64_t> in_using_addr;
```

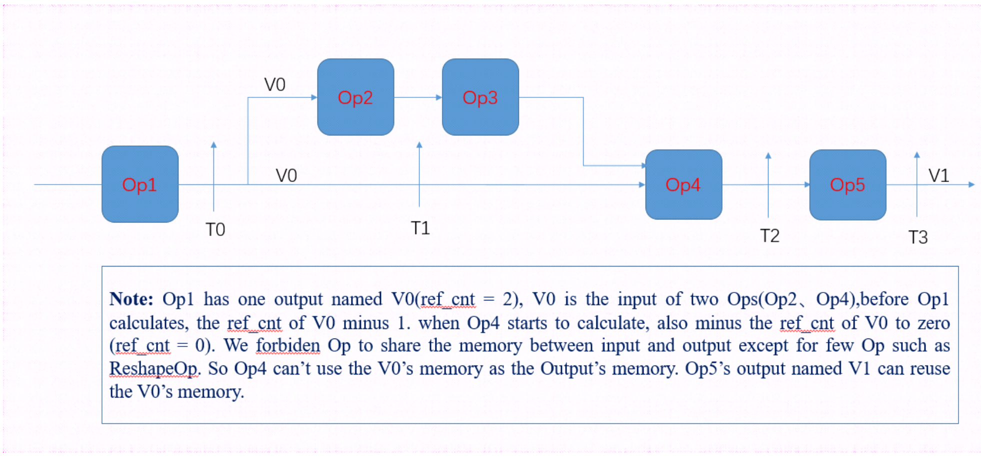
b. Flow description:

- **Iterate through each Op, and determine if the input tensor of the Op is in rec_tbl, if yes, then determine if ref_cnt >= 1, if still yes, ref_cnt –. This operation means that the number of references to the input tensor is reduced by one.**

  If ref_cnt is equal to 0, it means that the life cycle of the tensor is over, and later tensors can reuse its address space.

- **When allocating the output tensor to each Op, we first check whether the EOL tensor address can be reused. In other words, the rec_tbl must meet the following 5 conditions before it can be reused:**
  - The corresponding tensor is not in the hold_edges.
  - The address of the corresponding tensor is not in_using_addr
  - The corresponding tensor is already EOL.
  - The address space of the corresponding tensor >= the space required by the current tensor.
  - The address of the input tensor of the current Op is different from the address of the corresponding tensor (e.g., the final result of some Op operations is incorrect, except for reshapeOp).
- Allocate GMEM to the output tensor of the current Op. Reuse it if step2 shows that it can be reused. Otherwise, open a new GMEM in ddr.
- Adjust the lifecycle of the current Op's input tensor and check if it is in hold_edges. If yes, look in rec_tbl and check if its ref_cnt is 0. If yes, remove it from hold_edges as well as its addr from in_using_addr. This

operation means that the input tensor has finished its life cycle and the address space has been released.



Note: EOL definition: end-of-life.

CHAPTER 12

CodeGen

The code generation (CodeGen) in TPU-MLIR is the final step of BModel creation. Its purpose is to convert MLIR files into the final BModel. This chapter introduces the CodeGen of models/operators in this project.

12.1 Main Work

The purpose of CodeGen is to convert the MLIR file into the BModel file. This process will execute the CodeGen interface of each op to generate cmdbuf, and use the Builder module to generate the final BModel in flatbuffers format.

12.2 Workflow

The general process of CodeGen can be divided into three parts: instruction generation, instruction storage and instruction retrieval.

> Instruction generation: Encapsulate the back-end functions of different processors into classes, execute the op' s CodeGen interface, and generate corresponding instructions (binary code);
>
> Instruction storage: Store the instruction (binary code) in the specified data structure through store_cmd;
>
> Instruction retrieval: After the binary codes of all ops are generated, the compiler will call the function encapsulated in the BM168X series class to retrieve the instructions, and finally generate the Bmodel.

The workflow is as follows:

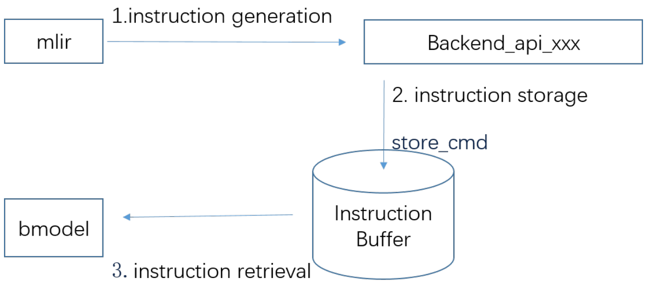


Fig. 12.1: CodeGen Workflow

The following introduces the data structures required in the CodeGen process:

The instructions differ based on the processor' s engine, e.g., 1684 has GDMA and TIU, while new architecture processors like sg2260 have sdma, cdma, etc. Using the most common engines, BDC (later renamed to TIU) and GDMA, as examples:

```
std::vector<uint32_t> bdc_buffer;
std::vector<uint32_t> gdma_buffer;
uint32_t gdma_total_id = 0;
uint32_t bdc_total_id = 0;
std::vector<uint32_t> gdma_group_id;
std::vector<uint32_t> bdc_group_id;
std::vector<uint32_t> gdma_bytes;
std::vector<uint32_t> bdc_bytes;
int cmdid_groupnum = 0;
CMD_ID_NODE *cmdid_node;
CMD_ID_NODE *bdc_node;
CMD_ID_NODE *gdma_node;
```

bdc_buffer: stores bdc instructions

gdma_buffer: stores gdma instructions

gdma_total_id: The total number of gdma instructions stored

bdc_total_id: The total number of bdc instructions stored

gdma_bytes: number of gdma instruction bytes

bdc_bytes: bdc instruction byte number

12.3 BM168X and Related classes in TPU-MLIR

These related classes are defined in the folder tpu-mlir/include/tpu_mlir/Backend. Their purpose is to encapsulate different processor backends, thereby isolating the backend from the CodeGen process.

The inheritance relationship is as follows:

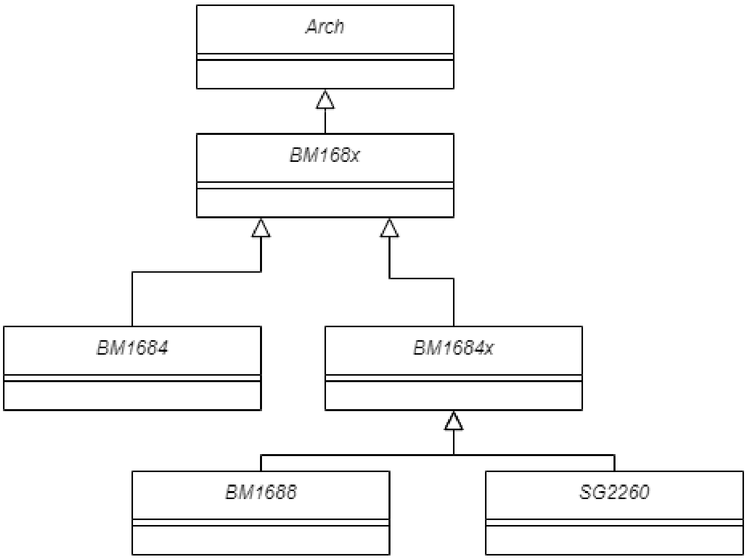


Fig. 12.2: BM168X and its related class inheritance relationships in TPU-MLIR

Only one class exists during a single run (singleton design pattern). When this class is initialized, it undergoes: reading the backend dynamic link library, loading functions (setting backend function pointers), initializing instruction data structures, and setting some hardware-related parameters like NPU_NUM, L2_SRAM starting address, etc.

12.4 Backend Function Loading

The backend is placed as a dynamic library in the TPU-MLIR project, specifically at third_party/nntoolchain/lib/libbackend_xxx.so. The loading method of the backend function is: first define the function pointer, and then load the dynamic library so that the function pointer points to the function in the dynamic library.

Take the synchronization function tpu_sync_all as an example, as we will add multi-core support later, it needs to be well-defined in the relevant backend cmodel library.

1. Make sure to keep the function name and parameters consistent: `typedef void (*tpu_sync_all)();
2. Add this function member within the class: `tpu_sync_all, dl_tpu_sync_all;
3. Add the macro, CAST_FUNCTION(tpu_sync_all), to the implementation of this type of load_functions function; This macro can point dl_tpu_sync_all to the function in the dynamic library.

After obtaining an instance of this class, we can use the functions in the dynamic library.

12.5 Backend store_cmd

The function store_cmd in the backend refers to the process where the compiler calls the operators and saves the configured instructions to the designated space. The key function in the backend is in store_cmd.cpp; for example, cmodel/src/store_cmd.cpp; cmodel/include/store_cmd.h. store_cmd has a series of EngineStorer and CmdStorer classes:

1. EngineStoreInterface (interface class), GDMAEngineStorer, BDEngineStorer and other specific classes that inherit from the EngineStoreInterface interface, EngineStorerDecorator (decoration class interface), VectorDumpEngineStorerDecorator and other specific decoration classes that inherit from EngineStorerDecorator
2. CmdStorerInterface (interface), ConcretCmdStorer inherited from the interface, StorerDecorator: decoration interface, VectorDumpStorerDecorator specific decoration class.

Relationship and Logic Among the Classes:

1. Using the singleton design pattern, there is only one ‘ConcretCmdStorer’ class in ‘store_cmd’, which will store all ‘EngineStorer’ classes. When different engines are called, different ‘EengineStorers’ will be called, as shown in the code below.

```
virtual void store_cmd(int engine_id, void *cmd, CMD_ID_NODE *cur_id_
↪node, int port) override
{
   switch (engine_id)
   {
   case ENGINE_BD:
   case ENGINE_GDMA:
   case ENGINE_HAU:
   case ENGINE_SDMA:
      port = 0;
      break;
   case ENGINE_CDMA:
      ASSERT(port < CDMA_NUM);
      break;
   case ENGINE_VSDMA:
      engine_id = ENGINE_SDMA;
      break;
   default:
      ASSERT(0);
      break;
   }
   return this->get(engine_id, port)->store(cmd, cur_id_node);
}
```

2. The function of ‘EngineStorer’ is to parse commands. ‘VectorDumpEngineStorerDecorator’ executes the ‘store’ function and ‘take_cmds’ function in the ‘EngineStorer’ class to store all instructions in output_.

```
class VectorDumpEngineStorerDecorator : public EngineStorerDecorator
{
private:
    std::vector<uint32_t> *&output_;

    void take_cmds()
    {
        auto cmds = EngineStorerDecorator::get_cmds();
        (*output_).insert((*output_).end(), cmds.begin(), cmds.end());
    }

public:
    VectorDumpEngineStorerDecorator(ComponentPtr component, std::vector
↪<uint32_t> **output)
        : EngineStorerDecorator(component), output_(*output) {}

    virtual void store(void *cmd, CMD_ID_NODE *cur_id_node) override
    {
        EngineStorerDecorator::store(cmd, cur_id_node);
        if (!enabled_)
            return;
        this->take_cmds();
    }

    virtual void store_cmd_end(unsigned dep) override
    {
        EngineStorerDecorator::store_cmd_end(dep);
        this->take_cmds();
    }
};
```

CHAPTER 13

MLIR Definition

This chapter introduces the definition of each element of MLIR, including Dialect, Interface, etc.

13.1 Top Dialect

13.1.1 Operations

AddOp

Brief intro
Add operation, $Y = coeff_0 * X_0 + coeff_1 * X_1$

Input

- inputs: tensor array, corresponding to 2 or more input tensors

Output

- output: tensor

Attributes

- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number
- coeff: the coefficient corresponding to each tensor, 1.0 by default

Output

- output: tensor

Interface

None

Example

```
%2 = "top.Add"(%0, %1) {do_relu = false} : (tensor<1x3x27x27xf32>, tensor
↪<1x3x27x27xf32>) -> tensor<1x3x27x27xf32> loc("add")
```

AvgPoolOp

Brief intro

Perform average pooling on the input tensor, $S = \frac{1}{width * height} \sum_{i,j} a_{ij}$, where *width* and *height* represent the width and height of the kernel_shape. $\sum_{i,j} a_{ij}$ means to sum the kernel_shape. A sliding window of a given size will sequentially pool the input tensor

Input

- input: tensor

Output

- output: tensor

Attributes

- kernel_shape: controls the size of the sliding window
- strides: step size, controlling each step of the sliding window
- pads: controls the shape of the padding
- pad_value: padding content, constant, 0 by default
- count_include_pad: whether the result needs to count the pads filled
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%90 = "top.AvgPool"(%89) {do_relu = false, kernel_shape = [5, 5], pads = [2, 2,
↪ 2, 2], strides = [1, 1]} : (tensor<1x256x20x20xf32>) -> tensor
↪<1x256x20x20xf32> loc("resnetv22_pool1_fwd_GlobalAveragePool")
```

Depth2SpaceOp

Brief intro

Depth to space operation, $Y = Depth2Space(X)$

Input

- inputs: tensor

Output

- output: tensor

Attributes

- block_h: tensor block size of h dimension, i64 type
- block_w: tensor block size of w dimension, i64 type
- is_CRD: column-row-depth. If true, the data is arranged in the depth direction according to the order of HWC, otherwise it is CHW, bool type
- is_inversed: if true, the shape of the result is: $[n, c * block_h * block_w, h/block_h, w/block_w]$, otherwise it is: $[n, c/(block_h * block_w), h * block_h, w * block_w]$, bool type

Output

- output: tensor

Interface

None

Example

```
%2 = "top.Depth2Space"(%0) {block_h = 2, block_w = 2, is_CRD = true, is_
↪inversed = false} : (tensor<1x8x2x3xf32>) -> tensor<1x2x4x6xf32> loc("add")
```

BatchNormOp

Brief intro

Perform Batch Normalization on a 4D input tensor. More details on batch normalization can be found in the paper "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift .

The specific calculation formula is as follows:

$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$

Input

- input: 4D input tensor

- mean: mean of the input tensor
- variance: variance of the input tensor
- gamma: γ tensor in the formula, can be None
- beta: β tensor in the formula, can be None

Output

- output: tensor

Attributes

- epsilon: constant ϵ in formula, 1e-05 by default
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%5 = "top.BatchNorm"(%0, %1, %2, %3, %4) {epsilon = 1e-05, do_relu = false}
↪ : (tensor<1x3x27x27xf32>, tensor<3xf32>, tensor<3xf32>, tensor<3xf32>,
↪tensor<3xf32>) -> tensor<1x3x27x27xf32> loc("BatchNorm")
```

CastOp

(To be implemented)

ClipOp

Brief intro

Constrain the given input to a certain range

Input

- input: tensor

Output

- output: tensor

Attributes

- min: the lower limit
- max: the upper limit

Output

- output: tensor

Interface

None

Example

```
%3 = "top.Clip"(%0) {max = 1%: f64,min = 2%: f64} : (tensor<1x3x32x32xf32>
↪) -> tensor<1x3x32x32xf32> loc("Clip")
```

ConcatOp

Brief intro

Concatenates the given sequence of tensors in the given dimension. All input tensors either have the same shape (except the dimension to be concatenated) or are all empty.

Input

- inputs: tensor array, corresponding to 2 or more input tensors

Output

- output: tensor

Attributes

- axis: the subscript of the dimension to be concatenated
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%2 = "top.Concat"(%0, %1) {axis = 1, do_relu = false} : (tensor
↪<1x3x27x27xf32>, tensor<1x3x27x27xf32>) -> tensor<1x6x27x27xf32> loc(
↪"Concat")
```

ConvOp

Brief intro

Perform 2D convolution operation on the input tensor.

In simple terms, the size of the given input is (N, C_{in}, H, W). The output $(N, C_{\text{out}}, H_{\text{out}}, W_{\text{out}})$ is calculated as:

$$\text{out}(N_i, C_{\text{out}_j}) = \text{bias}(C_{\text{out}_j}) + \sum_{k=0}^{C_{\text{in}}-1} \text{weight}(C_{\text{out}_j}, k) \star \text{input}(N_i, k),$$

where $\star$ is a valid cross-correlation operation, N is the batch size, C is the number of channels, H, W is the input image height and width.

Input

- input: tensor
- filter: parameter tensor. The shape is

$(\text{out\_channels}, \frac{\text{in\_channels}}{\text{groups}}, \text{kernel\_size}[0], \text{kernel\_size}[1])$

- bias: learnable bias tensor with the shape of $(out\_channels)$

Output

- output: tensor

Attributes

- kernel_shape: the size of the convolution kernel
- strides: strides of convolution
- pads: the number of layers to add 0 to each side of the input
- group: the number of blocked connections from the input channel to the output channel, the default is 1
- dilations: the spacing between convolution kernel elements, optional
- inserts: optional
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%2 = "top.Conv"(%0, %1) {kernel_shape = [3, 5], strides = [2, 1], pads = [4, 2]}
↪ : (tensor<20x16x50x100xf32>, tensor<33x3x5xf32>) -> tensor
↪<20x33x28x49xf32> loc("Conv")
```

DeconvOp

Brief intro

Perform a deconvolution operation on the input tensor.

Input

- input: tensor
- filter: parameter tensor. The shape is

$(\text{out\_channels}, \frac{\text{in\_channels}}{\text{groups}}, \text{kernel\_size}[0], \text{kernel\_size}[1])$

- bias: learnable bias tensor with the shape of $(out\_channels)$

Output

- output: tensor

Attributes

- kernel_shape: the size of the convolution kernel
- strides: strides of convolution
- pads: the number of layers to add 0 to each side of the input
- group: the number of blocked connections from the input channel to the output channel, the default is 1
- dilations: the spacing between convolution kernel elements, optional
- inserts: optional
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%2 = "top.Deconv"(%0, %1) {kernel_shape = (3, 5), strides = (2, 1), pads = (4,
↪ 2)} : (tensor<20x16x50x100xf32>, tensor<33x3x5xf32>) -> tensor
↪<20x33x28x49xf32> loc("Deconv")
```

DivOp

Brief intro

Division operation, $Y = X_0/X_1$

Input

- inputs: tensor array, corresponding to 2 or more input tensors

Output

- output: tensor

Attributes

- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number
- multiplier: the multiplier for quantization, the default is 1
- rshift: right shift for quantization, 0 by default

Output

- output: tensor

Interface

None

Example

```
%2 = "top.Div"(%0, %1) {do_relu = false, relu_limit = -1.0, multiplier = 1,
↪rshift = 0} : (tensor<1x3x27x27xf32>, tensor<1x3x27x27xf32>) -> tensor
↪<1x3x27x27xf32> loc("div")
```

InputOp

(To be implemented)

LeakyReluOp

Brief intro

Apply the LeakyRelu function on each element in the tensor. The function can be expressed as: f(x) = alpha * x for x < 0, f(x) = x for x >= 0

Input

- input: tensor

Output

- output: tensor

Attributes

- alpha: the coefficients corresponding to each tensor

Output

- output: tensor

Interface

None

Example

```
%4 = "top.LeakyRelu"(%3) {alpha = 0.67000001668930054 : f64} : (tensor
↪<1x32x100x100xf32>) -> tensor<1x32x100x100xf32> loc("LeakyRelu")
```

LSTMOp

Brief intro

Perform the LSTM operation of the RNN

Input

- input: tensor

Output

- output: tensor

Attributes

- filter: convolution kernel
- recurrence: recurrence unit
- bias: parameter of LSTM
- initial_h: Each sentence in LSTM will get a state after the current cell. The state is a tuple(c, h), where h=[batch_size, hidden_size]
- initial_c: c=[batch_size, hidden_size]
- have_bias: whether to set bias, the default is false
- bidirectional: set the LSTM of the bidirectional loop, the default is false
- batch_first: whether to put the batch in the first dimension, the default is false

Output

- output: tensor

Interface

None

Example

```
%6 = "top.LSTM"(%0, %1, %2, %3, %4, %5) {batch_first = false, bidirectional
↪= true, have_bias = true} : (tensor<75x2x128xf32>,tensor<2x256x128xf32>,
↪ tensor<2x256x64xf32>, tensor<2x512xf32>, tensor<2x2x64xf32>, tensor
↪<2x2x64xf32>) -> tensor<75x2x2x64xf32> loc("LSTM")
```

LogOp

Brief intro
Perform element-wise logarithm on the given input tensor

Input

- input: tensor

Output

- output: tensor

Attributes
None

Output

- output: tensor

Interface
None

Example

```
%1 = "top.Log"(%0) : (tensor<1x3x32x32xf32>) -> tensor<1x3x32x32xf32> loc(
↪"Log")
```

MaxPoolOp

Brief intro
Perform max pool on the given input tensor

Input

- input: tensor

Output

- output: tensor

Attributes

- kernel_shape: controls the size of the sliding window
- strides: step size, controlling each step of the sliding window

- pads: controls the shape of the padding
- pad_value: padding content, constant, 0 by default
- count_include_pad: whether the result needs to count the pads filled
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%8 = "top.MaxPool"(%7) {do_relu = false, kernel_shape = [5, 5], pads = [2, 2,
↪ 2, 2], strides = [1, 1]} : (tensor<1x256x20x20xf32>) -> tensor
↪<1x256x20x20xf32> loc("resnetv22_pool0_fwd_MaxPool")
```

MatMulOp

Brief intro

2D matrix multiplication operation, $C = A * B$

Input

- input: tensor: matrix of size m*k
- right: tensor: matrix of size k*n

Output

- output: tensor: matrix of size m*n

Attributes

- bias: the bias_scale will be calculated according to the bias during quantization (can be empty)
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Output

- output: tensor

Interface

None

Example

```
%2 = "top.MatMul"(%0, %1) {do_relu = false, relu_limit = -1.0} : (tensor
↪<3x4xf32>, tensor<4x5xf32>) -> tensor<3x5xf32> loc("matmul")
```

MulOp

Brief intro

multiplication operation, $Y = X_0 * X_1$

Input

- inputs: tensor array, corresponding to 2 or more input tensors

Output

- output: tensor

Attributes

- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number
- multiplier: the multiplier for quantization, the default is 1
- rshift: right shift for quantization, default is 0

Output

- output: tensor

Interface

None

Example

```
%2 = "top.Mul"(%0, %1) {do_relu = false, relu_limit = -1.0, multiplier = 1,
↪rshift = 0} : (tensor<1x3x27x27xf32>, tensor<1x3x27x27xf32>) -> tensor
↪<1x3x27x27xf32> loc("mul")
```

MulConstOp

Brief intro

Multiply with a constant, $Y = X * Const_Val$

Input

- inputs: tensor

Output

- output: tensor

Attributes

- const_val: constants of type f64
- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Output

- output: tensor

Interface

None

Example

```
%1 = arith.constant 4.7 : f64
%2 = "top.MulConst"(%0) {do_relu = false, relu_limit = -1.0} : (tensor
↪<1x3x27x27xf64>, %1) -> tensor<1x3x27x27xf64> loc("mulconst")
```

PermuteOp

Brief intro

Change the tensor layout. Change the order of tensor data dimensions, and rearrange the input tensor according to the given order

Input

- inputs: tensor array, tensor of any types

Attributes

- order: the order in which tensors are rearranged

Output

- output: rearranged tensor

Interface

None

Example

```
%2 = "top.Permute"(%1) {order = [0, 1, 3, 4, 2]} : (tensor<4x3x85x20x20xf32>
↪) -> tensor<4x3x20x20x85xf32> loc("output_Transpose")
```

ReluOp

Brief intro
Performs the ReLU function on each element in the input tensor, if the limit is zero, the upper limit is not used

Input

- input: tensor

Output

- output: tensor

Attributes

- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Output

- output: tensor

Interface
None

Example

```
%1 = "top.Relu"(%0) {relu_limit = 6.000000e+00 : f64} : (tensor
↪<1x3x32x32xf32>) -> tensor<1x3x32x32xf32> loc("Clip")
```

ReshapeOp

Brief intro
Reshape operator, which returns a tensor of the given shape with the same type and internal values as the input tensor. Reshape may operate on any row of the tensor. No data values will be modified during the reshaping process

Input

- input: tensor

Output

- output: tensor

Attributes
None

Interface
None

Example

```
%133 = "top.Reshape"(%132) : (tensor<1x255x20x20xf32>) -> tensor
↪<1x3x85x20x20xf32> loc("resnetv22_flatten0_reshape0_Reshape")
```

ScaleOp

Brief intro

Scale operation $Y = X * S + B$, where the shape of X/Y is [N, C, H, W], and the shape of S/B is [1, C, 1, , 1].

Input

- input: tensor
- scale: the magnification of the input
- bias: the bias added after scaling

Output

- output: tensor

Attributes

- do_relu: whether to perform Relu operation on the result, False by default
- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Interface

None

Example

```
%3 = "top.Scale"(%0, %1, %2) {do_relu = false} : (tensor<1x3x27x27xf32>,
↪tensor<1x3x1x1xf32>, tensor<1x3x1x1xf32>) -> tensor<1x3x27x27xf32> loc(
↪"Scale")
```

SigmoidOp

Brief intro

The activation function, which maps elements in the tensor to a specific interval, [0, 1] by default. The calculation method is:

$$Y = \frac{scale}{1 + e^{-X}} + bias$$

Input

- inputs: tensor array, tensor of any types

Attributes

- scale: the magnification of the input, 1 by default
- bias: default is 0

Output

- output: tensor

Interface
None

Example

```
%2 = "top.Sigmoid"(%1) {bias = 0.000000e+00 : f64, scale = 1.000000e+00 : f64}
↪ : (tensor<1x16x64x64xf32>) -> tensor<1x16x64x64xf32> loc("output_
↪Sigmoid")
```

SiLUOp

Brief intro
The activation function, $Y = \frac{X}{1+e^{-X}}$ or $Y = X * Sigmoid(X)$

Input

- input: tensor array, tensor of any types

Attributes
None

Output

- output: tensor

Interface
None

Example

```
%1 = "top.SiLU"(%0) : (tensor<1x16x64x64xf32>) -> tensor<1x16x64x64xf32>
↪ loc("output_Mul")
```

SliceOp

Brief intro
Tensor slice, slicing each dimension of the input tensor according to the offset and step size in the offset and steps arrays to generate a new tensor

Input

- input: tensor array, tensor of any types

Attributes

- offset: an array for storing slice offsets. The index of the offset array corresponds to the dimension index of the input tensor
- steps: an array that stores the step size of the slice. The index of the steps array corresponds to the index of the input tensor dimension

Output

- output: tensor

Interface

None

Example

```
%1 = "top.Slice"(%0) {offset = [2, 10, 10, 12], steps = [1, 2, 2, 3]} : (tensor
↪<5x116x64x64xf32>) -> tensor<3x16x16x8xf32> loc("output_Slice")
```

SoftmaxOp

Brief intro

For the input tensor, the normalized index value is calculated on the dimension of the specified axis. The calculation method is as follows:

$$\sigma(Z)_i = \frac{e^{\beta Z_i}}{\sum_{j=0}^{K-1} e^{\beta Z_j}},$$

where $\sum_{j=0}^{K-1} e^{\beta Z_j}$ does the exponential summation on the axis dimension. j ranges from 0 to K-1 and K is the size of the input tensor in the axis dimension.

For example, the size of the input tensor is (N, C, W, H), and the Softmax is calculated on the channel of axis=1. The calculation method is:

$$Y_{n,i,w,h} = \frac{e^{\beta X_{n,i,w,h}}}{\sum_{j=0}^{C-1} e^{\beta X_{n,j,w,h}}}$$

Input

- input: tensor array, tensor of any types

Attributes

- axis: dimension index, which is used to specify the dimension to perform softmax. It can take the value from [-r, r-1], where r is the number of dimensions of the input tensor. When axis is negative, it means the reverse order dimension
- beta: The scaling factor for the input in the tflite model, invalid for non-tflite models, 1.0 by default.

Output

- output: the tensor on which the softmax is performed.

Interface
None

Example

```
%1 = "top.Softmax"(%0) {axis = 1 : i64} : (tensor<1x1000x1x1xf32>) -> tensor
↪<1x1000x1x1xf32> loc("output_Softmax")
```

SqueezeOp

Brief intro
Crop the input tensor with the specified dimension and return the cropped tensor

Input

- input: tensor

Output

- output: tensor

Attributes

- axes: specifies the dimension to be cropped. 0 represents the first dimension and -1 represents the last dimension

Interface
None

Example

```
%133 = "top.Squeeze"(%132) {axes = [-1]} : (tensor<1x255x20x20xf32) -> tensor
↪<1x255x20xf32> loc(#loc278)
```

UpsampleOp

Brief intro
Upsampling op, upsampling the input tensor nearest and returning the tensor

Input
tensor

Attributes

- scale_h: the ratio of the height of the target image to the original image
- scale_w: the ratio of the width of the target image to the original image
- do_relu: whether to perform Relu operation on the result, False by default

- relu_limit: specify the upper limit value if doing Relu. There is no upper limit if it is a negative number

Output

- output: tensor

Interface

None

Example

```
%179 = "top.Upsample"(%178) {scale_h = 2 : i64, scale_w = 2 : i64} : (tensor
↪<1x128x40x40xf32>) -> tensor<1x128x80x80xf32> loc("268_Resize")
```

WeightOp

Brief intro

The weight op, including the reading and creation of weights. Weights will be stored in the npz file. The location of the weight corresponds to the tensor name in npz.

Input

None

Attributes

None

Output

- output: weight Tensor

Interface

- read: read weight data, the type is specified by the model
- read_as_float: convert the weight data to float type for reading
- read_as_byte: read the weight data in byte type
- create: create weight op
- clone_bf16: convert the current weight to bf16 and create a weight Op
- clone_f16: convert the current weight to f16 and create a weight Op

Example

```
%1 = "top.Weight"() : () -> tensor<32x16x3x3xf32> loc("filter")
```

CHAPTER 14

Accuracy Validation

14.1 Introduction

14.1.1 Objects

The accuracy validation in TPU-MLIR is mainly for the mlir model, fp32 uses the mlir model of the top layer while the int8 symmetric and asymmetric quantization uses the mlir model of the tpu layer.

14.1.2 Metrics

Currently, the validation is mainly used for classification and object detection networks. The metrics for classification networks are Top-1 and Top-5 accuracy, while the object detection networks use 12 metrics of COCO, as shown below. Generally, we record the Average

Precision when IoU=0.5 (i.e., PASCAL VOC metric).

$$
\begin{aligned}
&\boldsymbol{AveragePrecision(AP)}: \\
&AP \quad \% \text{ AP at IoU=.50:.05:.95 (primary challenge metric)} \\
&AP^{IoU} = .50 \quad \% \text{ AP at IoU=.50 (PASCAL VOC metric)} \\
&AP^{IoU} = .75 \quad \% \text{ AP at IoU=.75 (strict metric)} \\
&\boldsymbol{APAcrossScales}: \\
&AP^{small} \quad \% \text{ AP for small objects: } area < 32^2 \\
&AP^{medium} \quad \% \text{ AP for medium objects: } 32^2 < area < 96^2 \\
&AP^{large} \quad \% \text{ AP for large objects: } area > 96^2 \\
&\boldsymbol{AverageRecall(AR)}: \\
&AR^{max=1} \quad \% \text{ AR given 1 detection per image} \\
&AR^{max=10} \quad \% \text{ AR given 10 detections per image} \\
&AR^{max=100} \quad \% \text{ AR given 100 detections per image} \\
&\boldsymbol{APAcrossScales}: \\
&AP^{small} \quad \% \text{ AP for small objects: } area < 32^2 \\
&AP^{medium} \quad \% \text{ AP for medium objects: } 32^2 < area < 96^2 \\
&AP^{large} \quad \% \text{ AP for large objects: } area > 96^2
\end{aligned}
$$

14.1.3 Datasets

In addition, the dataset used for validation needs to be downloaded by yourself. Classification networks use the validation set of ILSVRC2012 (50,000 images, https://www.image-net.org/challenges/LSVRC/2012/). There are two ways to place the images in the dataset. One is that there are 1000 subdirectories under the dataset directory, corresponding to 1000 classes, and each class has 50 images. In this case, no additional label file is required. The other way is that all images are in the same dataset directory, and there is an additional label file. According to the sequence of images’ names, each line in the txt file uses a number from 1 to 1000 to indicate the class of each image.

Object detection networks use the COCO2017 validation set (5000 images, https://cocodataset.org/#download). All images are under the same dataset directory. The corresponding json label file needs to be downloaded as well.

14.2 Validation Interface

TPU-MLIR provides the command for accuracy validation:

```
$ model_eval.py \
    --model_file mobilenet_v2.mlir \
    --count 50 \
    --dataset_type imagenet \
    --postprocess_type topx \
    --dataset datasets/ILSVRC2012_img_val_with_subdir
```

The supported parameters are shown below:

Table 14.1: Function of model_eval.py parameters

Name	Required?	Explanation
model_file	Y	Model file
dataset	N	Directory of dataset
dataset_type	N	Dataset type. Currently mainly supports imagenet, coco. The default is imagenet
postprocess_type	Y	Metric. Currently supports topx and coco_mAP
label_file	N	txt label file, which may be needed when validating the accuracy of classification networks
coco_annotation	N	json label file, required when validating object detection networks
count	N	The number of images used for validation. The default is to use the entire dataset.

14.3 Validation Example

In this section, mobilenet_v2 and yolov5s are used as the representative of the classification network and the object detection network for accuracy validation.

14.3.1 mobilenet_v2

1. Dataset Downloading

   Download the ILSVRC2012 validation set to the datasets/ILSVRC2012_img_val_with_subdir directory. Images of the dataset are placed in subdirectories, so no additional label files are required.

2. Model Conversion

   Use the model_transform.py interface to convert the original model to the mobilenet_v2.mlir model, and obtain mobilenet_v2_cali_table through the run_calibration.py interface. Please refer to the "User Interface" chapter for specific usage. The INT8 model of the tpu layer is obtained through the command below. After running the command, an intermediate file named mobilenet_v2_bm1684x_int8_sym_tpu.mlir will be generated. We will use this intermediate file to validate the accuracy of the INT8 symmetric quantized model:

```
# INT8 Sym Model
$ model_deploy.py \
  --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 0.95,0.69 \
  --model mobilenet_v2_int8.bmodel
```

3. Accuracy Validation

   Use the model_eval.py interface to validate:

```
# F32 model validation
$ model_eval.py \
   --model_file mobilenet_v2.mlir \
   --count 50000 \
   --dataset_type imagenet \
   --postprocess_type topx \
   --dataset datasets/ILSVRC2012_img_val_with_subdir

# INT8 sym model validation
$ model_eval.py \
   --model_file mobilenet_v2_bm1684x_int8_sym_tpu.mlir \
   --count 50000 \
   --dataset_type imagenet \
   --postprocess_type topx \
   --dataset datasets/ILSVRC2012_img_val_with_subdir
```

The accuracy validation results of the F32 model and the INT8 symmetric quantization model are as follows:

```
# mobilenet_v2.mlir validation result
2022/11/08 01:30:29 - INFO : idx:50000, top1:0.710, top5:0.899
INFO:root:idx:50000, top1:0.710, top5:0.899

# mobilenet_v2_bm1684x_int8_sym_tpu.mlir validation result
2022/11/08 05:43:27 - INFO : idx:50000, top1:0.702, top5:0.895
INFO:root:idx:50000, top1:0.702, top5:0.895
```

14.3.2 yolov5s

1. Dataset Downloading

   Download the COCO2017 validation set to the datasets/val2017 directory, which contains 5,000 images for validation. The corresponding label file instances_val2017.json is downloaded to the datasets directory.

2. Model Conversion

   The conversion process is similar to mobilenet_v2.

3. Accuracy Validation

   Use the model_eval.py interface to validate:

```
# F32 model validation
$ model_eval.py \
   --model_file yolov5s.mlir \
   --count 5000 \
   --dataset_type coco \
   --postprocess_type coco_mAP \
   --coco_annotation datasets/instances_val2017.json \
   --dataset datasets/val2017

# INT8 sym model validation
$ model_eval.py \
   --model_file yolov5s_bm1684x_int8_sym_tpu.mlir \
   --count 5000 \
   --dataset_type coco \
   --postprocess_type coco_mAP \
   --coco_annotation datasets/instances_val2017.json \
   --dataset datasets/val2017
```

The accuracy validation results of the F32 model and the INT8 symmetric quantization model are as follows:

```
# yolov5s.mlir validation result
Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.369
Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.561
Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.393
Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.217
Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.422
Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.470
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.300
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.502
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.542
Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.359
Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.602
Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.670

# yolov5s_bm1684x_int8_sym_tpu.mlir validation result
Average Precision  (AP) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.337
```

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```
Average Precision  (AP) @[ IoU=0.50      | area=   all | maxDets=100 ] = 0.544
Average Precision  (AP) @[ IoU=0.75      | area=   all | maxDets=100 ] = 0.365
Average Precision  (AP) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.196
Average Precision  (AP) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.382
Average Precision  (AP) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.432
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=  1 ] = 0.281
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets= 10 ] = 0.473
Average Recall     (AR) @[ IoU=0.50:0.95 | area=   all | maxDets=100 ] = 0.514
Average Recall     (AR) @[ IoU=0.50:0.95 | area= small | maxDets=100 ] = 0.337
Average Recall     (AR) @[ IoU=0.50:0.95 | area=medium | maxDets=100 ] = 0.566
Average Recall     (AR) @[ IoU=0.50:0.95 | area= large | maxDets=100 ] = 0.636
```

CHAPTER 15

quantzation aware traing

15.1 Basic Principles

Compared with the precision loss caused by post-training quantization because it is not the global optimal, QAT quantization perception training can achieve the global optimal based on loss optimization and reduce the quantization precision loss as far as possible. The basic principle is as follows:In fp32 model training, weight and activation errors caused by inference quantization are introduced in advance, and task loss is used to optimize learnable weight and quantized scale and zp values on the training set. Even under the influence of this quantization error, task loss can reach relatively low loss value through learning.In this way, when the real inference deployment of quantization later, because the error introduced by quantization has already been well adapted in the training, as long as the inference and the calculation of training can be guaranteed to be completely aligned, theoretically, there will be no precision loss in the inference quantization.

15.2 tpu-mlir QAT implementation scheme and characteristics

15.2.1 Main body flow

During user training, model QAT quantization API is called to modify the training model:In reasoning, after op fusion, a pseudo-quantization node is inserted before the input (including weight and bias) of the op that needs to be quantized (the quantization parameters of this node can be configured, such as per-chan/layer, symmetry or not, number of quantization bits, etc.), and then the user uses the modified model for normal training process. After completing a few rounds of training,Call the transformation deployment API interface to convert the trained model into the FP32-weighted onnx model, extract the parameters from the pseudo-quantization node and export them to the quantization parameter text file. Finally, input the optimized onnx model and the quantization parameter file into the tpu-mlir tool chain, and convert and deploy according to the post-training quantization method mentioned above.

15.2.2 Features of the Scheme

Feature 1:Based on pytorch;QAT is an additional finetune part of the training pipeline, and only deep integration with the training environment can facilitate users to use various scenarios. Considering pytorch has the most extensive usage rate, the current scheme is based on pytorch only. If qat supports other frameworks in the future, the scheme will be very different.Its trace and module replacement mechanisms are deeply dependent on the support of the native training platform.

Feature 2:Users basically have no sense;Different from earlier schemes that require deep manual intervention in model transformation, this scheme based on pytorch fx can automatically complete model trace, pseudo-quantization node insertion, custom module replacement and other operations. In most cases, users can complete model transformation with one click using the default configuration.

Feature 3:This scheme is based on Sensetime’s open source mqbench qat training framework, which has a certain community foundation and is convenient for industry and academia to evaluate reasoning performance and accuracy on our tpu.

15.3 Installation Method

15.3.1 Install from source

1、Run the command to get the latest code on github:git clone https://github.com/sophgo/MQBench。

2、Execute after entering the MQBench directory:

```
pip install -r requirements.txt  #Note: torch version 1.10.0 is currently required
python setup.py install
```

3、If python -c ‘import mqbench’ does not return any error, the installation is correct. If the installation is incorrect, run pip uninstall mqbench and try again.

15.3.2 Installing the wheel file

Download the python whl package from https://MQBench-1.0.0-py3-none-any.whl and run pip3 install MQBench-1.0.0-py3-none-any.whl to install it directly.

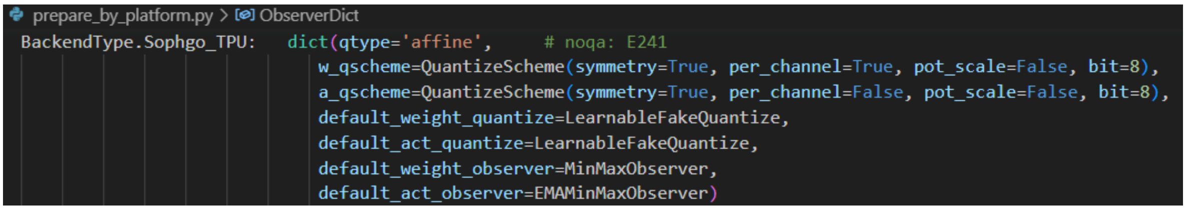
15.4 Basic Steps

15.4.1 Step 1: Interface import and model prepare

Add the following python module import interface to the training file:

```
#Initializing Interface
from mqbench.prepare_by_platform import prepare_by_platform, BackendType
#Calibrate and quantify switches
from mqbench.utils.state import enable_calibration, enable_quantization
#Transform Deployment interface
from mqbench.convert_deploy import convert_deploy
#Use the pre-trained resnet18 model in torchvision model zoo
model = torchvision.models.__dict__["resnet18"](pretrained=True)
Backend = BackendType.sophgo_tpu
#1.trace model and then add quantization nodes in a specific way based on the requirements of
↪sophgo_tpu hardware
model_quantized = prepare_by_platform(model, Backend)
```

When sophgo_tpu backend is selected on the above interface, the third parameter prepare_custom_config_dict of this interface is not configured by default. In this case, the default quantization configuration is shown as the following figure:


```
prepare_by_platform.py > ObserverDict
BackendType.Sophgo_TPU:   dict(qtype='affine',     # noqa: E241
                            w_qscheme=QuantizeScheme(symmetry=True, per_channel=True, pot_scale=False, bit=8),
                            a_qscheme=QuantizeScheme(symmetry=True, per_channel=False, pot_scale=False, bit=8),
                            default_weight_quantize=LearnableFakeQuantize,
                            default_act_quantize=LearnableFakeQuantize,
                            default_weight_observer=MinMaxObserver,
                            default_act_observer=EMAMinMaxObserver)
```

In the above figure, items in the dict behind sophgo_tpu in order of top to bottom meaning are:

1、The weight quantization scheme is: per-chan symmetric 8bit quantization, the scale coefficient is not power-of-2, but arbitrary

2、The activation quantization scheme is per-layer symmetric 8bit quantization

3/4、The weights and activation pseudo-quantization schemes are: LearnableFakeQuantize, namely LSQ algorithm

5/6、The dynamic range statistics and scale calculation scheme of weights are as follows: MinMaxObserver, and the activation is EMAMinMaxObserver with moving average

15.4.2 Step 2: Calibration and quantization training

```
#1.Turn on the calibration switch to allow the pytorch observer object to collect the activation distribution and calculate the initial scale and zp when reasoning on the model
enable_calibration(model_quantized)
# iterations of calibration
for i, (images, _) in enumerate(cali_loader):
    model_quantized(images)  #All you need is forward reasoning
#3.After the pseudo-quantization switch is turned on, the quantization error will be introduced by invoking the QuantizeBase subobject to conduct the pseudo-quantization operation when reasoning on the model
enable_quantization(model_quantized)
# iterations of training
for i, (images, target) in enumerate(train_loader):
    #Forward reasoning and calculation loss
    output = model_quantized(images)
    loss = criterion(output, target)
    #Back to back propagation gradient
    loss.backward()
    #Update weights and pseudo-quantization parameters
    optimizer.step()
```

15.4.3 Step 3: Export tuned fp32 model

```
#Here the batch-size can be adjusted according to the need, do not have to be consistent with the training batch-size
input_shape={ 'data' : [4, 3, 224, 224]}
#4. Before export, the conv+bn layer is fused (conv+bn is true fusion when train is used in the front), and the parameters in the pseudo-quantization node are saved to the parameter file, and then removed。
convert_deploy(model_quantized, backend, input_shape)
```

15.4.4 Step 4: Initiate the training

Set reasonable training hyperparameters. The suggestions are as follows:

–epochs=1:About 1~3 can be;

–lr=1e-4:The learning rate should be the learning rate when fp32 converges, or even lower;

–optim=sgd:The default is sgd;

15.4.5 Step 5: Transform deployment

The transformation deployment to sophg-tpu hardware was completed using the model_transform.py and model_deploy.py scripts of tpu-mlir;

15.5 Use Examples-resnet18

Run example/imagenet_example/main.py to qat train resent18 as follows:

```
python3 imagenet_example/main.py
    --arch=resnet18
    --batch-size=192
    --epochs=1
    --lr=1e-4
    --cuda=0
    --pretrained
    --backend=sophgo_tpu
    --optim=sgd
    --deploy_batch_size=10
    --train_data=/data/imagenet/for_train_val/
    --val_data=/data/imagenet/for_train_val/
    --output_path=/workspace/classify_models
```

The command output log above contains the following(Original onnx model accuracy) accuracy information of the original model (it can be compared with the accuracy on the official webpage to confirm the correct training environment, such as the official nominal name:Acc@1 69.76 Acc@5 89.08,The link is:https://pytorch.apachecn.org/#/docs/1.0/torchvision_models) :

```
=> using pre-trained model 'resnet18'
原始onnx模型精度
Test: [  0/261] Time  3.447 ( 3.447)    Loss 6.8051e-01 (6.8051e-01)    Acc@1  80.21 ( 80.21)
Test: [100/261] Time  0.504 ( 0.483)    Loss 8.1262e-01 (9.0736e-01)    Acc@1  73.96 ( 76.23)
Test: [200/261] Time  0.099 ( 0.467)    Loss 1.0743e+00 (1.1929e+00)    Acc@1  80.21 ( 70.82)
 * Acc@1 69.758 Acc@5 89.078
```

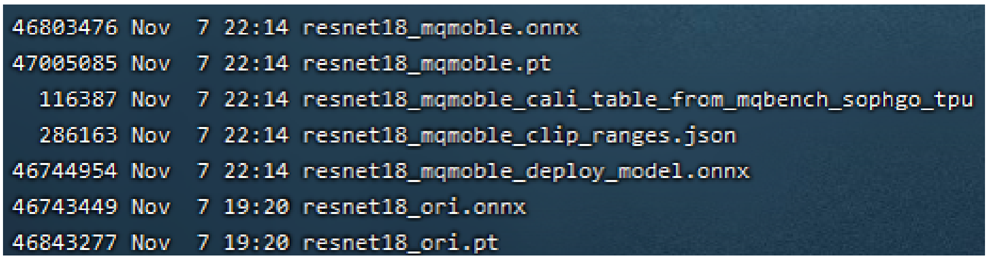
Fig. 15.1: Original onnx model accuracy

After completing the qat training, the eval accuracy of the running band quantization node, theoretically the int8 accuracy of the tpu-mlir should be exactly aligned with this, as shown in the figure(resnet18 qat training accuracy) below:

```
qat训练后的带量化节点的eval精度:
Test: [  0/391] Time  2.255 ( 2.255)    Loss 6.4446e-01 (6.4446e-01)    Acc@1  82.81
Test: [100/391] Time  0.130 ( 0.427)    Loss 7.2533e-01 (8.9875e-01)    Acc@1  80.47
Test: [200/391] Time  0.129 ( 0.424)    Loss 1.1836e+00 (1.0291e+00)    Acc@1  66.41
Test: [300/391] Time  0.128 ( 0.421)    Loss 1.3070e+00 (1.1715e+00)    Acc@1  73.44
 * Acc@1 69.986 Acc@5 89.256
```

Fig. 15.2: resnet18 qat training accuracy

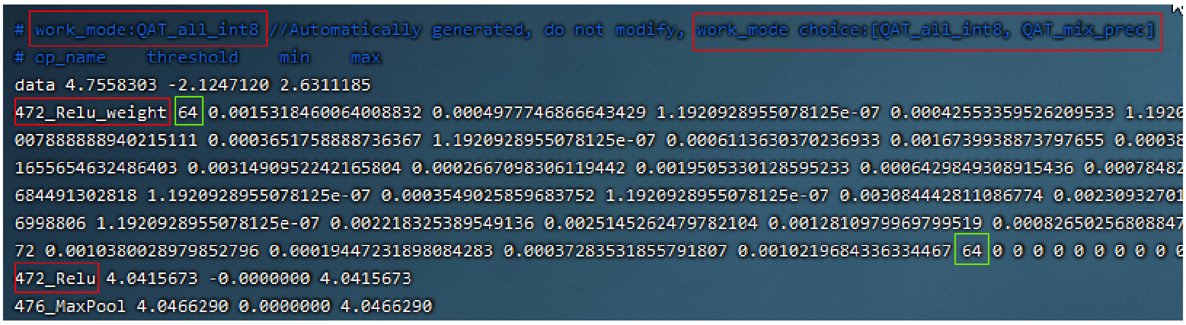
The final output directory is as follows(resnet18 qat training output model directory):



```
46803476 Nov  7 22:14 resnet18_mqmoble.onnx
47005085 Nov  7 22:14 resnet18_mqmoble.pt
  116387 Nov  7 22:14 resnet18_mqmoble_cali_table_from_mqbench_sophgo_tpu
  286163 Nov  7 22:14 resnet18_mqmoble_clip_ranges.json
46744954 Nov  7 22:14 resnet18_mqmoble_deploy_model.onnx
46743449 Nov  7 19:20 resnet18_ori.onnx
46843277 Nov  7 19:20 resnet18_ori.pt
```

Fig. 15.3: resnet18 qat training output model directory

The one with _ori in the figure above is the original pt of pytorch model zoo and the transferred onnx file. This resnet18_ori.onnx is quantified by PTQ with the tpu-mlir tool chain, and its symmetry and asymmetry quantization accuracy are measured as the baseline and resnet18_mqmoble_cali_table_from_mqbench_sophgo_tpu is the exported quantization parameter file with the following contents(resnet18 Sample qat quantization parameter table):



```
# work_mode:QAT_all_int8 //Automatically generated, do not modify, work_mode choice:[QAT_all_int8, QAT_mix_prec]
# op_name    threshold    min    max
data 4.7558303 -2.1247120 2.6311185
472_Relu_weight 64 0.0015318460064008832 0.0004977746866643429 1.1920928955078125e-07 0.00042553359526209533 1.1920
007888888940215111 0.0003651758888736367 1.1920928955078125e-07 0.0006113630370236933 0.0016739938873797655 0.00038
1655654632486403 0.0031490952242165804 0.0002667098306119442 0.0019505330128595233 0.0006429849308915436 0.00078482
684491302818 1.1920928955078125e-07 0.0003549025859683752 1.1920928955078125e-07 0.003084442811086774 0.00230932701
6998806 1.1920928955078125e-07 0.002218325389549136 0.0025145262479782104 0.001281097996979519 0.00082650256808847
72 0.0010380028979852796 0.00019447231898084283 0.00037283531855791807 0.0010219684336334467 64 0 0 0 0 0 0 0 0 0 0
472_Relu 4.0415673 -0.0000000 4.0415673
476_MaxPool 4.0466290 0.0000000 4.0466290
```

Fig. 15.4: resnet18 Sample qat quantization parameter table

a、In the red box of the first row in the figure above, work_mode is QAT_all_int8, indicating int8 quantization of the whole network. It can be selected from [QAT_all_int8, QAT_mix_prec], and quantization parameters such as symmetry and asymmetry will also be included。

b、In the figure above, 472_Relu_weight represents the QAT-tuned scale and zp parameters of conv weight. The first 64 represents the scale followed by 64, and the second 64 represents the zp followed by 64.tpu-mlir imports the weight_scale attribute of the top weight. If this attribute exists in the int8 lowering time, it is directly used. When it does not, it is recalculated according to the maximum lowering value。

c、In the case of asymmetric quantization, min and max above are calculated according to the scale, zp, qmin and qmax tuned by the activated qat. threshold is calculated according to the activated scale in the case of symmetric quantization, and both are not valid at the same time。

15.6 Tpu-mlir QAT test environment

15.6.1 Adding a cfg File

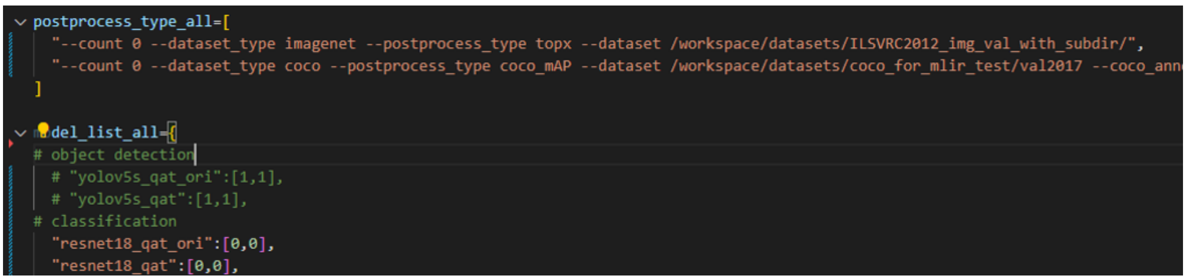
Go to the tpu-mlir/regression/eval directory and add {model_name}_qat.cfg to the qat_config subdirectory. For example, the contents of the resnet18_qat.cfg file are as follows:

```
dataset=${REGRESSION_PATH}/dataset/ILSVRC2012
test_input=${REGRESSION_PATH}/image/cat.jpg
input_shapes=[[1,3,224,224]]  #Modified according to the actual shape
#The following is the image preprocessing parameters, fill in according to the actual situation
resize_dims=256,256
mean=123.675,116.28,103.53
scale=0.0171,0.0175,0.0174
pixel_format=rgb
int8_sym_tolerance=0.97,0.80
int8_asym_tolerance=0.98,0.80
debug_cmd=use_pil_resize
```

You can also add {model_name}_qat_ori.cfg file: Quantify the original pytorch model as baseline, which can be exactly the same as {model_name}_qat.cfg above;

15.6.2 Modify and execute run_eval.py

In the following figure, fill in more command strings of different precision evaluation methods in postprocess_type_all, such as the existing imagenet classification and coco detection precision calculation strings in the figure;In the following figure, model_list_all fills in the mapping of the model name to the parameter, for example:resnet18_qat' s [0,0], where the first parameter represents the first command string in postprocess_type_all, and the second parameter represents the first directory in qat_model_path (separated by commas):



After configuring the postprocess_type_all and model_list_all arrays as needed, execute the following run_eval.py command:

```
python3 run_eval.py
    --qat_eval        #In qat validation mode, the default is to perform regular model accuracy
↪testing using the configuration in the tpu-mlir/regression/config
    --fast_test       #Quick test before the official test (only test the accuracy of 30 graphs) to
↪confirm that all cases can run
```

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```
    --pool_size 20    #By default, 10 processes run. If the machine has many idle resources, you
↪can configure more
    --batch_size 10   #qat exports the batch-size of the model. The default is 1
    --qat_model_path '/workspace/classify_models/,/workspace/yolov5/qat_models'  #Directory
↪of the qat model,For example, the value of model_list_all[' resnet18_qat '][1] is 0, indicating
↪the first directory address of the model target in the qat_model_path:/workspace/classify_
↪models/
    --debug_cmd use_pil_resize      #Use pil resize
```

After or during the test, view the model_eval script output log file starting with log_ in the subdirectory named {model_name}_qat,For example, log_resnet18_qat.mlir indicates the log of testing resnet18_qat.mlir in the directory.log_resnet18_qat_bm1684x_tpu_int8_sym.mlir Indicates the test log of resnet18_qat_bm1684x_tpu_int8_sym.mlir in this directory.

15.7 Use Examples-yolov5s

Similar to resnet18, run the following command in example/yolov5_example to start qat training:

```
python3 train.py
    --cfg=yolov5s.yaml
    --weights=yolov5s.pt
    --data=coco.yaml
    --epochs=5
    --output_path=/workspace/yolov5/qat_models
    --batch-size=8
    --quantize
```

After the training is completed, the same test and transformation deployment process as resnet18 before can be adopted。

CHAPTER 16

TpuLang Interface

This chapter mainly introduces the process of converting models using TpuLang.

16.1 Main Work

TpuLang provides mlir external interface functions. Users can directly build their own network through Tpulang, and convert the model to the Top layer (hardware-independent layer) mlir model (the Canonicalize part is not included, so the generated file name is "*_origin.mlir"). This process will create and add operators (Op) one by one according to the input interface functions. Finally, a mlir model file and a corresponding weight npz file will be generated.

16.2 Work Process

1. Initialization: Set up the platform and create the graph.
2. Add OPs: cyclically add OPs of the model
   - The input parameters are converted to dict format;
   - Inference output shape, and create output tensor;
   - Set the quantization parameters of the tensor (scale, zero_point);
   - Create op(op_type, inputs, outputs, params) and insert it into the graph.
3. Set the input and output tensor of the model. Get all model information.
4. Initialize TpuLangConverter (initMLIRImporter)

5. generate_mlir
   - Create the input op, the nodes op in the middle of the model and the return op in turn, and add them to the mlir text (if the op has weight, an additional weight op will be created)
6. Output
   - Convert the generated text to str and save it as “.mlir” file
   - Save model weights (tensors) as “.npz” files
7. End: Release the graph.

The workflow of TpuLang conversion is shown in the figure (TpuLang conversion process)。

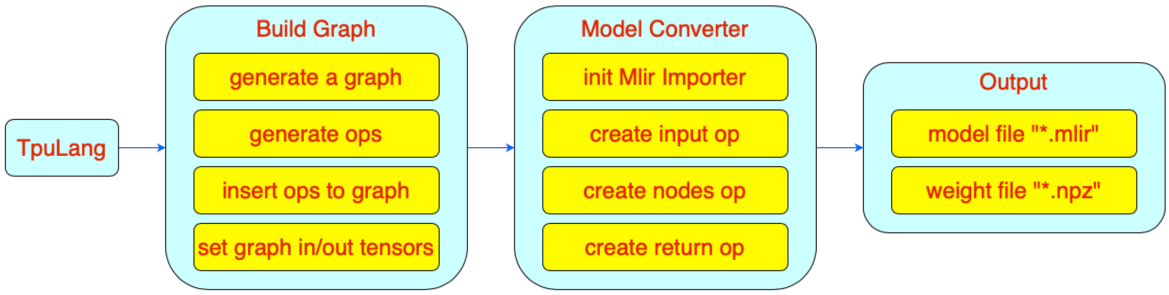

Fig. 16.1: TpuLang conversion process

Supplementary Note:

- The op interface requires:
  - The input tensor of the op (i.e., the output tensor of the previous operator or the graph input tensor and coeff);
  - According to the parameters extracted by the interface, the output_shape is obtained by inference (i.e., shape_inference is required);
  - attrs extracted from the interface. Attrs will be set by MLIRImporter as attributes corresponding to the ones defined in TopOps.td;
  - If the interface includes quantization parameters (i.e., scale and zero_point), the tensor corresponding to this parameter needs to set (or check) the quantization parameters.
  - Return the output tensor(tensors) of the op.
- After all operators are inserted into the graph and the input/output tensors of the graph are set, the conversion to mlir text will start. This part is implemented by TpuLangConverter.
- The conversion process of TpuLang Converter is the same as onnx front-end part. Please refer to (Front-end Conversion).

16.3 Operator Conversion Example

This section takes the Conv operator as an example to convert a single Conv operator model to Top mlir. The original model definition is shown in the figure (Single Conv Model)

```
def model_de():
    bml.init("BM1684X", True)
    in_shape = [1,3,173,141]
    k_shape = [64,1,7,7]
    x = bml.Tensor(dtype='float32', shape=in_shape)        You, 现在 • Uncommitted changes
    weight_data = np.random.random(k_shape).astype(np.float32)
    weight = bml.Tensor(dtype='float32', shape=k_shape, data=weight_data, is_const=True)
    bias_data = np.random.random(k_shape[0]).astype(np.float32)
    bias = bml.Tensor(dtype='float32', shape=k_shape[0], data=bias_data, is_const=True)
    conv = bml.conv_v2(x, weight, bias=bias, stride=[2,2], pad=[0,0,1,1],
                        out_dtype="float32")
    bml.compile("model_def", inputs=[x], outputs=[conv], cmp=True)
    bml.deinit()
```

Fig. 16.2: Single Conv Model

The conversion process:

1. Interface definition

   The conv_v2 interface is defined as follows:

   ```
   def conv_v2(tensor_i,
               weight,
               bias = None,
               stride = None,
               dilation = None,
               pad = None,
               group = 1,
               input_zp = None,
               weight_zp = None,
               out_dtype = None,
               out_name = None):
     # pass
   ```

   Parameter Description

   - tensor_i: Tensor type, indicating the input Tensor with 4-dimensional NCHW format.
   - weight: Tensor type, representing the convolution kernel Tensor with 4-dimensional [oc, ic, kh, kw] format. oc indicates the number of output channels, ic indicates the number of input channels, kh is kernel_h, and kw is kernel_w.
   - bias: Tensor type, indicating the bias Tensor. There is no bias when it is None. Otherwise, the shape is required to be [1, oc, 1, 1].

- dilation: List[int], indicating the size of holes. None means dilation equals [1,1]. Otherwise, the length is required to be 2 and the order of List is [length, width].
- pad: List[int], indicating the padding size, if it is None, no padding is applied. Otherwise, the length is required to be 4. The order in the List is [Up, Down, Left, Right].
- stride: List[int], indicating the step size, [1,1] when it is None. Otherwise, the length is required to be 2 and the order in the List is [length, width].
- groups: int type, indicating the number of groups in the convolutional layer. If ic=oc=groups, the convolution is depthwise conv
- input_zp: List[int] type or int type, indicating the input offset. If None, input_zp equals 0. Otherwise, the length of List is required to be ic.
- weight_zp: List[int] type or int type, indicating the convolution kernel offset. If None, weight_zp equals 0. Otherwise, the length of list is required to be ic, where ic represents the number of input channels.
- out_dtype: string type or None, indicating the type of the output Tensor. When the input tensor type is float16/float32, None indicates that the output tensor type is consistent with the input. Otherwise, None means int32. Value range: /int32/uint32/float32/float16.
- out_name: string type or None, indicating the name of the output Tensor. When it is None, the name will be automatically generated.

Define the Top.Conv operator in TopOps.td, the operator definition is as shown in the figure (Conv Operator Definition)

1. Build Graph

- Initialize the model: create an empty Graph.
- Model input: Create input tensor x given shape and data type. A tensor name can also be specified here.
- conv_v2 interface:
  - Call the conv_v2 interface with specified input tensor and input parameters.
  - Inference output shape, and generate output tensor

```
def _shape_inference():
    kh_ext = dilation[0] * (weight.shape[2] - 1) + 1
    kw_ext = dilation[1] * (weight.shape[3] - 1) + 1
    oh = (input.shape[2] + pad[0] + pad[1] - kh_ext) // stride[0] + 1
    ow = (input.shape[3] + pad[2] + pad[3] - kw_ext) // stride[1] + 1
    return [input.shape[0], weight.shape[0], oh, ow]
output = Tensor(_shape_inference(), dtype=out_dtype, name=out_name)
```

  - attributes, pack the input parameters into attributes defined by (Conv Operator Definition) include > tpu_mlir > Dialect > Top > IR > TopOps.td

```
def Top_ConvOp: Top_Op<"Conv", [SupportFuseRelu]> {
  let summary = "Convolution operator";

  let description = [{
    In the simplest case, the output value of the layer with input size
    .......
  }];

  let arguments = (ins
    AnyTensor:$input,
    AnyTensor:$filter,
    AnyTensorOrNone:$bias,
    I64ArrayAttr:$kernel_shape,
    I64ArrayAttr:$strides,
    I64ArrayAttr:$pads, // top,left,bottom,right
    DefaultValuedAttr<I64Attr, "1">:$group,
    OptionalAttr<I64ArrayAttr>:$dilations,
    OptionalAttr<I64ArrayAttr>:$inserts,
    DefaultValuedAttr<BoolAttr, "false">:$do_relu,
    OptionalAttr<F64Attr>:$upper_limit,
    StrAttr:$name
  );

  let results = (outs AnyTensor:$output);
  let extraClassDeclaration = [{
    void parseParam(int64_t &n, int64_t &ic, int64_t &ih, int64_t &iw, int64_t &oc,
                    int64_t &oh, int64_t &ow, int64_t &g, int64_t &kh, int64_t &kw, int64_t &ins_h,
                    int64_t &ins_w, int64_t &sh, int64_t &sw, int64_t &pt, int64_t &pb, int64_t &pl,
                    int64_t &pr, int64_t &dh, int64_t &dw, bool &is_dw, bool &with_bias, bool &do_relu,
                    float &relu_upper_limit);
  }];
}
```

Fig. 16.3: Conv Operator Definition

```
attr = {
   "kernel_shape": ArrayAttr(weight.shape[2:]),
   "strides": ArrayAttr(stride),
   "dilations": ArrayAttr(dilation),
   "pads": ArrayAttr(pad),
   "do_relu": Attr(False, "bool"),
   "group": Attr(group)
}
```

- Insert conv op. Insert Top.ConvOp into Graph.
- return the output tensor

· Set the input of Graph and output tensors.

3. init_MLIRImporter:

   Get the corresponding input_shape and output_shape from shapes according to input_names and output_names. Add model_name, and generate the initial mlir text MLIRImporter.mlir_module, as shown in the figure (Initial mlir text).

```
module attributes {module.chip = "ALL", module.name = "Conv2d", module.state = "TOP_F
32", module.weight_file = "conv2d_top_f32_all_weight.npz"} {
  func.func @main(%arg0: tensor<1x16x100x100xf32>) -> tensor<1x32x100x100xf32> {
    %0 = "top.None"() : () -> none
  }
}
```

Fig. 16.4: Initial Mlir Text

3. generate_mlir

   · Build input op, the generated Top.inputOp will be inserted into MLIRImporter.mlir_module.

   · Call Operation.create to create Top.ConvOp, and the parameters required by the create function are:

     - Input op: According to the interface definition, the inputs of the Conv operator include input, weight and bias. The inputOp has been created, and the op of weight and bias is created through getWeightOp().
     - output_shape: get output shape from the output tensor stored in the Operator.
     - Attributes: Get attributes from Operator, and convert attributes to Attributes that can be recognized by MLIRImporter

     After Top.ConvOp is created, it will be inserted into the mlir text

   · Get the corresponding op from operands according to output_names, create return_op and insert it into the mlir text. By this point, the generated mlir text is as shown (Full Mlir Text).

4. Output

```
#loc = loc(unknown)
module attributes {module.FLOPs = 109428480 : i64, module.chip = "ALL", module.name = "model_def", module.state = "TOP_F32", module.weigh
t_file = "model_def_top_f32_all_weight.npz"} {
  func.func @main(%arg0: tensor<1x3x173x141xf32> loc(unknown)) -> tensor<1x64x84x69xf32> {
    %0 = "top.Input"(%arg0) : (tensor<1x3x173x141xf32>) -> tensor<1x3x173x141xf32> loc(#loc1)
    %1 = "top.Weight"() : () -> tensor<64x1x7x7xf32> loc(#loc2)
    %2 = "top.Weight"() : () -> tensor<64xf32> loc(#loc3)
    %3 = "top.Conv"(%0, %1, %2) {dilations = [1, 1], do_relu = false, group = 1 : i64, kernel_shape = [7, 7], pads = [0, 0, 1, 1], relu_l
imit = -1.000000e+00 : f64, strides = [2, 2]} : (tensor<1x3x173x141xf32>, tensor<64x1x7x7xf32>, tensor<64xf32>) -> tensor<1x64x84x69xf32>
 loc(#loc4)
    return %3 : tensor<1x64x84x69xf32> loc(#loc)
  } loc(#loc)
} loc(#loc)
#loc1 = loc("BMTensor0")
#loc2 = loc("BMTensor1")
#loc3 = loc("BMTensor2")
#loc4 = loc("BMTensor3")
```

Fig. 16.5: Full Mlir Text

Save the mlir text as Conv_origin.mlir and the weights in tensors as Conv_TOP_F32_all_weight.npz.

CHAPTER 17

Custom Operators

17.1 Overview

TPU-MLIR already includes a rich library of operators that can fulfill the needs of most neural network models. However, in certain scenarios, there may be a requirement for users to define their own custom operators to perform computations on tensors. This need arises when:

1. TPU-MLIR does not support a specific operator, and it cannot be achieved by combining existing operators.
2. The operator is private.
3. Combining multiple operator APIs does not yield optimal computational performance, and custom operations at the TPU-Kernel level can improve execution efficiency.

The functionality of custom operators allows users to freely use the interfaces in TPU-Kernel to compute tensors on the TPU, and encapsulate this computation process as backend operators (refer to the TPU-KERNEL Technical Reference Manual for backend operator development). The backend operator calculation involves operations related to the global layer and local layer:

a. The operator must implement the global layer. The input and output data of the global layer are stored in DDR. The data needs to be transferred from global memory to local memory for execution and then transferred back to global memory. The advantage is that local memory can be used flexibly, but it has the disadvantage of generating a considerable number of GDMA transfers, resulting in lower the Tensor Competing Processor utilization.

b. The operator can optionally implement the local layer. The input and output data of the local layer are stored in local memory. It can be combined with other layers for layer group optimization, avoiding the need to transfer data to and from global memory during the calculation of this layer. The advantage is that it saves GDMA transfers and achieves higher computational efficiency. However, it is more complex to implement. The local memory needs to be allocated in advance during model deployment, limiting its usage and making it impractical for certain operators.

The frontend can build models containing custom operators using tpulang or Caffe, and finally deploy the models through the model conversion interface of TPU-MLIR. This chapter primarily introduces the process of using custom operators in the TPU-MLIR release package.

17.2 Custom Operator Addition Process

17.2.1 Add TpuLang Custom Operator

1. Load TPU-MLIR

The following operations need to be in a Docker container. For the use of Docker, please refer to Setup Docker Container.

```
$ tar zxf tpu-mlir_xxxx.tar.gz
$ source tpu-mlir_xxxx/envsetup.sh
```

envsetup.sh adds the following environment variables:

Table 17.1: Environment variables

Name	Value	Explanation
TPUC_ROOT	tpu-mlir_xxx	The location of the SDK package after decompression
MODEL_ZOO_PATH	${TPUC_ROOT}/../model-zoo	The location of the model-zoo folder, at the same level as the SDK
REGRESSION_PATH	${TPUC_ROOT}/regression	The location of the regression folder

envsetup.sh modifies the environment variables as follows:

```
export PATH=${TPUC_ROOT}/bin:$PATH
export PATH=${TPUC_ROOT}/python/tools:$PATH
export PATH=${TPUC_ROOT}/python/utils:$PATH
export PATH=${TPUC_ROOT}/python/test:$PATH
export PATH=${TPUC_ROOT}/python/samples:$PATH
export PATH=${TPUC_ROOT}/customlayer/python:$PATH
export LD_LIBRARY_PATH=$TPUC_ROOT/lib:$LD_LIBRARY_PATH
export PYTHONPATH=${TPUC_ROOT}/python:$PYTHONPATH
export PYTHONPATH=${TPUC_ROOT}/customlayer/python:$PYTHONPATH
```

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```
export MODEL_ZOO_PATH=${TPUC_ROOT}/../model-zoo
export REGRESSION_PATH=${TPUC_ROOT}/regression
```

2. Develop backend operators based on TPU-Kernel

   Assuming the current path is $TPUC_ROOT/customlayer, add the backend_{op_name}.h header file in the ./include directory to declare the custom operator functions for the global layer and local layer (void backend_{op_name}_global and void backend_{op_name}_local, respectively). Then, add the backend_{op_name}.c file in the ./src directory and invoke the TPU-Kernel interfaces to implement the corresponding functions.

3. Define the operator' s parameter structure and write the operator' s interface

   a. Add the corresponding structure {op_name}_param_t in the ./include/backend_custom_param.h header file to receive parameters from the frontend of toolchain, based on the parameters required by the operator.

   b. Add the api_{op_name}.h header file in the ./include directory to declare the interfaces for the custom operator functions (void api_{op_name}_global and void api_{op_name}_local). Then, add the api_{op_name}.c file in the ./src directory and implement the corresponding interfaces.

   c. Additionally, users need to implement corresponding functions to parse the parameters passed from the frontend of toolchain based on the parameters required by the operator. Parameters are passed through a pointer to a custom_param_t array, where each custom_param_t structure contains information about a parameter, and the parameter value is stored in the corresponding member variables in custom_param_t (which includes integer, floating-point number, integer array, and floating-point array variables). The order of the parameters is the same as the order in which the user provides them when calling the TpuLang interface. The definition of the custom_param_t is as follows:

```
typedef struct {
  int int_t;
  float float_t;
  // max size of int and float array is set as 16
  int int_arr_t[16];
  float float_arr_t[16];
} custom_param_t;
```

4. Define the backend interface

   In ./src/backend_custom_api.cpp, build the backend interface using macro definitions. This interface will be called during Codegen in the frontend of toolchain. The format is as follows:

```
IMPL_CUSTOM_API_GLB({op_name}, {op_name}_param_t)

IMPL_CUSTOM_API_LOC({op_name}, {op_name}_param_t)
```

5. Compile and install the dynamic library

   By running the build.sh script in $TPUC_ROOT/customlayer, the compilation of the custom operator will be completed. It will generate the backend_custom_api.so dynamic library and install it in $TPUC_ROOT/lib.

6. Invoke TpuLang to build the model

   Refer to the TPULang Interface section for instructions on how to use TpuLang.

   TpuLang provides the TpuLang.custom interface to build custom operators in the frontend of toolchain (ensure that the op_name part matches the name of the backend operator):

```
TpuLang.custom(tensors_in: list,
               shape_func,
               op_name: str,
               out_dtypes: list,
               out_names: list = None,
               params: dict = None)
'''
    The custom op
    Arguments:
        tensors_in: list of input tensors (including weight tensors)
        shape_func: function for doing shape inference, taking tensors_in as the
                    parameter, return is the list of output tensors shape
        op_name: name of the custom operator,
        out_dtypes: list of outputs' data type
        out_name: list of output names
        params: parameters of the custom op

    Return:
        tensors_out: list of output tensors
'''
```

17.2.2 Add Caffe Custom Operator

Steps 1-5 are the same as in Add TpuLang Custom Operator section, and will not be repeated here.

6. Defining custom operators in Caffe

   To define custom operators in Caffe, you need to define a class in the file $TPUC_ROOT/customlayer/python/my_layer.py that inherits from caffe.Layer and override the setup, reshape, forward, and backward functions as needed.

7. Implementing the frontend conversion function

The type of custom operators implemented in python is "Python", so you need to implement a corresponding conversion function of MyCaffeConverter class defined in the file $TPUC_ROOT/customlayer/python/my_converter.py, based on the definition in step 6.

After the definition, you can call my_converter.py interface for Top MLIR conversion:

```
my_converter.py \
--model_name # the model name \
--model_def # .prototxt file \
--model_data # .caffemodel file \
--input_shapes # list of input shapes (e.g., [[1,2,3],[3,4,5]]) \
--mlir # output mlir file
```

17.3 Custom Operator Example

This section assumes that the tpu-mlir release package has been loaded.

17.3.1 Example of TpuLang

This subsection provides a sample of swapchanel operator implementation and application through TpuLang interface.

1. Backend Operator Implementation

   The following is the declaration in the header file

   ${TPUC_ROOT}/customlayer/include/backend_swapchannel.h:

```
#ifndef BACKEND_SWAPCHANNEL_H_
#define BACKEND_SWAPCHANNEL_H_

#include "tpu_kernel.h"

#ifdef __cplusplus
extern "C" {
#endif

void backend_swapchannel_global(
    global_addr_t input_global_addr,
    global_addr_t output_global_addr,
    const int *shape,
    const int *order,
    data_type_t dtype);

#ifdef __cplusplus
}
#endif
```

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```
#endif
```

The code of ${TPUC_ROOT}/customlayer/src/backend_swapchannel.c:

```
#include "backend_swapchannel.h"
#include "common.h"

void backend_swapchannel_global(
    global_addr_t input_global_addr,
    global_addr_t output_global_addr,
    const int *shape,
    const int *order,
    data_type_t dtype)
{
    dim4 channel_shape = {.n = shape[0], .c = 1, .h = shape[2], .w = shape[3]};
    int data_size = tpu_data_type_size(dtype);
    int offset = channel_shape.w * channel_shape.h * data_size;
    for (int i = 0; i < 3; i++) {
        tpu_gdma_cpy_S2S(
            output_global_addr + i * offset,
            input_global_addr + order[i] * offset,
            &channel_shape,
            NULL,
            NULL,
            dtype);
    }
}
```

2. Operator Parameter Structure and Implementation of the Operator Interface

   The definition of swapchannel_param_t in

   ${TPUC_ROOT}/customlayer/include/backend_custom_param.h is as follows:

```
typedef struct swapchannel_param {
  int order[3];
} swapchannel_param_t;
```

   The following is the declaration in the header file

   ${TPUC_ROOT}/customlayer/include/api_swapchannel.h:

```
#pragma once
#include "api_common.h"
#include "backend_custom_param.h"

#ifdef __cplusplus
extern "C" {
#endif
```

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```
void api_swapchannel_global(
    global_tensor_spec_t *input,
    global_tensor_spec_t *output,
    custom_param_t *param);

#ifdef __cplusplus
}
#endif
```

The code of ${TPUC_ROOT}/customlayer/src/api_swapchannel.c:

```
#include "tpu_utils.h"
#include "api_swapchannel.h"
#include "backend_swapchannel.h"

// parse param function
swapchannel_param_t parsParam(custom_param_t* param) {
    swapchannel_param_t sc_param = {0};
    for (int i = 0; i < 3; i++) {
        sc_param.order[i] = param[0].int_arr_t[i];
    }
    return sc_param;
}

// global api function
void api_swapchannel_global(
    global_tensor_spec_t *input,
    global_tensor_spec_t *output,
    custom_param_t *param)
{
    swapchannel_param_t sc_param = parsParam(param);

    backend_swapchannel_global(
        input->addr,
        output->addr,
        input->shape,
        sc_param.order,
        tpu_type_convert(input->dtype));
}
```

3. Backend Interface

The code of ${TPUC_ROOT}/customlayer/src/backend_custom_api.cpp:

```
#include "backend_helper.h"
#include "common_def.h"
#include "api_common.h"

// 1. include head file of api function
#include "api_swapchannel.h"

```

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```
// 2. global backend api functions
IMPL_CUSTOM_API_GLB(swapchannel, swapchannel_param_t)
```

After completing the implementation of the backend interface, you can run $TPUC_ROOT/customlayer/build.sh to compile and install the custom operator dynamic library.

4. TpuLang Interface Invocation

   Here is an example of Python code that utilizes the TpuLang interface to build a custom operator model:

```python
import numpy as np
import transform.TpuLang as tpul

# 1. initialize tpulang
tpul.init("BM1684X", True)

# 2. prepare the input
dtype = "float32"
input_shape = [1, 3, 14, 14]
x_data = np.random.random(input_shape).astype(np.float32)
x = tpul.Tensor(dtype=dtype, shape=input_shape, data=x_data)

# 3. build model
def shape_func(tensors_in):
    # the shape inference function
    return [tensors_in[0].shape]

out_names = ["out"]
params = {"order": [2, 1, 0]}

outs = tpul.custom(
        tensors_in=[x],
        shape_func=shape_func,
        # op_name should be consistent with the backend
        op_name="swapchannel",
        params=params,
        out_dtypes=[dtype],
        out_names=out_names)

# 4. compile to Top mlir file, the input will be saved in {top_mlir}_in_f32.
↪npz
top_mlir = "tpulang_test_net"
tpul.compile(top_mlir, [x], outs, False, 2, has_custom=True)
```

   By running the above code, you can obtain the Top MLIR file tpulang_test_net.mlir. For the subsequent model deployment process, please refer to the User Interface chapter.

17.3.2 Example of Caffe

This subsection provides application examples of custom operators absadd and ceiladd in Caffe.

1. Backend operator and interface implementation

   The implementation of absadd and ceiladd is similar to the swapchannel operator and can be found in $TPUC_ROOT/customlayer/include and $TPUC_ROOT/customlayer/src.

2. Defining Caffe custom operators

   The definition of absadd and ceiladd in Caffe can be found in $TPUC_ROOT/customlayer/python/my_layer.py as follows:

```python
import caffe
import numpy as np

# Define the custom layer
class AbsAdd(caffe.Layer):

    def setup(self, bottom, top):
        params = eval(self.param_str)
        self.b_val = params['b_val']

    def reshape(self, bottom, top):
        top[0].reshape(*bottom[0].data.shape)

    def forward(self, bottom, top):
        top[0].data[...] = np.abs(np.copy(bottom[0].data)) + self.b_val

    def backward(self, top, propagate_down, bottom):
        pass

class CeilAdd(caffe.Layer):

    def setup(self, bottom, top):
        params = eval(self.param_str)
        self.b_val = params['b_val']

    def reshape(self, bottom, top):
        top[0].reshape(*bottom[0].data.shape)

    def forward(self, bottom, top):
        top[0].data[...] = np.ceil(np.copy(bottom[0].data)) + self.b_val

    def backward(self, top, propagate_down, bottom):
        pass
```

   The expression of corresponding operators in Caffe prototxt is as follows:

```
layer {
  name: "myabsadd"
  type: "Python"
  bottom: "input0_bn"
  top: "myabsadd"
  python_param {
    module: "my_layer"
    layer: "AbsAdd"
    param_str: "{ 'b_val': 1.2}"
  }
}

layer {
  name: "myceiladd"
  type: "Python"
  bottom: "input1_bn"
  top: "myceiladd"
  python_param {
    module: "my_layer"
    layer: "CeilAdd"
    param_str: "{ 'b_val': 1.5}"
  }
}
```

3. Implement operator front-end conversion functions

   Define a convert_python_op function of the MyCaffeConverter class in $TPUC_ROOT/customlayer/python/my_converter.py, the code is as follows:

```python
def convert_python_op(self, layer):
    assert (self.layerType(layer) == "Python")
    in_op = self.getOperand(layer.bottom[0])
    p = layer.python_param

    dict_attr = dict(eval(p.param_str))
    params = dict_attr_convert(dict_attr)

    # p.layer.lower() to keep the consistency with the backend op name
    attrs = {"name": p.layer.lower(), "params": params, 'loc': self.get_loc(layer.top[0])}

    # The output shape compute based on reshape function in my_layer
    out_shape = self.getShape(layer.top[0])
    outs = top.CustomOp([self.mlir.get_tensor_type(out_shape)], [in_op],
                        **attrs,
                        ip=self.mlir.insert_point).output
    # add the op result to self.operands
    self.addOperand(layer.top[0], outs[0])
```

4. Caffe front-end conversion

   Complete the conversion of Caffe model in the $TPUC_ROOT/customlayer/test directory (i.e., my_model.prototxt and my_model.caffemodel, which contain absadd and ceiladd operators) by calling the my_converter.py interface, the command is as follows:

```
my_converter.py \
--model_name caffe_test_net \
--model_def $TPUC_ROOT/customlayer/test/my_model.prototxt \
--model_data $TPUC_ROOT/customlayer/test/my_model.caffemodel \
--input_shapes [[1,3,14,14],[1,3,24,26]] \
--mlir caffe_test_net.mlir
```

So far, the Top MLIR file caffe_test_net.mlir has been obtained. For the subsequent model deployment process, please refer to the user interface chapter.

CHAPTER 18

Appendix.01: Migrating from NNTC to tpu-mlir

NNTC is using docker version sophgo/tpuc_dev:v2.1, for MLIR docker version reference and environment initialization please refer to Environment Setup.

In the following, we will use yolov5s as an example to explain the similarities and differences between nntc and mlir in terms of quantization, and for compiling floating-point models, please refer to <TPU-MLIR_Quick_Start> Compile the ONNX model.

First, refer to the section Compile the ONNX model to prepare the yolov5s model.

18.1 ONNX to MLIR

To quantize a model in mlir, first convert the original model to a top-level mlir file, this step can be compared to generating a fp32umodel in step-by-step quantization in nntc.

1. MLIR's model conversion command

```
$ model_transform.py \
    --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
```

TPU-MLIR can directly encode image preprocessing into the converted MLIR file.

2. Model transformation commands for NNTC

```
$ python3 -m ufw.tools.on_to_umodel \
    -m ../yolov5s.onnx \
    -s '(1,3,640,640)' \
    -d 'compilation' \
    --cmp
```

When importing a model with NNTC, you cannot specify the preprocessing method.

18.2 Make a quantization calibration table

If you want to generate a fixed-point model, you need a quantization tool to quantize the model, nntc uses calibration_use_pb for step-by-step quantization, and mlir uses run_calibration.py for step-by-step quantization.

The number of input data is about 100~1000 depending on the situation, using the existing 100 images from COCO2017 as an example, perform calibration.

To use stepwise quantization in nntc, you need to make your own mdb quantization dataset using the image quantization dataset, and modify fp32_protoxt to point the data input to the lmdb file.

Note: For the NNTC quantization dataset, please refer to the "Model Quantization" chapter in the <TPU-NNTC Development Reference Manual>, and note that the lmdb dataset is not compatible with TPU-MLIR. TPU-MLIR can directly use raw images as input for quantization tools. If it is voice, text or other non-image data, it needs to be converted to npz file.

---

1. MLIR Quantization Model

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

After quantization you will get the quantization table yolov5s_cali_table

2. NNTC Quantization Model

```
$ calibration_use_pb quantize \
     --model=./compilation/yolov5s_bmneto_test_fp32.prototxt \
     --weights=./compilation/yolov5s_bmneto.fp32umodel \
     -save_test_proto=True --bitwidth=TO_INT8
```

In nntc, after quantization, you get int8umodel and prototxt.

It is worth mentioning that mlir also has a run_qtable tool to help generate mixed-precision models

18.3 Generating int8 models

To convert to an INT8 symmetric quantized model, execute the following command.

1. MLIR:

```
$ model_deploy.py \
    --mlir yolov5s.mlir \
    --quantize INT8 \
    --calibration_table yolov5s_cali_table \
    --processor bm1684 \
    --test_input yolov5s_in_f32.npz \
    --test_reference yolov5s_top_outputs.npz \
    --tolerance 0.85,0.45 \
    --model yolov5s_1684_int8_sym.bmodel
```

   At the end of the run you get yolov5s_1684_int8_sym.bmodel.

2. NNTC:

   In nntc, the int8 bmodel is generated using int8umodel and prototxt using the bmnetu tool.

```
$ bmnetu --model=./compilation/yolov5s_bmneto_deploy_int8_unique_top.prototxt \
    --weight=./compilation/yolov5s_bmneto.int8umodel
```

   At the end of the run you get compilation.bmodel.