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RKNN-Toolkit User Guide

(Technology Department, Graphic Computing Platform Center)

Mark: [ ] Editing [√] Released	Version	V1.7.1
	Author	Rao Hong
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Revision History

Version	Modifier	Date	Modify description	Reviewer
V0.1	Yang Huacong	2018-08-25	Initial version	Vincent
V0.9.1	Rao Hong	2018-09-29	Added user guide for RKNN-Toolkit, including main features, system dependencies, installation steps, usage scenarios, and detailed descriptions of each API interface.	Vincent
V0.9.2	Randall	2018-10-12	Optimize the way of performance evaluation	Vincent
V0.9.3	Yang Huacong	2018-10-24	Add instructions of connection to development board hardware	Vincent
V0.9.4	Yang Huacong	2018-11-03	Add instructions of docker image	Vincent
V0.9.5	Rao Hong	2018-11-19	1. Add an npy file as a usage specification for the quantized rectified data 2. The instructions of pre-compile parameter in build interface 3. Improve the instructions of reorder_channel parameter in the config interface	Vincent
V0.9.6	Rao Hong	2018-11-24	1. Add the instructions of get_perf_detail_on_hardware and get_run_duration interfaces 2. Update the instructions of RKNN initialization interface	Vincent

Version	Modifier	Date	Modify description	Reviewer
V0.9.7	Rao Hong	2018-12-29	1. Interface optimization: delete the instructions of get_run_duration, get_perf_detail_on_hardware 2. Rewrite the instructions of eval_ perf interface 3. Rewrite the instructions of RKNN() interface 4. Add instructions of the init_runtime interface	Vincent
V0.9.7.1	Rao Hong	2019-01-11	1. Solve the bug that the program may hang after multiple calls to inference 2. Interface adjustment: init_runtime does not need to specify host, the tool will automatically determine	Vincent
V0.9.8	Rao Hong	2019-01-30	1. New feature：if set verbose parameter to True when init RKNN object, users can fetch detailed log information.	Vincent
V0.9.9	Rao Hong	2019-03-06	1. New feature: add eval_memory interface to check memory usage when model running. 2. Optimize inference interface; Optimize error message. 3. Add description for API interface: get_sdk_version.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.0.0	Rao Hong	2019-05-06	1. Add async mode for init_runtime interface. 2. Add input passthrough mode for inference interface. 3. New feature: hybrid quantization. 4. Optimize initialize time of pre-compiled model. Pre-compiled model generated by RKNN-Toolkit-v1.0.0 can not run on device installed old driver (NPU driver version < 0.9.6), and pre-compiled model generated by old RKNN-Toolkit (version < 1.0.0) can not run on device installed new NPU driver (NPU drvier version == 0.9.6). 5. Adjust the shape of the inference results: Before version 1.0.0, if the output of the original model is arranged in "NHWC" (such as TensorFlow models), the tool will convert the result to "NCHW"; starting from version 1.0.0, this conversion will not be done, but keep consistent with the original model.	Vincent
V1.1.0	Rao Hong	2019-06-28	1. Support TB-RK1808S0 AI Compute Stick. 2. New interface: list_devices, used to query devices connected to PC or RK3399Pro Linux development board. 3. Support run on ARM64 platform with python 3.5. 4. Support run on Windows / Mac OS X.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.2.0	Rao Hong	2019-08-21	1. Add support for model with multiple inputs. 2. New feature: batch inference. 3. New feature: model segmentation. 4. New feature: custom op.	Vincent
V1.2.1	Rao Hong	2019-09-26	1. New feature: load_rknn interface supports direct loading of RKNN in NPU. 2. Adjust the default value of batch_size and epochs in config interface. 3. Bug fix.	Vincent
V1.3.0	Rao Hong	2019-12-23	1. Solve the problem of creating RKNN object for too long. 2. New feature: support loading PyTorch model. 3. New feature: support loading mxnet model. 4. New feature: added support for 4-channel input. 5. New feature: error analysis caused by quantization. 6. New feature: visualization. 7. New feature: model optimization level. 8. Optimize hybrid quantization.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.3.2	Rao Hong	2020-04-03	1. Support for new chips: RV1109 / RV1126 2. Improve eval_perf function, no longer need to fill in inputs. 3. TensorFlow: Add support for reducemax; improve support for dilated convolution. TFLite: Add support for dilated convolution. Caffe: Add support for CRNN. ONNX: Add support for Gather and Cast; improve support for avg_pool. PyTorch: Add support for upsample_nearest2d, contiguous, softmax, permute, leaky_relu, prelue, log, deconv and sub; improve support for Reshape, Constant. MXNet: Add support for Crop, UpSampling, SoftmaxActivation, _minus_scalar, log. RKNN: Add support for reshape, concat, split. 4. Fix some known bugs.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.4.0	Rao Hong	2020-08-13	1. New features: add layer-by-layer quantitative analysis sub-function; Input preprocessing supports multiple std_values; support to export pre-compiled models from the development board. 2. Function optimization: optimize the channel_mean_value parameter and change it to mean_values/std_values; remove mean_values and std_values in the load_tensorflow interface; the visualizaion improves support for multiple inputs, add support for RK1806/RV1109/RV1126; the accuracy analysis function adds non-normalized cosine distance and Euclidean distance. 3. TensorFlow: add support for dense. TFLite: add support for split_v; imporove support for pad. ONNX: add support forprelu, deconvolution, avg_pool / clip. PyTorch: add support for pixel_shuffle, unsqueeze, sum,select, hardtanh, elu, slice, squeeze, exp,relu6, threshold_, matmul, exp, pad; improve support for adaptive_avg_pool2d, upsample_bilinear, relu6. MXNet: improve support for fc. Darknet: add support for mish; improve support for route. 4. Fix some known bugs.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.6.0	Rao Hong Chifred	2020-12-31	1. New features: Support Keras and support h5 model exported by TensorFlow 2.0; support PyTorch 1.6.0; support ONNX 1.6.0; add model encryption function; support list devices with command line; offline pre-compile supports multi-inputs model. 2. Function optimization: optimize accuracy analysis function; optimize the pre-process of input, improve model inference performance; optimize performance evaluation function, when printing details, streamline ops of each layer;the model segmentation feature is limited to RK1806 / RK1808 / RV1109 / RV1126 chip range; the operate system of docker image update to Ubuntu 18.04, Python version updates to 3.6. 3. Improve support ops for each deep learning framework. 4. Fix known bugs.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.6.1	Rao Hong	2021-05-21	1. New features: Add quantization parameter optimization method MMSE; support exporting the distribution histogram of each layer of weight, bias and output data for analyzing accuracy problems. 2. Function optimization: improve the prompt message when the mean_values, std_values are set improperly. 3. Improve support ops for each deep learning framework. 4. Fix known bugs.	Vincent
V1.7.0	Rao Hong	2021-08-08	1. New features: Support quantized ONNX model(related onnxruntime version 1.5.2); support specifying input and output nodes when loading ONNX model. 2. Function optimization: improve the hybrid quantization interface; improve the accuracy analysis interface; improve visualization related functions. 3. Improve support ops for each deep learning framework. 4. Add example for pass_through in inference interface; add example for accuracy analysis; improve the example of yolov3. 5. Fix known bugs.	Vincent

Version	Modifier	Date	Modify description	Reviewer
V1.7.1	Rao Hong	2021-11-20	1. New features: Support quantized PyTorch model. 2. Function optimization: improve accuracy analysis performance; improve input preprocess; improve log function. 3. Improve support ops for each deep learning framework. 4. Add example to show how to convert ONNX/PyTorch/TFLite quantized model; add example to show how to convert PyTorch Yolov5. 5. Fix known bugs.	Vincent

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1 Overview

1.1 Main function description

RKNN-Toolkit is a development kit that provides users with model conversion, inference and performance evaluation on PC and Rockchip NPU platforms. Users can easily complete the following functions through the Python interface provided by the tool:

1） Model conversion: Support the conversion of Caffe、TensorFlow、TensorFlow Lite、ONNX、Darknet、PyTorch、MXNet or Keras model to RKNN model.

- Since version 1.2.0, support the conversion of multi-input models
- Since version 1.3.0, support PyTorch and MXNet
- Since version 1.6.0, support for Keras and H5 model exported by TensorFlow 2.0 since version 1.6.0.

2） Quantization: Support to convert float model to quantization model, currently the available quantized methods including asymmetric quantization (asymmetric_quantized-u8) and dynamic fixed point quantization (dynamic_fixed_point-i8 and dynamic_fixed_point-i16). Starting from version 1.0.0, RKNN-Toolkit began to support hybrid quantization. For more detail about hybrid quantization, please refer to Section 3.3.

- Since version 1.6.1, RKNN-Toolkit provides quantized-parameter-optimization algorithm MMSE and KL divergence.
- Since version 1.7.0, RKNN-Toolkit support loading quantized ONNX models.
- Since version 1.7.1, RKNN-Toolkit support loading quantized PyTorch models.

3） Model inference: Support simulating Rockchip NPU and run RKNN model on PC (Linux x86 platform) and get the inference result. And it is allowed to distribute the RKNN model to the specified NPU device to inference for the results.

4） Performance evaluation: Support simulating Rockchip NPU and run RKNN model on PC (Linux x86 platform), and evaluate model performance (including full-model and each layer inference-time). And it is allowed to distribute the RKNN model to the specified NPU device to inference and evaluate the model performance with the actual device.

5） Memory evaluation: Evaluate system and NPU memory consumption at runtime of the model. It is allowed to distribute the RKNN model to the specified NPU device to inference, and then call the relevant interface to obtain memory usage information. This feature is supported since version 0.9.9.

6） Model pre-compilation: With pre-compilation method, model loading-time can be decreased on NPU devices, and model size can also be reduced for some models. However, the pre-compiled RKNN model can only be run on a hardware platform with an NPU, and this feature is currently only supported by the x86_64 Ubuntu platform. RKNN-Toolkit supports the model pre-compilation feature from version 0.9.5, and the pre-compilation method has been upgraded in 1.0.0. Noting that the upgraded precompiled model is not compatible with the previous driver. Since version 1.4.0, ordinary RKNN models can also be converted into precompiled models through NPU device. For more details, please refer to the Chacter 7.14 for the instruction of export_rknn_precompile_model interface

7） Model segmentation: This function is used in a scenario where multiple models run simultaneously. One single model can be divided into multiple segments to be executed on the NPU, avoiding the NPU-occupying model inference takes too much time and stop other models to run. This feature is supported since version 1.2.0. Currently, only RK1806/RK1808/RV1109/RV1126 support this feature and the NPU driver version must be greater than 0.9.8.

8） Custom OP: If the model contains an OP that is not supported by RKNN-Toolkit, it will fail during the model conversion phase. At this time, you can use the custom layer feature to define an unsupported OP so that the model can be converted and run successfully. RKNN-Toolkit supports this feature since version 1.2.0. Please refer to the *Rockchip_Developer_Guide_RKNN_-Toolkit_Custom_OP_CN* document for the use and development of custom OP. Currently this function only support TensorFlow model.

9） Quantization-error analysis: This function will compute the Euclidean or cosine distance of the inference float results for each layer, compared to its quantized results. This can be used to analyze where quantization-error occurs, and provide ideas for improving the accuracy of quantized models. This feature is supported since version 1.3.0.

Since version 1.4.0, new feature called individual-quantization-accuracy analysis was added. Float results of last layer will be recorded and pushed to the quantized next layer. This can avoid cumulative error and more accurately reflect the influence of quantization on each layer.

10）Visualization: This function presents various functions of RKNN-Toolkit with graphical interface, simplifying the user's operation steps. Users can complete model conversion and inference by filling out forms and clicking function buttons, and no need to write scripts manually. Please refer to the *Rockchip_User_Guide_RKNN_Toolkit_Visualization_EN* document for the use of visualization.

- Version 1.4.0 improves the support for multi-inputs models and supports new NPU devices such as RK1806/RV1109/RV1126 as target.
- Since version 1.6.0, keras model is support in visualization function.

11）Model optimization level: RKNN-Toolkit optimizes the model during model conversion. The default optimization selection may have some impact on model accuracy. By setting the optimization level, you can turn off some or all optimization options to analyze the impact of RKNN-Toolkit model optimization options on accuracy. For specific usage of optimization level, please refer to the description of optimization_level option in config interface. This feature is supported since version 1.3.0.

12）Model encryption: Use the specified encryption method to encrypt the RKNN model. This feature is supported since version 1.6.0. While the encryption of the RKNN model is done in the NPU driver, the encryption model can be loaded just like a normal RKNN model, and the NPU driver will automatically decrypt it.

Note: Some features are limited by the operating system or chip platform and cannot be used on some operating systems or platforms. The feature support list of each operating system (platform) is as follows:

Table 1-1-1 Support list of each platform function

	Ubuntu 16.04/18.04	Windows 7/10	Debian 9.8 / 10 (ARM 64)	MacOS Mojave / Catalina
Model conversion	yes	yes	yes	yes
Quantization	yes	yes	Partial support (do not support MMSE)	yes
Model inference	yes	yes	yes	yes
Performance evaluation	yes	yes	yes	yes
Memory evaluation	yes	yes	yes	yes
Model pre-compilation	yes	Partial support (support online pre-compilation)	Partial support (support online pre-compilation)	Partial support (support online pre-compilation)
Model segmentation	yes	yes	yes	yes
Custom OP	yes	no	no	no
Multiple inputs	yes	yes	yes	yes
Batch inference	yes	yes	yes	yes
List devices	yes	yes	yes	yes
Query SDK version	yes	yes	yes	yes
Quantitative error analysis	yes	yes	yes	yes
Visualization	yes	yes	no	yes
Model optimization	yes	yes	yes	yes

level				
Model encryption	yes	yes	yes	yes

1.2 Applicable chip model

RKNN-Toolkit supports the following chips with NPU that Rockchip has released:

- RK1806
- RK1808
- RK3399Pro
- RV1109
- RV1126

Note: RK3566 and RK3568 need to use RKNN-Toolkit2. Please refer to the following project for more information:

https://github.com/rockchip-linux/rknn-toolkit2

1.3 Applicable Operating System

RKNN-Toolkit is a cross-platform development kit. The supported operating systems are as follows:

- Ubuntu: 16.04 (x64) or later
- Windows: 7 (x64) or later
- MacOS: 10.13.5 (x64) or later
- Debian: 9.8 (aarch64) or later

1.4 Applicable Deep Learning Framework

The deep learning frameworks supported by RKNN Toolkit include TensorFlow, TensorFlow Lite, Caffe, ONNX, Darknet and Keras.

The corresponding relationship between RKNN Toolkit and the version of each deep learning framework is as follows:

Table 1-4-1 Support status of each deep learning framework

RKNN Toolkit	TensorFlow	TF Lite	Caffe	ONNX	Darknet	Pytorch	MXNet	Keras
1.0.0	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.3.0	Commit number：810d7f7	Not support	Not support	Not support
1.1.0	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.3.0	Commit number：810d7f7	Not support	Not support	Not support
1.2.0	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.4.1	Commit number：810d7f7	Not support	Not support	Not support
1.2.1	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.4.1	Commit number：810d7f7	Not support	Not support	Not support
1.3.0	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.4.1	Commit number：810d7f7	>=1.0.0, <=1.2.0	>=1.4.0, <=1.5.1	Not support
1.3.2	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.4.1	Commit number：810d7f7	>=1.0.0, <=1.2.0	>=1.4.0, <=1.5.1	Not support
1.4.0	>=1.10.0, <=1.13.2	Schema version = 3	1.0	Release version 1.4.1	Commit number：810d7f7	>=1.0.0, <=1.2.0	>=1.4.0, <=1.5.	Not support

							1	
1.6.0	>=1.10.0, <=2.0.0	Schema version = 3	1.0	Release version 1.6.0	Commit number：810d7f7	>=1.0.0, <=1.6.0	>=1.4.0, <=1.5.1	>=2.1.6-tf
1.6.1	>=1.10.0, <=2.0.0	Schema version = 3	1.0	Release version 1.6.0	Commit number：810d7f7	>=1.0.0, <=1.6.0	>=1.4.0, <=1.5.1	>=2.1.6-tf
1.7.0	>=1.10.0, <=2.0.0	Schema version = 3	1.0	Release version 1.6.0	Commit number：810d7f7	>=1.0.0, <=1.6.0	>=1.4.0, <=1.5.1	>=2.1.6-tf
1.7.1	>=1.10.0, <=2.0.0	Schema version = 3	1.0	Release version 1.6.0	Commit number：810d7f7	>=1.5.1, <=1.9.0	>=1.4.0, <=1.5.1	>=2.1.6-tf

Note:

1. According to the protobuf version, any graph or checkpoint built with a certain version of TensorFlow can be loaded and evaluated by a higher (minor or patch) version of TensorFlow in the same major version. Theoretically, the pb files generated by TensorFlow with versions before 1.14 are supported by RKNN Toolkit 1.0.0 and later versions. For more information about the compatibility of different TensorFlow versions, please refer to official documentation:

   https://www.tensorflow.org/guide/version_compat?hl=zh-CN

2. Since the schemas of different versions of tflite are incompatible with each other, tflite model exported from a different schema compared to the schema version RKNN Toolkit relies may

cause loading failure. The tflite schema currently used by RKNN Toolkit is based on the following submission on the TensorFlow Lite's official GitHub master branch: 0c4f5dfea4ceb3d7c0b46fc04828420a344f7598. The specific schema link is as follows:

https://github.com/tensorflow/tensorflow/commits/master/tensorflow/lite/schema/schema.fbs

3. There are two caffe protocols used by RKNN Toolkit: one is the protocol based on the official modification of berkeley, the other one is the protocol containing the LSTM layer support.

   The protocol based on berkeley's official modification comes from: https://github.com/BVLC/caffe/tree/master/src/caffe/proto, and the commit ID is 21d0608. RKNN Toolkit adds some OPs on this basis.

   As for the protocol containing the LSTM layer support, please refers to the following link: https://github.com/xmfbit/warpctc-caffe/tree/master/src/caffe/proto，and the commit number is bd6181b. These two protocols are specified by the proto parameter in the load_caffe interface.

4. For the relationship between ONNX release versions and opset versions and IR versions, please refer to the official website:

   https://github.com/microsoft/onnxruntime/blob/master/docs/Versioning.md

ONNX release version	ONNX opset version	Supported ONNX IR version
1.3.0	8	3
1.4.1	9	3
1.6.0	11	6

5. The official Github link of Darknet: https://github.com/pjreddie/darknet. RKNN Toolkit's current conversion rules are based on the latest submission of the master branch (commit number: 810d7f7).

6. When loading the Pytorch model (torchscript model), it is recommended using the same version of Pytorch to export model and convert model to RKNN model. Inconsistency may result in

failure when transferring to the RKNN model.

7. Currently, RKNN Toolkit mainly supports the versions of Keras with TensorFlow as the backend. The tested Keras versions are those that come with TensorFlow.

2 Development environment setup

This chapter introduces the preparation of the development environment before using RKNN Toolkit. The problems that may be encountered in environment setup will be given in section 2.4 FAQ.

2.1 Reference system configuration

The system configuration recommended for RKNN Toolkit is as follows:

Hardware/operating system	Recommand
CPU	Intel Core i3 or above or equivalent Xeon / AMD processor
RAM	16G or above
operating system	Linux: Ubuntu 16.04 64bit or Ubuntu 18.04 64bit MacOS: 10.13.5 Windows: 7 or 10

Note: It is recommended to use the PC with the recommended configuration to complete the model conversion stage. Model conversion can also be completed when using specified firmware on RK3399Pro, RK1808 computing card and other devices, but because of the limited CPU and memory resources of these devices, it is not recommended to use them for model conversion.

2.2 Requirements/Dependencies

It is recommended to meet the following requirements in the operating system environment:

Table 2-2-1 run time environments

Operation System	Ubuntu16.04（x64）or later Windows 7（x64）or later Mac OS X 10.13.5（x64） or later Debian 9.8（aarch64）or later
Python	3.5/3.6/3.7
Python Requirements	'numpy == 1.16.3' 'scipy == 1.3.0' 'Pillow == 5.3.0' 'h5py == 2.8.0' 'lmdb == 0.93' 'networkx == 1.11' 'flatbuffers == 1.10', 'protobuf == 3.11.2' 'onnx == 1.6.0' 'onnx-tf == 1.2.1' 'flask == 1.0.2' 'tensorflow == 1.11.0' or 'tensorflow-gpu' 'dill==0.2.8.2' 'ruamel.yaml == 0.15.81' 'psutils == 5.6.2' 'ply == 3.11' 'requests == 2.22.0' 'torch == 1.2.0' or 'torch == 1.5.1' or 'torch==1.6.0' 'mxnet == 1.5.0' 'sklearn == 0.0' 'opencv-python == 4.0.1.23' 'Jinja2 == 2.10'

Note:

1. Windows only support Python 3.6 currently.
2. MacOS support python 3.6 and python 3.7.
3. Arm64 platform support python 3.5 and python 3.7.
4. Because Pytorch/TensorFlow, etc. gradually stopped supporting Python3.5, the next major version of RKNN Toolkit will remove the Python3.5 wheel package on the Linux x86 platform, and instead provide Python3.6 and Python3.7 wheel packages.

5. Scipy version on MacOS should be 1.3.0, other platform is >=1.1.0.

6. The application on ARM64 platform does not need to require sklearn and opencv-python.

7. Jinja2 is only used when creating custom op.

2.3 Installation

There are two ways to install RKNN-Toolkit: one is through the Python-package-installation and management-tool pip, the other is running docker image with full RKNN-Toolkit environment. The specific steps of the two installation ways are described below.

Note: Please refer to the following link for the installation process of Toybrick devices: http://t.rock-chips.com/wiki.php?mod=view&id=36

2.3.1 Install by pip command

1. Create virtualenv environment. If there are multiple versions of the Python environment in the system, it is recommended to use virtualenv to manage the Python environment.

```
sudo apt install virtualenv
sudo apt-get install libpython3.5-dev
sudo apt install python3-tk

virtualenv -p /usr/bin/python3 venv
source venv/bin/activate
```

2. Install dependent libraries: TensorFlow and opencv-python

```
# Install tensorflow gpu
pip install tensorflow-gpu==1.11.0
# Install tensorflow cpu. Only one version of tensorflow can be installed.
pip install tensorflow==1.11.0
# Install PyTorch and torchvision
pip3 install torch==1.5.1 torchvision==0.4.0
# Install mxnet
pip3 install mxnet==1.5.0
```

Note: the PyTorch example can not run on torchvision 0.6.1, so install torchvison 0.4.0. Please install the corresponding version of torchvision according to your own needs

3. Install RKNN-Toolkit

```
pip install package/rknn_toolkit-1.7.1-cp35-cp35m-linux_x86_64.whl
```

Please select corresponding installation package (located at the *packages/* directory) according to different python versions and processor architectures:

- **Python3.5 for x86_64**： rknn_toolkit-1.7.1-cp35-cp35m-linux_x86_64.whl
- **Python3.5 for arm_x64**： rknn_toolkit-1.7.1-cp35-cp35m-linux_aarch64.whl
- **Python3.6 for x86_64**： rknn_toolkit-1.7.1-cp36-cp36m-linux_x86_64.whl
- **Python3.7 for arm_x64**: rknn_toolkit-1.7.1-cp37-cp37m-linux_aarch64.whl
- **Python3.6 for Windows x86_64:** rknn_toolkit-1.7.1-cp36-cp36m-win_amd64.whl
- **Python3.6 for Mac OS X:** rknn_toolkit-1.7.1-cp36-cp36m-macosx_10_15_x86_64.whl
- **Python3.7 for Mac OS X:** rknn_toolkit-1.7.1-cp37-cp37m-macosx_10_15_x86_64.whl
- **Python3.7 for arm_x64:** rknn_toolkit-1.7.1-cp37-cp37m-linux_aarch64.whl

2.3.2 Install by the Docker Image

In docker folder, there is a Docker image that has been packaged for all development requirements. After loading the image, user can directly use RKNN-toolkit. Using steps are as follows:

1. Install Docker

Please install Docker according to the official manual:

https://docs.docker.com/install/linux/docker-ce/ubuntu/

2. Load Docker image

Execute the following command to load Docker image:

```
docker load --input rknn-toolkit-1.7.1-docker.tar.gz
```

After loading successfully, execute “docker images” command and the image of rknn-toolkit appears as follows:

```
REPOSITORY        TAG        IMAGE ID            CREATED         SIZE
rknn-toolkit       1.7.1       50105e3a4110         1 hours ago       3.54GB
```

3. Run image

Execute the following command to run the docker image. Then it will enter the bash environment.

```
docker run -t -i --privileged -v /dev/bus/usb:/dev/bus/usb rknn-toolkit:1.7.1 /bin/bash
```

Mapping the folder to the Docker environment can be achieved through additional parameters “-v <host src folder>:<image dst folder>” , for example:

```
docker run -t -i --privileged -v /dev/bus/usb:/dev/bus/usb -v /home/rk/test:/test rknn-toolkit:1.7.1 /bin/bash
```

4. Run demo

```
cd /example/tflite/mobilenet_v1
python test.py
```

Note: The Docker image is based on Ubuntu 18.04 and Python 3.6 since RKNN-Toolkit version 1.6.0. This image can only be used on Linux x86 platform.

2.3.3 Installation FAQs

For common problems of RKNN Toolkit installation, please refer to Chapter 1.1 of *Rockchip_Trouble_Shooting_RKNN_Toolkit_EN.pdf*.

2.4 Connect to Rockchip NPU device

During model evaluation or deployment, Rockchip NPU equipment needs to be connected. This section will give the connection method of RK3399Pro, RK1808, RV1109, RV1126 development board, and how to confirm whether the device is successfully connected.

Note:

1.If you are using the Toybrick development board, please refer to the boot and serial port debugging content in the following link:

https://t.rock-chips.com/wiki.php?filename=%E7%BD%91%E7%AB%99%E5%AF%BC%E8%88%AA/%E9%A6%96%E9%A1%B5

2.To use the simulator for model evaluation, you only need an x86_64 Linux PC with RKNN Toolkit. Considering the difference between the simulator and the development board and long-time cost, it is recommended that perform evaluation with a development board.

2.4.1 Connect to the device through the USB-OTG port

The connection between RKNN Toolkit and Rockchip NPU development board is created base on the USB-OTG interface. In the stage of model evaluation or model deployment, it is necessary to connect the PC and Rockchip NPU device for the related function.

The position of the RK3399Pro USB-OTG interface is shown in the red circle as shown in the figure below, and it is connected to the PC through the USB Type-C cable:

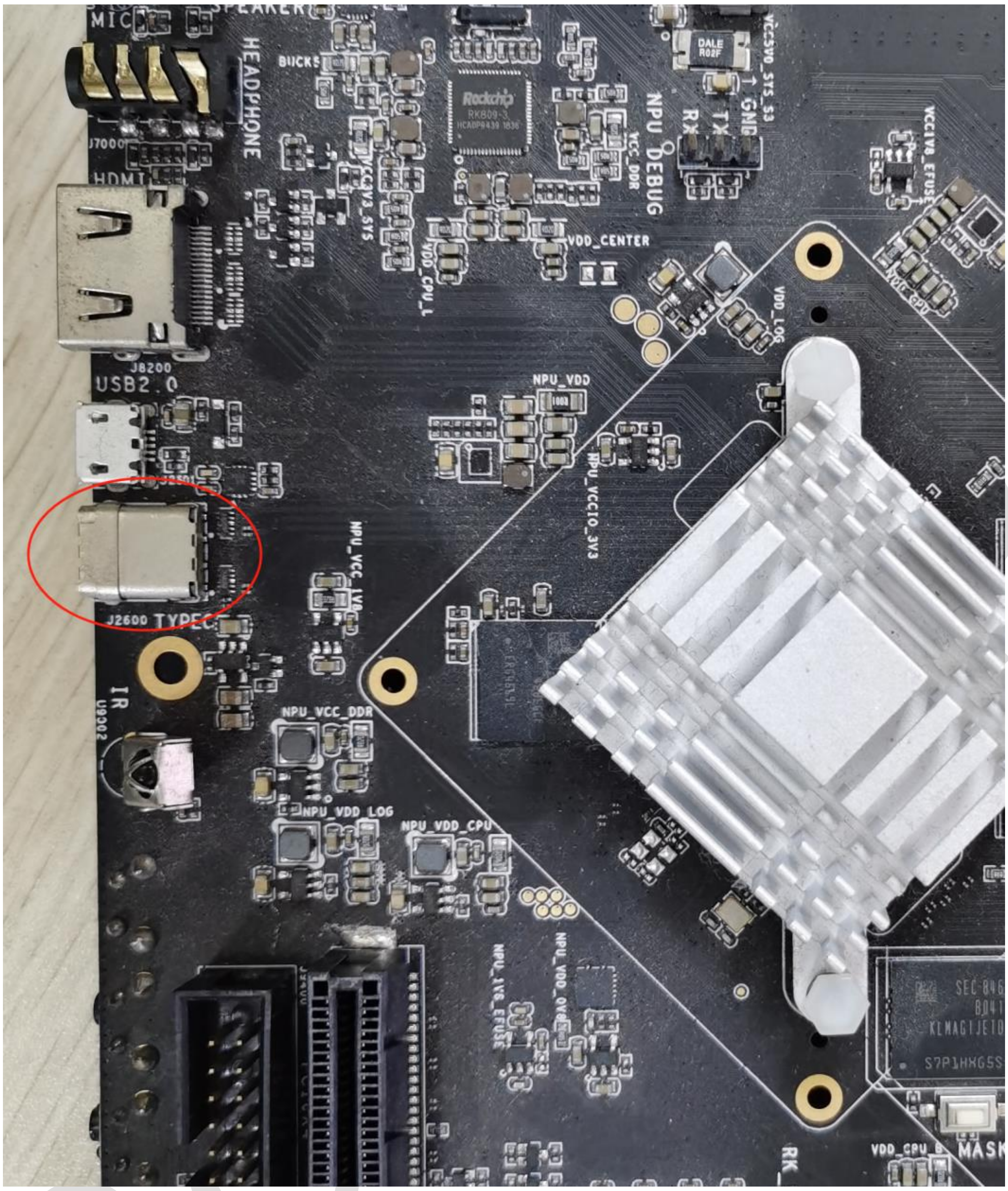


Figure 2-4-1-1 RK3399Pro USB-OTG port

The location of the RK1808 USB-OTG interface is shown in the figure below, and it is connected to the PC via a Micro-USB cable:

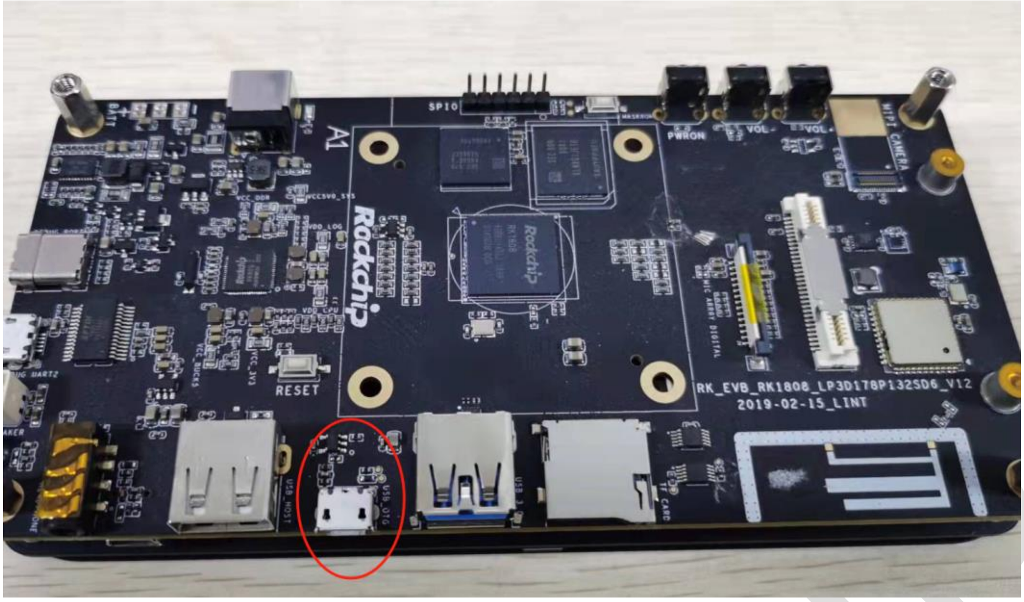


Figure 2-4-1-2 RK1808 USB-OTG port

The position of the USB-OTG interface of RV1109/RV1126 is shown in the red circle as shown in the figure below, and it is connected to the PC through the Micro-USB cable:

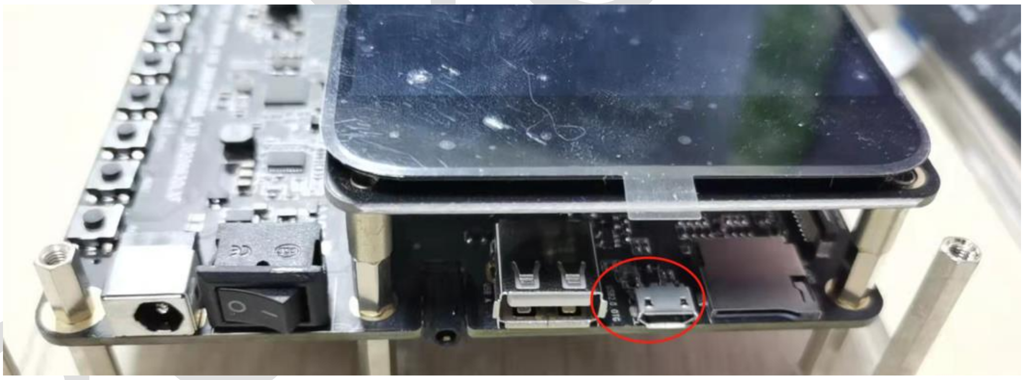


Figure 2-4-1-3 RV1109/RV1126 USB-OTG port

2.4.2 Connect the device through the DEBUG port

In the model evaluation or model deployment step, if you encounter an error on the development board, connection to the NPU device through the DEBUG port can help to grab the error log.

The location of the RK3399Pro NPU DEBUG interface is shown in the figure below. It is connected to the PC through the USB-serial conversion board. The PC needs to install Minicom or Putty etc. software:

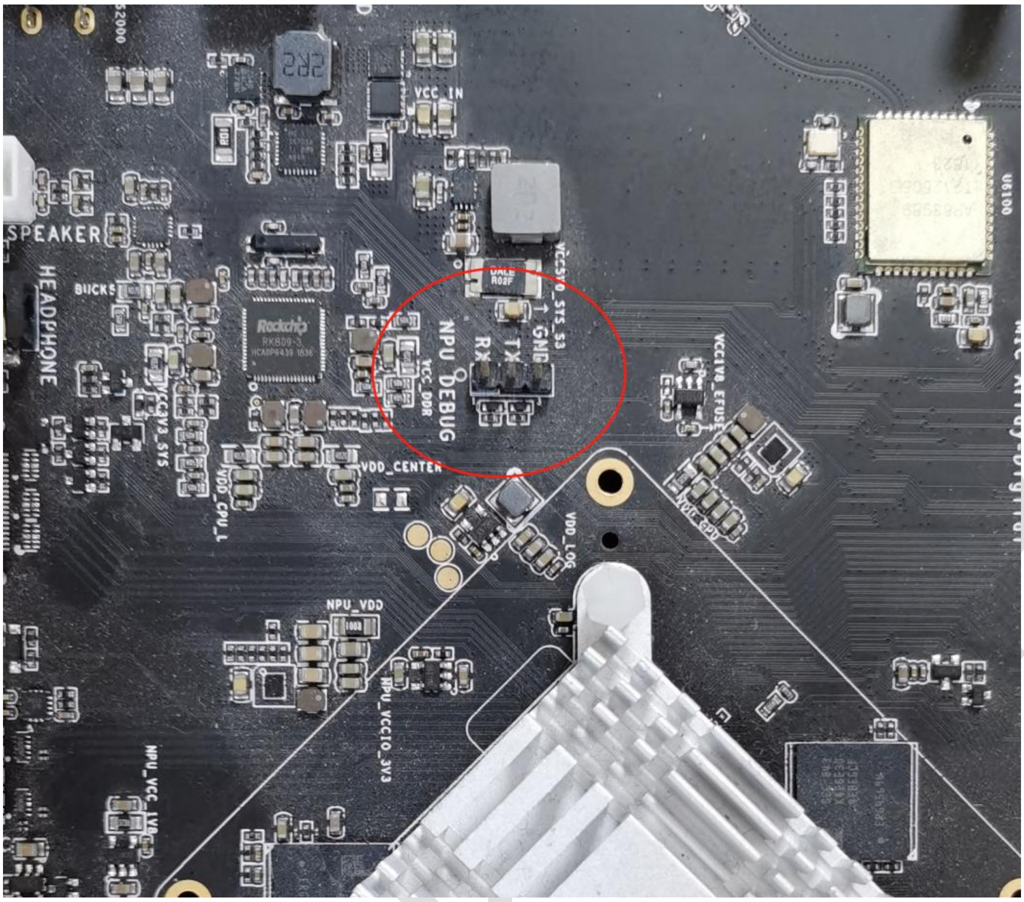


Figure 2-4-2-1 RK3399Pro DEBUG port

The position of the RK1808 DEBUG interface is shown in the red circle in the figure below, and it is connected to the PC through the Micro-USB cable:

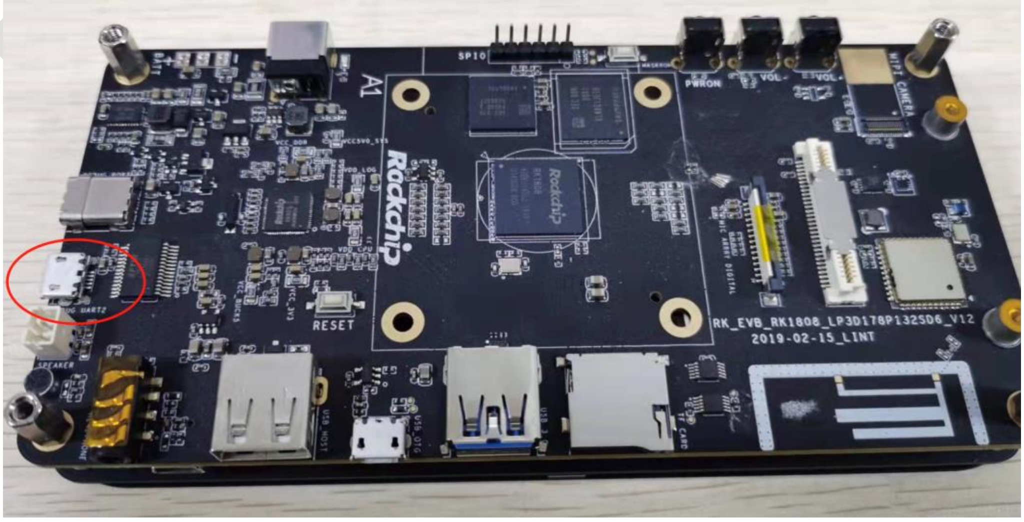


Figure 2-4-2-2 RK1808 DEBUG port

The position of the RV1109/RV1126 DEBUG interface is shown in the red circle in the figure below, and it is connected to the PC through the Micro-USB cable:

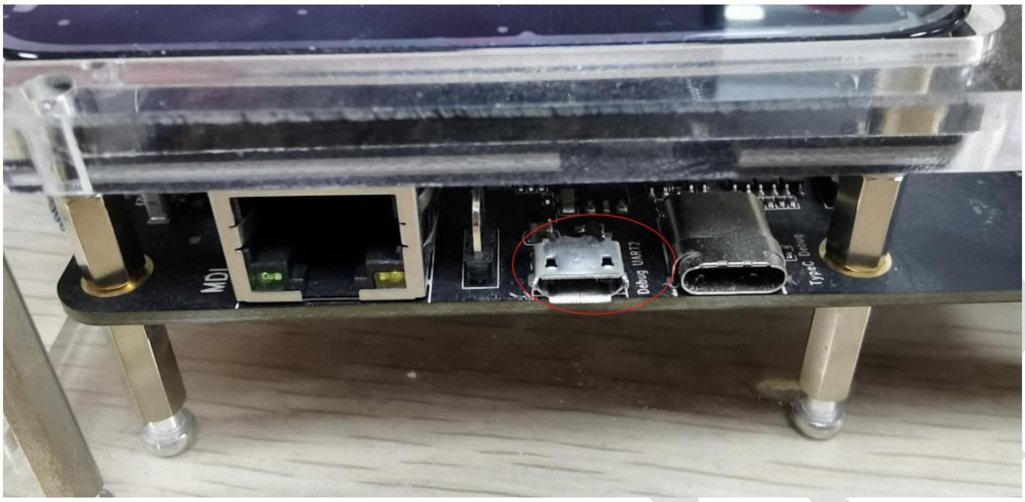


Figure 2-4-2-3 RV1109/RV1126 DEBUG port

2.4.3 Confirm that the device is already connected

If the device is connected correctly, execute the "python -m rknn.bin.list_devices" command on the PC's terminal to list the IDs of the connected devices. The reference output is as follows:

```
*************************
all device(s) with adb mode:
cf8f01ae745b49ce
all device(s) with ntb mode:
1126
*************************
```

It's shown that the PC is currently connected to two development boards, the device id of the first development board is cf8f01ae745b49ce, and the device id of the second development board is 1126.

Note:

1.If you are using an x86_64 Linux system, you may need to update the USB device permissions, for the first time to connect to a Rockchip NPU devices, otherwise the system may not have read and write permissions on the devices. The update way is to execute the update_rk1808_usb_rule.sh script in the platform-tools/update_rk_usb_rule/linux/ directory, and restart the PC system on after execution.

2.If you are using Rockchip NPU device on Windows, you need to turn on the NTB communication mode first (RK1808 and Toybrick development boards are turned on by default). For tuning on NTB mode, enter the development board system through adb and modify the file /etc/init.d/.usb_config, Add one line in this file: usb_ntb_en, and then restart the development board. The original line usb_adb_en should be retained, otherwise the development board system cannot be accessed through adb.

2.4.4 Connection FAQs

For common problems of device connection, please refer to chapter 1.5 of the document *Rockchip_Trouble_Shooting_RKNN_Toolkit_EN.pdf*.

3 Usage

3.1 Main steps

The main usege steps of RKNN-Toolkit can be divided into three stages:

1. Model conversion: Convert the model trained and exported from the opensource DL framework (Caffe, Darknet, etc.) into an RKNN model that RKNPU can excute.

2. Model evaluation: Through inference, eval_perf, eval_memory and other interfaces to evaluate the accuracy, performance, and memory usage of the RKNN model.

3. Model deployment: After confirming that the RKNN model meets the deployment requirements through the model evaluation, the RKNN model can be deployed through the RKNN Toolkit Python API or the RKNN C API. For more detail about using RKNN Toolkit Python API for model deployment, please refer to Chapter 3.4; for more detail about using RKNN C API for model deployment, please refer to RKNN C API related documents:

https://github.com/rockchip-linux/rknpu/tree/master/rknn/doc

3.2 Model conversion

In model conversion stage, RKNN Toolkit convert the models, exported by various opensource DL frameworks, and generate RKNN models that Rockchip NPU can excute. Please refer to section 1.4 for the support of RKNN Toolkit for each DL framework.

Note: Because the model conversion requires more CPU (or GPU), memory and other resources, it is recommended to perform this operation on a PC that meets the system configuration requirements of chapter 2.1, but not do it on development borad.

3.2.1 Model conversion process

The main workflow of model conversion is shown in the figure below:

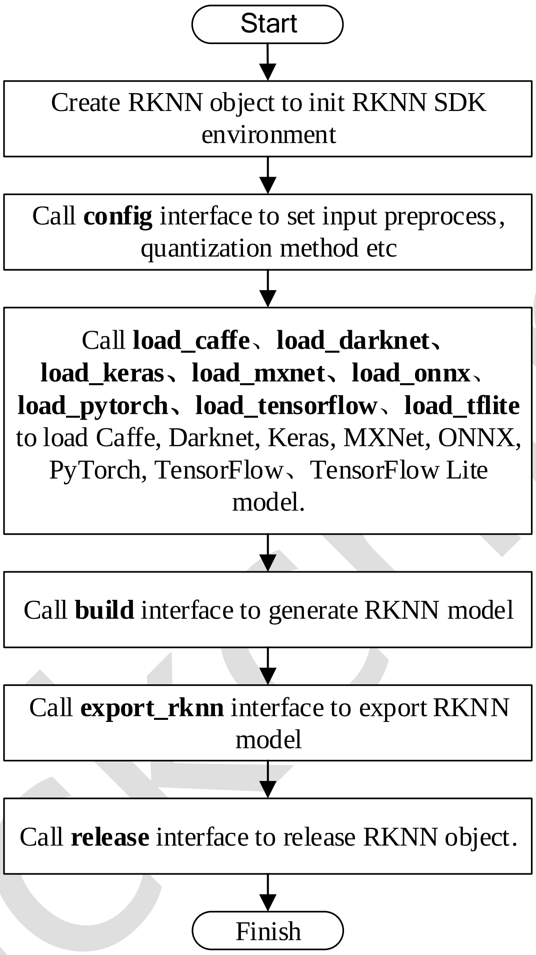

Start
Create RKNN object to init RKNN SDK environment
Call **config** interface to set input preprocess, quantization method etc
Call **load_caffe**、**load_darknet**、**load_keras**、**load_mxnet**、**load_onnx**、**load_pytorch**、**load_tensorflow**、**load_tflite** to load Caffe, Darknet, Keras, MXNet, ONNX, PyTorch, TensorFlow、TensorFlow Lite model.
Call **build** interface to generate RKNN model
Call **export_rknn** interface to export RKNN model
Call **release** interface to release RKNN object.
Finish

Figure 3-2-1-1 RKNN model conversion process

After successfully performing the above steps, the RKNN model will be saved in the specified directory. The subsequent evaluation and deployment will be based on the RKNN model.

Note: Please refer to Chapter 7 for the detailed description of each interface used in the above process.

3.2.2 Model quantization

3.2.2.1 Model quantization overview

When use this method, user loads the well-trained float point model, and RKNN Toolkit will do the quantization according to the dataset provided by user. Dataset should try to cover as many input type of model as possible. To make example simple, generally put only one picture. Suggest to put more.

RKNN supports two kinds for model quantization:

- RKNN Toolkit quantize the float model according to the calibration dataset and generate the quantized RKNN model.
    - Support quantize type: int16, int8, uint8
    - Quantize method: Post Training Static Quantization
    - Support quantize schema: per-tensor(or per-layer), **per-channel is not supported**
- Loading quantized model, which exported from the opensource DL framework, RKNN Toolkit can use the already exists quantization information to generate the quantized RKNN model.
    - Support framework(The main supported versions are in brackets, it's recommanded to export the quantized model by that version):

      Pytoch(v1.9.0)、Onnx(Onnxruntime v1.5.1)、Tensorflow、Tflite
    - Quantized method: Post Training Static Quantization, Quantization Aware Training(QAT)

3.2.2.2 Model quantization detail

- **Post training static quantization**

Currently RKNN Toolkit supports three kinds of quantization methods:

- asymmetric_quantized-u8（default）

This is the quantization method supported by tensorflow, which is also recommended by Google. According to the description in the article of Quantizing deep convolutional networks for efficient inference: A whitepaper, the accuracy loss of this quantization method is the smallest for most networks.

Its calculation formula is as follows：

$$quant = round\left(\frac{float\_num}{scale}\right) + zero\_po\,\mathrm{int}$$
$$quant = cast\_to\_bw$$

Where 'quant' represents the quantized number; 'float_num' represents float; data type of 'scalse' if float32; data type of 'zero-points' is int32, it represents the corresponding quantized value when the real number is 0. Finally saturate ‘quant’ to [range_min, range_max].

$$range\_\max = 255$$
$$range\_\min = 0$$

Currently only supports the inverse quantization of u8, the calculation formula is as follows:

$$float\_num = scale(quant - zero\_po\text{int})$$

- dynamic_fixed_point-8

For some models, the quantization accuracy of dynamic_fixed_point-8 is higher than asymmetric_quantized-u8.

Its calculation formula is as follows：

$$quant = round(\text{float}\_num * 2^{fl})$$
$$quant = cast\_to\_bw$$

Where ‘quant’ represents the quantized number; ‘float_num’ represents float; ‘fl’ is the number of digits shifted to the left. Finally saturate ‘quant’ to [range_min, range_max].

$$range\_\max = 2^{bw-1} - 1$$
$$range\_\min = -\left(2^{bw-1} - 1\right)$$

If ‘bw’ equals 8, the range is [-127, 127].

- dynamic_fixed_point-16

The quantization formula of dynamic_fixed_point-16 is the same as dynamic_fixed_point-8, except bw=16. For RK3399pro/RK1808, there is 300Gops int16 computing unit inside NPU, for some quantized to 8 bit network with relatively high accuracy loss, you can consider to use this quantization method.

- **Quantization aware training(QAT)**

A model with quantized params/weights can be obtained through the Quantization-aware training. RKNN Toolkit currently supports TensorFlow and PyTorch frameworks for QAT models. Please refer to the following link for the technical details of QAT:

Tensorflow:

https://www.tensorflow.org/model_optimization/guide/quantization/training

PyTorch:

https://pytorch.org/blog/introduction-to-quantization-on-pytorch/

This method requires to use the original framework to train (or fine tune) to obtain a quantized model, and then use RKNN Toolkit to import the quantized model (you need to set do_quantization=False in the build setting during model conversion). At this time, RKNN Toolkit will use the quantized parameters of the model, so theoretically there will be almost no loss of accuracy comparing quantization via RKNN Toolkit.

Note: RKNN Toolkit also supports post-training quantization models of ONNX, PyTorch, TensorFlow, and TensorFlow Lite. The model conversion method is the same as the quantization-aware training model. Do_quantization should be set to False when calling the build interface. Update to RKNN Toolkit v1.7.0 or later for loading quantized onnx model. Update to RKNN Toolkit v1.7.1 or later for loading quantized pytorch model.

3.2.3 Model convert example

Taking PyTorch framework for example, a case of model conversion is as follows:

```
import torchvision.models as models
import torch
from rknn.api import RKNN

PT_PATH = './resnet18.pt'

def export_pytorch_model():
    net = models.resnet18(pretrained=True)
    net.eval()
    trace_model = torch.jit.trace(net, torch.Tensor(1,3,224,224))
    trace_model.save(PT_PATH)

if __name__ == '__main__':

    # export PT model
    export_pytorch_model()
    # create RKNN module
    rknn = RKNN()

    # Setting preprocess parameters
    rknn.config(mean_values=[[123.675, 116.28, 103.53]], std_values=[[58.395, 58.395, 58.395]], reorder_channel='0 1 2')

    # load pytorch model
    ret = rknn.load_pytorch(model=PT_PATH, input_size_list=[[3, 224, 224]])
    if ret != 0:
        print('Load Pytorch model failed!')
        exit(ret)

    # build quantized RKNN model
    ret = rknn.build(do_quantization=True, dataset='./dataset.txt')
    if ret != 0:
        print('Build model failed!')
        exit(ret)

    # export RKNN model to specific path
    ret = rknn.export_rknn('./resnet18.rknn')
    if ret != 0:
        print('Export resnet18.rknn failed!')
        exit(ret)

    rknn.release()
```

For other frameworks, please refer to the examples in the SDK/examples directory.

For the quantized models conversion, please refer to the examples in the SDK/examples/common_function_demos/ directory.

3.2.4 Model conversion FAQs

For common problems of model conversion, please refer to chapter 1.3 of the document *Rockchip_Trouble_Shooting_RKNN_Toolkit_CN.pdf*.

3.3 Model evaluation

After the RKNN model is obtained through model conversion, the Python interface provided by RKNN Toolkit can be used to evaluate the accuracy, performance, and memory usage of RKNN model on the Rockchip NPU development board (or simulator, which only supported for x86_64 Linux).

Note:

1. When using the simulator for evaluation, there is no need to connect the Rockchip NPU development board, but the RKNN Toolkit is required to be installed on the x86_64 Linux system, and it will take a long time to use the simulator for evaluation.

2. Before using the Rockchip NPU development board for evaluation, please refer to chapter 2.4 to correctly connect the PC with the development board, and ensure that the RKNN Toolkit can recognize the device.

3. If it is evaluated on the RK3399Pro development board, because it has own NPU, there is no need to connect the Rockchip NPU device again. The RKNN Toolkit Python interface only supports running on the RK3399Pro with Debian firmware. If the firmware of the development board is an Android system, please use the PC to connect to RK3399Pro for evaluation.

The typical evaluation process is shown in the figure below:

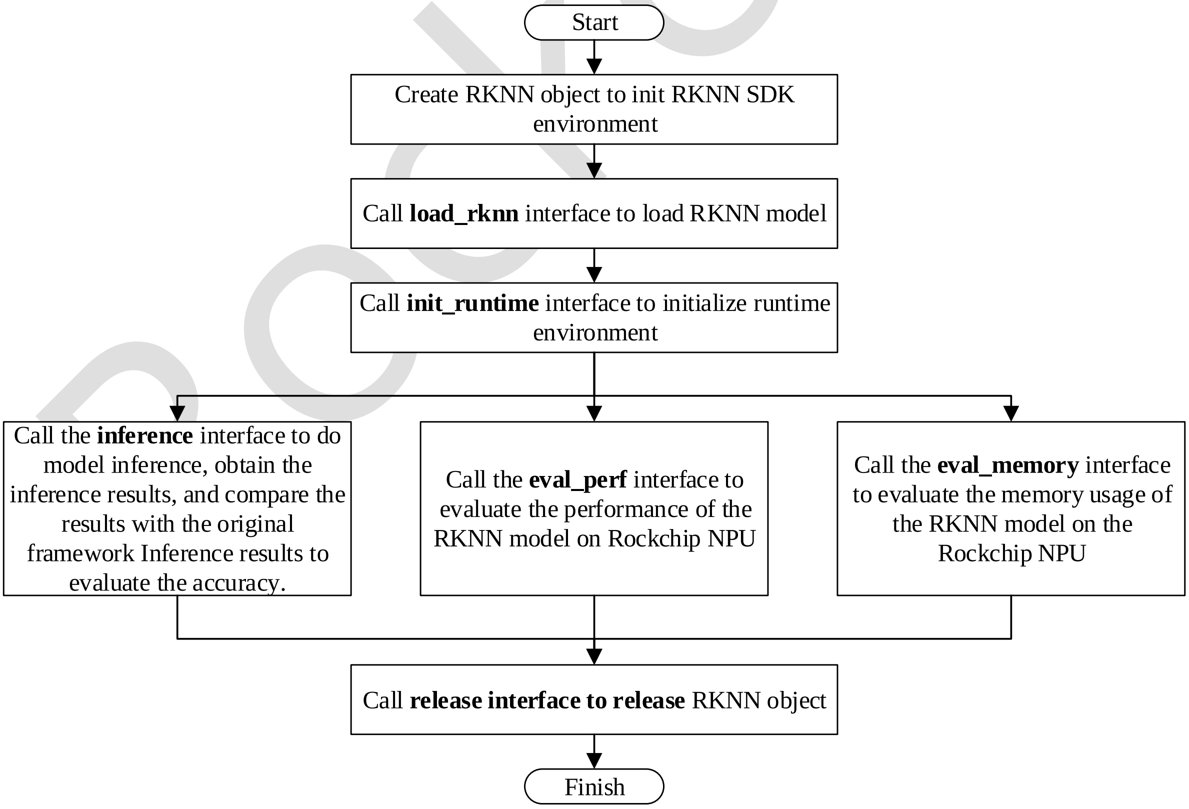

Start
Create RKNN object to init RKNN SDK environment
Call load_rknn interface to load RKNN model
Call init_runtime interface to initialize runtime environment
Call the inference interface to do model inference, obtain the inference results, and compare the results with the original framework Inference results to evaluate the accuracy.
Call the eval_perf interface to evaluate the performance of the RKNN model on Rockchip NPU
Call the eval_memory interface to evaluate the memory usage of the RKNN model on the Rockchip NPU
Call release interface to release RKNN object
Finish

Figure 3-3-1 RKNN model evaluation process

Model evaluation is mainly divided into three parts: accuracy evaluation, performance evaluation and memory evaluation.

- **Accuracy evaluation**: Evaluate the accuracy of the inference results of the RKNN model.
- **Performance evaluation**: Evaluate the time-consuming inference of the RKNN model on the development board.
- **Memory evaluation**: Evaluate the memory usage on Rockchip NPU during RKNN model inference.

Accuracy evaluation related content will be expanded in detail in Chapter 4, performance evaluation related content will be expanded in detail in Chapter 5, and memory evaluation related content will be expanded in detail in Chapter 6.

3.4 Model deployment

This section mainly introduces how to use the Python interface provided by RKNN Toolkit for deploying the RKNN model, already evaluated and meets the accuracy requirement in the previous step, on a Rockchip NPU device.

3.4.1 Prepare project files

The simplest application only needs to include input data, RKNN model and application script.

Here is an ImageNet image classifier based on the resnet18 model as an example. The project contains the following files:

```
ai_demo/
 ├── imagenet_classes.txt
 ├── imgs
 │    └── space_shuttle_224.jpg
 ├── resnet18_classifier.py
 └── resnet18.rknn
```

The file description is as follows:

- imagenet_classes.txt: A file that records image categories.
- imgs directory: Store pictures to be classified, here is only one picture space_shuttle_224.jpg,

you can store more pictures if needed.

- resnet18_classifier.py: The main program for image classification. The detailed description of the program will be given in the next section.
- resnet18.rknn: The RKNN model converted according to Chapter 3.2 (Note: The target device of this model is RK1808, which can only be deployed on RK1808 or RK3399Pro. If you want to deploy on RV1109 or RV1126, you need to modify the target_platform parameter of the build interface, please refer to Chapter 8.2 for specific instructions).

3.4.2 Application example

The running process of the simplest application is shown in the figure below:

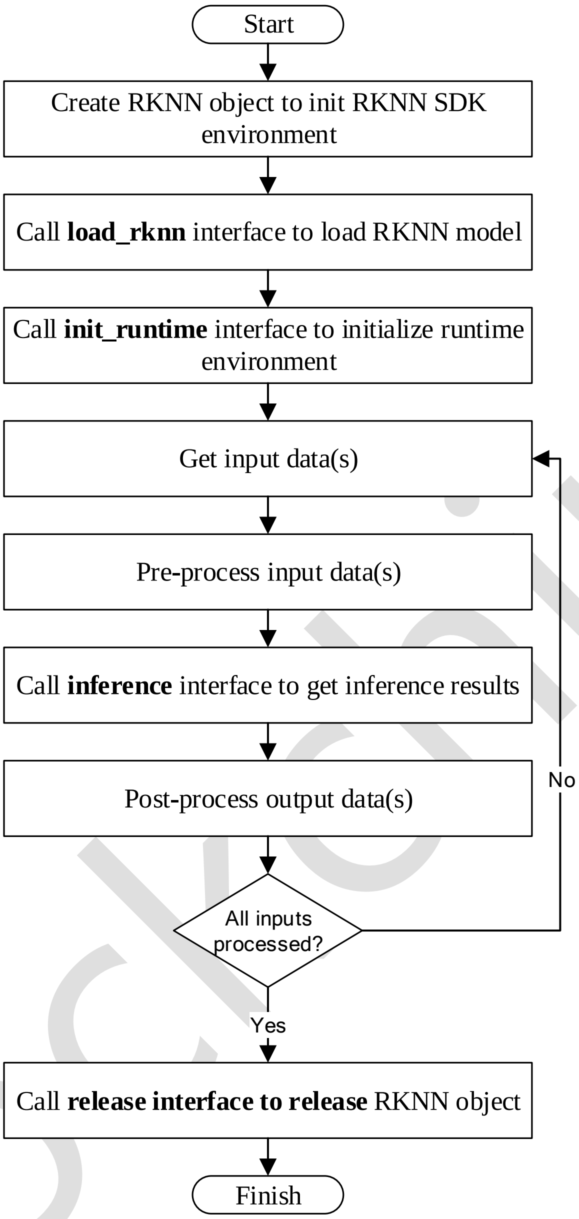

Start
Create RKNN object to init RKNN SDK environment
Call load_rknn interface to load RKNN model
Call init_runtime interface to initialize runtime environment
Get input data(s)
Pre-process input data(s)
Call inference interface to get inference results
Post-process output data(s)
All inputs processed?
No
Yes
Call release interface to release RKNN object
Finish

Figure 3-4-2-1 Simple application flowchart

In this process, the core steps are to load the RKNN model, initialize the runtime environment, prepare the input data, model inference and post-processing of the results.

Here is an example of image classification to show how to deploy the classification model resnet18.rknn to the RK1808 development board.

```
import os
import cv2
import torch
import numpy as np
from rknn.api import RKNN

RKNN_PATH = './resnet18.rknn'
IMGS_DIR = './imgs'

def classification_post_process(output, categories):
    output = output.reshape(-1)
    probabilites = np.exp(output)/sum(np.exp(output))
    reverse_sort_index = np.argsort(output)[::-1]
    print('-----TOP 1-----')
    for i in range(1):
        print(categories[reverse_sort_index[i]], ':', probabilites[reverse_sort_index[i]])

if __name__ == '__main__':
    # Create RKNN object
    rknn = RKNN()

    # Load RKNN model
    ret = rknn.load_rknn(path=RKNN_PATH)
    if ret != 0:
        print('Load Pytorch model failed!')
        exit(ret)

    # Init_runtime, set the target as RK1808
    # If there is only one device connected, device_id can be left blank
    ret = rknn.init_runtime(target='rk1808', device_id='1808')
    if ret != 0:
        print('Init runtime environment failed')
        exit(ret)

    # load imagenet_classes.txt to abtain class info
    with open("imagenet_classes.txt", "r") as f:
        categories = [s.strip() for s in f.readlines()]

    for img_file in os.listdir(IMGS_DIR):
        img_path = os.path.join(IMGS_DIR, img_file)

        # load image, resize to target shape, convert BGR2RGB.
        img = cv2.imread(img_path)
        img = cv2.resize(img, (224, 224), interpolation=cv2.INTER_CUBIC)
        img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

        # Call the inference interface
        outputs = rknn.inference(inputs=[img])
```

```
            # Call the post-processing interface to get the category, print category and probability
of the picture
            classification_post_process(outputs[0], categories)


        # After all the images are processed, released RKNN object.
        rknn.release()
```

For the deployment of the target detection model, please refer to SDK/examples/caffe/vgg-ssd, SDK/examples/darknet/yolov3, SDK/examples/onnx/yolov5, etc.

For the deployment of the image segmentation model, please refer to SDK/examples/mxnet/fcn_resnet101, etc.

For the deployment of other classification models, please refer to SDK/examples/caffe/mobilenet_v2, SDK/examples/keras/xception, SDK/examples/mxnet/resnext50, etc.

Note:

1. If the Python interface is used in the final product deployment, it is recommended to use RKNN Toolkit Lite, which only keep the inference function of RKNN Toolkit, which can greatly reduce the space occupied by the SDK. For a detailed introduction of RKNN Toolkit Lite, please refer to the document: *Rockchip_User_Guide_RKNN_Toolkit_Lite_EN.pdf.*

2. If you use RKNN C API when deploying the final product, please refer to the RKNN C API documentation and examples:

- RK1808 / RV1109 / RV1126:

https://github.com/rockchip-linux/rknpu/tree/master/rknn

- RK3399Pro:

https://github.com/rockchip/linux/RKNPUTools/tree/rk33/mid/8.1/develop/rknn-api

3.4.3 Application excution

As in the example in chapter 3.4.2, you can directly execute the "python resnet18_classifier.py" command in the python environment where RKNN Toolkit is installed.

Note: Please connect the Rockchip NPU development board first according to the instructions in chapter 2.4.

3.4.4 Model pre-compile

When Rockchip NPU loads the RKNN model, it constructs a run-time graph based on the network structure, and then converts it into a command to run on the NPU. For a model with a larger network structure, this step will consume a lot of time. In order to solve this problem, RKNN Toolkit provides a model pre-compilation function, which reduces the model initialization time to less than 1 second.

RKNN Toolkit provides two pre-compilation methods for models:

- Offline pre-compilation: Set the pre-compile parameter to True when calling the build interface. This method is only supported by x86_64 Linux platform.
- Online pre-compile: complete through the online precompile interface export_rknn_precompile_model. The Rockchip NPU development board needs to be connected when using this pre-compilation method.

For using online pre-compilation, you can refer to the following examples:

SDK/examples/common_function_demos/export_rknn_precompile_model/

3.4.5 Model encryption

In order to avoid the leakage of information such as model structure and weight, RKNN Toolkit provides model encryption function.

RKNN Toolkit provides 3 encryption levels. The higher the level, the higher the security and the more time-consuming decryption; on the contrary, the lower the security, the faster the decryption.

The model encryption process is shown in the following figure:

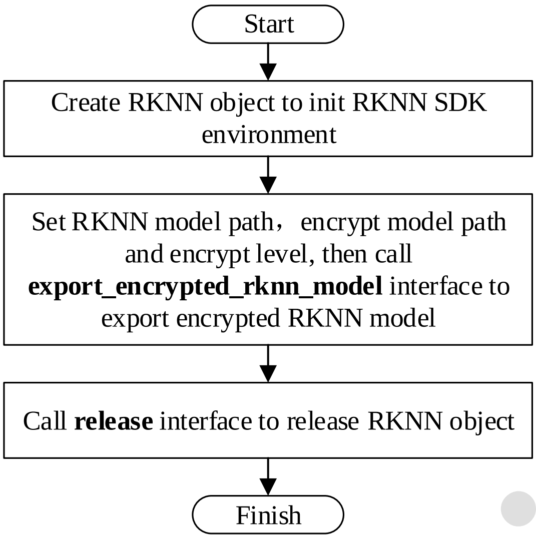

Start
Create RKNN object to init RKNN SDK environment
Set RKNN model path， encrypt model path and encrypt level, then call **export_encrypted_rknn_model** interface to export encrypted RKNN model
Call **release** interface to release RKNN object
Finish

Figure 3-4-5-1 RKNN model encrypt process

The deployment process of the encryption model is the same as normal, no additional operations such as decryption are required.

3.4.6 Multi-model scheduling

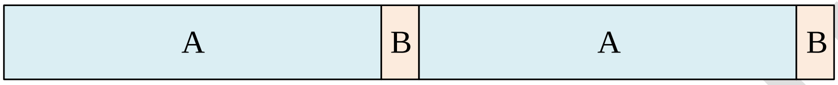
In the scenario of multiple RKNN models, each RKNN model needs to use limited NPU resources to complete inference tasks, which leads to the problem of NPU resource preemption. NPUs such as RK1808 and RV1109 do not have the task preemption function. Once a model starts inference, it can only release NPU resources after the inference of this model ends, and other models will wait for the resouce. This makes it easy for the NPU resource to be occupied by the large model for a long time, and the small model with a higher priority has no chance to run. In order to solve this problem, RKNN Toolkit provides the function of model segmentation, and provides a simple and feasible scheduling method from the software level.

3.4.6.1 Introduction to model segmentation function

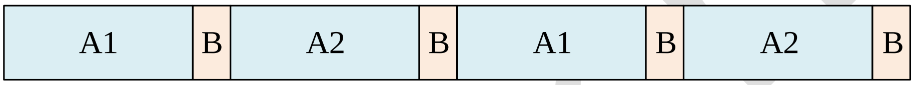
RKNN-Toolkit can divides the ordinary RKNN model into multiple segments through the export_rknn_sync_model interface. Each segment (the model without the model segmentation function is recognize as single-segment) has an equal chance of preempting the NPU. After the execution of a segment is completed, the NPU will be actively surrendered (if the model has another segment) , The segment will be added to the end of the command queue again). At this time, if there are segments of other models waiting to be executed, the segments of other models will be executed in the order of the command queue.

Examples are as follows:

The current application uses two models, model A takes 200ms for inference, and model B takes 20ms for inference. When initializing, initialize A first, and then initialize B. If model segmentation is not used, the inference queue is as follows:



Model B infers once and wait 200ms for the next one. But if we divide model A into 2 segments, each segment is 100ms, the reasoning queue is as follows:



At this time, Model B infers once and only needs to wait for 100ms. In actual use, you can segment the model according to your needs.

Note: Turning on the model segmentation function will reduce the efficiency of single-model reasoning, so in a single-model scenario, it is recommended to turn off this function (do not use the model segmentation function).

3.4.6.2 Model segmentation using process

The model segmentation process is shown in the figure below:

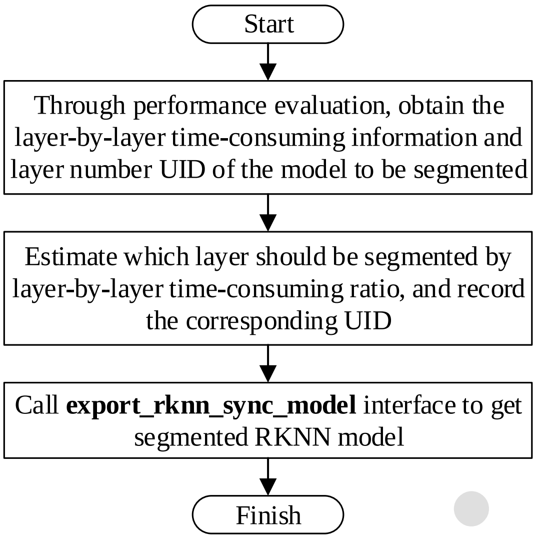

Start
Through performance evaluation, obtain the layer-by-layer time-consuming information and layer number UID of the model to be segmented
Estimate which layer should be segmented by layer-by-layer time-consuming ratio, and record the corresponding UID
Call **export_rknn_sync_model** interface to get segmented RKNN model
Finish

Figure 3-4-6-2-1 RKNN model segmentation process

Note:

1. Obtaining each layer performance evaluation of the model may take a long time, so it is recommended to use proportional conversion when calculating. For example, the model has three layers, and the performance evaluation takes 10ms for the A layer, 20ms for the B layer, and 10ms for the C layer. But the actual model inference time is only 24ms. According to the scale, the actual time may be 7ms for the A layer, 14ms for the B layer, and 7ms for the C layer.

2. There are two IDs for performance evaluation, Layer ID and Uid. Record the Uid and use in model segment function.

3.4.7 Deployment FAQs

Please refer to document: *Rockchip_Trouble_Shooting_RKNN_Toolkit_EN.pdf*

4 Accuracy evaluation

This chapter will explain the methods of RKNN model accuracy evaluation in detail, common problems and common accuracy troubleshooting methods.

4.1 evaluation method

The simplest evaluation method is to compare the inference result of the RKNN model with the inference result of the original framework, and use Euclidean distance or cosine distance to evaluate the similarity of the two results. You can also use post-processing to verify the accuracy of the results, or directly perform accuracy tests on the data set.

Take the simplest calculation of cosine distance to evaluate the accuracy of the inference result as an example, the code is as follows:

```
import cv2
import torch
import numpy as np
from rknn.api import RKNN


PT_PATH = './resnet18.pt'
RKNN_PATH = './resnet18.rknn'
MEANS = [123.675, 116.28, 103.53]
STDS = [58.395, 58.395, 58.395]

def inference_with_rknn(target, device_id, inputs):
    # Create RKNN object
    rknn = RKNN()

    # Load RKNN model
    ret = rknn.load_rknn(path=RKNN_PATH)
    if ret != 0:
        print('Load Pytorch model failed!')
        exit(ret)

    # Init runtime
    ret = rknn.init_runtime(target=target, device_id=device_id)
    if ret != 0:
        print('Init runtime environment failed')
        exit(ret)
    # call inference interface to get result
    outputs = rknn.inference(inputs=inputs)

    # release RKNN object
    rknn.release()

    return outputs

def inference_with_torch(img):
    # Preprocess for input image
    img = (img - MEANS) / STDS
    # Loading image via OpenCV, the image channel order is HWC, need
    # to convect to NCHW for PyTorch inference.
    img = img.reshape((1, 224, 224, 3))
    img = img.transpose((0, 3, 1, 2))
    img = img.astype(np.float32)
    torch_inputs = [torch.from_numpy(img)]

    # Load PyTorch model
    net = torch.load(PT_PATH)

    # Call forward for PyTorch inference
    outputs = net.forward(*torch_inputs)
    return outputs

def compute_cos_dis(x, y):
    cos_dist= (x* y)/(np.linalg.norm(x)*(np.linalg.norm(y)))
    return cos_dist.sum()

if __name__ == '__main__':

    # Load test image
    img = cv2.imread('./space_shuttle_224.jpg')
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)

    # Use RKNN Toolkit inference interface to get result with the RK1808
# develop board.
    rknn_outs = inference_with_rknn(target='rk1808', device_id='1808', inputs=[img])

    # Get result with PyTorch model
    torch_outs = inference_with_torch(img=img)

    # compute and print the cos_distance between result.
    cos_dis = compute_cos_dis(rknn_outs[0],
torch_outs[0].cpu().detach().numpy())
    print("Cosine distance of RKNN output and Torch output: {}".format(cos_dis))
```

4.2 Troubleshooting for accuracy issues

If the accuracy evaluation result is not satisfactory and the accuracy of the RKNN model does not reach the expected effect, please refer to the following steps to troubleshoot:

- First, ensure that the accuracy of the floating-point RKNN model is similar to the original frame test result;
  - When using the build interface to build an RKNN model, set the value of the do_quantization parameter to False;
  - Correctly set the mean_values, std_values, reorder_channel and other parameters in the config interface to ensure that these parameters are consistent with the model training;
  - If the model input is a picture, make sure that the channel order of the test picture is RGB (the image read by OpenCV has default channel order for BGR). Regardless of the order of the image channels used during training, the RKNN model will be used for RGB input when testing;
  - If the model input is 4-dimensional, make sure that the data arrangement format of the test picture is consistent with the data_format parameter in the inference interface. OpenCV reads the image format is HWC, for a single image, the arrangement order is as the same as NHWC.
- When the model is quantized, it is recommended to include more representative data (the number is between 100 and 500) for the input data in the calibration data set, and do not include data independent with the testing scenario. When the calibration data set has a lot of data, it may fail due to insufficient memory when using the build interface to build the RKNN model. At this time, it is recommended to set the batch_size parameter in the config interface to a smaller value, such as 8, 16, etc.
- If you use a data set for evaluation, try to use a larger data set for evaluation. The classification network compares the accuracy of top1, top5, and the mAP, Recall, etc. of the detection network comparison data set.

After checking the above factors, if the inference result of the RKNN model is still incorrect, the following analysis can be done to find the operator that caused the error. Considering time-consuming and other factors, it is recommended to use a single input data for further analysis.

4.2.1 Troubleshooting for float model

RKNN Toolkit (x86_64 Linux) built-in simulator or Rockchip NPU can output the result of the middle layer through special interface. Comparing the results of the middle layer with the original framework, you can locate which operator has a problem. If the operator with an error through the inference result, which can be replaced with another operator, please try to replace it, and then retrain the model and convert it to RKNN for evaluation (train a few epochs for verification, and then complete training after the checking pass); if surrogate operator cannot be found, please collect the operator, parameters, input and output information or provide the minimum recurrence model containing the operator and feed back to the Rockchip NPU team for further analysis.

The specific method to get results of the middle layer is as follows:

1. If simulator is used for evaluation, execute the following command to set the environment variable and then execute the model inference script: export NN_LAYER_DUMP=1. The results of each layer during inference will be saved in the current directory.

2. If Rockchip development board is used for evaluation, there are two ways to get the layer results. The first one is using the RKNN Toolkit Python interface with the connection of the development board through the serial port. Find a folder on the development board to store the results of the middle layer and store it in the folder. Set the environment variable NN_LAYER_DUMP, and need to restart the rknn_server process, the specific command is "export NN_LAYER_DUMP=1 && restart_rknn.sh"; The second one is using the RKNN C API interface for evaluation, at this time, just set the NN_LAYER_DUMP environment variable on the development board, the specific command is "export NN_LAYER_DUMP=1”. The results of the middle layer will be saved in the directory where the inference program is executed.

Note: If the development board is RK3399Pro, you need to perform the above operations on the built-in NPU.

After obtaining the results of the middle layer, compare these results with the original framework. About how to obtaining the middle layer results of the original framework, please refer to the relevant information of each framework.

When comparing data, if you find that the results of the first layer are very different (the cosine distance is less than 0.98), this is usually caused by the inconsistency of the input preprocessing between RKNN and the original framework. Please first check whether the mean_values, std_values, reorder_channel and other parameters in the config are correctly set, or whether the data passed to the inference interface during inference is correct.

In other cases, please feedback the specific operator or minimum recurrence model to the Rockchip NPU team for further analysis.

4.2.2 Troubleshooting for quantized model accuracy

- First, check whether the inference result of the float model is correct, following the previous section to achieve it; if correct, proceed to the next step.
- Using *accuracy_analysis* interface for accuracy analysis. You can also refer to the method in the previous section to manually export the inference results of each layer, comparing with the original frame inference results to find the layers that caused the loss of accuracy.
- Analyze the layers with reduced accuracy.

  After quantization, the accuracy may decrease in the following three situations:

  - RKNN Toolkit has problems with the matching of this layer of operators. Or the driver has problems on the implementation of this operator (the inference result of this layer is usually very different from the result of the float model, and the cosine distance is less than 0.5). For this case, using hybrid quantization can always get a better result.
  - The data distribution of this layer (such as weight of convolution) is not friendly to quantization (for example, the data distribution range It is relatively wide, and the accuracy loss is serious after low-precision expression). For this case, using MMSE or KL divergence quantization method may help. Otherwise considering using hybrid quantization with the higher-precision method for the quantization-unfriendly operator. After all, trying to do the quantization with the original framework, such as TensorFlow or PyTorch for quantization-

aware-training, and then convert the quantized model to RKNN model.

- Some graph optimizations done by RKNN Toolkit or NPU may cause accuracy to decrease, such as replacing add or average pool with convolution. In this case, you can try to lower the optimization level (like setting the optimization_level to 2 or 1 in the config interface).

If the accuracy of the model still cannot meet the requirements after trying the above methods, please feedback the relevant model, accuracy analysis results and accuracy test methods to the Rockchip NPU team for further analysis.

Note:

1. For detail in using the accuracy analysis function, please refer to chapter 4.3

2. For detail of the MMSE quantization parameter optimization algorithm, please refer to chapter 4.4.

3. For detail in using hybrid quantization interfaces, please refer to chapter 4.5.

4.3 Accuracy analysis

4.3.1 Function description

The accuracy analysis function of RKNN Toolkit can save the intermediate results of each layer of floating-point model and quantitative model inference, and use Euclidean distance and cosine distance to evaluate their similarity. By observing the changes in the similarity of each layer, you can initially locate which operators have incorrect calculation results or are unfriendly to quantization.

4.3.2 Usage steps

The usage steps of the quantized model accuracy analysis function are as follows:

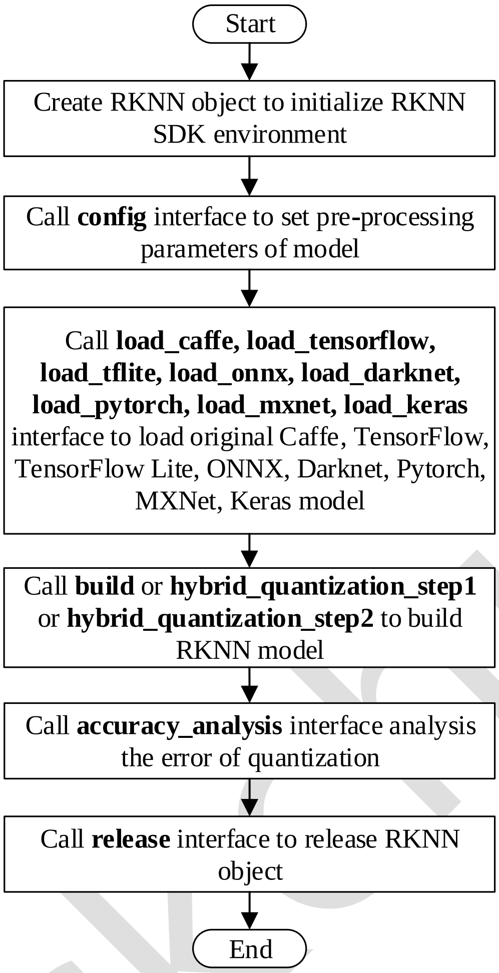

Start
Create RKNN object to initialize RKNN SDK environment
Call **config** interface to set pre-processing parameters of model
Call **load_caffe, load_tensorflow, load_tflite, load_onnx, load_darknet, load_pytorch, load_mxnet, load_keras** interface to load original Caffe, TensorFlow, TensorFlow Lite, ONNX, Darknet, Pytorch, MXNet, Keras model
Call **build** or **hybrid_quantization_step1** or **hybrid_quantization_step2** to build RKNN model
Call **accuracy_analysis** interface analysis the error of quantization
Call **release** interface to release RKNN object
End

Figure 4-3-2-1 Quantitative accuracy analysis use process

Note:

1. The quantitative method to be analyzed needs to be specified in config.

2. The inputs specified in accuracy_analysis can only contain one row of data.

3. The calling order of the above interfaces cannot be changed.

4.3.3 Output file

The directory structure of the accuracy analysis output is as follows:

```
├── entire_qnt
├── entire_qnt_error_analysis.txt
├── fp32
├── individual_qnt
├── individual_qnt_error_analysis.txt
```

The meaning of each file/directory is as follows:

- Directory entire_qnt: Save the results of each layer when the entire quantitative model is fully run (The data has been converted to float32).
- File entire_qnt_error_analysis.txt: Record the cosine distance/Euclidean distance between each layer result and the floating-point model during the complete calculation of the quantized model, and the normalized cosine distance/Euclidean distance. The smaller the cosine distance or the larger the Euclidean distance, the greater the decrease in accuracy after quantization.
- Directory fp32: Save the results of each layer when the entire floating-point model is completely run down, and correspond to the original model according to the order of the order.txt records in the directory. If the result of the floating-point model itself is not correct, please compare the results of each layer in the catalog with the results of each layer in the original framework inference to determine which layer is the problem. Then feedback to the Rockchip NPU team.
- Directory individual_qnt: Split the quantitative model into layers and run layer by layer. The input of each layer during inference is the result of the previous layer's inference in the floating point model. This can avoid accumulated errors.
- File individual_qnt_error_analysis.txt: Record the cosine distance/Euclidean distance between the result of each layer and the floating-point model when the quantized model is run layer by layer, and the normalized cosine distance/Euclidean distance. The smaller the cosine distance or the larger the Euclidean distance, the greater the decrease in accuracy after quantization.

If the target is set, the following content will appear in the directory:

```
├── individual_qnt_error_analysis_on_npu.txt
└── qnt_npu_dump
```

- File individual_qnt_error_analysis_on_npu.txt: Record the cosine distance/Euclidean distance between the result of each layer and the floating-point model when the quantized model runs layer by layer on the hardware device, and the normalized cosine distance/Euclidean distance. The smaller the cosine distance or the larger the Euclidean distance, the greater the decrease in accuracy after quantization.

- Directory qnt_npu_dump: Split the quantized model into layers and put them to run on the NPU device one by one. The input used is the result of the previous layer of the floating-point model. This directory saves the result of the quantized model when it is actually run on the NPU layer by layer (The data has been converted to float32).

4.4 Optimized Quantization

RKNN Toolkit provides two methods of quantization parameter optimization: MMSE and KL divergence, which search for the optimal combination of quantitative parameters according to their respective algorithms to improve accuracy.

If you want to use the MMSE quantization parameter optimization method, specify the value of the quantized_algorithm parameter as "mmse" in the config interface, and if you want to use the KL dispersion method, specify the value of the parameter as "kl_divergence".

4.5 Hybrid quantization

The quantization function provided by RKNN-Toolkit can ensure the accuracy of the model as much as possible on the basis of improving the speed of model inference. However, there are still some special models that have more accuracy drops after quantization. In order to achieve a better balance between performance and accuracy, RKNN-Toolkit has provided hybrid quantization function starting from version 1.0.0. Users can specify whether each layer should be quantized, and the quantization parameters can also be modified.

Note:

1. The examples/common_function_demos directory provides a hybrid quantization example named hybrid_quantization. Users can refer to this example for hybrid quantification practice.

4.5.1 Instructions of hybrid quantization

Currently, RKNN-Toolkit has three kind of ways to use hybrid quantization:

1. Convert quantized layer to non-quantized layer (for example: using float32). Due to the low non-quantitative computing power on the NPU, the inference speed will be reduced to a certain extent
2. Convert non-quantized layer to quantized layer.
3. Modify quantization parameters of pointed quantized layer.

4.5.2 Hybrid quantization profile

When using the hybrid quantization feature, the first step is to generate a hybrid quantization profile, which is briefly described in this section.

When the hybrid quantization interface hybrid_quantization_step1 is called, a YAML configuration file named “{model_name}.quantization.cfg” is generated in the current directory. The configuration file format is as follows：

```
%YAML 1.2
---
# add layer name and corresponding quantized_dtype to customized_quantize_layers, e.g conv2_3: float32
customized_quantize_layers: {}
quantize_parameters:
    ‘@attach_concat_1/out0_0:out0’:
        dtype: asymmetric_affine
        method: layer
        max_value:
        -    10.097497940063477
        min_value:
        -    -52.340476989746094
        zero_point:
        -    214
        scale:
        -    0.24485479295253754
        qtype: u8

……

    ‘@FeatureExtractor/MobilenetV2/Conv/Conv2D_230:bias’:
        dtype: asymmetric_affine
        method: layer
```

```
            max_value:
            min_value:
            zero_point: 0
            scale:
            -    0.00026041566161438823
            qtype: i32
```

First line is the version of yaml. Second line is separator. Third line is comment. Followed by the main content of the configuration file.

The first line of the body of the configuration file is a dictionary of customized quantize layers, add the layer names and their corresponding quantized type(choose from **asymmetric_affine-u8, dynamic_fixed_point-i8, dynamic_fixed_point-i16, float32**) to be changed to customized quantize layers. Since version 1.6.0, the first step of hybrid quantization will give the layers that may improve the accuracy according to certain rules, and specify the quantization method as dynamic_fixed_point-i16. These layers are for reference only. If you only want to modify the following quantization parameters without using other quantization methods, you need to add {} after this line.

Next is a list of model layers, each layer is a dictionary. The key of each dictionary is composed of @{layer_name}_{layer_id}:[weight/bias/out{port}], where layer_name is the name of this layer and layer_id is an identification of this layer. RKNN-Toolkit usually quantize weight/bias/out when do quantization, and use multiple out0, out1, etc. for multiple outputs. The value of the dictionary is the quantization parameter. If the layer is not be quantized, there is only “dtype” item, and the value of “dtype” is None.

4.5.3 Usage flow of hybrid quantization

When using the hybrid quantization function, the specific steps are carried out in four steps.

Step1, load the original model and generate a quantize configuration file, a model structure file and a model weight bias file. The specific interface call process is as follows:

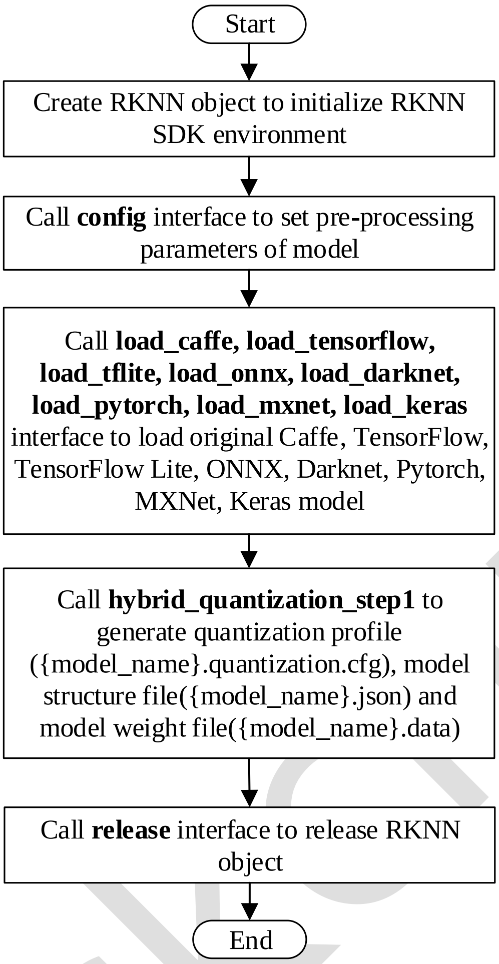

Start
Create RKNN object to initialize RKNN SDK environment
Call **config** interface to set pre-processing parameters of model
Call **load_caffe, load_tensorflow, load_tflite, load_onnx, load_darknet, load_pytorch, load_mxnet, load_keras** interface to load original Caffe, TensorFlow, TensorFlow Lite, ONNX, Darknet, Pytorch, MXNet, Keras model
Call **hybrid_quantization_step1** to generate quantization profile ({model_name}.quantization.cfg), model structure file({model_name}.json) and model weight file({model_name}.data)
Call **release** interface to release RKNN object
End

Figure 4-5-3-1 call process of hybrid quantization step 1

Step 2, Modify the quantization configuration file generated in the first step.

- If some quantization layers is changed to a non-quantization layer, find the layer that is not to be quantized, and add these layers name and float32 to customized_quantize_layers, such as "<layername>: float32". Other quantization methods can also be used. For example, the original asymmetric_affine-u8 is used, but it can also be changed to dynamic_fixed_point-i8 or dynamic_fixed_point-i16. But a model can only have two quantitative methods at most at the same time. The layer name is best enclosed in double quotes to avoid parsing failure due to special characters.
- If some layers are changed from non-quantization to quantization, add these layers named and corresponding quantize type to customized_quantize_layers, such as "<layername>: asymmetric_affine-u8".

- If the quantization parameter is to be modified, directly modify the quantization parameter of the specified layer.

Note: The quantization config file will give some suggestions for hybrid quantization since version 1.6.0. This suggestions are for reference only.

Step 3, generate hybrid quantized RKNN model. The specific interface call flow is as follows:

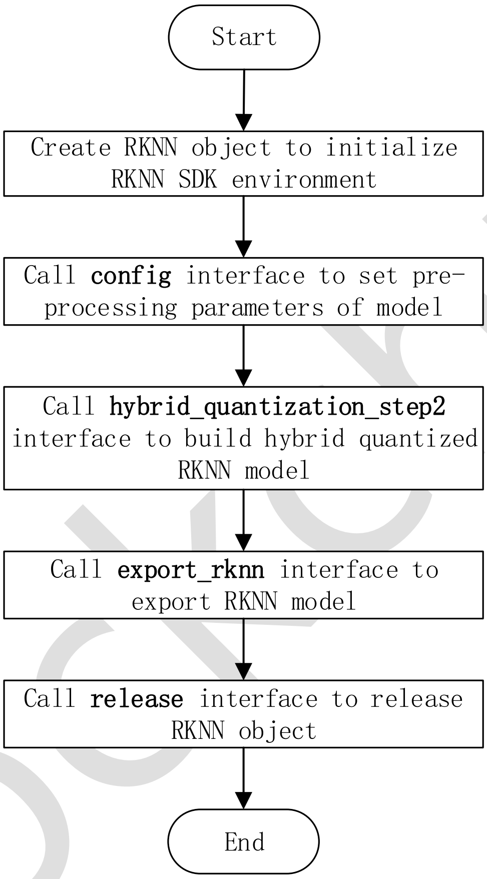

Start
Create RKNN object to initialize RKNN SDK environment
Call config interface to set pre-processing parameters of model
Call hybrid_quantization_step2 interface to build hybrid quantized RKNN model
Call export_rknn interface to export RKNN model
Call release interface to release RKNN object
End

Figure 3-3-3-2 call process of hybrid quantization step 3

Step 4, use the RKNN model generated in the previous step to inference.

4.6 FAQs

For accuracy evaluation FAQs, please refer to the documentation *Rockchip_Trouble_Shooting_RKNN_Toolkit_EN* for Chacter 3.

5 Performance evaluation

This section will explain in detail for performance evaluation methods, optimization methods，common problems about RKNN model.

5.1 Evaluation method

RKNN Toolkit provides model performance evaluation interface eval_perf. This interface can evaluate the inference-time for the model run on Rockchip NPU. The evalutation record inference-time for both full-model and each layer .

The main inferfaces and their config parameters involved in the performance evaluation step are as follows:

- init_runtime: Initialize the runtime environment. The **target** and **perf_debug** parameters determine the target device during performance evaluation and whether to evaluate the time-consuming of each layer.
- eval_perf: Performance evaluation interface. Calling this interface will return the time used for each inference of the RKNN model on the specified device according to the parameters set by the init_runtime interface. If the **perf_debug** parameter is set to True, the inference-time information of each layer will also be returned. The **loop_cnt** parameter of this interface can specify the number of loop inferences.

  Note:

  1. If evaluated on the simulator, no matter whether **perf_debug** is set to True or not, the inference-time information of each layer will be given. The evaluation result with the simulator may differ from that of the actual EVB board, and it is recommended to perform the evaluation with the connection of EVB board before model deployment.
  2. If the **perf_debug** parameter sets True, in order to collect the inference-time information of each layer, the NPU driver will repeatedly recall some code in each layer, resulting in a total inference-

time higher than the actual case, which is normal and needn’t worry about it.

3. For more detail about init_runtime and eval_perf interfaces, please refer to chapters 7.7 and 7.9.

5.2 Evaluation example

Please refer to the following code to use the RKNN Toolkit interface to complete the performance evaluation:

```
import cv2
import torch
import numpy as np
from rknn.api import RKNN

RKNN_PATH = './resnet18.rknn'

def eval_perf_with_simulator():
    # create RKNN object
    rknn = RKNN()

    # load RKNN model resnet_18 from current directory
    ret = rknn.load_rknn(path=RKNN_PATH)
    if ret != 0:
        print('Load Pytorch model failed!')
        exit(ret)

    # init RKNN runtime
    ret = rknn.init_runtime()
    if ret != 0:
        print('Init runtime environment failed')
        exit(ret)

    # call eval_perf interface to do performance evaluation
    rknn.eval_perf()

    # release RKNN object
    rknn.release()

def eval_perf_with_rk1808():
    # create RKNN object
    rknn = RKNN()

    # load RKNN model resnet_18 from current directory
    ret = rknn.load_rknn(path=RKNN_PATH)
    if ret != 0:
        print('Load Pytorch model failed!')
        exit(ret)

    # init RKNN runtime
    ## The default perf_debug is False.
## If you want to evaluate the time-consuming of each layer, set the value of this
## parameter to True
    ret = rknn.init_runtime(target='rk1808', device_id='1808', perf_debug=True)
    if ret != 0:
        print('Init runtime environment failed')
        exit(ret)

    # call eval_perf interface to do performance evaluation
# loop_cnt specifies the number of loops and returns the average time
    rknn.eval_perf(loop_cnt=100)

    # release RKNN object
    rknn.release()

if __name__ == '__main__':

   # Use the simulator for performance evaluation (only available on x86_64 Linux)
   # eval_perf_with_simulator()

   # Use RK1808 for performance evaluation
   eval_perf_with_rk1808()
```

Note: For models with higher fps, it is recommended to set loop_cnt to a larger value to obtain stable performance data.

5.3 Description of evaluation results

The simulator evaluation results are slightly different from the evaluation results on the development board. The following sections describe their evaluation results respectively.

5.3.1 Description of simulator performance evaluation results

Examples of simulator performance evaluation results are as follows:

```
Layer ID     Name                                      Time(us)
3            convolution.relu.pooling.layer2_2         238
4            pooling.layer2_3                           240
7            convolution.relu.pooling.layer2_2         126
8            convolution.relu.pooling.layer2_2         140
11           convolution.relu.pooling.layer2_2         84
14           convolution.relu.pooling.layer2_2         141
15           convolution.relu.pooling.layer2_2         141
18           convolution.relu.pooling.layer2_2         84
21           convolution.relu.pooling.layer2_2         192
22           convolution.relu.pooling.layer2_2         131
24           convolution.relu.pooling.layer2_2         37
27           convolution.relu.pooling.layer2_2         52
30           convolution.relu.pooling.layer2_2         131
31           convolution.relu.pooling.layer2_2         131
34           convolution.relu.pooling.layer2_2         52
37           convolution.relu.pooling.layer2_2         220
38           convolution.relu.pooling.layer2_2         184
40           convolution.relu.pooling.layer2_2         32
43           convolution.relu.pooling.layer2_2         38
46           convolution.relu.pooling.layer2_2         184
47           convolution.relu.pooling.layer2_2         184
50           convolution.relu.pooling.layer2_2         38
53           convolution.relu.pooling.layer2_2         430
54           convolution.relu.pooling.layer2_2         710
56           convolution.relu.pooling.layer2_2         51
59           convolution.relu.pooling.layer2_2         63
62           convolution.relu.pooling.layer2_2         710
63           convolution.relu.pooling.layer2_2         710
66           convolution.relu.pooling.layer2_2         63
67           pooling.layer2                              17
69           fullyconnected.relu.layer_3                 57
Total Time(us): 5611
FPS(600MHz): 133.67
FPS(800MHz): 178.22
Note: Time of each layer is converted according to 800MHz!
```

The simulator performance evaluation results consist of the following:

- Inference-time layer by layer: includes the layer ID, the layer name and the inference-time of the layer (calculated according to the 800MHz NPU frequency).
- Total Time: in microseconds.
- FPS (600MHz): The frame rate calculated according to the 600MHz NPU frequency;
- FPS (800MHz): The frame rate calculated according to the 800MHz NPU frequency.

Note:

1. When using the simulator for performance evaluation, the simulated NPU is determined by the **target_platform** of the model, which is specified by the **target_platform** of the config during the model conversion phase.
2. The performance evaluated by the simulator may deviate from the actual performance. It is recommended to use the development board for evaluation.

5.3.2 Description of the performance evaluation results of the development board

When perf_debug is set to False, only the average inference time (unit is us) and the corresponding frame rate are printed.

For example:

```
==============================================================
    Average inference Time(us): 5438.98
    FPS: 183.86
==============================================================
```

When **perf_debug** sets True, the performance evaluation result consists of the following:

- inference-time layer by layer: includes layer ID, layer name, operator name, UID and the inference-time;
- Total time: the inference-time of the whole model.
- FPS: The frame rate calculated according to the total time.

When perf_debug sets True, the performance evaluation results of the development board are as follows:

```
===================================================================
Layer ID    Name                              Operator          Uid   Time(us)
2           convolution_at_input0.1_1_1_2     CONVOLUTION        1     2739
0           max_pooling_at_input.10_4_4_0     POOLING            4     482
3           convolution_at_input.14_5_5_2     CONVOLUTION        5     315
4           convolution_at_input.13_8_8_2     CONVOLUTION        8     263
23          add_at_input.15_10_10_2           CONVOLUTION       10     236
5           convolution_at_input.17_12_12_2   CONVOLUTION       12     252
6           convolution_at_input.19_15_15_2   CONVOLUTION       15     238
24          add_at_input.20_17_17_2           CONVOLUTION       17     234
7           convolution_at_input.21_19_19_2   CONVOLUTION       19     336
9           convolution_at_input.23_22_22_2   CONVOLUTION       22     239
8           convolution_at_input.24_24_24_0   RESHUFFLE          24     444
                                              CONVOLUTION
25          add_at_input.25_26_26_2           CONVOLUTION       26     186
10          convolution_at_input.26_28_28_2   CONVOLUTION       28     238
11          convolution_at_input.28_31_31_2   CONVOLUTION       31     236
26          add_at_input.29_33_33_2           CONVOLUTION       33     181
12          convolution_at_input.30_35_35_2   CONVOLUTION       35     310
14          convolution_at_input.32_38_38_2   CONVOLUTION       38     261
13          convolution_at_input.33_40_40_0   RESHUFFLE         40    447
                                              CONVOLUTION
27          add_at_input.34_42_42_2           CONVOLUTION       42     184
15          convolution_at_input.35_44_44_2   CONVOLUTION        44     260
16          convolution_at_input.37_47_47_2   CONVOLUTION        47     255
28          add_at_input.38_49_49_2           CONVOLUTION        49     122
17          convolution_at_input.6_51_51_2    CONVOLUTION        51     359
19          convolution_at_input.5_54_54_2    CONVOLUTION        54     556
18          convolution_at_input.8_56_56_0    RESHUFFLE          56     387
                                              CONVOLUTION
29          add_at_input.9_58_58_2            CONVOLUTION        58     487
20          convolution_at_input.3_60_60_2    CONVOLUTION        60     739
21          convolution_at_input.1_63_63_2    CONVOLUTION        63     666
30          add_at_input.2_65_65_2            CONVOLUTION        65     202
1           avg_pooling_at_x.1_67_67_1        POOLING            67     417
22          linear_at_539_70_69_0             FULLYCONNECTED    69     388
Total Time(us): 12659
FPS: 79.00
===================================================================
```

5.4 Common performance optimization methods

1. If the model initialization cost too much time, please refer to chapter 3.4.4 for model pre-compilation.

2. If RKNN C API used for deployment, and setting input or obtaining inference results takes too much time, please refer to the document *Rockchip_User_Guide_RKNN_API_EN.pdf* for optimization.
3. Refer to the *Rockchip_Trouble_Shooting_RKNN_Toolkit.pdf* document for the optimizing advices of convolutional neural networks. Try to optimize the network structure and improve the performance of the model on Rockchip NPU.

6 Memory evaluation

This section explains in detail how to use the RKNN Toolkit interface to obtain the memory usage of the RKNN model at runtime.

6.1 Evaluation method

RKNN Toolkit provides the RKNN model memory evaluation interface eval_memory. This interface can evaluate the memory usage of the RKNN model during inference on Rockchip NPU.

Note: Cannot use simulator for memory evaluation.

6.2 Evaluation example

Please refer to the following code to use the RKNN Toolkit interface to complete the memory evaluation.

```
from rknn.api import RKNN

RKNN_PATH = './resnet18.rknn'

def eval_mem_with_rk1808():
    # Create RKNN object
    rknn = RKNN()

    # load RKNN model resnet_18 from current directory
    ret = rknn.load_rknn(path=RKNN_PATH)
    if ret != 0:
        print('Load Pytorch model failed!')
        exit(ret)

    # init RKNN runtime
    ## Set eval_mem to True to enter the memory evaluation mode
    ret = rknn.init_runtime(target='rk1808', device_id='1808', eval_mem=True)
    if ret != 0:
        print('Init runtime environment failed')
        exit(ret)

     # Call the eval_memory interface to count the memory usage of the model when it is
inferencing
    rknn.eval_memory()
```

```
        # Release RKNN object
        rknn.release()

if __name__ == '__main__':

    # Do memory evaluation on RK1808 EVB board.
    eval_mem_with_rk1808()
```

6.3 Description of evaluation results

The memory evaluation interface returns the memory usage of the RKNN model inference, encapsulated in the dictionary memory_detail. The memory_detail consists of the following:

```
{
    'system_memory', {
        'maximum_allocation': 128000000,
        'total_allocation': 152000000
    },
    'npu_memory', {
        'maximum_allocation': 30000000,
        'total_allocation': 40000000
    },
    'total_memory', {
        'maximum_allocation': 158000000,
        'total_allocation': 192000000
    }
}
```

- system_memory: System memory allocated by non-NPU drivers, including memory allocated in the system for models and input data.
- npu_memory: Indicates the memory allocated by the NPU driver during model inference.
- total_memory: the sum of system_memory and npu_memory.
- maximum_allocation: the peak memory usage, the unit is Byte. Indicates the maximum allocation value of memory from the beginning to the end of the model inference.
- total_allocation: represents the sum of all memory allocated during the operation of the RKNN model.

7 RKNN-Toolkit API description

This chapter explains in detail how to use each interface of RKNN Toolkit.

7.1 RKNN object initialization and release

Before using any API interface of RKNN Toolkit, RKNN object must be determine by call RKNN(). After all the task finished, call release() to release the RKNN object.

When the RKNN object is initing, the users can set **verbose** and **verbose_file** parameters, which allow showing detailed log information of model loading, building and so on. The data type of verbose parameter is bool. If the value sets True, the RKNN-Toolkit will show detailed log information on screen. The data type of verbose_file is string. If the value sets with a file path, the detailed log information will be written to this file (**verbose** also need set True). If running error occurs and the **verbose_file** is not set, the error log will be automatically written to the log_feedback_to_the_rknn_toolkit_dev_team.log file.

When feedback error information to Rockchip NPU team, it is recommended to feedback the complete log.

The sample code is as follows:

```
# Show the detailed log information on screen, and saved to
# mobilenet_build.log
rknn = RKNN(verbose=True, verbose_file='./mobilenet_build.log')
# Only show the detailed log information on screen.
rknn = RKNN(verbose=True)
…
rknn.release()
```

7.2 RKNN model configuration

Before the RKNN model is built, the model needs to be configured first through the **config** interface.

API	**config**
Description	Set model parameters
Parameter	**batch_size**: The size of each batch of data sets. The default value is 100. When quantifying, the amount of data fed in each batch will be determined according to this parameter to correct the quantization results. If the amount of data in the dataset is less than batch_size, this parameter will automatically adjust the amount of data in the dataset. If there is insufficient memory during quantization, it is recommended to set this value to a smaller value, such as 8.
	mean_values: The mean values of the input. This parameter and the channel_mean_value parameter can not be set at the same time. The parameter format is a list. The list contains one or more mean sublists. The multi-input model corresponds to multiple sublists. The length of each sublist is consistent with the number of channels of the input. For example, if the parameter is [[128,128,128]], it means an input subtract 128 from the values of the three channels. If reorder_channel is set to "2 1 0", the channel adjustment will be done first, and then the average value will be subtracted.
	std_values: The normalized value of the input. This parameter and the channel_mean_value parameter can not be set at the same time. The parameter format is a list. The list contains one or more normalized value sublists. The multi-input model corresponds to multiple sublists. The length of each sublist is consistent with the number of channels of the input. For example, if the parameter is [[128,128,128]], it means the value of the three channels of an input minus the average value and then divide by 128. If reorder_channel is set to "2 1 0", the channel adjustment will be performed first, followed by subtracting the mean value and dividing by the normalized value.
	epochs: Number of iterations in quantization. Quantization parameter calibration is

	performed with specified data at each iteration. Default value is -1, in this situation, the number of iteration is automatically calculated based on the amount of data in the dataset.
	reorder_channel: A permutation of the dimensions of input image **(for three-channel input only, other channel formats can be ignored)**. The new tensor dimension i will correspond to the original input dimension reorder_channel[i]. For example, if the original image is RGB format, ‘2 1 0’ indicates that it will be converted to BGR. If there are multiple inputs, the corresponding parameters for each input is split with ‘#’, such as ’0 1 2#0 1 2’. Default value of this parameter is None, for Caffe model which input is 3 channel, it means input channel will be reversed, for other framework, the input will not be reversed. **Note**: each value of reorder_channel must not be set to the same value.
	need_horizontal_merge: Indicates whether to merge horizontal, the default value is False. If the model is inception v1/v3/v4, it is recommended to enable this option, it can improve the performance of inference.
	quantized_dtype: Quantization type, the quantization types currently supported are asymmetric_quantized-u8,dynamic_fixed_point-i8,dynamic_fixed_point-i16. The default value is asymmetric_quantized-u8.
	quantized_algorithm: Quantization parameter optimization algorithm. Currently supported algorithms are “normal”, “mmse” and “kl_divergence”, and the default value is “normal”. Among them, the normal algorithm is characterized by faster speed. The mmse algorithm, because of the need to adjust the quantization parameters many times, its speed will be much slower, but it can usually get higher accuracy than the normal algorithm. The “kl_divergence” algorithm will take more time than normal, but will be much less than mmse. In some scenarios, better improvement effects can be obtained by “kl_divergence”.
	mmse_epoch: The number of iterations of the mmse quantization algorithm, the default value is 3. Generally, the more iterations, the higher the accuracy.

	optimization_level: Model optimization level. By modifying the model optimization level, you can turn off some or all of the optimization rules used in the model conversion process. The default value of this parameter is 3, and all optimization options are turned on. When the value is 2 or 1, turn off some optimization options that may affect the accuracy of some models. Turn off all optimization options when the value is 0.
	target_platform: Specify which target chip platform the RKNN model is based on. RK1806, RK1808, RK3399Pro, RV1109 and RV1126 are currently supported. The RKNN model generated based on RK1806, RK1808 or RK3399pro can be used on both platforms, and the RKNN model generated based on RV1109 or RV1126 can be used on both platforms. If the model is to be run on RK1806, RK1808 or RK3399Pro, the value of this parameter can be ["rk1806"], ["rk1808"], ["rk3399pro"] or ["rk1806", "rk1808", "rk3399pro"], etc. If the model is to be run on RV1109 or RV1126, the value of this parameter can be ["rv1126"], ["rv1109"] or ["rv1109", "rv1126"], etc. But you cannot fill in ["rk1808", "rv1109"], because these two chips are incompatible, the RKNN model generated based on them cannot be run on another chip platform. If this parameter is not set, the default is ["rk1808"], and the generated RKNN model can be run on RK1806, RK1808 and RK3399Pro platforms.
	quantize_input_node: If sets True, regardless of whether the entire model is quantized in the build phase, the input-node will be forced to be quantized. Generally, model with quantized input-node consumes less time while using rknn_input_set interface on NPU devices. Consider to set True when RKNN-Toolkit does not quantize the input-nodes of model as it supposed to be done(in this case, only support model with image as input), or converting a quantized model, generated by others DL framework(in this case, if first layer is quantize_layer, it will be merged into the input node). The default value is False.
	merge_dequant_layer_and_output_node: Merge the model output-node and the last layer(need to be dequantize-layer) into a quantized output-node, allowing the model to return uint8 or float type inference results on NPU devices. This configuration is only

	effective when loading quantized model generated by other DL framework. The default is False.
Return Value	None

The sample code is as follows:

```
# model config
rknn.config(mean_values=[[103.94, 116.78, 123.68]],
            std_values=[[58.82, 58.82, 58.82]],
            reorder_channel=’0 1 2’,
            need_horizontal_merge=True,
            target_platform=[’rk1808’, ’rk3399pro’])
```

7.3 Loading non-RKNN model

RKNN-Toolkit currently supports Caffe, Darknet, Keras, MXNet, ONNX, PyTorch, TensorFlow, TensorFlow Lite. There are different interfaces when loading models, the loading interfaces for these frameworks are described in detail below.

7.3.1 Loading Caffe model

API	**load_caffe**
Description	Load Caffe model
Parameter	**model**: The path of Caffe model structure file (suffixed with “.prototxt”).
	proto: Caffe model format (valid value is ‘caffe’ or ‘lstm_caffe’). Plaese use ‘lstm_caffe’ when the model is RNN model.
	blobs: The path of Caffe model binary data file (suffixed with “.caffemodel”). The value can be None, RKNN-Toolkit will randomly generate parameters such as weights.
Return Value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load the mobilenet_v2 Caffe model in the current path
ret = rknn.load_caffe(model='./mobilenet_v2.prototxt',
                      proto='caffe',
                      blobs='./mobilenet_v2.caffemodel')
```

7.3.2 Loading Darknet model

API	**load_darknet**
Description	Load Darknet model
Parameter	**model**: The path of Darknet model structure file (suffixed with “.cfg”).
	weight: The path of weight file (suffixed with “.weight”).
Return Value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load the yolov3-tiny darknet model in the current path
ret = rknn.load_darknet(model = './yolov3-tiny.cfg',
                        weight= './yolov3.weights')
```

7.3.3 Loading Keras model

API	**load_keras**
Description	Load Keras model
Parameter	**model**: The path of Keras model file (suffixed with “.h5”)
Return Value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load the keras xception model in the current path
ret = rknn.load_keras(model=’./xception_v3.h5’)
```

7.3.4 Loading MXNet model

API	**load_mxnet**
Description	Load MXNet model
Parameter	**symbol**：Network structure file of MXNet model, suffixed with “json”. Required.
	params：Network parameters file of MXNet model, suffixed with “params”. Required.
	input_size_list：The size and number of channels of each input node. For example, [[1,224,224],[3,224,224]] means there are two inputs. One of the input shapes is [1, 224, 224], and the other input shape is [3, 224, 224]. Required.
Return Value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load the mxnet model resnext50 in the current path
ret = rknn.load_mxnet(symbol='resnext50_32x4d-symbol.json',
                      params='resnext50_32x4d-4ecf62e2.params',
                      input_size_list=[[3,224,224]])
```

7.3.5 Loading ONNX model

API	**load_onnx**
Description	Load ONNX model
Parameter	**model**: The path of ONNX model file (suffixed with “.onnx”)
	inputs: Specify model input nodes. The data type is list. For example, in the resnet50v2 model in the demo, the input node is ['data']. Default value of this parameter is None, the toolkit will query input nodes from model. Optional.
	input_size_list: Specify the shapes of model input tensors. For example, in the resnet50v2 model in the demo, the input tensor shape is [[3, 224, 224]]. Optional. **Note:** **1. Do not fill in the batch dimension when filling in the input data shape. If you want to batch inference, please use the rknn_batch_size parameter of the build interface.** 2. **If the inputs node is specified, this parameter must be filled in.**
	outputs: Specify model output nodes. The data type is list. For example, in the resnet50v2 model in the demo, the output node is ['resnetv24_dense0_fwd']. Default value of this parameter is None, the toolkit will query output nodes from model. Optional.
Return Value	0: Import successfully
	-1: Import failed

Note:

Since RKNN Toolkit version 1.7.0, quantized ONNX model is supported to load. The currently supported quantization model is obtained through the static quantization method of onnxruntime (version 1.5.0 to 1.5.2). For related quantification methods, please refer to the link below:

https://onnxruntime.ai/docs/how-to/quantization.html

The sample code is as follows:

```
# Load the resnet50v2 onnx model in the current path
ret = rknn.load_onnx(model = './resnet50v2.onnx',
                     inputs = ['data'],
                     input_size_list = [[3, 224, 224]],
                     outputs=['resnetv24_dense0_fwd'])
```

7.3.6 Loading PyTorch model

API	**load_pytorch**
Description	Load PyTorch model
Parameter	**model**：The path of PyTorch model structure file (suffixed with “.pt”), and need a model in the torchscript format. Required.
	input_size_list：The size and number of channels of each input node. For example, [[1,224,224],[3,224,224]] means there are two inputs. One of the input shapes is [1, 224, 224], and the other input shape is [3, 224, 224]. Required.
Return Value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load the PyTorch model resnet18 in the current path
ret = rknn. load_pytorch(model = './resnet18.pt',
                         input_size_list=[[3,224,224]])
```

7.3.7 Loading TensorFlow model

API	**load_tensorflow**
Description	Load TensorFlow model
Parameter	**tf_pb**: The path of TensorFlow model file (suffixed with ".pb").
	inputs: The input node of model, input with multiple nodes is supported now. All the input node string are placed in a list.
	input_size_list: The size and number of channels of the image corresponding to the input node. As in the example of mobilenet_v1 model, the input_size_list parameter should be set to [224,224,3].
	outputs: The output node of model, output with multiple nodes is supported now. All the output nodes are placed in a list.
	predef_file: In order to support some controlling logic, a predefined file in npz format needs to be provided. This predefined fie can be generated by the following function call: np.savez('prd.npz', [placeholder name]=prd_value)。 If there are / in placeholder name, use # to replace.
Return value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load ssd_mobilenet_v1_coco_2017_11_17 TF model in the current path
ret = rknn.load_tensorflow(
        tf_pb='./ssd_mobilenet_v1_coco_2017_11_17.pb',
        inputs=['FeatureExtractor/MobilenetV1/MobilenetV1/Conv2d_0
                 /BatchNorm/batchnorm/mul_1'],
        outputs=['concat', 'concat_1'],
        input_size_list=[[300, 300, 3]])
```

7.3.8 Loading TensorFlow Lite model

API	**load_tflite**

Description	Load TensorFlow Lite model. Note: RKNN-Toolkit uses the tflite schema commits as in link: https://github.com/tensorflow/tensorflow/commits/master/tensorflow/lite/schema/schema.fbs commit hash: 0c4f5dfea4ceb3d7c0b46fc04828420a344f7598 Because the tflite schema may not compatible with each other, tflite models in older or newer schema may not be imported successfully.
Parameter	**model**: The path of TensorFlow Lite model file (suffixed with ".tflite").
Return Value	0: Import successfully
	-1: Import failed

The sample code is as follows:

```
# Load the mobilenet_v1 TF-Lite model in the current path
ret = rknn.load_tflite(model = './mobilenet_v1.tflite')
```

7.4 Building RKNN model

API	**build**
Description	Build corresponding RKNN model according to the loaded model structure and weight data.
Parameter	**do_quantization**: Whether to quantize the model, optional values are True and False.
	dataset: A input data set for rectifying quantization parameters. Currently supports text file format, the user can place the path of picture(jpg or png) or npy file which is used for rectification. A file path for each line. Such as: a.jpg b.jpg or a.npy b.npy If there are multiple inputs, the corresponding files are divided by space. Such as: a.jpg a2.jpg b.jpg b2.jpg or a.npy a2.npy b.npy b2.npy
	pre_compile: Model precompilation switch. Pre-compiled RKNN model can reduce model initialization time, but cannot be used for reasoning or performance evaluation through the simulator. If the NPU driver is updated, the pre-compiled model usually needs to be rebuilt. **Note:** **1. The pre_compile is only supported on x86_64 Linux.** **2. Pre-compiled model generated by RKNN-Toolkit-v1.0.0 or later can not run on device installed old driver (NPU driver version < 0.9.6), and pre-compiled model**

	generated by old RKNN-Toolkit (version < 1.0.0) can not run on device installed new NPU driver (NPU drvier version >= 0.9.6). The get_sdk_version interface can be called to fetch driver version.
	rknn_batch_size：batch size of input, default is 1. If greater than 1, NPU can inference multiple frames of input image or input data in one inference. For example, original input of MobileNet is [1, 224, 224, 3], output shape is [1, 1001]. When rknn_batch_size is set to 4, the input shape of MobileNet becomes [4, 224, 224, 3], output shape becomes [4, 1001]. **Note：** **1. The adjustment of rknn_batch_size does not improve the performance of the general model on the NPU, but it will significantly increase memory consumption and increase the delay of single frame.** **2. The adjustment of rknn_batch_size can reduce the consumption of the ultra-small model on the CPU and improve the average frame rate of the ultra-small model. (Applicable to the model is too small, CPU overhead is greater than the NPU overhead)** **3. The value of rknn_batch_size is recommended to be less than 32, to avoid the memory usage is too large and the reasoning fails.** **4. After the rknn_batch_size is modified, the shape of input and output will be modified. So the inputs of inference should be set to correct size. It`s also needed to process the returned outputs on post processing.**
Return value	0: Build successfully
	-1: Build failed

Note: If the RKNN_DRAW_DATA_DISTRIBUTE environment variable sets 1 before executing the script, the RKNN Toolkit will save the histogram of each layer`s weight, bias (if available) and output data in the dump_data_distribute folder in the current directory during quantization. When exporting the historgram of data, it is recommended to put only one set of input data in the calibration dataset.

The sample code is as follows:

```
# Build and quantize RKNN model
ret = rknn.build(do_quantization=True, dataset='./dataset.txt')
```

7.5 Export RKNN model

The RKNN model built by this tool can be exported and stored as an RKNN model file through this interface for model deployment.

API	**export_rknn**
Description	Save RKNN model in the specified file (suffixed with “.rknn”).
Parameter	**export_path**: The path of generated RKNN model file.
Return Value	0: Export successfully
	-1: Export failed

The sample code is as follows:

```
# save the built RKNN model as a mobilenet_v1.rknn file in the current     # path
ret = rknn.export_rknn(export_path = './mobilenet_v1.rknn')
```

7.6 Loading RKNN model

API	**load_rknn**
Description	Load RKNN model
Parameter	**path**: The path of RKNN model file.
	load_model_in_npu: Whether to load RKNN model in NPU directly. The path parameter should fill in the path of the model in NPU. It can be set to True only when RKNN-Toolkit run on RK3399Pro Linux or NPU device(RK3399Pro, RK1808 or TB-RK1808 AI Compute Stick) is connected. Default value is False.
Return Value	0: Load successfully
	-1: Load failed

The sample code is as follows:

```
# Load the mobilenet_v1 RKNN model in the current path
ret = rknn.load_rknn(path='./mobilenet_v1.rknn')
```

7.7 Initialize the runtime environment

Before model inference or performance evaluation, the runtime environment must be initialized, and the operating platform of the model (specific target hardware platform or software simulator) must be clarified.

API	**init_runtime**
Description	Initialize the runtime environment. Set the device information (hardware platform, device ID). Determine whether to enable debug mode to obtain more detailed performance information for performance evaluation.
Parameter	**target**: Target hardware platform, now supports "rk3399pro", "rk1806", "rk1808", "rv1109", "rv1126". The default value is "None", which indicates model runs on default hardware platform and system. Specifically, if RKNN-Toolkit is used in PC, the default device is simulator, and if RKNN-Toolkit is used in RK3399Pro Linux development board, the default device is RK3399Pro. The "rk1808" includes TB-RK1808 AI Compute Stick.
	device_id: Device identity number, if multiple devices are connected to PC, this parameter needs to be specified which can be obtained by calling "***list_devices***" interface. The default value is "None ". Note: Mac OS X platform does not supple multiple devices.
	perf_debug: Debug mode option for performance evaluation. In debug mode, the running time of each layer can be obtained, otherwise, only the total running time of model can be given. The default value is False.
	eval_mem: Whether enter memory evaluation mode. If set True, the eval_memory interface can be called later to fetch memory usage of model running. The default value is False.
	async_mode: Whether to use asynchronous mode. When calling the inference interface, it involves setting the input picture, model running, and fetching the inference result. If the asynchronous mode is enabled, setting the input of the current frame will be performed simultaneously with the inference of the previous frame, so in addition to the first frame,

	each subsequent frame can hide the setting input time, thereby improving performance. In asynchronous mode, the inference result returned each time is the previous frame. The default value for this parameter is False.
Return Value	0: Initialize the runtime environment successfully
	-1: Initialize the runtime environment failed

The sample code is as follows:

```
# Initialize the runtime environment
ret = rknn.init_runtime(target='rk1808', device_id='012345789AB')
if ret != 0:
     print('Init runtime environment failed')
     exit(ret)
```

7.8 Inference with RKNN model

Before model inference, an RKNN model must be built or loaded first.

API	**inference**
Description	Use the model to perform inference with specified input and get the inference result. Detailed scenarios are as follows: 1. If RKNN-Toolkit is running on PC and the target is set to Rockchip NPU when initializing the runtime environment, the inference of model is performed on the specified hardware platform. 2. If RKNN-Toolkit is running on PC and the target is not set when initializing the runtime environment, the inference of model is performed on the simulator. The simulator can simulate RK1808 or RV1126. Which chip to simulate depends on the target_platform parameter value of the RKNN model 3. If RKNN-Toolkit is running on RK3399Pro Linux development board, the inference of model is performed on the actual hardware.
Parameter	**inputs**: Inputs to be inferred, such as images processed by cv2. The object type is ndarray list.
	data_type: The numerical type of input data. Optional values are ’float32’, ‘float16’, ‘int8’, ‘uint8’, ‘ing16’. The default value is ’uint8’.
	data_format: The shape format of input data. Optional values are “nchw”, “nhwc”. The default value is ‘nhwc’.
	inputs_pass_through: Pass the input transparently to the NPU driver. In non-transparent mode, the tool will reduce the mean, divide the variance, etc. before the input is passed to the NPU driver; in transparent mode, these operations will not be performed. The value of this parameter is an array. For example, to pass input0 and not input1, the value of this parameter is [1, 0]. The default value is None, which means that all input is not transparent.
Return	**results**: The result of inference, the object type is ndarray list。

Value	

The sample code is as follows (refer to *example/tfilte/mobilenet_v1* for the complete code):

```
# Preform inference for a picture with a model and get a top-5 result
……
outputs = rknn.inference(inputs=[img])
show_outputs(outputs)
……
```

The result of top-5 is as follows:

```
-----TOP 5-----
[156]: 0.85107421875
[155]: 0.09173583984375
[205]: 0.01358795166015625
[284]: 0.006465911865234375
[194]: 0.002239227294921875
```

For more examples, please refer to other demos in SDK/examples/.

7.9 Evaluate model performance

API	**eval_perf**
Description	Evaluate model performance. Detailed scenarios are as follows: 1. If running on PC and not setting the target when initializing the runtime environment, the performance information is obtained from simulator, which contains the running time of each layer and the total running time of model. 2. If running on Rockchip NPU device which connected to PC and setting perf_debug to False when initializing runtime environment, the performance information is obtained from Rockchip NPU, which only contains the total running time of model. And if the perf_debug is set to True, the running time of each layer will also be captured in detail. 3. If running on RK3399Pro Linux development board and setting perf_debug to False when initializing runtime environment, the performance information is obtained from RK3399Pro, which only contains the total running time of model. And if the perf_debug is set to True, the running time of each layer will also be captured in detail.
Parameter	**loop_cnt**: Specify the number of inferences of the RKNN model to calculate the average inference time. This parameter only takes effect when perf_debug of init_runtime is False and evaluating performance on hardware.
Return Value	**perf_result**: Performance information. For details, please refer to chapter 5.3

The sample code is as follows:

```
# Evaluate model performance
……
rknn.eval_perf(inputs=[image], is_print=True)
……
```

7.10 Evaluating memory usage

API	**eval_memory**
Description	Fetch memory usage when model is running on hardware platform. Model must run on Rockchip NPU devices. Note: When users use this API, the driver version must on 0.9.4 or later. Users can get driver version via get_sdk_version interface.
Parameter	**is_print**: Whether to print performance evaluation results in the canonical format. The default value is True.
Return Value	**memory_detail**：Memory usage during model inference. For details, please refer to chapter 6.3.

The sample code is as follows:

```
# eval memory usage
……
memory_detail = rknn.eval_memory()
……
```

For tflite/mobilenet_v1 in example directory, the memory usage shows as follows:

```
==============================================
                    Memory Profile Info Dump
==============================================
System memory:
       maximum allocation : 22.65 MiB
       total allocation      : 72.06 MiB
NPU memory:
       maximum allocation : 33.26 MiB
       total allocation      : 34.57 MiB

Total memory:
       maximum allocation : 55.92 MiB
       total allocation      : 106.63 MiB

INFO: When evaluating memory usage, we need consider
the size of model, current model size is: 4.10 MiB
==============================================
```

7.11 Hybrid Quantization

7.11.1 hybrid_quantization_step1

When using the hybrid quantization function, the main interface called in the first phase is hybrid_quantization_step1, which is used to generate the model structure file ({model_name}.json), the weight file ({model_name}.data), and the quantization configuration file ({model_name}.quantization. Cfg). Interface details are as follows：

API	**hybrid_quantization_step1**
Description	Corresponding model structure files, weight files, and quantization profiles are generated according to the loaded original model.
Parameter	**dataset**: A input data set for rectifying quantization parameters. Currently supports text file format, the user can place the path of picture(jpg or png) or npy file which is used for rectification. A file path for each line. Such as: a.jpg b.jpg or a.npy b.npy
Return Value	0: success
	-1: failure

The sample code is as follows：

```
# Call hybrid_quantization_step1 to generate quantization config
……
ret = rknn.hybrid_quantization_step1(dataset='./dataset.txt')
……
```

7.11.2 hybrid_quantization_step2

When using the hybrid quantization function, the primary interface for generating a hybrid quantized RKNN model phase call is hybrid_quantization_step2. The interface details are as follows:

API	**hybrid_quantization_step2**
Description	The model structure file, the weight file, the quantization profile, and the correction data set are received as inputs, and the hybrid quantized RKNN model is generated.
Parameter	**model_input**: The model structure file generated in the first step, which is shaped like "{model_name}.json". The data type is a string. Required parameter.
	data_input: The model weight file generated in the first step, which is shaped like "{model_name}.data". The data type is a string. Required parameter.
	model_quantization_cfg: The modified model quantization profile, whick is shaped like "{model_name}.quantization.cfg". The data type is a string. Required parameter.
	dataset: A input data set for rectifying quantization parameters. Currently supports text file format, the user can place the path of picture(jpg or png) or npy file which is used for rectification. A file path for each line. Such as: a.jpg b.jpg or a.npy b.npy
	pre_compile: Model precompilation switch. Pre-compiled RKNN model can reduce model initialization time, but cannot be used for reasoning or performance evaluation through the simulator. If the NPU driver is updated, the pre-compiled model usually needs to be rebuilt. **Note:** **1. The pre_compile is only supported on x86_64 Linux.** **2. Pre-compiled model generated by RKNN-Toolkit-v1.0.0 or later can not run on**

	device installed old driver (NPU driver version < 0.9.6), and pre-compiled model generated by old RKNN-Toolkit (version < 1.0.0) can not run on device installed new NPU driver (NPU drvier version >= 0.9.6). The get_sdk_version interface can be called to fetch driver version.
Return Value	0: success
	-1: failure

The sample code is as follows：

```
# Call hybrid_quantization_step2 to generate hybrid quantized RKNN model
……
ret = rknn.hybrid_quantization_step2(
            model_input='./ssd_mobilenet_v2.json',
            data_input='./ssd_mobilenet_v2.data',
            model_quantization_cfg='./ssd_mobilenet_v2.quantization.cfg',
            dataset='./dataset.txt')
……
```

7.12 Accuracy analysis

This interface compares the inference results of each layer of the floating-point model and the quantized model, and is used to analyze the problem of the accuracy decline after the quantization of the model.

API	**accuracy_analysis**
Description	This interface will compare the output results of the floating-point model and the quantized model layer by layer, and show the cosine distance and Euclidean distance. It is used to analyze the reasons for the decline in the accuracy of the quantitative model. **Note:** 1. **this interface can be called after build or hybrid_quantization_step1 or hybrid_quantization_step2, and the original model should be a non-quantized model, otherwise the call will fail.** **2. The quantization method used by this interface is consistent with the setting in config.**
Parameter	**inputs**: The dataset file that include input image or data. (same as “dataset” parameter of build, see section “Building RKNN model”, but only can include one set of input)
	output_dir: The output directory, all snapshot data will stored here. For a detailed description of the contents of this directory, see section 4.3.3.
	calc_qnt_error: Whether to calculate quantitative error. (default is True)
	target: Specify target device. If target is set, in the individual quantization error analysis, the toolkit will connect to the NPU to obtain the real results of each layer. Then compared with the float result. It can more accurately reflect the actual runtime error.
	device_id: Used to specify the ID of the specific device.
	dump_file_type: The accuracy analysis process will dump the results of each layer of the model. This parameter specifies the type of the output file. Valid values are ‘tensor’ and ‘npy’, the default value is ‘tensor’. If specify the data type as 'npy', the time-consuming of

	this interface can be reduced.
Return Value	0: success
	-1: failure

Note: If the RKNN_DRAW_DATA_DISTRIBUTE environment variable is set to 1 before executing the script, the RKNN Toolkit will save the histogram of each layer`s weight, bias (if any) and output data in the dump_data_distribute folder in the current directory during quantization. When exporting the historgram of data, it is recommended to put only one set of input data in the calibration dataset.

The sample code is as follows：

```
......

print('--> config model')
rknn.config(channel_mean_value='0 0 0 1', reorder_channel='0 1 2')
print('done')

print('--> Loading model')
ret = rknn.load_onnx(model='./mobilenetv2-1.0.onnx')
if ret != 0:
    print('Load model failed! Ret = {}'.format(ret))
    exit(ret)
print('done')

# Build model
print('--> Building model')
ret = rknn.build(do_quantization=True, dataset='./dataset.txt')
if ret != 0:
    print('Build rknn failed!')
    exit(ret)
print('done')

print('--> Accuracy analysis')
rknn.accuracy_analysis(inputs='./dataset.txt', target='rk1808')
print('done')

......
```

7.13 Register Custom OP

API	**register_op**
Description	Register custom op.
Parameter	**op_path**: rknnop file path of custom op build output
Return Value	Void

The sample code is as follows. Note that this interface need be called before model converted. Please refer to the "Rockchip_Developer_Guide_RKNN_Toolkit_Custom_OP_CN" document for the use and development of custom operators.

```
rknn.register_op('./resize_area/ResizeArea.rknnop')

rknn.load_tensorflow(…)
```

7.14 Export a pre-compiled model(online pre-compilation)

When building an RKNN model, you can specify pre-compilation options(set pre_compile=True) to export the pre-compiled model, which is called offline compilation. Similarly, RKNN-Toolkit also provides an interface for online compilation: export_rknn_precompile_model. Using this interface, you can convert ordinary RKNN models into pre-compiled models.

API	**export_rknn_precompile_model**
Description	Export the pre-compiled model after online compilation. Note: 1. Before using this interface, you must first call the load_rknn interface to load the normal rknn model; 2. Before using this interface, the init_runtime interface must be called to initialize the model running environment. The target must be an RK NPU device, not a simulator; and the rknn2precompile parameter must be set to True.
Parameter	**export_path**: Export model path. Required.
Return Value	0: success
	-1: failure

The sample code is as follows：

```
from rknn.api import RKNN

if __name__ == '__main__':
    # Create RKNN object
    rknn = RKNN()

    # Load rknn model
    ret = rknn.load_rknn('./test.rknn')
    if ret != 0:
        print('Load RKNN model failed.')
        exit(ret)

    # init runtime
    ret = rknn.init_runtime(target='rk1808', rknn2precompile=True)
    if ret != 0:
        print('Init runtime failed.')
        exit(ret)

    # Note: the rknn2precompile must be set True when call init_runtime
    ret = rknn.export_rknn_precompile_model('./test_pre_compile.rknn')
    if ret != 0:
        print('export pre-compile model failed.')
        exit(ret)

    rknn.release()
```

7.15 Export a segmentation model

The function of this interface is to convert the ordinary RKNN model into a segment model, and the position of the segment is specified by the user.

API	**export_rknn_sync_model**
Description	Insert a sync layer after the user-specified layer to segment the model and export the segmented model.
Parameter	input_model: the model which need segment. Data type is string, required.
	sync_uids: uids of the layer which need insert sync layer. Note: 1. Uid can be obtained through the eval_perf interface, and perf_debug should be set to True when call init_runtime interface. When we want to obtain uids, we need connect a RK1806 or RK1808 or TB-RK1808 AI Compute Stick or RV1109 or RV1126. 2. The value of sync_uids cannot be filled in at will. It must be obtained by eval_perf interface, Otherwise unpredictable consequences may occur.
	output_model: export rknn model path.
Return Value	0: success
	-1: failure

The sample code is as follows：

```
from rknn.api import RKNN

if __name__ == '__main__':
    rknn = RKNN()
    ret = rknn.export_rknn_sync_model(
input_model='./ssd_inception_v2.rknn',
                  sync_uids=[206, 186, 152, 101, 96, 67, 18, 17],
                  output_model='./ssd_inception_v2_sync.rknn')
    if ret != 0:
        print('export sync model failed.')
        exit(ret)
    rknn.release()
```

7.16 Export encrypted RKNN model

API	**export_encrypted_rknn_model**
Description	The common RKNN model is encrypted according to the encryption level specified by the user.
Parameter	input_model: The path of the RKNN model to be encrypted. String. Required.
	output_model: Save path of encrypted model. String. Optional, if None, the {original_model_name}.crypt.rknn will be save path of encrypted model.
	crypt_level: Crypt level. The higher the level, the higher the security and the more time-consuming decryption; on the contrary, the lower the security, the faster the decryption. Integer. Optional, default value is 1. Currently, support level 1, 2 or 3.
Return Value	0: Success
	-1: Failure.

The sample code is as follows：

```
from rknn.api import RKNN

if __name__ == '__main__':
    rknn = RKNN()
    ret = rknn.export_encrypted_rknn_model('test.rknn')
    if ret != 0:
        print('Encrypt RKNN model failed.')
        exit(ret)
    rknn.release()
```

7.17 Get SDK version

API	**get_sdk_version**
Description	Get API version and driver version of referenced SDK. Note: Before use this interface, users must load model and initialize runtime first. And this interface can only be used when the target is Rockchip NPU or RKNN-Toolkit running on RK3399Pro Linux development board.
Parameter	None
Return Value	**sdk_version**：API and driver version. Data type is string.

The sample code is as follows：

```
# Get SDK version
……
sdk_version = rknn.get_sdk_version()
……
```

The SDK version looks like below：

```
==============================================
RKNN VERSION:
        API: 1.7.1 (566a9b6 build: 2021-10-28 14:53:41)
        DRV: 1.7.1 (566a9b6 build: 2021-11-12 20:24:57)
==============================================
```

7.18 List Devices

API	**list_devices**
Description	List connected RK3399PRO/RK1808/TB-RK1808S0 AI Compute Stick/RV1109/RV1126. Note: There are currently two device connection modes: ADB and NTB. RK1808 and RV1109/RV1126 support both ADB and NTB, RK3399Pro only support ADB, TB-RK1808 AI Compute Stick only support NTB. Make sure their modes are the same when connecting multiple devices
Parameter	None

Return Value	Return adb_devices list and ntb_devices list. If there are no devices connected to PC, it will return two empty list.
	For example, there are two TB-RK1808 AI Compute Sticks connected to PC, it`s return looks like below:
	`adb_devices = []`
	`ntb_devices = ['TB-RK1808S0', '515e9b401c060c0b']`

The sample code is as follows：

```
from rknn.api import RKNN

if __name__ == '__main__':
       rknn = RKNN()
       rknn.list_devices()
       rknn.release()
```

The devices list looks like below：

```
*************************
all device(s) with adb mode:
['515e9b401c060c0b', 'XGOR2N4EZR']
*************************
```

Note: When using multiple devices, you need to ensure that their connection modes are consistent, otherwise it will cause conflicts and cause device communication to fail.

7.19 Query RKNN model runnable platform

API	**list_support_target_platform**
Description	Query the chip platform that a given RKNN model can run on.
Parameter	**rknn_model**: RKNN model path. If the model path is not specified, the chip platforms currently supported by the RKNN-Toolkit are printed by category
Return Value	support_target_platform (dict):

The sample code is as follows:

```
rknn.list_support_target_platform(rknn_model='mobilenet_v1.rknn')
```

The runnable chip platforms look like below：

```
**************************************************
Target platforms filled in RKNN model:          []
Target platforms supported by this RKNN model: ['RK1806', 'RK1808', 'RK3399PRO']
**************************************************
```

8 Appendix

8.1 Reference documents

OP support list:

RKNN_OP_Support.md

RKNN Toolkit manual:

Rockchip_User_Guide_RKNN_Toolkit_EN.pdf

Quick start manual:

Rockchip_Quick_Start_RKNN_Toolkit_EN.pdf

Trouble shooting manual:

Rockchip_Trouble_Shooting_RKNN_Toolkit_EN.pdf

Custom OP define manual:

Rockchip_Developer_Guide_RKNN_Toolkit_Custom_OP_EN.pdf

Visualization function manual:

Rockchip_User_Guide_RKNN_Toolkit_Visualization_EN.pdf

RKNN Toolkit Lite manual:

Rockchip_User_Guide_RKNN_Toolkit_Lite_EN.pdf

The above documents can be found in the SDK/doc directory. You can also visit the following link to view: https://github.com/rockchip-linux/rknn-toolkit/tree/master/doc

8.2 Issue feedback

All the issue can be feedback via the follow ways:

QQ group: 1025468710

Github link: https://github.com/rockchip-linux/rknn-toolkit/issues

Rockchip Redmine: https://redmine.rock-chips.com/

Note: Redmine account can only be registered by an authorized sales. If your

development board is from the third-party manufacturer, please contact them to report the issue.