MACE

Apr 03, 2020

Introduction

Welcome to Mobile AI Compute Engine documentation.

The main documentation is organized into the following sections:

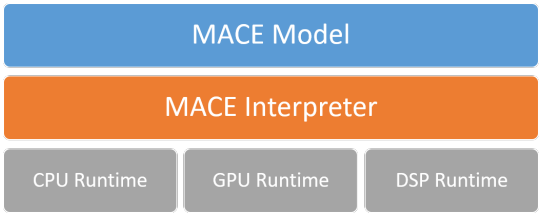
CHAPTER 1

Introduction

MACE (Mobile AI Compute Engine) is a deep learning inference framework optimized for mobile heterogeneous computing platforms. MACE provides tools and documents to help users to deploy deep learning models to mobile phones, tablets, personal computers and IoT devices.

1.1 Architecture

The following figure shows the overall architecture.



1.1.1 MACE Model

MACE defines a customized model format which is similar to Caffe2. The MACE model can be converted from exported models by TensorFlow, Caffe or ONNX Model.

1.1.2 MACE Interpreter

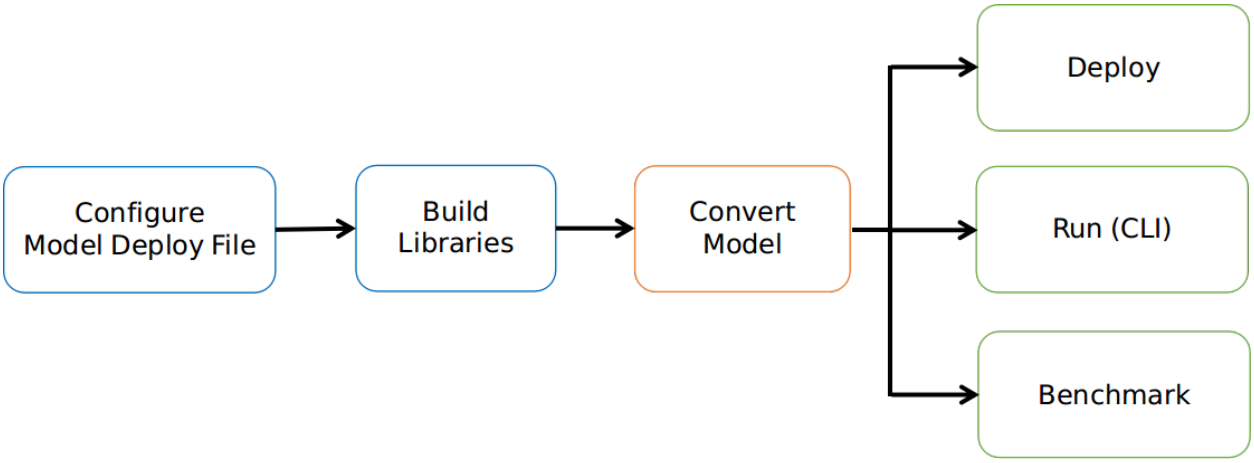
Mace Interpreter mainly parses the NN graph and manages the tensors in the graph.

1.1.3 Runtime

CPU/GPU/DSP runtime correspond to the Ops for different devices.

1.2 Workflow

The following figure shows the basic work flow of MACE.



1.2.1 1. Configure model deployment file

Model deploy configuration file (.yml) describes the information of the model and library, MACE will build the library based on the file.

1.2.2 2. Build libraries

Build MACE dynamic or static libraries.

1.2.3 3. Convert model

Convert TensorFlow, Caffe or ONNX model to MACE model.

1.2.4 4.1. Deploy

Integrate the MACE library into your application and run with MACE API.

1.2.5 4.2. Run (CLI)

MACE provides *mace_run* command line tool, which could be used to run model and validate model correctness against original TensorFlow or Caffe results.

1.2.6 4.3. Benchmark

MACE provides benchmark tool to get the Op level profiling result of the model.

CHAPTER 2

Environment requirement

MACE requires the following dependencies:

2.1 Required dependencies

Software	Installation command	Tested version
Python		2.7 or 3.6
CMake	Linux:`apt-get install cmake` Mac:`brew install cmake`	>= 3.11.3
Jinja2	pip install jinja2==2.10	2.10
PyYaml	pip install pyyaml==3.12	3.12.0
sh	pip install sh==1.12.14	1.12.14
Numpy	pip install numpy==1.14.0	Required by model validation
six	pip install six==1.11.0	Required for Python 2 and 3 compatibility

For Bazel, install it following installation guide. For python dependencies,

```
pip install -U --user -r setup/requirements.txt
```

2.2 Optional dependencies

Software	Installation command	Remark
Android NDK	NDK installation guide	Required by Android build, r15b or higher version for bazel users, r17b or higher version for cmake users.
Bazel	bazel installation guide	0.13.0
ADB	Linux:`apt-get install android-tools-adb` Mac:`brew cask install android-platform-tools`	Required by Android run, >= 1.0.32
TensorFlow	pip install tensorflow==1.8.0	Required by TensorFlow model
Docker	docker installation guide	Required by docker mode for Caffe model
Scipy	pip install scipy==1.0.0	Required by model validation
FileLock	pip install filelock==3.0.0	Required by run on Android
ONNX	pip install onnx==1.5.0	Required by ONNX model

For python dependencies,

```
pip install -U --user -r setup/optionals.txt
```

Note:

- For Android build, *ANDROID_NDK_HOME* must be confifigured by using `export ANDROID_NDK_HOME=/path/to/ndk`
- It will link `libc++` instead of `gnustl` if `NDK version >= r17b` and `bazel version >= 0.13.0`, please refer to NDK cpp-support.
- For Mac, please install Homebrew at first before installing other dependencies. Set ANDROID_NDK_HOME in `/etc/bashrc` and then run `source /etc/bashrc`. This installation was tested with macOS Mojave(10.14).

rs.

CHAPTER 3

Using docker

3.1 Pull or build docker image

MACE provides docker images with dependencies installed and also Dockerfiles for images building, you can pull the existing ones directly or build them from the Dockerfiles. In most cases, the `lite edition` image can satisfy developer's basic needs.

Note: It's highly recommended to pull built images.

- `lite edition` docker image.

```
# You can pull lite edition docker image from docker repo (recommended)
docker pull registry.cn-hangzhou.aliyuncs.com/xiaomimace/mace-dev-lite
# Or build lite edition docker image by yourself
docker build -t registry.cn-hangzhou.aliyuncs.com/xiaomimace/mace-dev-lite ./docker/
↪mace-dev-lite
```

- `full edition` docker image (which contains multiple NDK versions and other dev tools).

```
# You can pull full edition docker image from docker repo (recommended)
docker pull registry.cn-hangzhou.aliyuncs.com/xiaomimace/mace-dev
# Or build full edition docker image by yourself
docker build -t registry.cn-hangzhou.aliyuncs.com/xiaomimace/mace-dev ./docker/mace-
↪dev
```

Note: We will show steps with lite edition later.

3.2 Using the image

Create container with the following command

```
# Create a container named `mace-dev`
docker run -it --privileged -d --name mace-dev \
           -v /dev/bus/usb:/dev/bus/usb --net=host \
           -v /local/path:/container/path \
           -v /usr/bin/docker:/usr/bin/docker \
           -v /var/run/docker.sock:/var/run/docker.sock \
           registry.cn-hangzhou.aliyuncs.com/xiaomimace/mace-dev-lite
# Execute an interactive bash shell on the container
docker exec -it mace-dev /bin/bash
```

3.3 Update images to repository

If you are mace inner developer and need update images in remote repository, it can be achieved by *docker/update_images.sh* script.

```
cd docker/
./update_images.sh
```

CHAPTER 4

Manual setup

The setup steps are based on `Ubuntu`, you can change the commands correspondingly for other systems. For the detailed installation dependencies, please refer to *Environment requirement*.

4.1 Install Bazel

Recommend bazel with version larger than `0.13.0` (Refer to Bazel documentation).

```
export BAZEL_VERSION=0.13.1
mkdir /bazel && \
    cd /bazel && \
    wget https://github.com/bazelbuild/bazel/releases/download/$BAZEL_VERSION/bazel-
↪$BAZEL_VERSION-installer-linux-x86_64.sh && \
    chmod +x bazel-*.sh && \
    ./bazel-$BAZEL_VERSION-installer-linux-x86_64.sh && \
    cd / && \
    rm -f /bazel/bazel-$BAZEL_VERSION-installer-linux-x86_64.sh
```

4.2 Install Android NDK

The recommended Android NDK versions includes r15b, r15c and r16b (Refers to NDK installation guide).

```
# Download NDK r15c
cd /opt/ && \
    wget -q https://dl.google.com/android/repository/android-ndk-r15c-linux-x86_64.
↪zip && \
    unzip -q android-ndk-r15c-linux-x86_64.zip && \
    rm -f android-ndk-r15c-linux-x86_64.zip

export ANDROID_NDK_VERSION=r15c
```

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```
export ANDROID_NDK=/opt/android-ndk-${ANDROID_NDK_VERSION}
export ANDROID_NDK_HOME=${ANDROID_NDK}

# add to PATH
export PATH=${PATH}:${ANDROID_NDK_HOME}
```

4.3 Install extra tools

```
apt-get install -y --no-install-recommends \
    cmake \
    android-tools-adb
pip install -i http://pypi.douban.com/simple/ --trusted-host pypi.douban.com␣
↪setuptools
pip install -i http://pypi.douban.com/simple/ --trusted-host pypi.douban.com \
    "numpy>=1.14.0" \
    scipy \
    jinja2 \
    pyyaml \
    sh==1.12.14 \
    pycodestyle==2.4.0 \
    filelock
```

4.4 Install TensorFlow (Optional)

```
pip install -i http://pypi.douban.com/simple/ --trusted-host pypi.douban.com␣
↪tensorflow==1.8.0
```

4.5 Install Caffe (Optional)

Please follow the installation instruction of Caffe.

4.6 Install ONNX (Optional)

Please follow the installation instruction of ONNX.

CHAPTER 5

Basic usage for CMake users

First of all, make sure the environment has been set up correctly already (refer to *Environment requirement*).

5.1 Clear Workspace

Before you do anything, clear the workspace used by build and test process.

```
tools/clear_workspace.sh [--expunge]
```

5.2 Build Engine

Please make sure you have CMake installed.

```
RUNTIME=GPU bash tools/cmake/cmake-build-armeabi-v7a.sh
```

which generate libraries in `build/cmake-build/armeabi-v7a`, you can use either static libraries or the `libmace.so` shared library.

You can also build for other target abis: `arm64-v8a`, `arm-linux-gnueabihf`, `aarch64-linux-gnu`, `host`; and runtime: `GPU`, `HEXAGON`, `HTA`, `APU`.

5.3 Model Conversion

When you have prepared your model, the first thing to do is write a model config in YAML format.

```
models:
  mobilenet_v1:
    platform: tensorflow
```

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```
    model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/
↪mobilenet-v1/mobilenet-v1-1.0.pb
    model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
    subgraphs:
      - input_tensors:
          - input
        input_shapes:
          - 1,224,224,3
        output_tensors:
          - MobilenetV1/Predictions/Reshape_1
        output_shapes:
          - 1,1001
    runtime: gpu
```

The following steps generate output to `build` directory which is the default build and test workspace. Suppose you have the model config in `../mace-models/mobilenet-v1/mobilenet-v1.yml`. Then run

```
python tools/python/convert.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml
```

which generate 4 files in `build/mobilenet_v1/model/`

```
├── mobilenet_v1.pb                 (model file)
├── mobilenet_v1.data               (param file)
├── mobilenet_v1_index.html         (visualization page, you can open it in␣
↪browser)
└── mobilenet_v1.pb_txt             (model text file, which can be for debug␣
↪use)
```

MACE also supports other platform: `caffe`, `onnx`. Beyond GPU, users can specify `cpu`, `dsp` to run on other target devices.

5.4 Model Test and Benchmark

We provide simple tools to test and benchmark your model.

After model is converted, simply run

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --validate
```

Or benchmark the model

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --benchmark
```

It will test your model on the device configured in the model config (`runtime`). You can also test on other device by specify `--runtime=cpu (dsp/hta/apu)` when you run test if you previously build engine for the device. The log will be shown if `--vlog_level=2` is specified.

5.5 Deploy your model into applications

Please refer to `mace/tools/mace_run.cc`for full usage. The following list the key steps.

```
// Include the headers
#include "mace/public/mace.h"

// 0. Declare the device type (must be same with ``runtime`` in configuration file)
DeviceType device_type = DeviceType::GPU;

// 1. configuration
MaceStatus status;
MaceEngineConfig config(device_type);
std::shared_ptr<GPUContext> gpu_context;
// Set the path to store compiled OpenCL kernel binaries.
// please make sure your application have read/write rights of the directory.
// this is used to reduce the initialization time since the compiling is too slow.
// It's suggested to set this even when pre-compiled OpenCL program file is provided
// because the OpenCL version upgrade may also leads to kernel recompilations.
const std::string storage_path ="path/to/storage";
gpu_context = GPUContextBuilder()
    .SetStoragePath(storage_path)
    .Finalize();
config.SetGPUContext(gpu_context);
config.SetGPUHints(
    static_cast<GPUPerfHint>(GPUPerfHint::PERF_NORMAL),
    static_cast<GPUPriorityHint>(GPUPriorityHint::PRIORITY_LOW));

// 2. Define the input and output tensor names.
std::vector<std::string> input_names = {...};
std::vector<std::string> output_names = {...};

// 3. Create MaceEngine instance
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;

// Create Engine from model file
create_engine_status =
    CreateMaceEngineFromProto(model_graph_proto,
                              model_graph_proto_size,
                              model_weights_data,
                              model_weights_data_size,
                              input_names,
                              output_names,
                              device_type,
                              &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // fall back to other strategy.
}

// 4. Create Input and Output tensor buffers
std::map<std::string, mace::MaceTensor> inputs;
std::map<std::string, mace::MaceTensor> outputs;
for (size_t i = 0; i < input_count; ++i) {
  // Allocate input and output
  int64_t input_size =
      std::accumulate(input_shapes[i].begin(), input_shapes[i].end(), 1,
```

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```
                      std::multiplies<int64_t>());
  auto buffer_in = std::shared_ptr<float>(new float[input_size],
                                          std::default_delete<float[]>());
  // Load input here
  // ...

  inputs[input_names[i]] = mace::MaceTensor(input_shapes[i], buffer_in);
}

for (size_t i = 0; i < output_count; ++i) {
  int64_t output_size =
      std::accumulate(output_shapes[i].begin(), output_shapes[i].end(), 1,
                      std::multiplies<int64_t>());
  auto buffer_out = std::shared_ptr<float>(new float[output_size],
                                           std::default_delete<float[]>());
  outputs[output_names[i]] = mace::MaceTensor(output_shapes[i], buffer_out);
}

// 5. Run the model
MaceStatus status = engine.Run(inputs, &outputs);
```

More details are in *Advanced usage for Bazel users*.

CHAPTER 6

Basic usage for Bazel users

6.1 Build and run an example model

At first, make sure the environment has been set up correctly already (refer to *Environment requirement*).

The followings are instructions about how to quickly build and run a provided model in MACE Model Zoo.

Here we use the mobilenet-v2 model as an example.

Commands

1. Pull MACE project.

```
git clone https://github.com/XiaoMi/mace.git
cd mace/
git fetch --all --tags --prune

# Checkout the latest tag (i.e. release version)
tag_name=`git describe --abbrev=0 --tags`
git checkout tags/${tag_name}
```

Note: It's highly recommended to use a release version instead of master branch.

2. Pull MACE Model Zoo project.

```
git clone https://github.com/XiaoMi/mace-models.git
```

3. Build a generic MACE library.

```
cd path/to/mace
# Build library
# output lib path: build/lib
bash tools/bazel-build-standalone-lib.sh
```

Note:

- This step can be skipped if you just want to run a model using `tools/converter.py`, such as commands in step 5.
- Libraries in `build/lib/armeabi-v7a/cpu_gpu/` means it can run on `cpu` or `gpu` devices.
- The results in `build/lib/armeabi-v7a/cpu_gpu_dsp/` need HVX supported.

4. Convert the pre-trained mobilenet-v2 model to MACE format model.

```
cd path/to/mace
# Build library
python tools/converter.py convert --config=/path/to/mace-models/mobilenet-v2/
↪mobilenet-v2.yml
```

5. Run the model.

Note: If you want to run on phone, please plug in at least one phone. Or if you want to run on embedded device, please give a *Advanced usage for Bazel users*.

```
# Run
python tools/converter.py run --config=/path/to/mace-models/mobilenet-v2/
↪mobilenet-v2.yml

# Test model run time
python tools/converter.py run --config=/path/to/mace-models/mobilenet-v2/
↪mobilenet-v2.yml --round=100

# Validate the correctness by comparing the results against the
# original model and framework, measured with cosine distance for similarity.
python tools/converter.py run --config=/path/to/mace-models/mobilenet-v2/
↪mobilenet-v2.yml --validate
```

6.2 Build your own model

This part will show you how to use your own pre-trained model in MACE.

6.2.1 1. Prepare your model

MACE now supports models from TensorFlow and Caffe (more frameworks will be supported).

- TensorFlow

  Prepare your pre-trained TensorFlow model.pb file.

- Caffe

  Caffe 1.0+ models are supported in MACE converter tool.

  If your model is from lower version Caffe, you need to upgrade it by using the Caffe built-in tool before converting.

```
# Upgrade prototxt
$CAFFE_ROOT/build/tools/upgrade_net_proto_text MODEL.prototxt MODEL.new.prototxt

# Upgrade caffemodel
$CAFFE_ROOT/build/tools/upgrade_net_proto_binary MODEL.caffemodel MODEL.new.
↪caffemodel
```

- ONNX

  Prepare your ONNX model.onnx file.

  Use ONNX Optimizer Tool to optimize your model for inference. This tool will improve the efficiency of inference like the Graph Transform Tool in TensorFlow.

```
# Optimize your model
$python MACE_ROOT/tools/onnx_optimizer.py model.onnx model_opt.onnx
```

6.2.2 2. Create a deployment file for your model

When converting a model or building a library, MACE needs to read a YAML file which is called model deployment file here.

A model deployment file contains all the information of your model(s) and building options. There are several example deployment files in *MACE Model Zoo* project.

The following shows two basic usage of deployment files for TensorFlow and Caffe models. Modify one of them and use it for your own case.

- TensorFlow

```
# The name of library
library_name: mobilenet
target_abis: [arm64-v8a]
model_graph_format: file
model_data_format: file
models:
  mobilenet_v1: # model tag, which will be used in model loading and must be␣
↪specific.
    platform: tensorflow
    # path to your tensorflow model's pb file. Support local path, http:// and␣
↪https://
    model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/mobilenet-
↪v1/mobilenet-v1-1.0.pb
    # sha256_checksum of your model's pb file.
    # use this command to get the sha256_checksum: sha256sum path/to/your/pb/file
    model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
    # define your model's interface
    # if there multiple inputs or outputs, write like blow:
    # subgraphs:
    # - input_tensors:
    #     - input0
    #     - input1
    #   input_shapes:
    #     - 1,224,224,3
    #     - 1,224,224,3
    #    output_tensors:
```

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```
    #       - output0
    #       - output1
    #     output_shapes:
    #       - 1,1001
    #       - 1,1001
    subgraphs:
      - input_tensors:
          - input
        input_shapes:
          - 1,224,224,3
        output_tensors:
          - MobilenetV1/Predictions/Reshape_1
        output_shapes:
          - 1,1001
    # cpu, gpu or cpu+gpu
    runtime: cpu+gpu
    winograd: 0
```

- Caffe

```
# The name of library
library_name: squeezenet-v10
target_abis: [arm64-v8a]
model_graph_format: file
model_data_format: file
models:
  squeezenet-v10: # model tag, which will be used in model loading and must be␣
↪specific.
    platform: caffe
    # support local path, http:// and https://
    model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/squeezenet/
↪squeezenet-v1.0.prototxt
    weight_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/
↪squeezenet/squeezenet-v1.0.caffemodel
    # sha256_checksum of your model's graph and data files.
    # get the sha256_checksum: sha256sum path/to/your/file
    model_sha256_checksum:␣
↪db680cf18bb0387ded9c8e9401b1bbcf5dc09bf704ef1e3d3dbd1937e772cae0
    weight_sha256_checksum:␣
↪9ff8035aada1f9ffa880b35252680d971434b141ec9fbacbe88309f0f9a675ce
    # define your model's interface
    # if there multiple inputs or outputs, write like blow:
    # subgraphs:
    # - input_tensors:
    #     - input0
    #     - input1
    #   input_shapes:
    #     - 1,224,224,3
    #     - 1,224,224,3
    #   output_tensors:
    #     - output0
    #     - output1
    #   output_shapes:
    #     - 1,1001
    #     - 1,1001
    subgraphs:
      - input_tensors:
```

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```
        - data
      input_shapes:
        - 1,227,227,3
      output_tensors:
        - prob
      output_shapes:
        - 1,1,1,1000
    runtime: cpu+gpu
    winograd: 0
```

- ONNX

```
# The name of library
library_name: mobilenet
target_abis: [arm64-v8a]
model_graph_format: file
model_data_format: file
models:
  mobilenet_v1: # model tag, which will be used in model loading and must be␣
↪specific.
    platform: onnx
    # path to your onnx model file. Support local path, http:// and https://
    model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/mobilenet-
↪v1/mobilenet-v1-1.0.pb
    # sha256_checksum of your model's onnx file.
    # use this command to get the sha256_checksum: sha256sum path/to/your/pb/file
    model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
    # define your model's interface
    # if there multiple inputs or outputs, write like blow:
    # subgraphs:
    # - input_tensors:
    #     - input0
    #     - input1
    #   input_shapes:
    #     - 1,224,224,3
    #     - 1,224,224,3
    #    output_tensors:
    #      - output0
    #      - output1
    #    output_shapes:
    #      - 1,1001
    #      - 1,1001
    subgraphs:
      - input_tensors:
          - input
        input_shapes:
          - 1,224,224,3
        output_tensors:
          - MobilenetV1/Predictions/Reshape_1
        output_shapes:
          - 1,1001
        # onnx backend framwork for validation. Suppport pytorch/caffe/tensorflow.
↪ Default is tensorflow.
        backend: tensorflow
    # cpu, gpu or cpu+gpu
    runtime: cpu+gpu
```

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```
    winograd: 0
```

More details about model deployment file are in *Advanced usage for Bazel users*.

6.2.3 3. Convert your model

When the deployment file is ready, you can use MACE converter tool to convert your model(s).

```
python tools/converter.py convert --config=/path/to/your/model_deployment_file.yml
```

This command will download or load your pre-trained model and convert it to a MACE model proto file and weights data file. The generated model files will be stored in `build/${library_name}/model` folder.

Warning: Please set `model_graph_format: file` and `model_data_format: file` in your deployment file before converting. The usage of `model_graph_format: code` will be demonstrated in *Advanced usage for Bazel users*.

6.2.4 4. Build MACE into a library

You could Download the prebuilt MACE Library from Github MACE release page.

Or use bazel to build MACE source code into a library.

```
cd path/to/mace
# Build library
# output lib path: build/lib
bash tools/bazel-build-standalone-lib.sh
```

The above command will generate dynamic library `build/lib/${ABI}/${DEVICES}/libmace.so` and static library `build/lib/${ABI}/${DEVICES}/libmace.a`.

Warning: Please verify that the target_abis param in the above command and your deployment file are the same.

6.2.5 5. Run your model

With the converted model, the static or shared library and header files, you can use the following commands to run and validate your model.

Warning: If you want to run on device/phone, please plug in at least one device/phone.

- **run**

  run the model.

```
# Test model run time
python tools/converter.py run --config=/path/to/your/model_deployment_
↪file.yml --round=100

# Validate the correctness by comparing the results against the
# original model and framework, measured with cosine distance for␣
↪similarity.
python tools/converter.py run --config=/path/to/your/model_deployment_
↪file.yml --validate

# If you want to run model on specified arm linux device, you should put␣
↪device config file in the working directory or run with flag `--device_
↪yml`
python tools/converter.py run --config=/path/to/your/model_deployment_
↪file.yml --device_yml=/path/to/devices.yml
```

- **benchmark**

  benchmark and profile the model. the details are in *Benchmark usage*.

```
# Benchmark model, get detailed statistics of each Op.
python tools/converter.py run --config=/path/to/your/model_deployment_
↪file.yml --benchmark
```

6.2.6 6. Deploy your model into applications

You could run model on CPU, GPU and DSP (based on the *runtime* in your model deployment file). However, there are some differences in different devices.

- **CPU**

  Almost all of mobile SoCs use ARM-based CPU architecture, so your model could run on different SoCs in theory.

- **GPU**

  Although most GPUs use OpenCL standard, but there are some SoCs not fully complying with the standard, or the GPU is too low-level to use. So you should have some fallback strategies when the GPU run failed.

- **DSP**

  MACE only supports Qualcomm DSP. And you need to push the hexagon nn library to the device.

```
# For Android device
adb root; adb remount
adb push third_party/nnlib/v6x/libhexagon_nn_skel.so /system/vendor/lib/
↪rfsa/adsp/
```

In the converting and building steps, you've got the static/shared library, model files and header files.

`${library_name}` is the name you defined in the first line of your deployment YAML file.

Note: When linking generated `libmace.a` into shared library, version script is helpful for reducing a specified set of symbols to local scope.

- The generated `static` library files are organized as follows,

```
build
├── include
│   └── mace
│       └── public
│           └── mace.h
├── lib
│   ├── arm64-v8a
│   │   └── cpu_gpu
│   │       ├── libmace.a
│   │       └── libmace.so
│   ├── armeabi-v7a
│   │   ├── cpu_gpu
│   │   │   ├── libmace.a
│   │   │   └── libmace.so
│   │   └── cpu_gpu_dsp
│   │       ├── libhexagon_controller.so
│   │       ├── libmace.a
│   │       └── libmace.so
│   └── linux-x86-64
│       ├── libmace.a
│       └── libmace.so
└── mobilenet-v1
    ├── model
    │   ├── mobilenet_v1.data
    │   └── mobilenet_v1.pb
    └── _tmp
        └── arm64-v8a
            └── mace_run_static
```

Please refer to `mace/tools/mace_run.cc`for full usage. The following list the key steps.

```
// Include the headers
#include "mace/public/mace.h"

// 0. Declare the device type (must be same with ``runtime`` in configuration file)
DeviceType device_type = DeviceType::GPU;

// 1. configuration
MaceStatus status;
MaceEngineConfig config(device_type);
std::shared_ptr<GPUContext> gpu_context;
// Set the path to store compiled OpenCL kernel binaries.
// please make sure your application have read/write rights of the directory.
// this is used to reduce the initialization time since the compiling is too slow.
// It's suggested to set this even when pre-compiled OpenCL program file is provided
// because the OpenCL version upgrade may also leads to kernel recompilations.
const std::string storage_path ="path/to/storage";
gpu_context = GPUContextBuilder()
    .SetStoragePath(storage_path)
    .Finalize();
config.SetGPUContext(gpu_context);
config.SetGPUHints(
    static_cast<GPUPerfHint>(GPUPerfHint::PERF_NORMAL),
    static_cast<GPUPriorityHint>(GPUPriorityHint::PRIORITY_LOW));

// 2. Define the input and output tensor names.
std::vector<std::string> input_names = {...};
```

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```
std::vector<std::string> output_names = {...};

// 3. Create MaceEngine instance
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;

// Create Engine from model file
create_engine_status =
    CreateMaceEngineFromProto(model_graph_proto,
                              model_graph_proto_size,
                              model_weights_data,
                              model_weights_data_size,
                              input_names,
                              output_names,
                              device_type,
                              &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // fall back to other strategy.
}

// 4. Create Input and Output tensor buffers
std::map<std::string, mace::MaceTensor> inputs;
std::map<std::string, mace::MaceTensor> outputs;
for (size_t i = 0; i < input_count; ++i) {
  // Allocate input and output
  int64_t input_size =
      std::accumulate(input_shapes[i].begin(), input_shapes[i].end(), 1,
                      std::multiplies<int64_t>());
  auto buffer_in = std::shared_ptr<float>(new float[input_size],
                                          std::default_delete<float[]>());
  // Load input here
  // ...

  inputs[input_names[i]] = mace::MaceTensor(input_shapes[i], buffer_in);
}

for (size_t i = 0; i < output_count; ++i) {
  int64_t output_size =
      std::accumulate(output_shapes[i].begin(), output_shapes[i].end(), 1,
                      std::multiplies<int64_t>());
  auto buffer_out = std::shared_ptr<float>(new float[output_size],
                                           std::default_delete<float[]>());
  outputs[output_names[i]] = mace::MaceTensor(output_shapes[i], buffer_out);
}

// 5. Run the model
MaceStatus status = engine.Run(inputs, &outputs);
```

More details are in *Advanced usage for Bazel users*.

CHAPTER 7

Advanced usage for CMake users

This part contains the full usage of MACE.

7.1 Deployment file

There are many advanced options supported.

- **Example**

  Here is an example deployment file with two models.

```
models:
  mobilenet_v1:
      platform: tensorflow
      model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/
↪mobilenet-v1/mobilenet-v1-1.0.pb
      model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
      subgraphs:
        - input_tensors:
            - input
          input_shapes:
            - 1,224,224,3
          output_tensors:
            - MobilenetV1/Predictions/Reshape_1
          output_shapes:
            - 1,1001
          validation_inputs_data:
            - https://cnbj1.fds.api.xiaomi.com/mace/inputs/dog.npy
      runtime: cpu+gpu
      limit_opencl_kernel_time: 0
      obfuscate: 0
      winograd: 0
  squeezenet_v11:
```

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```
    platform: caffe
    model_file_path: http://cnbj1-inner-fds.api.xiaomi.net/mace/mace-
↪models/squeezenet/SqueezeNet_v1.1/model.prototxt
    weight_file_path: http://cnbj1-inner-fds.api.xiaomi.net/mace/mace-
↪models/squeezenet/SqueezeNet_v1.1/weight.caffemodel
    model_sha256_checksum:␣
↪625c952063da1569e22d2f499dc454952244d42cd8feca61f05502566e70ae1c
    weight_sha256_checksum:␣
↪72b912ace512e8621f8ff168a7d72af55910d3c7c9445af8dfbff4c2ee960142
    subgraphs:
      - input_tensors:
          - data
        input_shapes:
          - 1,227,227,3
        output_tensors:
          - prob
        output_shapes:
          - 1,1,1,1000
        accuracy_validation_script:
          - path/to/your/script
    runtime: cpu+gpu
    limit_opencl_kernel_time: 0
    obfuscate: 0
    winograd: 0
```

- **Configurations**

Options	Usage
model_name	model name should be unique if there are more than one models. **LIMIT: if build_type is code, model_name will be used in c++ code so that model_name must comply with c++ name specification.**
platform	The source framework, tensorflow or caffe.
model_file_path	The path of your model file which can be local path or remote URL.
model_sha256_checksum	The SHA256 checksum of the model file.
weight_file_path	[optional] The path of Caffe model weights file.
weight_sha256_checksum	[optional] The SHA256 checksum of Caffe model weights file.
subgraphs	subgraphs key. **DO NOT EDIT**
input_tensors	The input tensor name(s) (tensorflow) or top name(s) of inputs' layer (caffe). If there are more than one tensors, use one line for a tensor.
output_tensors	The output tensor name(s) (tensorflow) or top name(s) of outputs' layer (caffe). If there are more than one tensors, use one line for a tensor.
input_shapes	The shapes of the input tensors, default is NHWC order.
output_shapes	The shapes of the output tensors, default is NHWC order.
input_ranges	The numerical range of the input tensors' data, default [-1, 1]. It is only for test.
validation_inputs_data	[optional] Specify Numpy validation inputs. When not provided, [-1, 1] random values will be used.
accuracy_validation_script	[optional] Specify the accuracy validation script as a plugin to test accuracy, see *doc*.
validation_threshold	[optional] Specify the similarity threshold for validation. A dict with key in 'CPU', 'GPU' and/or 'HEXAGON' and value <= 1.0.
backend	The onnx backend framework for validation, could be [tensorflow, caffe2, pytorch], default is tensorflow.
runtime	The running device, one of [cpu, gpu, dsp, cpu+gpu]. cpu+gpu contains CPU and GPU model definition so you can run the model on both CPU and GPU.
data_type	[optional] The data type used for specified runtime. [fp16_fp32, fp32_fp32] for GPU, default is fp16_fp32, [fp32] for CPU and [uint8] for DSP.
input_data_types	[optional] The input data type for specific op(eg. gather), which can be [int32, float32], default to float32.
input_data_formats	[optional] The format of the input tensors, one of [NONE, NHWC, NCHW]. If there is no format of the input, please use NONE. If only one single format is specified, all inputs will use that format, default is NHWC order.
output_data_formats	[optional] The format of the output tensors, one of [NONE, NHWC, NCHW]. If there is no format of the output, please use NONE. If only one single format is specified, all inputs will use that format, default is NHWC order.
limit_opencl_kernel_time	[optional] Whether splitting the OpenCL kernel within 1 ms to keep UI responsiveness, default is 0.
opencl_queue_window_size	[optional] Limit the max commands in OpenCL command queue to keep UI responsiveness, default is 0.
obfuscate	[optional] Whether to obfuscate the model operator name, default to 0.
winograd	[optional] Which type winograd to use, could be [0, 2, 4]. 0 for disable winograd, 2 and 4 for enable winograd, 4 may be faster than 2 but may take more memory.

Note: Some command tools:

```
# Get device's soc info.
adb shell getprop | grep platform

# command for generating sha256_sum
sha256sum /path/to/your/file
```

7.2 Advanced usage

There are three common advanced use cases:

- run your model on the embedded device(ARM LINUX)
- converting model to C++ code.
- tuning GPU kernels for a specific SoC.

7.3 Run you model on the embedded device(ARM Linux)

The way to run your model on the ARM Linux is nearly same as with android, except you need specify a device config file.

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --validate --device_yml=/path/to/devices.yml
```

There are two steps to do before run:

1. configure login without password

   MACE use ssh to connect embedded device, you should copy your public key to embedded device with the blow command.

   ```
   cat ~/.ssh/id_rsa.pub | ssh -q {user}@{ip} "cat >> ~/.ssh/authorized_keys"
   ```

2. write your own device yaml configuration file.

   - **Example**

     Here is an device yaml config demo.

     ```
     # one yaml config file can contain multi device info
     devices:
       # The name of the device
       nanopi:
       # arm64 or armhf
         target_abis: [arm64, armhf]
       # device soc, you can get it from device manual
         target_socs: RK3399
       # device model full name
         models: FriendlyElec Nanopi M4
       # device ip address
         address: 10.0.0.0
       # login username
         username: user
       raspberry:
     ```

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```
    target_abis: [armv7l]
    target_socs: BCM2837
    models: Raspberry Pi 3 Model B Plus Rev 1.3
    address: 10.0.0.1
    username: user
```

- **Configuration** The detailed explanation is listed in the blow table.

Options	Usage
target_abis	Device supported abis, you can get it via `dpkg --print-architecture` and `dpkg --print-foreign-architectures` command, if more than one abi is supported, separate them by commas.
target_socs	device soc, you can get it from device manual, we haven't found a way to get it in shell.
models	device models full name, you can get via get `lshw` command (third party package, install it via your package manager). see it's product value.
address	Since we use ssh to connect device, ip address is required.
username	login username, required.

7.4 Model Protection

Model can be encrypted by obfuscation.

```
python tools/python/encrypt.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml
```

It will override `mobilenet_v1.pb` and `mobilenet_v1.data`. If you want to compiled the model into a library, you should use options `--gencode_model --gencode_param` to generate model code, i.e.,

```
python tools/python/encrypt.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --gencode_model --gencode_param
```

It will generate model code into `mace/codegen/models` and also generate a helper function `CreateMaceEngineFromCode` in `mace/codegen/engine/mace_engine_factory.h` by which you can create an engine with models built in it.

After that you can rebuild the engine.

```
RUNTIME=GPU RUNMODE=code bash tools/cmake/cmake-build-armeabi-v7a.sh
```

`RUNMODE=code` means you compile and link model library with MACE engine.

When you test the model in code format, you should specify it in the script as follows.

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --gencode_model --gencode_param
```

Of course you can generate model code only, and use parameter file.

When you need to integrate the libraries into your applications, you can link *libmace_static.a* and *libmodel.a* to your target. These are under the directory: `build/cmake-build/armeabi-v7a/install/lib/`, the header files you need are under `build/cmake-build/armeabi-v7a/install/include`.

Refer to `mace/tools/mace_run.cc`for full usage. The following list the key steps.

```
// Include the headers
#include "mace/public/mace.h"
// If the model_graph_format is code
#include "mace/public/${model_name}.h"
#include "mace/public/mace_engine_factory.h"

// ... Same with the code in basic usage

// 4. Create MaceEngine instance
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;
// Create Engine from compiled code
create_engine_status =
    CreateMaceEngineFromCode(model_name.c_str(),
                             model_data_ptr, // nullptr if model_data_format␣
↪is code
                             model_data_size, // 0 if model_data_format is␣
↪code
                             input_names,
                             output_names,
                             device_type,
                             &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // Report error or fallback
}

// ... Same with the code in basic usage
```

7.5 Transform models after conversion

If `model_graph_format` or `model_data_format` is specified as *file*, the model or weight file will be generated as a *.pb* or *.data* file after model conversion. After that, more transformations can be applied to the generated files, such as compression or encryption. To achieve that, the model loading is split to two stages: 1) load the file from file system to memory buffer; 2) create the MACE engine from the model buffer. So between the two stages, transformations can be inserted to decompress or decrypt the model buffer. The transformations are user defined. The following lists the key steps when both `model_graph_format` and `model_data_format` are set as *file*.

```
// Load model graph from file system
std::unique_ptr<mace::port::ReadOnlyMemoryRegion> model_graph_data =
    make_unique<mace::port::ReadOnlyBufferMemoryRegion>();
if (FLAGS_model_file != "") {
  auto fs = GetFileSystem();
  status = fs->NewReadOnlyMemoryRegionFromFile(FLAGS_model_file.c_str(),
      &model_graph_data);
  if (status != MaceStatus::MACE_SUCCESS) {
    // Report error or fallback
  }
}
// Load model data from file system
```

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```
std::unique_ptr<mace::port::ReadOnlyMemoryRegion> model_weights_data =
    make_unique<mace::port::ReadOnlyBufferMemoryRegion>();
if (FLAGS_model_data_file != "") {
  auto fs = GetFileSystem();
  status = fs->NewReadOnlyMemoryRegionFromFile(FLAGS_model_data_file.c_str(),
      &model_weights_data);
  if (status != MaceStatus::MACE_SUCCESS) {
    // Report error or fallback
  }
}
if (model_graph_data == nullptr || model_weights_data == nullptr) {
  // Report error or fallback
}

std::vector<unsigned char> transformed_model_graph_data;
std::vector<unsigned char> transformed_model_weights_data;
// Add transformations here.
...
// Release original model data after transformations
model_graph_data.reset();
model_weights_data.reset();

// Create the MACE engine from the model buffer
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;
create_engine_status =
    CreateMaceEngineFromProto(transformed_model_graph_data.data(),
                              transformed_model_graph_data.size(),
                              transformed_model_weights_data.data(),
                              transformed_model_weights_data.size(),
                              input_names,
                              output_names,
                              config,
                              &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // Report error or fallback
}
```

7.6 Tuning for specific SoC's GPU

If you want to use the GPU of a specific device, you can tune the performance for particular devices, which may get 1~10% performance improvement.

You can specify *–tune* option when you want to run and tune the performance at the same time.

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --tune
```

It will generate OpenCL tuned parameter binary file in *build/mobilenet_v1/opencl* directory.

```
└── mobilenet_v1_tuned_opencl_parameter.MIX2S.sdm845.bin
```

It specifies your test platform model and SoC. You can use it in production to reduce latency on GPU.

To deploy it, change the names of files generated above for not collision and push them to **your own device's directory**.

Use like the previous procedure, below lists the key steps differently.

```
// Include the headers
#include "mace/public/mace.h"
// 0. Declare the device type (must be same with ``runtime`` in␣
↪configuration file)
DeviceType device_type = DeviceType::GPU;

// 1. configuration
MaceStatus status;
MaceEngineConfig config(device_type);
std::shared_ptr<GPUContext> gpu_context;

const std::string storage_path ="path/to/storage";
gpu_context = GPUContextBuilder()
    .SetStoragePath(storage_path)
    .SetOpenCLBinaryPaths(path/to/opencl_binary_paths)
    .SetOpenCLParameterPath(path/to/opencl_parameter_file)
    .Finalize();
config.SetGPUContext(gpu_context);
config.SetGPUHints(
    static_cast<GPUPerfHint>(GPUPerfHint::PERF_NORMAL),
    static_cast<GPUPriorityHint>(GPUPriorityHint::PRIORITY_LOW));

// ... Same with the code in basic usage.
```

7.7 Multi Model Support (optional)

If multiple models are configured in config file. After you test it, it will generate more than one tuned parameter files. Then you need to merge them together.

```
python tools/python/gen_opencl.py
```

After that, it will generate one set of files into *build/opencl* directory.

```
├── compiled_opencl_kernel.bin
└── tuned_opencl_parameter.bin
```

You can also generate code into the engine by specify `--gencode`, after which you should rebuild the engine.

7.8 Validate accuracy of MACE model

MACE supports **python validation script** as a plugin to test the accuracy, the plugin script could be used for below two purpose.

1. Test the **accuracy(like Top-1)** of MACE model(specifically quantization model) converted from other framework(like tensorflow)
2. Show some real output if you want to see it.

The script define some interfaces like *preprocess* and *postprocess* to deal with input/outut and calculate the accuracy, you could refer to the sample code for detail. the sample code show how to calculate the Top-1 accuracy with imagenet validation dataset.

7.9 Reduce Library Size

Remove the registration of the ops unused for your models in the `mace/ops/ops_register.cc`, which will reduce the library size significantly. the final binary just link the registered ops' code.

```
#include "mace/ops/ops_register.h"

namespace mace {
namespace ops {
// Just leave the ops used in your models

...

}  // namespace ops


OpRegistry::OpRegistry() : OpRegistryBase() {
// Just leave the ops used in your models

  ...

  ops::RegisterMyCustomOp(this);

  ...

}

}  // namespace mace
```

7.10 Reduce Model Size

Model file size can be a bottleneck for the deployment of neural networks on mobile devices, so MACE provides several ways to reduce the model size with no or little performance or accuracy degradation.

1. Save model weights in half-precision floating point format

The data type of a regular model is float (32bit). To reduce the model weights size, half (16bit) can be used to reduce it by half with negligible accuracy degradation. Therefore, the default storage type for a regular model in MACE is half. However, if the model is very sensitive to accuracy, storage type can be changed to float.

In the deployment file, `data_type` is `fp16_fp32` by default and can be changed to `fp32_fp32`.

For CPU, `fp16_fp32` means that the weights are saved in half and actual inference is in float.

For GPU, `fp16_fp32` means that the ops in GPU take half as inputs and outputs while kernel execution in float.

2. Save model weights in quantized fixed point format

Weights of convolutional (excluding depthwise) and fully connected layers take up a major part of model size. These weights can be quantized to 8bit to reduce the size to a quarter, whereas the accuracy usually decreases only by 1%-3%. For example, the top-1 accuracy of MobileNetV1 after quantization of weights is 68.2% on the ImageNet validation set. `quantize_large_weights` can be specified as 1 in the deployment file to save these weights in 8bit and actual inference in float. It can be used for both CPU and GPU.

CHAPTER 8

Advanced usage for Bazel users

This part contains the full usage of MACE.

8.1 Overview

As mentioned in the previous part, a model deployment file defines a case of model deployment. The building process includes parsing model deployment file, converting models, building MACE core library and packing generated model libraries.

8.2 Deployment file

One deployment file will generate one library normally, but if more than one ABIs are specified, one library will be generated for each ABI. A deployment file can also contain multiple models. For example, an AI camera application may contain face recognition, object recognition, and voice recognition models, all of which can be defined in one deployment file.

- **Example**

  Here is an example deployment file with two models.

```
# The name of library
library_name: mobile_squeeze
# host, armeabi-v7a or arm64-v8a
target_abis: [arm64-v8a]
# soc's name or all
target_socs: [all]
# The build mode for model(s).
# 'code' for transferring model(s) into cpp code, 'file' for keeping␣
↪model(s) in protobuf file(s) (.pb).
model_graph_format: code
# 'code' for transferring model data(s) into cpp code, 'file' for keeping␣
↪model data(s) in file(s) (.data).
```

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```
model_data_format: code
# One yaml config file can contain multi models' deployment info.
models:
  mobilenet_v1:
      platform: tensorflow
      model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/
↪mobilenet-v1/mobilenet-v1-1.0.pb
      model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
      subgraphs:
        - input_tensors:
            - input
          input_shapes:
            - 1,224,224,3
          output_tensors:
            - MobilenetV1/Predictions/Reshape_1
          output_shapes:
            - 1,1001
          validation_inputs_data:
            - https://cnbj1.fds.api.xiaomi.com/mace/inputs/dog.npy
      runtime: cpu+gpu
      limit_opencl_kernel_time: 0
      obfuscate: 0
      winograd: 0
  squeezenet_v11:
      platform: caffe
      model_file_path: http://cnbj1-inner-fds.api.xiaomi.net/mace/mace-
↪models/squeezenet/SqueezeNet_v1.1/model.prototxt
      weight_file_path: http://cnbj1-inner-fds.api.xiaomi.net/mace/mace-
↪models/squeezenet/SqueezeNet_v1.1/weight.caffemodel
      model_sha256_checksum:␣
↪625c952063da1569e22d2f499dc454952244d42cd8feca61f05502566e70ae1c
      weight_sha256_checksum:␣
↪72b912ace512e8621f8ff168a7d72af55910d3c7c9445af8dfbff4c2ee960142
      subgraphs:
        - input_tensors:
            - data
          input_shapes:
            - 1,227,227,3
          output_tensors:
            - prob
          output_shapes:
            - 1,1,1,1000
          accuracy_validation_script:
            - path/to/your/script
      runtime: cpu+gpu
      limit_opencl_kernel_time: 0
      obfuscate: 0
      winograd: 0
```

- **Configurations**

Options	Usage
library_name	Library name.
target_abis	The target ABI(s) to build, could be 'host', 'armeabi-v7a' or 'arm64-v8a'. If more than one ABIs will

Table 1 – continued from

Options	Usage
target_socs	[optional] Build for specific SoCs.
model_graph_format	model graph format, could be 'file' or 'code'. 'file' for converting model graph to ProtoBuf file(.pb) ar
model_data_format	model data format, could be 'file' or 'code'. 'file' for converting model weight to data file(.data) and 'c
model_name	model name should be unique if there are more than one models. **LIMIT: if build_type is code, mode**
platform	The source framework, tensorflow or caffe.
model_file_path	The path of your model file which can be local path or remote URL.
model_sha256_checksum	The SHA256 checksum of the model file.
weight_file_path	[optional] The path of Caffe model weights file.
weight_sha256_checksum	[optional] The SHA256 checksum of Caffe model weights file.
subgraphs	subgraphs key. **DO NOT EDIT**
input_tensors	The input tensor name(s) (tensorflow) or top name(s) of inputs' layer (caffe). If there are more than on
output_tensors	The output tensor name(s) (tensorflow) or top name(s) of outputs' layer (caffe). If there are more than
input_shapes	The shapes of the input tensors, default is NHWC order.
output_shapes	The shapes of the output tensors, default is NHWC order.
input_ranges	The numerical range of the input tensors' data, default [-1, 1]. It is only for test.
validation_inputs_data	[optional] Specify Numpy validation inputs. When not provided, [-1, 1] random values will be used.
accuracy_validation_script	[optional] Specify the accuracy validation script as a plugin to test accuracy, see *doc*.
validation_threshold	[optional] Specify the similarity threshold for validation. A dict with key in 'CPU', 'GPU' and/or 'HE
backend	The onnx backend framework for validation, could be [tensorflow, caffe2, pytorch], default is tensorflo
runtime	The running device, one of [cpu, gpu, dsp, cpu+gpu]. cpu+gpu contains CPU and GPU model definitio
data_type	[optional] The data type used for specified runtime. [fp16_fp32, fp32_fp32] for GPU, default is fp16_f
input_data_types	[optional] The input data type for specific op(eg. gather), which can be [int32, float32], default to float
input_data_formats	[optional] The format of the input tensors, one of [NONE, NHWC, NCHW]. If there is no format of th
output_data_formats	[optional] The format of the output tensors, one of [NONE, NHWC, NCHW]. If there is no format of t
limit_opencl_kernel_time	[optional] Whether splitting the OpenCL kernel within 1 ms to keep UI responsiveness, default is 0.
opencl_queue_window_size	[optional] Limit the max commands in OpenCL command queue to keep UI responsiveness, default is
obfuscate	[optional] Whether to obfuscate the model operator name, default to 0.
winograd	[optional] Which type winograd to use, could be [0, 2, 4]. 0 for disable winograd, 2 and 4 for enable w

Note: Some command tools:

```
# Get device's soc info.
adb shell getprop | grep platform

# command for generating sha256_sum
sha256sum /path/to/your/file
```

8.3 Advanced usage

There are three common advanced use cases:

- run your model on the embedded device(ARM LINUX)
- converting model to C++ code.
- tuning GPU kernels for a specific SoC.

8.4 Run you model on the embedded device(ARM Linux)

The way to run your model on the ARM Linux is nearly same as with android, except you need specify a device config file.

```
python tools/converter.py run --config=/path/to/your/model_deployment_file.yml --
↪device_yml=/path/to/devices.yml
```

There are two steps to do before run:

1. configure login without password

   MACE use ssh to connect embedded device, you should copy your public key to embedded device with the blow command.

   ```
   cat ~/.ssh/id_rsa.pub | ssh -q {user}@{ip} "cat >> ~/.ssh/authorized_keys"
   ```

2. write your own device yaml configuration file.

   - **Example**

     Here is an device yaml config demo.

     ```
     # one yaml config file can contain multi device info
     devices:
       # The name of the device
       nanopi:
       # arm64 or armhf
         target_abis: [arm64, armhf]
       # device soc, you can get it from device manual
         target_socs: RK3399
       # device model full name
         models: FriendlyElec Nanopi M4
       # device ip address
         address: 10.0.0.0
       # login username
         username: user
       raspberry:
         target_abis: [armv7l]
         target_socs: BCM2837
         models: Raspberry Pi 3 Model B Plus Rev 1.3
         address: 10.0.0.1
         username: user
     ```

   - **Configuration** The detailed explanation is listed in the blow table.

Options	Usage
target_abis	Device supported abis, you can get it via `dpkg --print-architecture` and `dpkg --print-foreign-architectures` command, if more than one abi is supported, separate them by commas.
target_socs	device soc, you can get it from device manual, we haven't found a way to get it in shell.
models	device models full name, you can get via get `lshw` command (third party package, install it via your package manager). see it's product value.
address	Since we use ssh to connect device, ip address is required.
username	login username, required.

8.5 Convert model(s) to C++ code

- **1. Change the model deployment file(.yml)**

  If you want to protect your model, you can convert model to C++ code. there are also two cases:

  - convert model graph to code and model weight to file with below model configuration.

```
model_graph_format: code
model_data_format: file
```

  - convert both model graph and model weight to code with below model configuration.

```
model_graph_format: code
model_data_format: code
```

  Note: Another model protection method is using `obfuscate` to obfuscate names of model's operators.

- **2. Convert model(s) to code**

```
python tools/converter.py convert --config=/path/to/model_deployment_file.
↪yml
```

  The command will generate **${library_name}.a** in **build/${library_name}/model** directory and ** *.h* * in **build/${library_name}/include** like the following dir-tree.

```
# model_graph_format: code
# model_data_format: file

build
├── include
│   └── mace
│       └── public
│           ├── mace_engine_factory.h
│           └── mobilenet_v1.h
└── model
    ├── mobilenet-v1.a
```

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```
      └── mobilenet_v1.data

# model_graph_format: code
# model_data_format: code

build
├── include
│   └── mace
│       └── public
│           ├── mace_engine_factory.h
│           └── mobilenet_v1.h
└── model
    └── mobilenet-v1.a
```

- **3. Deployment**
  - Link *libmace.a* and *${library_name}.a* to your target.
  - Refer to `mace/tools/mace_run.cc`for full usage. The following list the key steps.

```
// Include the headers
#include "mace/public/mace.h"
// If the model_graph_format is code
#include "mace/public/${model_name}.h"
#include "mace/public/mace_engine_factory.h"

// ... Same with the code in basic usage

// 4. Create MaceEngine instance
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;
// Create Engine from compiled code
create_engine_status =
    CreateMaceEngineFromCode(model_name.c_str(),
                             model_data_ptr, // nullptr if model_data_format␣
↪is code
                             model_data_size, // 0 if model_data_format is␣
↪code
                             input_names,
                             output_names,
                             device_type,
                             &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // Report error or fallback
}

// ... Same with the code in basic usage
```

8.6 Transform models after conversion

If `model_graph_format` or `model_data_format` is specified as *file*, the model or weight file will be generated as a *.pb* or *.data* file after model conversion. After that, more transformations can be applied to the generated files, such as compression or encryption. To achieve that, the model loading is split to two stages: 1) load the file from file system to memory buffer; 2) create the MACE engine from the model buffer. So between the two stages, transformations can be inserted to decompress or decrypt

the model buffer. The transformations are user defined. The following lists the key steps when both `model_graph_format` and `model_data_format` are set as *file*.

```
// Load model graph from file system
std::unique_ptr<mace::port::ReadOnlyMemoryRegion> model_graph_data =
    make_unique<mace::port::ReadOnlyBufferMemoryRegion>();
if (FLAGS_model_file != "") {
  auto fs = GetFileSystem();
  status = fs->NewReadOnlyMemoryRegionFromFile(FLAGS_model_file.c_str(),
      &model_graph_data);
  if (status != MaceStatus::MACE_SUCCESS) {
    // Report error or fallback
  }
}
// Load model data from file system
std::unique_ptr<mace::port::ReadOnlyMemoryRegion> model_weights_data =
    make_unique<mace::port::ReadOnlyBufferMemoryRegion>();
if (FLAGS_model_data_file != "") {
  auto fs = GetFileSystem();
  status = fs->NewReadOnlyMemoryRegionFromFile(FLAGS_model_data_file.c_str(),
      &model_weights_data);
  if (status != MaceStatus::MACE_SUCCESS) {
    // Report error or fallback
  }
}
if (model_graph_data == nullptr || model_weights_data == nullptr) {
  // Report error or fallback
}

std::vector<unsigned char> transformed_model_graph_data;
std::vector<unsigned char> transformed_model_weights_data;
// Add transformations here.
...
// Release original model data after transformations
model_graph_data.reset();
model_weights_data.reset();

// Create the MACE engine from the model buffer
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;
create_engine_status =
    CreateMaceEngineFromProto(transformed_model_graph_data.data(),
                              transformed_model_graph_data.size(),
                              transformed_model_weights_data.data(),
                              transformed_model_weights_data.size(),
                              input_names,
                              output_names,
                              config,
                              &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // Report error or fallback
}
```

8.7 Tuning for specific SoC's GPU

If you want to use the GPU of a specific device, you can just specify the `target_socs` in your YAML file and then tune the MACE lib for it (OpenCL kernels), which may get 1~10% performance improvement.

- **1. Change the model deployment file(.yml)**

  Specify `target_socs` in your model deployment file(.yml):

```
target_socs: [sdm845]
```

  Note: Get device's soc info: *adb shell getprop | grep platform*

- **2. Convert model(s)**

```
python tools/converter.py convert --config=/path/to/model_
↪deployment_file.yml
```

- **3. Tuning**

  The tools/converter.py will enable automatic tuning for GPU kernels. This usually takes some time to finish depending on the complexity of your model.

  Note: You should plug in device(s) with the specific SoC(s).

```
python tools/converter.py run --config=/path/to/model_deployment_
↪file.yml --validate
```

  The command will generate two files in *build/${library_name}/opencl*, like the following dir-tree.

```
build
└── mobilenet-v2
    ├── model
    │   ├── mobilenet_v2.data
    │   └── mobilenet_v2.pb
    └── opencl
        └── arm64-v8a
            ├── moblinet-v2_compiled_opencl_kernel.MiNote3.sdm660.
↪bin
            ├── moblinet-v2_compiled_opencl_kernel.MiNote3.sdm660.
↪bin.cc
            ├── moblinet-v2_tuned_opencl_parameter.MiNote3.sdm660.
↪bin
            └── moblinet-v2_tuned_opencl_parameter.MiNote3.sdm660.
↪bin.cc
```

  - **mobilenet-v2-gpu_compiled_opencl_kernel.MI6.msm8998.bin** stands for the OpenCL binaries used for your models, which could accelerate the initialization stage. Details please refer to OpenCL Specification.
  - **mobilenet-v2-gpu_compiled_opencl_kernel.MI6.msm8998.bin.cc** contains C++ source code which defines OpenCL binary data as const array.

  - **mobilenet-v2-tuned_opencl_parameter.MI6.msm8998.bin** stands for the tuned OpenCL parameters for the SoC.
  - **mobilenet-v2-tuned_opencl_parameter.MI6.msm8998.bin.cc** contains C++ source code which defines OpenCL binary data as const array.

- **4. Deployment**
  - Change the names of files generated above for not collision and push them to **your own device's directory**.
  - Use like the previous procedure, below lists the key steps differently.

```
// Include the headers
#include "mace/public/mace.h"
// 0. Declare the device type (must be same with ``runtime`` in␣
↪configuration file)
DeviceType device_type = DeviceType::GPU;

// 1. configuration
MaceStatus status;
MaceEngineConfig config(device_type);
std::shared_ptr<GPUContext> gpu_context;

const std::string storage_path ="path/to/storage";
gpu_context = GPUContextBuilder()
    .SetStoragePath(storage_path)
    .SetOpenCLBinaryPaths(path/to/opencl_binary_paths)
    .SetOpenCLParameterPath(path/to/opencl_parameter_file)
    .Finalize();
config.SetGPUContext(gpu_context);
config.SetGPUHints(
    static_cast<GPUPerfHint>(GPUPerfHint::PERF_NORMAL),
    static_cast<GPUPriorityHint>(GPUPriorityHint::PRIORITY_LOW));

// ... Same with the code in basic usage.
```

8.8 Validate accuracy of MACE model

MACE supports **python validation script** as a plugin to test the accuracy, the plugin script could be used for below two purpose.

1. Test the **accuracy(like Top-1)** of MACE model(specifically quantization model) converted from other framework(like tensorflow)
2. Show some real output if you want to see it.

The script define some interfaces like *preprocess* and *postprocess* to deal with input/outut and calculate the accuracy, you could refer to the sample code for detail. the sample code show how to calculate the Top-1 accuracy with imagenet validation dataset.

8.9 Useful Commands

- **run the model**

```
# Test model run time
python tools/converter.py run --config=/path/to/model_deployment_file.yml --round=100

# Validate the correctness by comparing the results against the
# original model and framework, measured with cosine distance for similarity.
python tools/converter.py run --config=/path/to/model_deployment_file.yml --validate

# Check the memory usage of the model(**Just keep only one model in deployment file**)
python tools/converter.py run --config=/path/to/model_deployment_file.yml --
↪round=10000 &
sleep 5
adb shell dumpsys meminfo | grep mace_run
kill %1
```

Warning: `run` rely on `convert` command, you should `convert` before `run`.

- **benchmark and profile model**

the detailed information is in *Benchmark usage*.

```
# Benchmark model, get detailed statistics of each Op.
python tools/converter.py run --config=/path/to/model_deployment_file.yml --benchmark
```

Warning: `benchmark` rely on `convert` command, you should `benchmark` after `convert`.

Common arguments

option	type	default	commands	explanation
–omp_num_threads	int	-1	`run`	number of threads
–cpu_affinity_policy	int	1	`run`	0:AFFINITY_NONE/1:AFFINITY_BIG_ONLY/2:AFFINITY_LITTLE_ONLY
–gpu_perf_hint	int	3	`run`	0:DEFAULT/1:LOW/2:NORMAL/3:HIGH
–gpu_priority_hint	int	3	`run`/`benchmark`	0:DEFAULT/1:LOW/2:NORMAL/3:HIGH

Use `-h` to get detailed help.

```
python tools/converter.py -h
python tools/converter.py build -h
python tools/converter.py run -h
```

8.10 Reduce Library Size

- **Build for your own usage purpose.**
  - **dynamic library**

    * If the models don't need to run on device `dsp`, change the build option `--define hexagon=true` to `false`. And the library will be decreased about `100KB`.
    * Futher more, if only `cpu` device needed, change `--define opencl=true` to `false`. This way will reduce half of library size to about `700KB` for `armeabi-v7a` and `1000KB` for `arm64-v8a`
    * About `300KB` can be reduced when add `--config symbol_hidden` building option. It will change the visibility of inner apis in libmace.so and lead to linking error when load model(s) in `code` but no effection for `file` mode.

  – **static library**

    * The methods in dynamic library can be useful for static library too. In additional, the static library may also contain model graph and model datas if the configs `model_graph_format` and `model_data_format` in deployment file are set to `code`.
    * It is recommended to use `version script` and `strip` feature when linking mace static library. The effect is remarkable.

- Remove the unused ops.

Remove the registration of the ops unused for your models in the `mace/ops/ops_register.cc`, which will reduce the library size significantly. the final binary just link the registered ops' code.

```
#include "mace/ops/ops_register.h"

namespace mace {
namespace ops {
// Just leave the ops used in your models

...

}  // namespace ops


OpRegistry::OpRegistry() : OpRegistryBase() {
// Just leave the ops used in your models

  ...

  ops::RegisterMyCustomOp(this);

  ...

}

}  // namespace mace
```

8.11 Reduce Model Size

Model file size can be a bottleneck for the deployment of neural networks on mobile devices, so MACE provides several ways to reduce the model size with no or little performance or accuracy degradation.

1. Save model weights in half-precision floating point format

The data type of a regular model is float (32bit). To reduce the model weights size, half (16bit) can be used to reduce it by half with negligible accuracy degradation. Therefore, the default storage type for a regular model in MACE is

half. However, if the model is very sensitive to accuracy, storage type can be changed to float.

In the deployment file, `data_type` is `fp16_fp32` by default and can be changed to `fp32_fp32`.

For CPU, `fp16_fp32` means that the weights are saved in half and actual inference is in float.

For GPU, `fp16_fp32` means that the ops in GPU take half as inputs and outputs while kernel execution in float.

2. Save model weights in quantized fixed point format

Weights of convolutional (excluding depthwise) and fully connected layers take up a major part of model size. These weights can be quantized to 8bit to reduce the size to a quarter, whereas the accuracy usually decreases only by 1%-3%. For example, the top-1 accuracy of MobileNetV1 after quantization of weights is 68.2% on the ImageNet validation set. `quantize_large_weights` can be specified as 1 in the deployment file to save these weights in 8bit and actual inference in float. It can be used for both CPU and GPU.

CHAPTER 9

Benchmark usage

This part contains the usage of MACE benchmark tools.

9.1 Overview

As mentioned in the previous part, there are two kinds of benchmark tools, one for operator and the other for model.

9.2 Operator Benchmark

Operator Benchmark is used for test and optimize the performance of specific operator.

9.2.1 Usage

For CMake users:

```
python tools/python/run_target.py \
    --target_abi=armeabi-v7a --target_socs=all --target_name=mace_cc_
↪benchmark \
    --filter=.*BM_CONV.*
```

or for Bazel users:

```
python tools/bazel_adb_run.py --target="//test/ccbenchmark:mace_cc_benchmark
↪" \
    --run_target=True  --args="--filter=.*BM_CONV.*"
```

9.2.2 Output

```
Benchmark                                                    Time(ns)␣
↪Iterations Input(MB/s)   GMACPS
-------------------------------------------------------------------------------
↪--------------------------
MACE_BM_CONV_2D_1_1024_7_7_K1x1S1D1_SAME_1024_float_CPU       1759129       ␣
↪479      114.09       29.21
MACE_BM_CONV_2D_1_1024_7_7_K1x1S1D1_SAME_1024_float_GPU       4031301       ␣
↪226       49.79       12.75
MACE_BM_CONV_2D_1_1024_7_7_K1x1S1D1_SAME_1024_half_GPU        3996357       ␣
↪266       25.11       12.86
MACE_BM_CONV_2D_1_1024_7_7_K1x1S1D1_SAME_1024_uint8_t_CPU      914994       ␣
↪1093       54.84       56.15
```

9.2.3 Explanation

Options	Usage
Benchmark	Benchmark unit name.
Time	Time of one round.
Iterations	the number of iterations to run, which is between 10 and 1000,000,000. the value is calculated based on the strategy total run time does not exceed 1s.
Input	The bandwidth of dealing with input. the unit is MB/s.
GMACPS	The speed of running MACs(multiply-accumulation). the unit is G/s.

9.3 Model Benchmark

Model Benchmark is used for test and optimize the performance of your model. This tool could record the running time of the model and the detailed running information of each operator of your model.

9.3.1 Usage

For CMake users:

```
python tools/python/run_model.py --config=/path/to/your/model_deployment.yml␣
↪--benchmark
```

or for Bazel users:

```
python tools/python/converter.py run --config=/path/to/your/model_deployment.
↪yml --benchmark
```

9.3.2 Output

```
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪------------------------------------------------------
I statistics.cc:343
↪                              Sort by Run Order
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪------------------------------------------------------
I statistics.cc:343 |         Op Type |  Start | First | Avg(ms) |     % |
↪ cdf% | GMACPS | Stride |   Pad |    Filter Shape |   Output Shape |
↪Dilation |                                                 name |
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪------------------------------------------------------
I statistics.cc:343 |       Transpose |  0.000 | 0.102 |   0.100 | 0.315 |
↪0.315 |  0.000 |        |       |                |  [1,3,224,224] |
↪    |                                              input |
I statistics.cc:343 |          Conv2D |  0.107 | 1.541 |   1.570 | 4.943 |
↪5.258 |  6.904 |  [2,2] |  SAME |      [32,3,3,3] | [1,32,112,112] |    [1,
↪1] |             MobilenetV1/MobilenetV1/Conv2d_0/Relu6 |
I statistics.cc:343 | DepthwiseConv2d |  1.724 | 0.936 |   0.944 | 2.972 |
↪8.230 |  3.827 |  [1,1] |  SAME |      [1,32,3,3] | [1,32,112,112] |    [1,
↪1] |   MobilenetV1/MobilenetV1/Conv2d_1_depthwise/Relu6 |
I statistics.cc:343 |         Softmax | 32.835 | 0.039 |   0.042 | 0.131 |
↪99.996 |  0.000 |        |       |                |       [1,1001] |
↪    |                    MobilenetV1/Predictions/Softmax |
I statistics.cc:343 |        Identity | 32.880 | 0.001 |   0.001 | 0.004 |
↪100.000 |  0.000 |        |       |                |       [1,1001] |
↪     | mace_output_node_MobilenetV1/Predictions/Reshape_1 |
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪------------------------------------------------------
I statistics.cc:343
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪---------------------------------------------
I statistics.cc:343
↪                     Sort by Computation Time
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪---------------------------------------------
I statistics.cc:343 | Op Type |  Start | First | Avg(ms) |     % |   cdf% |
↪GMACPS | Stride |  Pad |    Filter Shape |   Output Shape | Dilation |
↪                                        name |
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪---------------------------------------------
I statistics.cc:343 |  Conv2D | 30.093 | 2.102 |   2.198 | 6.922 |  6.922 |
↪23.372 |  [1,1] | SAME | [1024,1024,1,1] |   [1,1024,7,7] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_13_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D |  7.823 | 2.115 |   2.164 | 6.813 | 13.735 |
↪23.747 |  [1,1] | SAME |   [128,128,1,1] |  [1,128,56,56] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_3_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D | 15.859 | 2.119 |   2.109 | 6.642 | 20.377 |
↪24.358 |  [1,1] | SAME |   [512,512,1,1] |  [1,512,14,14] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_7_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D | 23.619 | 2.087 |   2.096 | 6.599 | 26.976 |
↪24.517 |  [1,1] | SAME |   [512,512,1,1] |  [1,512,14,14] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_10_pointwise/Relu6 |
```

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```
I statistics.cc:343 |  Conv2D | 26.204 | 2.081 |   2.093 | 6.590 | 33.567 |
↪24.549 |  [1,1] | SAME |   [512,512,1,1] |  [1,512,14,14] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_11_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D | 21.038 | 2.036 |   2.091 | 6.585 | 40.152 |
↪24.569 |  [1,1] | SAME |   [512,512,1,1] |  [1,512,14,14] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_9_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D | 18.465 | 2.034 |   2.082 | 6.554 | 46.706 |
↪24.684 |  [1,1] | SAME |   [512,512,1,1] |  [1,512,14,14] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_8_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D |  2.709 | 1.984 |   2.058 | 6.482 | 53.188 |
↪12.480 |  [1,1] | SAME |     [64,32,1,1] | [1,64,112,112] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_1_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D | 12.220 | 1.788 |   1.901 | 5.986 | 59.174 |
↪27.027 |  [1,1] | SAME |   [256,256,1,1] |  [1,256,28,28] |    [1,1] |
↪MobilenetV1/MobilenetV1/Conv2d_5_pointwise/Relu6 |
I statistics.cc:343 |  Conv2D |  0.107 | 1.541 |   1.570 | 4.943 | 64.117 |
↪6.904 |  [2,2] | SAME |      [32,3,3,3] | [1,32,112,112] |    [1,1] |
↪      MobilenetV1/MobilenetV1/Conv2d_0/Relu6 |
I statistics.cc:343 ------------------------------------------------------------
↪------------------------------------------------------------------------------
↪--------------------------------------------
I statistics.cc:343
I statistics.cc:343 ------------------------------------------------------------
↪-------------------------------------
I statistics.cc:343                                          Stat by Op Type
I statistics.cc:343 ------------------------------------------------------------
↪-------------------------------------
I statistics.cc:343 |         Op Type | Count | Avg(ms) |      % |    cdf% |
↪       MACs | GMACPS | Called times |
I statistics.cc:343 ------------------------------------------------------------
↪-------------------------------------
I statistics.cc:343 |          Conv2D |    15 |  24.978 | 78.693 |  78.693 |
↪551,355,392 | 22.074 |           15 |
I statistics.cc:343 | DepthwiseConv2d |    13 |   6.543 | 20.614 |  99.307 |
↪ 17,385,984 |  2.657 |           13 |
I statistics.cc:343 |       Transpose |     1 |   0.100 |  0.315 |  99.622 |
↪           0 |  0.000 |            1 |
I statistics.cc:343 |         Pooling |     1 |   0.072 |  0.227 |  99.849 |
↪           0 |  0.000 |            1 |
I statistics.cc:343 |         Softmax |     1 |   0.041 |  0.129 |  99.978 |
↪           0 |  0.000 |            1 |
I statistics.cc:343 |         Squeeze |     1 |   0.006 |  0.019 |  99.997 |
↪           0 |  0.000 |            1 |
I statistics.cc:343 |        Identity |     1 |   0.001 |  0.003 | 100.000 |
↪           0 |  0.000 |            1 |
I statistics.cc:343 ------------------------------------------------------------
↪-------------------------------------
I statistics.cc:343
I statistics.cc:343 ------------------------------------------------------------
I statistics.cc:343           Stat by MACs(Multiply-Accumulation)
I statistics.cc:343 ------------------------------------------------------------
I statistics.cc:343 |       total | round | first(G/s) | avg(G/s) |     std |
I statistics.cc:343 ------------------------------------------------------------
I statistics.cc:343 | 568,741,376 |   100 |     18.330 |   17.909 | 301.326 |
I statistics.cc:343 ------------------------------------------------------------
I statistics.cc:343 ------------------------------------------------------------
↪---------------
```

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```
I statistics.cc:343                              Summary of Ops' Stat
I statistics.cc:343 ------------------------------------------------------------
↪---------------
I statistics.cc:343 | round | first(ms) | curr(ms) | min(ms) | max(ms) |␣
↪avg(ms) |      std |
I statistics.cc:343 ------------------------------------------------------------
↪---------------
I statistics.cc:343 |   100 |    31.028 |   32.093 |  31.028 |  32.346 |  31.
↪758 | 301.326 |
I statistics.cc:343 ------------------------------------------------------------
↪---------------
```

9.3.3 Explanation

There are 8 sections of the output information.

1. **Warm Up**

This section lists the time information of warm-up run. The detailed explanation is list as below.

Key	Explanation
round	the number of round has been run.
first	the run time of first round. unit is millisecond.
curr	the run time of last round. unit is millisecond.
min	the minimal run time of all rounds. unit is millisecond.
max	the maximal run time of all rounds. unit is millisecond.
avg	the average run time of all rounds. unit is millisecond.
std	the standard deviation of all rounds.

2. **Run without statistics**

This section lists the run time information without statistics code. the detailed explanation is the same as the section of Warm Up.

3. **Run with statistics**

This section lists the run time information with statistics code, the time maybe longer compared with the second section. the detailed explanation is the same as the section of Warm Up.

4. **Sort by Run Order**

This section lists the detailed run information of every operator in your model. The operators is listed based on the run order, Every line is an operator of your model. The detailed explanation is list as below.

Key	Explanation
Op Type	the type of operator.
Start	the start time of the operator. unit is millisecond.
First	the run time of first round. unit is millisecond.
Avg	the average run time of all rounds. unit is millisecond.
%	the percentage of total running time.
cdf%	the cumulative percentage of running time.
GMACPS	The number of run MACs(multiply-accumulation) per second. the unit is G/s.
Stride	the stride parameter of the operator if exist.
Pad	the pad parameter of the operator if exist.
Filter Shape	the filter shape of the operator if exist.
Output Shape	the output shape of the operator.
Dilation	the dilation parameter of the operator if exist.
Name	the name of the operator.

5. **Sort by Computation time**

This section lists the top-10 most time-consuming operators. The operators is listed based on the computation time, the detailed explanation is the same as previous section.

6. **Stat by Op Type**

This section stats the run information about operators based on operator type.

Op Type	the type of operator.
Count	the number of operators with the type.
Avg	the average run time of the operator. unit is millisecond.
%	the percentage of total running time.
cdf%	the cumulative percentage of running time.
MACs	The number of MACs(multiply-accumulation).
GMACPS	The number of MACs(multiply-accumulation) runs per second. the unit is G/s.
Called times	the number of called times in all rounds.

7. **Stat by MACs**

This section stats the MACs information of your model.

total	the number of MACs of your model.
round	the number of round has been run.
First	the GMAPS of first round. unit is G/s.
Avg	the average GMAPS of all rounds. unit is G/s.
std	the standard deviation of all rounds.

8. **Summary of Ops' Stat**

This section lists the run time information which is summation of every operator's run time. which may be shorter than the model's run time with statistics. the detailed explanation is the same as the section of Warm Up.

CHAPTER 10

Operator lists

Operator	Supported	Remark
AVERAGE_POOL_2D	Y	
ARGMAX	Y	Only CPU and TensorFlow is supported.
BATCH_NORM	Y	Fusion with activation is supported.
BATCH_TO_SPACE_ND	Y	
BIAS_ADD	Y	
CAST	Y	Only CPU and TensorFlow model is supported.
CHANNEL_SHUFFLE	Y	
CONCATENATION	Y	For GPU only support channel axis concatenation.
CONV_2D	Y	Fusion with BN and activation layer is supported.
CROP	Y	Only Caffe's crop layer is supported (in GPU, offset on channel-dim sho
DECONV_2D	Y	Supports Caffe's Deconvolution and TensorFlow's tf.layers.conv2d_tran
DEPTHWISE_DECONV2D	Y	Supports Caffe's Group and Depthwise Deconvolution. For GPU only su
DEPTHWISE_CONV_2D	Y	Only multiplier = 1 is supported; Fusion is supported.
DEPTH_TO_SPACE	Y	
DEQUANTIZE	Y	Model quantization will be supported later.
ELEMENT_WISE	Y	ADD/MUL/DIV/MIN/MAX/NEG/ABS/SQR_DIFF/POW/RSQRT/SQR
EMBEDDING_LOOKUP	Y	
EXPANDDIMS	Y	Only CPU and TensorFlow is supported.
FILL	Y	Only CPU and TensorFlow is supported.
FLATTEN	Y	Only Caffe is supported.
FULLY_CONNECTED	Y	
GROUP_CONV_2D		Caffe model with group count = channel count is supported.
IDENTITY	Y	Only TensorFlow model is supported.
LOCAL_RESPONSE_NORMALIZATION	Y	
LOGISTIC	Y	
LSTM		
MATMUL	Y	Only CPU is supported.
MAX_POOL_2D	Y	

Table 1 – continued from previous page

Operator	Supported	Remark
ONE_HOT	Y	Only TensorFlow model is supported.
PAD	Y	
PSROI_ALIGN	Y	
PRELU	Y	Only Caffe model is supported
PRIOR_BOX	Y	Only Caffe model is supported
REDUCE_MEAN	Y	Only TensorFlow model is supported. For GPU only H + W axis reduce
RELU	Y	
RELU1	Y	
RELU6	Y	
RELUX	Y	
RESHAPE	Y	Limited support: GPU only supports softmax-like usage, CPU only supp
RESIZE_BICUBIC	Y	Only Tensorflow is supported
RESIZE_BILINEAR	Y	Only Tensorflow is supported
RESIZE_NEAREST_NEIGHBOR	Y	Only Tensorflow is supported
REVERSE	Y	Only CPU and Tensorflow is supported
RNN		
RPN_PROPOSAL_LAYER	Y	
SHAPE	Y	Only CPU and TensorFlow is supported.
STACK	Y	Only CPU and TensorFlow is supported.
STRIDEDSLICE	Y	Only CPU and TensorFlow is supported.
SPLIT	Y	In Caffe, this op is equivalent to SLICE; For GPU only support channel
SOFTMAX	Y	
SPACE_TO_BATCH_ND	Y	
SPACE_TO_DEPTH	Y	
SQUEEZE	Y	Only CPU and TensorFlow is supported.
TANH	Y	
TRANSPOSE	Y	Only CPU and TensorFlow is supported.
UNSTACK	Y	Only CPU and TensorFlow is supported.

CHAPTER 11

Quantization

MACE supports two kinds of quantization mechanisms, i.e.,

- **Quantization-aware training (Recommend)**

After pre-training model using float point, insert simulated quantization operations into the model. Fine tune the new model. Refer to Tensorflow quantization-aware training.

- **Post-training quantization**

After pre-training model using float point, estimate output range of each activation layer using sample inputs.

Note: *quantize_weights* and *quantize_nodes* should not be specified when using *TransformGraph* tool if using MACE quantization.

11.1 Quantization-aware training

It is recommended that developers fine tune the fixed-point model, as experiments show that by this way accuracy could be improved, especially for lightweight models, e.g., MobileNet. The only thing you need to make it run using MACE is to add the following config to model yaml file:

1. *input_ranges*: the ranges of model's inputs, e.g., -1.0,1.0.
2. *quantize*: set *quantize* to be 1.

11.2 Post-training quantization

MACE supports post-training quantization if you want to take a chance to quantize model directly without fine tuning. This method requires developer to calculate tensor range of each activation layer statistically using sample inputs. MACE provides tools to do statistics with following steps (using *inception-v3* from MACE Model Zoo as an example):

1. Convert original model to run on CPU host without obfuscation (by setting *target_abis* to *host*, *runtime* to *cpu*, and *obfuscate* to *0*, appending *:0* to *output_tensors* if missing in yaml config).

```
# For CMake users:
python tools/python/convert.py --config ../mace-models/inception-v3/
↪inception-v3.yml
  --quantize_stat

# For Bazel users:
python tools/converter.py convert --config ../mace-models/inception-v3/
↪inception-v3.yml
  --quantize_stat
```

2. Log tensor range of each activation layer by inferring several samples on CPU host. Sample inputs should be representative to calculate the ranges of each layer properly.

```
# Convert images to input tensors for MACE, see image_to_tensor.py for more␣
↪arguments.
python tools/image/image_to_tensor.py --input /path/to/directory/of/input/
↪images
  --output_dir /path/to/directory/of/input/tensors --image_shape=299,299,3

# Rename input tensors to start with input tensor name(to differentiate␣
↪multiple
# inputs of a model), input tensor name is what you specified as "input_
↪tensors"
# in yaml config. For example, "input" is the input tensor name of␣
↪InceptionV3 as below.
rename 's/^/input/' *

# Run with input tensors
# For CMake users:
python tools/python/run_model.py --config ../mace-models/inception-v3/
↪inception-v3.yml
  --quantize_stat --input_dir /path/to/directory/of/input/tensors > range_log

# For Bazel users:
python tools/converter.py run --config ../mace-models/inception-v3/inception-
↪v3.yml
  --quantize_stat --input_dir /path/to/directory/of/input/tensors > range_log
```

3. Calculate overall range of each activation layer. You may specify *–percentile* or *–enhance* and *–enhance_ratio* to try different ranges and see which is better. Experimentation shows that the default *percentile* and *enhance_ratio* works fine for several common models.

```
python tools/python/quantize/quantize_stat.py --log_file range_log > overall_
↪range
```

4. Convert quantized model (by setting *target_abis* to the final target abis, e.g., *armeabi-v7a*, *quantize* to *1* and *quantize_range_file* to the overall_range file path in yaml config).

11.3 Mixing usage

As *quantization-aware training* is still evolving, there are some operations that are not supported, which leaves some activation layers without tensor range. In this case, *post-training quantization* can be used to calculate these missing

ranges. To mix the usage, just get a *quantization-aware training* model and then go through all the steps of *post-training quantization*. MACE will use the tensor ranges from the *overall_range* file of *post-training quantization* if the ranges are missing from the *quantization-aware training* model.

11.4 Supported devices

MACE supports running quantized models on ARM CPU and other acceleration devices, e.g., Qualcomm Hexagon DSP, MediaTek APU. ARM CPU is ubiquitous, which can speed up most of edge devices. However, AI specialized devices may run much faster than ARM CPU, and in the meantime consume much lower power. Headers and libraries of these devices can be found in *third_party* directory.

- To run models on **ARM CPU**, users should
    1. Set *runtime* in yaml config to *cpu* (*Armv8.2+dotproduct* instructions will be used automatically if detected by *getauxval*, which can greatly improve convolution/gemm performance).
- To run models on **Hexagon DSP**, users should
    1. Set *runtime* in yaml config to *dsp*.
    2. Make sure SOCs of the phone is manufactured by Qualcomm and has HVX supported.
    3. Make sure the phone disables secure boot (once enabled, cannot be reversed, so you probably can only get that type phones from manufacturers). This can be checked by executing the following command.

        ```
        adb shell getprop ro.boot.secureboot
        ```

        The return value should be 0.
    4. Root the phone.
    5. Sign the phone by using testsig provided by Qualcomm. (Download Qualcomm Hexagon SDK first, plugin the phone to PC, run scripts/testsig.py)
    6. Push *third_party/nnlib/v6x/libhexagon_nn_skel.so* to */system/vendor/lib/rfsa/adsp/*. You can check *docs/feature_matrix.html* in Hexagon SDK to make sure which version to use.

Then, there you go, you can run Mace on Hexagon DSP. This indeed seems like a whole lot of work to do. Well, the good news is that starting in the SM8150 family(some devices with old firmware may still not work), signature-free dynamic module offload is enabled on cDSP. So, steps 2-4 can be skipped. This can be achieved by calling *SetHexagonToUnsignedPD()* before creating MACE engine.

- To run models on **MediaTek APU**, users should
    1. Set *runtime* in yaml config to *apu*.
    2. Make sure SOCs of the phone is manufactured by MediaTek and has APU supported.
    3. Push *third_party/apu/mtxxxx/libapu-platform.so* to */vendor/lib64/*.

CHAPTER 12

Contributing guide

12.1 License

The source file should contain a license header. See the existing files as the example.

12.2 Python coding style

Changes to Python code should conform to PEP8 Style Guide for Python Code.

You can use pycodestyle to check the style.

12.3 C++ coding style

Changes to C++ code should conform to Google C++ Style Guide.

You can use cpplint to check the style and use clang-format to format the code:

```
clang-format -style="{BasedOnStyle: google,           \
                      DerivePointerAlignment: false,  \
                      PointerAlignment: Right,        \
                      BinPackParameters: false}" $file
```

12.4 C++ logging guideline

VLOG is used for verbose logging, which is configured by environment variable `MACE_CPP_MIN_VLOG_LEVEL`. The guideline of VLOG level is as follows:

```
0. Ad hoc debug logging, should only be added in test or temporary ad hoc
   debugging
1. Important network level Debug/Latency trace log (Op run should never
   generate level 1 vlog)
2. Important op level Latency trace log
3. Unimportant Debug/Latency trace log
4. Verbose Debug/Latency trace log
```

12.5 C++ marco

C++ macros should start with `MACE_`, except for most common ones like `LOG` and `VLOG`.

CHAPTER 13

Adding a new Op

You can create a custom op if it is not supported yet.

To add a custom op, you need to follow these steps:

13.1 Implement the Operation

The Best way is to refer to the implementation of other operator(e.g. `/mace/ops/activation.cc`)

Define the new Op class in `mace/ops/my_custom_op.cc`.

1. ARM kernels: Kernel about NEON is located at `mace/ops/arm/my_custom_op.cc`
2. GPU kernels: OpenCL kernel API is defined in `mace/ops/opencl/my_custom_op.h`,
   - Kernel based on Image is realized in `mace/ops/opencl/image/my_custom_op.cc`,
   - Kernel based on Buffer is realized in `mace/ops/opencl/buffer/my_custom_op.cc`.
   - OpenCL kernel file is realized in `mace/ops/opencl/cl/my_custom_op.cl`.
   - Add the path of opencl kernel file in file `mace/repository/opencl-kernel/opencl_kernel_configure.bzl`

The structure of Op is like the following code.

```
#include "mace/core/operator.h"

namespace mace {
namespace ops {

template <DeviceType D, class T>
class MyCustomOp;

template <>
class MyCustomOp<DeviceType::CPU, float> : public Operation {
```

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```
...
}

#ifdef MACE_ENABLE_OPENCL
template<>
class MyCustomOp<DeviceType::GPU, float> : public Operation {
...
};
#endif  // MACE_ENABLE_OPENCL

void RegisterMyCustomOp(OpRegistryBase *op_registry) {
  MACE_REGISTER_OP(op_registry, "MyCustomOp", MyCustomOp,
                   DeviceType::CPU, float);

  MACE_REGISTER_GPU_OP(op_registry, "MyCustomOp", MyCustomOp);
}

}  // namespace ops
}  // namespace mace
```

13.2 Register the Operation

Register the new Op in `mace/ops/ops_register.cc`.

```
#include "mace/ops/ops_register.h"

namespace mace {
namespace ops {
// Keep in lexicographical order

...

extern void RegisterMyCustomOp(OpRegistryBase *op_registry);

...

}  // namespace ops


OpRegistry::OpRegistry() : OpRegistryBase() {
  // Keep in lexicographical order

  ...

  ops::RegisterMyCustomOp(this);

  ...

}

}  // namespace mace
```

13.3 Add UTs

Add operation unit tests in `mace/ops/my_custom_op_test.cc`

13.4 Add benchmark

Add operation benchmark in `mace/ops/my_custom_op_benchmark.cc` It's strongly recommended to add unit tests and micro benchmarks for your new Op. If you wish to contribute back, it's required.

13.5 Add Op in model converter

You need to add this new Op in the model converter.

13.6 Document the new Op

Finally, add an entry in operator table in the document.

CHAPTER 14

How to run tests

To run tests, you need to first cross compile the code, push the binary into the device and then execute the binary. To automate this process, MACE provides `tools/bazel_adb_run.py` tool.

You need to make sure your device has been connected to your dev pc before running tests.

14.1 Run unit tests

MACE use gtest for unit tests.

- Run all unit tests defined in a Bazel target, for example, run `mace_cc_test`:

For CMake users:

```
python tools/python/run_target.py \
    --target_abi=armeabi-v7a --target_socs=all --target_name=mace_cc_test
```

For Bazel users:

```
python tools/bazel_adb_run.py --target="//test/ccunit:mace_cc_test" \
                              --run_target=True
```

- Run unit tests with gtest filter, for example, run `Conv2dOpTest` unit tests:

For CMake users:

```
python tools/python/run_target.py \
    --target_abi=armeabi-v7a --target_socs=all --target_name=mace_cc_test \
    --gtest_filter=Conv2dOpTest*
```

For Bazel users:

```
python tools/bazel_adb_run.py --target="//test/ccunit:mace_cc_test" \
                              --run_target=True \
                              --args="--gtest_filter=Conv2dOpTest*"
```

14.2 Run micro benchmarks

MACE provides a micro benchmark framework for performance tuning.

- Run all micro benchmarks defined in a Bazel target, for example, run all `mace_cc_benchmark` micro benchmarks:

For CMake users:

```
python tools/python/run_target.py \
    --target_abi=armeabi-v7a --target_socs=all --target_name=mace_cc_benchmark
```

For Bazel users:

```
python tools/bazel_adb_run.py --target="//test/ccbenchmark:mace_cc_benchmark" \
                              --run_target=True
```

- Run micro benchmarks with regex filter, for example, run all `CONV_2D` GPU micro benchmarks:

For CMake users:

```
python tools/python/run_target.py \
    --target_abi=armeabi-v7a --target_socs=all --target_name=mace_cc_benchmark \
    --filter=MACE_BM_CONV_2D_.*_GPU
```

For Bazel users:

```
python tools/bazel_adb_run.py --target="//test/ccbenchmark:mace_cc_benchmark" \
                              --run_target=True \
                              --args="--filter=MACE_BM_CONV_2D_.*_GPU"
```

CHAPTER 15

How to debug

15.1 Debug correctness

MACE provides tools to examine correctness of model execution by comparing model's output of MACE with output of training platform (e.g., Tensorflow, Caffe). Three metrics are used as comparison results:

- **Cosine Similarity**:

$$Cosine\ Similarity = \frac{X \cdot X'}{\|X\|\|X'\|}$$

This metric will be approximately equal to 1 if output is correct.

- **SQNR** (Signal-to-Quantization-Noise Ratio):

$$SQNR = \frac{P_{signal}}{P_{noise}} = \frac{\|X\|^2}{\|X - X'\|^2}$$

It is usually used to measure quantization accuracy. The higher SQNR is, the better accuracy will be.

- **Pixel Accuracy**:

$$Pixel\ Accuracy = \frac{\sum_{b=1}^{batch} equal(\text{argmax}X_b, \text{argmax}X'_b)}{batch}$$

It is usually used to measure classification accuracy. The higher the better.

where X is expected output (from training platform) whereas X' is actual output (from MACE) .

You can validate it by specifying *–validate* option while running the model.

MACE automatically validate these metrics by running models with synthetic inputs. If you want to specify input data to use, you can add an option in yaml config under 'subgraphs', e.g.,

```
models:
  mobilenet_v1:
    platform: tensorflow
    model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/mobilenet-v1/
↪mobilenet-v1-1.0.pb
```

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```
    model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
    subgraphs:
      - input_tensors:
          - input
        input_shapes:
          - 1,224,224,3
        output_tensors:
          - MobilenetV1/Predictions/Reshape_1
        output_shapes:
          - 1,1001
        check_tensors:
          - MobilenetV1/Logits/Conv2d_1c_1x1/BiasAdd:0
        check_shapes:
          - 1,1,1,1001
        validation_inputs_data:
          - https://cnbj1.fds.api.xiaomi.com/mace/inputs/dog.npy
```

If model's output is suspected to be incorrect, it might be useful to debug your model layer by layer by specifying an intermediate layer as output, or use binary search method until suspicious layer is found.

You can also specify *–layers* after *–validate* to validate all or some of the layers of the model(excluding some layers changed by MACE, e.g., BatchToSpaceND), it only supports TensorFlow now. You can find validation results in *build/your_model/model/runtime_in_yaml/log.csv*.

For quantized model, if you want to check one layer, you can add *check_tensors* and *check_shapes* like in the yaml above. You can only specify MACE op's output.

15.2 Debug with crash

When MACE crashes, a complete stacktrace is useful in debugging. But because of selinux problem, symbols table is not loaded in memory, which leading to no symbol in stack trace. To circumvent this problem, you can rebuild *mace_run* with *–debug_mode* option to reserve debug symbols, e.g.,

For CMake users, modify the cmake configuration located in `tools/cmake/` as `-DCMAKE_BUILD_TYPE=Debug`, and rebuild the engine.

For Bazel users,

```
python tools/converter.py run --config=/path/to/config.yml --debug_mode
```

For android, you can use ndk-stack tools to symbolize stack trace, e.g.,

```
adb logcat | $ANDROID_NDK_HOME/ndk-stack -sym /path/to/local/binary/
↪directory/
```

15.3 Debug memory usage

The simplest way to debug process memory usage is to use `top` command. With `-H` option, it can also show thread info. For android, if you need more memory info, e.g., memory used of all categories, `adb shell dumpsys meminfo` will help. By watching memory usage, you can check if memory usage meets expectations or if any leak happens.

15.4 Debug performance

Using MACE, you can benchmark a model by examining each layer's duration as well as total duration. Or you can benchmark a single op. The detailed information is in *Benchmark usage*.

15.5 Debug model conversion

After model is converted to MACE model, a literal model graph is generated in directory *mace/codegen/models/your_model*. You can refer to it when debugging model conversion.

MACE also provides model visualization HTML generated in *build* directory, generated after converting model.

15.6 Debug engine using log

MACE implements a similar logging mechanism like glog. There are two types of logs, LOG for normal logging and VLOG for debugging.

LOG includes four levels, sorted by severity level: `INFO`, `WARNING`, `ERROR`, `FATAL`. The logging severity threshold can be configured via environment variable, e.g. `MACE_CPP_MIN_LOG_LEVEL=WARNING` to set as `WARNING`. Only the log messages with equal or above the specified severity threshold will be printed, the default threshold is `INFO`. We don't support integer log severity value like glog, because they are confusing with VLOG.

VLOG is verbose logging which is logged as `LOG(INFO)`. VLOG also has more detailed integer verbose levels, like 0, 1, 2, 3, etc. The threshold can be configured through environment variable, e.g. `MACE_CPP_MIN_VLOG_LEVEL=2` to set as `2`. With VLOG, the lower the verbose level, the more likely messages are to be logged. For example, when the threshold is set to 2, both `VLOG(1)`, `VLOG(2)` log messages will be printed, but `VLOG(3)` and highers won't.

By using `mace_run` tool, VLOG level can be easily set by option, e.g., `--vlog_level=2`

If models are run on android, you might need to use `adb logcat` to view logs.

15.7 Debug engine using GDB

GDB can be used as the last resort, as it is powerful that it can trace stacks of your process. If you run models on android, things may be a little bit complicated.

```
# push gdbserver to your phone
adb push $ANDROID_NDK_HOME/prebuilt/android-arm64/gdbserver/gdbserver /data/
↪local/tmp/


# set system env, pull system libs and bins to host
export SYSTEM_LIB=/path/to/android/system_lib
export SYSTEM_BIN=/path/to/android/system_bin
mkdir -p $SYSTEM_LIB
adb pull /system/lib/. $SYSTEM_LIB
mkdir -p $SYSTEM_BIN
adb pull /system/bin/. $SYSTEM_BIN


# Suppose ndk compiler used to compile Mace is of android-21
```

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```
export PLATFORMS_21_LIB=$ANDROID_NDK_HOME/platforms/android-21/arch-arm/usr/
↪lib/


# start gdbserver, make gdb listen to port 6000
# adb shell /data/local/tmp/gdbserver :6000 /path/to/binary/on/phone/example_
↪bin
adb shell LD_LIBRARY_PATH=/dir/to/dynamic/library/on/phone/ /data/local/tmp/
↪gdbserver :6000 /data/local/tmp/mace_run/example_bin
# or attach a running process
adb shell /data/local/tmp/gdbserver :6000 --attach 8700
# forward tcp port
adb forward tcp:6000 tcp:6000


# use gdb on host to execute binary
$ANDROID_NDK_HOME/prebuilt/linux-x86_64/bin/gdb [/path/to/binary/on/host/
↪example_bin]


# connect remote port after starting gdb command
target remote :6000


# set lib path
set solib-search-path $SYSTEM_LIB:$SYSTEM_BIN:$PLATFORMS_21_LIB

# then you can use it as host gdb, e.g.,
bt
```

CHAPTER 16

Memory layout

16.1 CPU runtime memory layout

The CPU tensor buffer is organized in the following order:

Tensor type	Buffer
Intermediate input/output	NCHW
Convolution Filter	OIHW
Depthwise Convolution Filter	MIHW
1-D Argument, length = W	W

16.2 GPU runtime memory layout

GPU runtime implementation base on OpenCL, which uses 2D image with CL_RGBA channel order as the tensor storage. This requires OpenCL 1.2 and above.

The way of mapping the Tensor data to OpenCL 2D image (RGBA) is critical for kernel performance.

In CL_RGBA channel order, each 2D image pixel contains 4 data items. The following tables describe the mapping from different type of tensors to 2D RGBA Image.

16.2.1 Input/Output Tensor

The Input/Output Tensor is stored in NHWC format:

Tensor type	Buffer	Image size [width, height]	Explanation
Channel-Major Input/Output	NHWC	[W * (C+3)/4, N * H]	Default Input/Output format
Height-Major Input/Output	NHWC	[W * C, N * (H+3)/4]	WinogradTransform and MatMul output format
Width-Major Input/Output	NHWC	[(W+3)/4 * C, N * H]	Unused now

Each Pixel of **Image** contains 4 elements. The below table list the coordination relation between **Image** and **Buffer**.

Tensor type	Pixel coordinate relationship	Explanation
Channel-Major Input/Output	P[i, j] = {E[n, h, w, c] | (n=j/H, h=j%H, w=i%W, c=[i/W * 4 + k])}	k=[0, 4)
Height-Major Input/Output	P[i, j] = {E[n, h, w, c] | (n=j%N, h=[j/H*4 + k], w=i%W, c=i/W)}	k=[0, 4)
Width-Major Input/Output	P[i, j] = {E[n, h, w, c] | (n=j/H, h=j%H, w=[i%W*4 + k], c=i/W)}	k=[0, 4)

16.2.2 Filter Tensor

Tensor	Buffer	Image size [width, height]	Explanation
Convolution Filter	OIHW	[I, (O+3)/4 * W * H]	Convolution filter format, There is no difference compared to [H*W*I, (O+3)/4]
Depthwise Convlution Filter	MIHW	[H * W * M, (I+3)/4]	Depthwise-Convolution filter format

Each Pixel of **Image** contains 4 elements. The below table list the coordination relation between **Image** and **Buffer**.

Tensor type	Pixel coordinate relationship	Explanation
Convolution Filter	P[m, n] = {E[o, i, h, w] | (o=[n/HW*4+k], i=m, h=T/W, w=T%W)}	HW= H * W, T=n%HW, k=[0, 4)
Depthwise Convlution Filter	P[m, n] = {E[0, i, h, w] | (i=[n*4+k], h=m/W, w=m%W)}	only support multiplier == 1, k=[0, 4)

16.2.3 1-D Argument Tensor

Tensor type	Buffer	Image size [width, height]	Explanation
1-D Argument	W	[(W+3)/4, 1]	1D argument format, e.g. Bias

Each Pixel of **Image** contains 4 elements. The below table list the coordination relation between **Image** and **Buffer**.

Tensor type	Pixel coordinate relationship	Explanation
1-D Argument	P[i, 0] = {E[w] | w=i*4+k}	k=[0, 4)

CHAPTER 17

Data Format

As we all know, input/output tensors in CNN model have data format like `NHWC`(tensorflow) or `NCHW`(caffe), but there is no data format for non-CNN model.

However, in MACE, CNN model run on `CPU` with `float` type using `NCHW` data format, while the others using `NHWC` data format.

To support all models, so there are some concepts in `MACE` you should know.

17.1 Source Data Format

Source Data Format(`src_df` for short) stands for the original data format where the model come from. For example, if you use caffe, the `src_df` is `NCHW`. We need this data format because some operators(Reshape etc.) are related to the data format.

17.2 Operators Partition

Generally, operators could be divided into 2 categories based on whether the operator needs inputs with fixed data format(`NHWC` or `NCHW`), one is the operators whose inputs have fixed data format(like `convolution`), the other is the operators whose inputs should be the same with source framework.

Since the data format the operators need in MACE may be inconsistent with the original framework, we need to add `Transpose` operator to transpose the input tensors if necessary.

However, for some operators like `concat`, we could transpose their arguments to eliminate `Transpose` op for acceleration.

Based on these conditions, We partition the ops into 3 categories.

1. Ops with fixed inputs' data format(`FixedDataFormatOps`): `Convolution`, `Depthwise Convolution`, etc.

2. Ops could eliminate `Transpose` by transposing their arguments(`TransposableDataFormatOps`): `Concat`, `Element-wise`, etc.
3. Ops keeping consistent with source platform(`SourceDataFormatOps`): `Reshape`, `ExpandDims`, etc.

By default, the operators not in either `FixedDataFormatOps` or `TransposableDataFormatOps` are listed in `SourceDataFormatOps`.

For detailed information, you could refer to code.

17.3 Data Format in Operator

Based on the operator partition strategy, every operator in `MACE` has data format argument which stands for the wanted inputs' data format, the values could be one of the [`NHWC`, `NCHW`, `AUTO`].

1. `NHWC` or `NCHW` represent `src_df`.
2. `AUTO` represents the operator's inputs must have fixed data format, and the real data format will be determined at runtime. the data format of operators in `FixedDataFormatOps` must be `AUTO`, while the data format of operators in `TransposableDataFormatOps` is determined based on their inputs' ops data format.

MACE will transpose the input tensors based on the data format information automatically at runtime.

17.4 Data Format of Model's Inputs/Outputs

1. If the model's inputs/outputs have data format, MACE supports the data format `NHWC` and `NCHW`.
2. If the model's inputs/outputs do not have data format, just set `NONE` for model's inputs and outputs at `model deployment file` and `MaceTensor`.

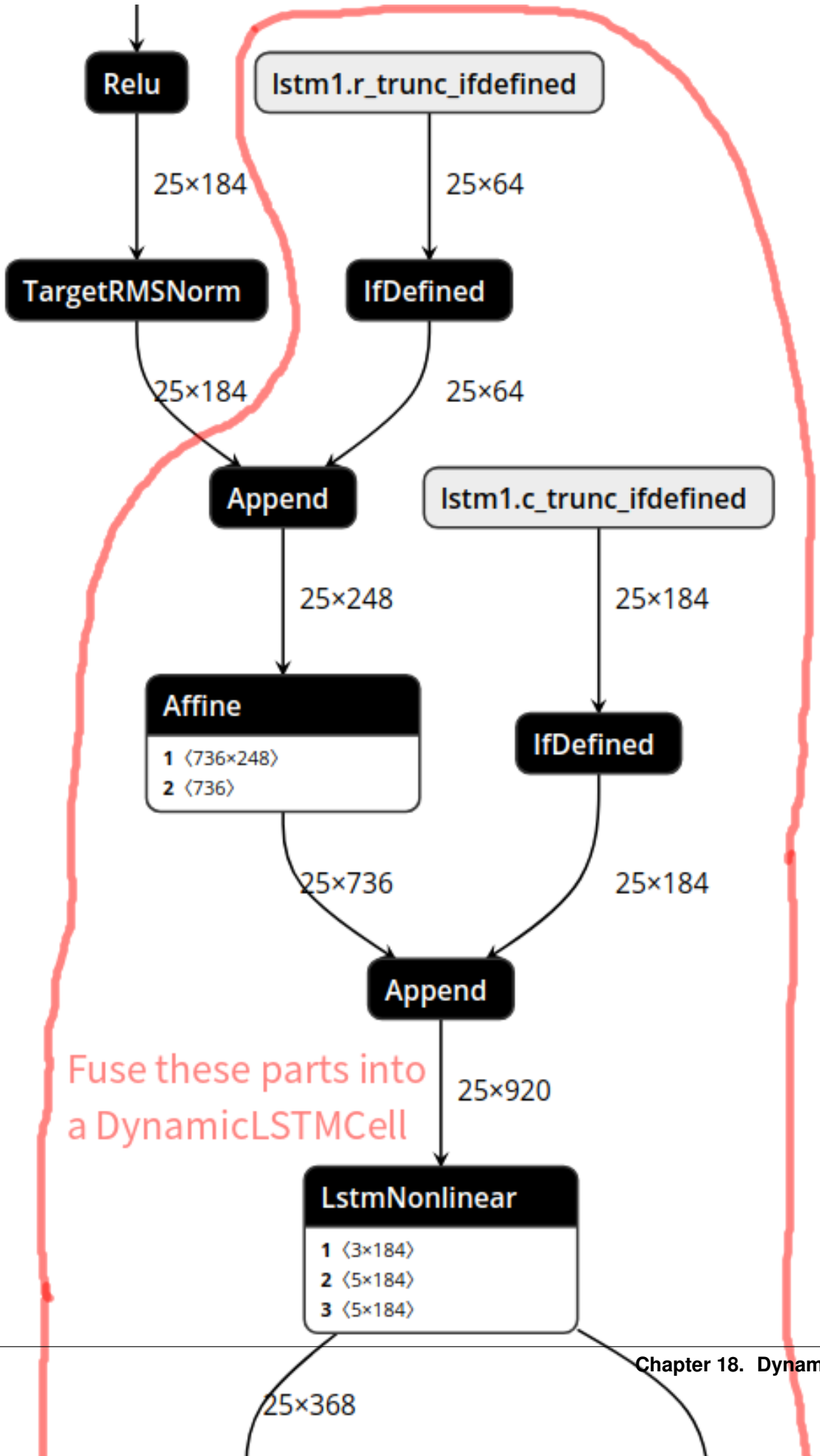
CHAPTER 18

Dynamic LSTM

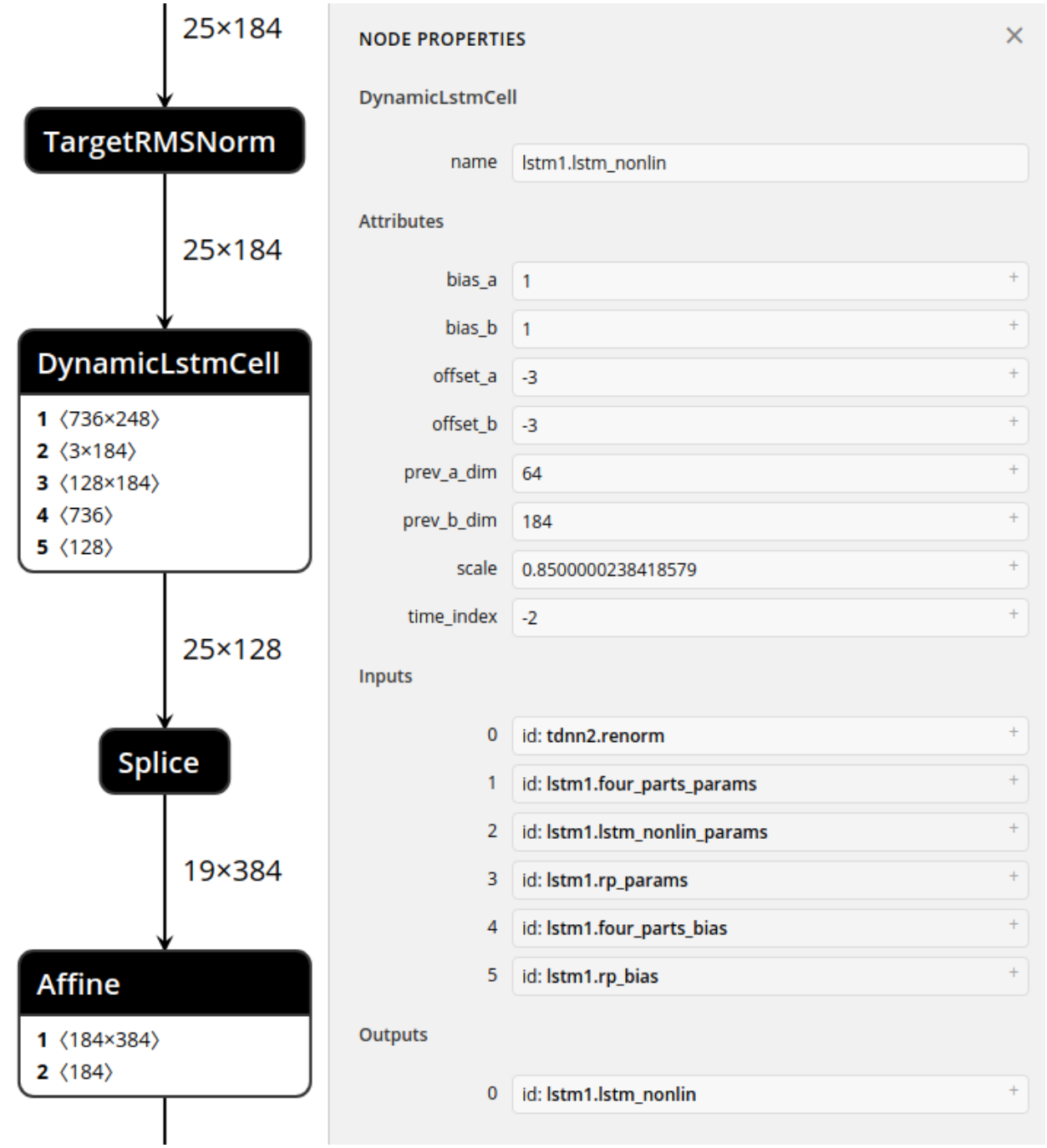
The DynamicLSTM in MACE is implemented for Kaldi's time delay RNN models.

The following pictures explain how to fuse components into a DynamicLSTMCell.

Before fusing:


Relu
lstm1.r_trunc_ifdefined
25×184
25×64
TargetRMSNorm
IfDefined
25×184
25×64
Append
lstm1.c_trunc_ifdefined
25×248
25×184
Affine
1 ⟨736×248⟩
2 ⟨736⟩
IfDefined
25×736
25×184
Append
Fuse these parts into
a DynamicLSTMCell
25×920
LstmNonlinear
1 ⟨3×184⟩
2 ⟨5×184⟩
3 ⟨5×184⟩
25×368

After fusing:



For more details about LSTMNonlinear in Kaldi, please refer to [LstmNonlinearityComponent](http://kaldi-asr.org/doc/nnet-combined-component_8h_source.html#l00255)

CHAPTER 19

Basic usage for Micro Controllers

19.1 Build and run an example model

At first, make sure the environment has been set up correctly already (refer to *Environment requirement*).

The followings are instructions about how to quickly build and run a provided model in MACE Model Zoo.

Here we use the har-cnn model as an example.

Commands

1. Pull MACE project.

```
git clone https://github.com/XiaoMi/mace.git
cd mace/
git fetch --all --tags --prune

# Checkout the latest tag (i.e. release version)
tag_name=`git describe --abbrev=0 --tags`
git checkout tags/${tag_name}
```

Note: It's highly recommended to use a release version instead of master branch.

2. Pull MACE Model Zoo project.

```
git clone https://github.com/XiaoMi/mace-models.git
```

3. Convert the pre-trained har-cnn model to c++ code.

```
cd path/to/mace
# output lib path: build/har-cnn/model/har_cnn_micro.tar.gz
CONF_FILE=/path/to/mace-models/micro-models/har-cnn/har-cnn.yml
python tools/converter.py convert --config=$CONF_FILE --enable_micro
```

4. Build Micro-Controllers engine and models to library on host.

```
# copy convert result to micro dir ``path/to/micro``
cp build/har-cnn/model/har_cnn_micro.tar.gz path/to/micro/
cd path/to/micro
tar zxvf har_cnn_micro.tar.gz
bazel build //micro/codegen:micro_engine
```

Note:

- This step can be skipped if you just want to run a model using `tools/python/run_micro.py`, such as commands in step 5.
- The build result `bazel-bin/micro/codegen/libmicro_engine.so`'s abi is host, if you want to run the model on micro controllers, you should build the code with the target abi.

5. Run the model on host.

```
CONF_FILE=/path/to/mace-models/micro-models/har-cnn/har-cnn.yml
# Run
python tools/python/run_micro.py --config $CONF_FILE --model_name har_cnn --
↪build

# Test model run time
python tools/python/run_micro.py --config $CONF_FILE --model_name har_cnn --
↪build --round=100

# Validate the correctness by comparing the results against the
# original model and framework, measured with cosine distance for similarity.
python tools/python/run_micro.py --config $CONF_FILE --model_name har_cnn --
↪build --validate
# Validate the layers' correctness.
python tools/python/run_micro.py --config $CONF_FILE --model_name har_cnn --
↪build --validate --layers 0:-1
```

19.2 Deploy your model into applications

Please refer to `/mace/micro/tools/micro_run.cc` for full usage. The following list the key steps.

```
// Include the headers
#include "micro/include/public/micro.h"

// 1. Create MaceMicroEngine instance
MaceMicroEngine *micro_engine = nullptr;
MaceStatus status = har_cnn::GetMicroEngineSingleton(&micro_engine);

// 1. Create and register Input buffers
std::vector<std::shared_ptr<char>> inputs;
std::vector<int32_t> input_sizes;
for (size_t i = 0; i < input_shapes.size(); ++i) {
  input_sizes.push_back(std::accumulate(input_shapes[i].begin(),
                                        input_shapes[i].end(), sizeof(float),
                                        std::multiplies<int32_t>()));
  inputs.push_back(std::shared_ptr<char>(new char[input_sizes[i]],
```

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```
                                          std::default_delete<char[]>()));
}
// TODO: fill data into input buffers
for (size_t i = 0; i < input_names.size(); ++i) {
  micro_engine->RegisterInputData(i, inputs[i].get(),
                                  input_shapes[i].data());
}

// 3. Run the model
MaceStatus status = micro_engine->Run();

// 4. Get the results
for (size_t i = 0; i < output_names.size(); ++i) {
  void *output_buffer = nullptr;
  const int32_t *output_dims = nullptr;
  uint32_t dim_size = 0;
  MaceStatus status =
      micro_engine->GetOutputData(i, &output_buffer, &output_dims, &dim_size);
  // TODO: the result data is in output_buffer, you can not delete output_buffer.
}
```

CHAPTER 20

Frequently asked questions

20.1 Does the tensor data consume extra memory when compiled into C++ code?

When compiled into C++ code, the tensor data will be mmaped by the system loader. For the CPU runtime, the tensor data are used without memory copy. For the GPU and DSP runtime, the tensor data are used once during model initialization. The operating system is free to swap the pages out, however, it still consumes virtual memory addresses. So generally speaking, it takes no extra physical memory. If you are short of virtual memory space (this should be very rare), you can use the option to load the tensor data from data file (can be manually unmapped after initialization) instead of compiled code.

20.2 Why is the generated static library file size so huge?

The static library is simply an archive of a set of object files which are intermediate and contain much extra information, please check whether the final binary file size is as expected.

20.3 Why is the generated binary file (including shared library) size so huge?

When compiling the model into C++ code, the final binary may contains extra debug symbols, they usually take a lot of space. Try to strip the shared library or binary and make sure you are following best practices to reduce the size of an ELF binary, including disabling C++ exception, disabling RTTI, avoiding C++ iostream, hidden internal functions etc. In most cases, the expected overhead should be less than {model weights size in float32}/2 + 3MB.

20.4 How to set the input shape in your model deployment file(.yml) when your model support multiple input shape?

Set the largest input shape of your model. The input shape is used for memory optimization.

20.5 OpenCL allocator failed with CL_OUT_OF_RESOURCES

OpenCL runtime usually requires continuous virtual memory for its image buffer, the error will occur when the OpenCL driver can't find the continuous space due to high memory usage or fragmentation. Several solutions can be tried:

- Change the model by reducing its memory usage
- Split the Op with the biggest single memory buffer
- Change from armeabi-v7a to arm64-v8a to expand the virtual address space
- Reduce the memory consumption of other modules of the same process

20.6 Why is the performance worse than the official result for the same model?

The power options may not set properly, see `mace/public/mace.h` for details.

20.7 Why is the UI getting poor responsiveness when running model with GPU runtime?

Try to set `limit_opencl_kernel_time` to `1`. If still not resolved, try to modify the source code to use even smaller time intervals or changed to CPU or DSP runtime.

For GPUs such as Arm Mali, sometimes even setting `limit_opencl_kernel_time` to a small time interval can not solve the problem. At this time, you can try to set `opencl_queue_window_size`, such as 16. This parameter means that the GPU command queue will contain only `opencl_queue_window_size` commands at most. You can adjust this parameter to achieve a balance between performance and UI response. You should not use this parameter unless you have to.

20.8 Why is MACE not working on DSP?

Running models on Hexagon DSP need a few prerequisites for DSP developers:

- You need to make sure SOCs of your phone is manufactured by Qualcomm and has HVX supported.
- You need a phone that disables secure boot (once enabled, cannot be reversed, so you probably can only get that type phones from manufacturers)
- You need to root your phone.
- You need to sign your phone by using testsig provided by Qualcomm. (Download Qualcomm Hexagon SDK first, plugin your phone to PC, run scripts/testsig.py)

- You need to push `third_party/nnlib/v6x/libhexagon_nn_skel.so` to `/system/vendor/lib/rfsa/adsp/`.

Then, there you go. You can run Mace on Hexagon DSP.

CHAPTER 21

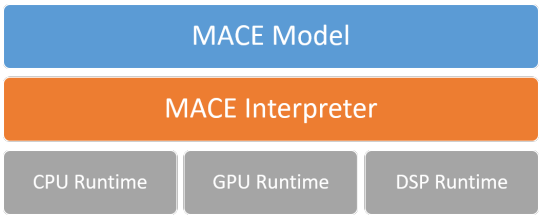
中文

21.1 简介

Mobile AI Compute Engine (MACE) 是一个专为移动端异构计算设备优化的深度学习前向预测框架。 MACE覆盖了常见的移动端计算设备（CPU、GPU、Hexagon DSP、Hexagon HTA、MTK APU），并且提供了完整的工具链和文档，用户借助MACE能够 很方便地在移动端部署深度学习模型。MACE已经在小米内部广泛使用并且被充分验证具有业界领先的性能和稳定性。

21.2 框架

下图描述了MACE的基本框架。



21.2.1 安装环境

MACE 需要安装下列依赖:

必须依赖

软件	安装命令	Python 版本
Python		2.7 or 3.6
CMake	Linux:`apt-get install cmake` Mac:`brew install cmake`	>= 3.11.3
Jinja2	pip install jinja2==2.10	2.10
PyYaml	pip install pyyaml==3.12	3.12.0
sh	pip install sh==1.12.14	1.12.14
Numpy	pip install numpy==1.14.0	仅测试使用

可选依赖

软件	安装命令	版本和说明
Android NDK	NDK 安装指南	Required by Android build, r15b, r15c, r16b, r17b
CMake	apt-get install cmake	>= 3.11.3
ADB	Linux:`apt-get install android-tools-adb` Mac:`brew cask install android-platform-tools`	Android 运行需要, >= 1.0.32
Tensor-Flow	pip install tensorflow==1.8.0	Tensorflow 模型转换需要
Docker	docker 安装指南	docker 模式用户需要
Scipy	pip install scipy==1.0.0	模型测试需要
File-Lock	pip install filelock==3.0.0	Android 运行需要
ONNX	pip install onnx==1.5.0	ONNX 模型需要

对于 Python 依赖，可直接执行,

```
pip install -U --user -r setup/optionals.txt
```

Note:

- 对于安卓开发, 环境变量 *ANDROID_NDK_HOME* 需要指定 `export ANDROID_NDK_HOME=/path/to/ndk`
- Mac 用户请先安装 Homebrew. 在 `/etc/bashrc` 中设置 *ANDROID_NDK_HOME*，之后执行 `source /etc/bashrc`.

21.2.2 基本使用方法

确保已安装所需环境 (refer to 安装环境).

清空工作目录

构建前，清空工作目录

```
tools/clear_workspace.sh
```

编译引擎

确保 CMake 已安装

```
RUNTIME=GPU bash tools/cmake/cmake-build-armeabi-v7a.sh
```

编译安装位置为 `build/cmake-build/armeabi-v7a`, 可以使用 libmace 静态库或者动态库。

除了 armeabi-v7，其他支持的 abi 包括: `arm64-v8a`, `arm-linux-gnueabihf`, `aarch64-linux-gnu`, `host`; 支持的目标设备 （RUNTIME) 包括: `GPU`, `HEXAGON`, `HTA`, `APU`.

转换模型

撰写模型相关的 YAML 配置文件:

```
models:
  mobilenet_v1:
    platform: tensorflow
    model_file_path: https://cnbj1.fds.api.xiaomi.com/mace/miai-models/
↪mobilenet-v1/mobilenet-v1-1.0.pb
    model_sha256_checksum:␣
↪71b10f540ece33c49a7b51f5d4095fc9bd78ce46ebf0300487b2ee23d71294e6
    subgraphs:
      - input_tensors:
          - input
        input_shapes:
          - 1,224,224,3
        output_tensors:
          - MobilenetV1/Predictions/Reshape_1
        output_shapes:
          - 1,1001
    runtime: gpu
```

假设模型配置文件的路径是: `../mace-models/mobilenet-v1/mobilenet-v1.yml`，执行:

```
python tools/python/convert.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml
```

将会在 `build/mobilenet_v1/model/` 中产生 4 个文件

```
├── mobilenet_v1.pb                 (模型结构文件)
├── mobilenet_v1.data               (模型参数文件)
├── mobilenet_v1_index.html         (可视化文件，可在浏览器中打开)
└── mobilenet_v1.pb_txt             (模型结构文本文件，可以 vim 进行查看)
```

除了 tensorflow，还支持训练平台: `caffe`, `onnx`; 除了 gpu， 亦可指定运行设备为 `cpu`, `dsp`。

模型测试与性能评测

我们提供了模型测试与性能评测工具。

模型转换后，执行下面命令进行测试:

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --validate
```

或下面命令进行性能评测:

```
python tools/python/run_model.py --config ../mace-models/mobilenet-v1/
↪mobilenet-v1.yml --benchmark
```

这两个命令将会自动在目标设备上测试模型，如果在移动设备上测试，请确保已经连接上。 如果想查看详细日志，可以提高日志级别，例如指定选项 `--vlog_level=2`

集成模型到应用

可以查看源码 `mace/tools/mace_run.cc`了解更多详情。下面简要介绍相关步骤:

```
// 添加头文件按
#include "mace/public/mace.h"

// 0. 指定目标设备
DeviceType device_type = DeviceType::GPU;

// 1. 运行配置
MaceStatus status;
MaceEngineConfig config(device_type);
std::shared_ptr<GPUContext> gpu_context;
// Set the path to store compiled OpenCL kernel binaries.
// please make sure your application have read/write rights of the directory.
// this is used to reduce the initialization time since the compiling is too slow.
// It's suggested to set this even when pre-compiled OpenCL program file is provided
// because the OpenCL version upgrade may also leads to kernel recompilations.
const std::string storage_path ="path/to/storage";
gpu_context = GPUContextBuilder()
    .SetStoragePath(storage_path)
    .Finalize();
config.SetGPUContext(gpu_context);
config.SetGPUHints(
    static_cast<GPUPerfHint>(GPUPerfHint::PERF_NORMAL),
    static_cast<GPUPriorityHint>(GPUPriorityHint::PRIORITY_LOW));

// 2. 指定输入输出节点
std::vector<std::string> input_names = {...};
std::vector<std::string> output_names = {...};

// 3. 创建引擎实例
std::shared_ptr<mace::MaceEngine> engine;
MaceStatus create_engine_status;

create_engine_status =
    CreateMaceEngineFromProto(model_graph_proto,
                              model_graph_proto_size,
                              model_weights_data,
                              model_weights_data_size,
                              input_names,
                              output_names,
                              device_type,
                              &engine);
if (create_engine_status != MaceStatus::MACE_SUCCESS) {
  // fall back to other strategy.
}
```

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```
// 4. 创建输入输出缓存
std::map<std::string, mace::MaceTensor> inputs;
std::map<std::string, mace::MaceTensor> outputs;
for (size_t i = 0; i < input_count; ++i) {
  // Allocate input and output
  int64_t input_size =
      std::accumulate(input_shapes[i].begin(), input_shapes[i].end(), 1,
                      std::multiplies<int64_t>());
  auto buffer_in = std::shared_ptr<float>(new float[input_size],
                                          std::default_delete<float[]>());
  // 读取输入数据
  // ...

  inputs[input_names[i]] = mace::MaceTensor(input_shapes[i], buffer_in);
}

for (size_t i = 0; i < output_count; ++i) {
  int64_t output_size =
      std::accumulate(output_shapes[i].begin(), output_shapes[i].end(), 1,
                      std::multiplies<int64_t>());
  auto buffer_out = std::shared_ptr<float>(new float[output_size],
                                           std::default_delete<float[]>());
  outputs[output_names[i]] = mace::MaceTensor(output_shapes[i], buffer_out);
}

// 5. 执行模型
MaceStatus status = engine.Run(inputs, &outputs);
```

更多信息可参考 *Advanced usage for CMake users*.