Security Class: Top-Secret ( ) Secret ( ) Internal ( ) Public (√)

RKNN-Toolkit Quick Start

(Technology Department, Graphic Computing Platform Center)

Mark: [ ] Editing [√] Released	Version	V1.7.0
	Author	Rao Hong
	Completed Date	2021-08-10
	Auditor	Vincent
	Reviewed Date	2021-08-10

瑞芯微电子股份有限公司

Rockchip Electronics Co., Ltd

Revision History

Version no.	Author	Revision Date	Revision description	Auditor
V0.9.9	Rao Hong	2019-03-25	Initial version release	Vincent
V1.0.0	Rao Hong	2019-05-08	Synchronize the modification contents of RKNN-Toolkit-V1.0.0	Vincent
V1.1.0	Rao Hong	2019-06-28	1. Synchronize the modification contents of RKNN-Toolkit-V1.1.0 2. Rename document, from <RKNN-Toolkit Quick Setup Guide> to <RKNN-Toolkit Quick Start> 3. Add quick start for Windows/Mac OS X/ARM64 platform.	Vincent
V1.2.0	Rao Hong	2019-08-21	Synchronize the modification contents of RKNN-Toolkit-V1.2.0	Vincent
V1.2.1	Rao Hong	2019-09-26	Synchronize the modification contents of RKNN-Toolkit-V1.2.1	Vincent
V1.3.0	Rao Hong	2019-12-23	Synchronize the modification contents of RKNN-Toolkit-V1.3.0	Vincent
V1.3.2	Rao Hong	2020-04-03	Synchronize the modification contents of RKNN-Toolkit-V1.3.2	Vincent
V1.4.0	Rao Hong	2020-08-13	Synchronize the modification contents of RKNN-Toolkit-V1.4.0	Vincent
V1.6.0	Rao Hong	2020-12-31	Synchronize the modification contents of RKNN-Toolkit-V1.6.0	Vincent
V1.6.1	Rao Hong	2021-05-21	Synchronize the modification contents of RKNN-Toolkit-V1.6.1	Vincent
v1.7.0	Xing Zheng	2021-08-10	Synchronize the modification contents of RKNN-Toolkit-V1.7.0	Vincent

Content

1 Main Features Introduction

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 to convert Caffe、TensorFlow、TensorFlow Lite、ONNX、Darknet、Pytorch、MXNet or Keras model to RKNN model, support RKNN model import/export, which can be used on Rockchip NPU platform later. Support for multiple input models since version 1.2.0. Support for Pytorch and MXNet since version 1.3.0. 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 support quantized methods including asymmetric quantization (asymmetric_quantized-u8) and dynamic fixed point quantization (dynamic_fixed_point-8 and dynamic_fixed_point-16). Since version 1.0.0, RKNN-Toolkit began to support hybrid quantization. Since version 1.6.1, RKNN Toolkit provides quantized parameter optimization algorithm MMSE. Since version 1.7.0, RKNN-Toolkit support loading quantized ONNX model.

3） Model inference: Able to simulate Rockchip NPU to run RKNN model on PC and get the inference result. This tool can also distribute the RKNN model to the specified NPU device to run, and get the inference results.

4） Performance evaluation: Able to simulate Rockchip NPU to run RKNN model on PC, and evaluate model performance (including total time and time-consuming information of each layer). This tool can also distribute the RKNN model to the specified NPU device to run, and evaluate the model performance in the actual device.

5） Memory evaluation: Evaluate system and NPU memory consumption at runtime of the model. When using this function, he RKNN model must be distributed to the NPU device to run, and then call the relevant interface to obtain memory information. This feature is supported since version 0.9.9.

6） Model pre-compilation: with pre-compilation techniques, model loading time can be reduced, and for some models, model size can also be reduced. 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. The upgraded precompiled model is not compatible with the old driver. Since version 1.4.0, ordinary RKNN models can also be converted into precompiled models through NPU device. For details, please refer to the instructions for export_rknn_precompile_model.

7） Model segmentation: This function is used in a scenario where multiple models run simultaneously. A single model can be divided into multiple segments to be executed on the NPU, thereby adjusting the execution time of multiple models occupying the NPU, and avoiding other models because one model occupies too much execution time. RKNN-Toolkit supports this feature since version 1.2.0. Currently, only RK1806/RK1808/RV1109/RV1126 chips support this feature and the NPU driver version is 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 normally. 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. This function only supported TensorFlow model.

9） Quantitative error analysis: This function will give the Euclidean or cosine distance of each layer of inference results before and after the model is quantized. This can be used to analyze how quantitative error occurs, and provide ideas for improving the accuracy of quantitative models. This feature is supported from version 1.3.0. Since version 1.4.0, new feature called individual quantization accuracy analysis provided. The tool assigns the input of each layer at runtime as the correct floating point value, and then calculates the quantized error of the layer. This can avoid misjudgments caused by the accumulation of errors layer by layer, and more accurately reflect the influence of quantization on each layer itself.

10) Visualization: This function presents various functions of RKNN-Toolkit in the form of a 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. Add support for Keras model since version 1.6.0.

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 from version 1.3.0.

12) Model encryption: Use the specified encryption method to encrypt the RKNN model as a whole. This feature is supported since version 1.6.0.

2 System Dependency Introduction

This software development kit supports running on the Ubuntu, Windows, Mac OS X or Debian operating system. It is recommended to meet the following requirements in the operating system environment:

Table 1 Operating system environment

Operating system version	Ubuntu16.04（x64）or later Windows 7 (x64) or later Mac OS X 10.13.5 (x64) or later Debian 9.8 (x64) or later
Python version	3.5/3.6
Python library dependencies	'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.

3 Ubuntu platform Quick Start Guide

This chapter mainly describes how to quickly setup and use RKNN-Toolkit based on Ubuntu 16.04, Python3.5.

3.1 Environment Preparation

- One x86_64 bit computer with ubuntu16.04
- One RK1808 or RV1126 EVB board.
- Connect RK1808 (or RV1126) device to PC through OTG USB, use 'adb devices' command to check, and the result is as below:

```
rk@rk:~$ adb devices
List of devices attached
515e9b401c060c0b        device
c3d9b8674f4b94f6        device
```

The content marked in red is the device ID, the first is the RK1808 development board, and the second is the RV1126 development board.

3.2 Install RKNN-Toolkit（Take Python3.5 as example）

1. Install Python3.5

```
sudo apt-get install python3.5
```

2. Install pip3

```
sudo apt-get install python3-pip
```

3. Obtain RKNN-Toolkit install package, and then execute below steps:

   a) Enter package directory:

```
cd package/
```

b) Install Python dependency

```
pip3 install tensorflow==1.14.0
pip3 install mxnet==1.5.0
pip3 install torch==1.5.1 torchvision==0.4.0
pip3 install gluoncv
```

c) Install RKNN-Toolkit

```
sudo pip3 install rknn_toolkit-1.7.0-cp35-cp35m-linux_x86_64.whl
```

d) Check if RKNN-Toolkit is installed successfully or not

```
rk@rk:~/rknn-toolkit-v1.7.0/package$ python3
>>> from rknn.api import RKNN
>>>
```

The installation is successful if the import of RKNN module doesn't fail.

3.3 Execute the example attached in the install package

3.3.1 Simulate the running example on PC

RKNN-Toolkit has a built-in RK1808/RV1126 simulator which can be used to simulate the action of the model running on RK1808 or RV1126. If users want to simulate RV1126, it`s needed to set target_platform=['rv1126'] in config interface.

Here take mobilenet_v1 as example. mobilenet_v1 in the example is a Tensorflow Lite model, used for picture classification, and it is running on simulator.

The running steps are as below:

1. Enter examples/lite/mobilenet_v1 directory

```
rk@rk:~/rknn-toolkit-v1.7.0/package$ cd ../examples/lite/mobilenet_v1
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$
```

2. Execute test.py script

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$ python3 test.py
```

3. Get the results after the script execution as below:

```
--> config model
done
--> Loading model
done
--> Building model
done
--> Export RKNN model
done
--> Init runtime environment
done
--> Running model
mobilenet_v1
-----TOP 5-----
[156]: 0.8642578125
[155]: 0.083740234375
[205]: 0.01241302490234375
[284]: 0.006565093994140625
[194]: 0.002044677734375

done
--> Begin evaluate model performance
W When performing performance evaluation, inputs can be set to None to use fake inputs.
=====================================================================
                                 Performance
=====================================================================
Layer ID      Name                                    Time(us)
60            openvx.tensor_transpose_3                72
1             convolution.relu.pooling.layer2_2       370
3             convolution.relu.pooling.layer2_2       213
5             convolution.relu.pooling.layer2_2       186
7             convolution.relu.pooling.layer2_2       299
9             convolution.relu.pooling.layer2_2       99
11            convolution.relu.pooling.layer2_2       140
13            convolution.relu.pooling.layer2_2       103
15            convolution.relu.pooling.layer2_2       133
17            convolution.relu.pooling.layer2_2       102
19            convolution.relu.pooling.layer2_2       110
21            convolution.relu.pooling.layer2_2       169
23            convolution.relu.pooling.layer2_2       112
25            convolution.relu.pooling.layer2_2       108
27            convolution.relu.pooling.layer2_2       127
29            convolution.relu.pooling.layer2_2       210
31            convolution.relu.pooling.layer2_2       127
33            convolution.relu.pooling.layer2_2       210
35            convolution.relu.pooling.layer2_2       127
37            convolution.relu.pooling.layer2_2       210
```

```
39              convolution.relu.pooling.layer2_2              127
41              convolution.relu.pooling.layer2_2              210
43              convolution.relu.pooling.layer2_2              127
45              convolution.relu.pooling.layer2_2              210
47              convolution.relu.pooling.layer2_2              109
49              convolution.relu.pooling.layer2_2              172
51              convolution.relu.pooling.layer2_2              220
53              convolution.relu.pooling.layer2_2              338
55              pooling.layer2                                34
56              fullyconnected.relu.layer_3                    110
58              softmaxlayer2.layer                            39
Total Time(us): 4923
FPS(600MHz): 152.35
FPS(800MHz): 203.13
Note: Time of each layer is converted according to 800MHz!
========================================================================

done
```

The main operations of this example include: create RKNN object, model configuration, load TensorFlow Lite model, structure RKNN model, export RKNN model, load pictures and infer to get TOP5 result, evaluate model performance, release RKNN object.

Other demos in the examples directory are executed the same way as mobilenet_v1. These models are mainly used for classification, target detection and image segmentation.

3.3.2 Example running on RK1808

Here take mobilenet_v1 as example. mobilenet_v1 example in the tool package is running on PC simulator. If want to run the example on RK1808 EVB board, you can refer to below steps:

1. Enter examples/lite/mobilenet_v1 directory

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$
```

2. Modify the parameter of initializing environment variable in test.py script

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$ vim test.py
# find the method of initializing environment variable in script init_runtime, as below
ret = rknn.init_runtime()
# modify the parameter of the method
ret = rknn.init_runtime(target='rk1808', device_id=' 0123456789ABCDEF')
# save and exit
```

3. Execute test.py script, and then get the result as below:

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$ python test.py
--> config model
done
--> Loading model
done
--> Building model
done
--> Export RKNN model
done
--> Init runtime environment
done
--> Running model
mobilenet_v1
-----TOP 5-----
[156]: 0.85205078125
[155]: 0.09185791015625
[205]: 0.012237548828125
[284]: 0.006473541259765625
[194]: 0.0024929046630859375

done
--> Begin evaluate model performance
W When performing performance evaluation, inputs can be set to None to use fake inputs.
========================================================================
                              Performance
========================================================================
Total Time(us): 5499
FPS: 181.85
========================================================================

done
```

3.3.3 Example running on RV1126

Runing on RV1126 is similar to RK1808 EVB board. But when calling the config interface, it`s needed to specify target_platform as RV1126. In init_runtime, target also fills in RV1126. Specific steps are as follows：

1. Enter examples/lite/mobilenet_v1 directory

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$
```

2. Modify the parameter of config and initializing environment variable in test.py script

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$ vim test.py
# find the method of config in script, as below
rknn.config(channel_mean_value='128 128 128 128', reorder_channel='0 1 2')
# modify the parameter of this interface
rknn.config(channel_mean_value='128 128 128 128', reorder_channel='0 1 2', target_platform=['rv1126'])
# find the method of initializing environment variable in script init_runtime, as below
ret = rknn.init_runtime()
# modify the parameter of the method
ret = rknn.init_runtime(target='rv1126', device_id='c3d9b8674f4b94f6')
# save and exit
```

3. Execute test.py script, and then get the result as below:

```
rk@rk:~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$ python test.py
--> config model
done
--> Loading model
done
--> Building model
done
--> Export RKNN model
done
--> Init runtime environment
done
--> Running model
mobilenet_v1
-----TOP 5-----
[156]: 0.8603515625
[155]: 0.0833740234375
[205]: 0.0123443603515625
[284]: 0.00726318359375
[260]: 0.002262115478515625

done
--> Begin evaluate model performance
========================================================================
                              Performance
========================================================================
Total Time(us): 4759
FPS: 210.13
========================================================================

done
```

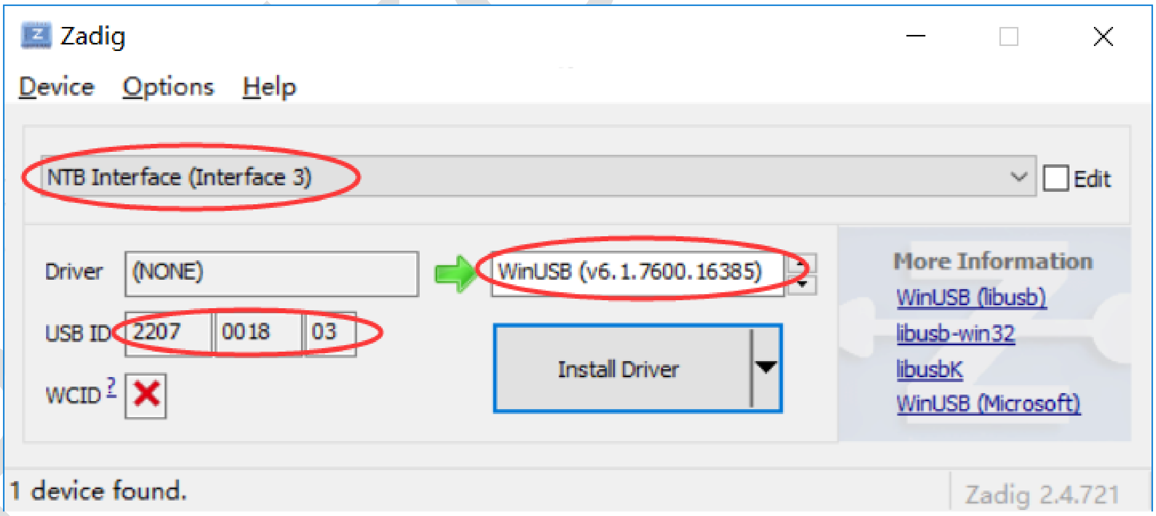
4 Windows platform Quick Start Guide

This chapter introduces how to use RKNN-Toolkit on Windows platforms with python 3.6.

4.1 Environmental preparations

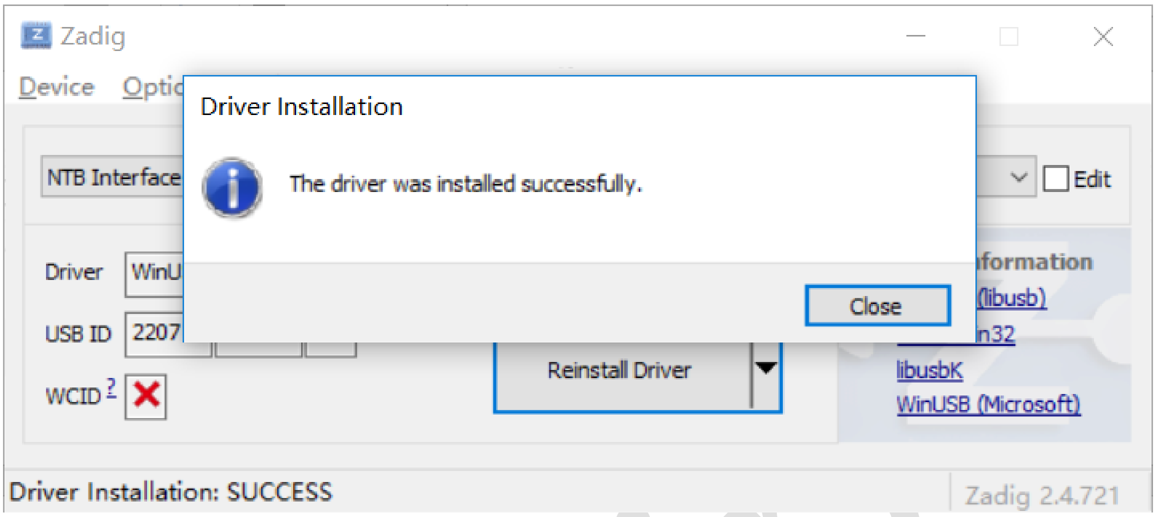
- One pc with Windows 7 (64bit) or Windows 10 (64bit).
- One RK1808 or RV1126 EVB board.
- Connect RK1808 (or RV1126) EVB board to PC through USB(OTG). If this is first time to use RK1808 (or RV1126) Compute Stick, we need install driver first. Installation method is as follows:
  - Open SDK package, and enter directory: platform-tools/drivers_installer/windows-x86_64, run the zadig-2.4.exe program as an administrator to install the computing stick driver:

    1. Confirm the equipment and the driver to be installed:

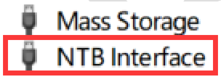


Note: The USB ID should start with **2207**; the driver choose default: WinUSB.

2. Click Install Driver.
3. If the installation is successful, the following interface will appear:



■ After installation, if the NTB Interface in the Windows Device Manager does not have an exclamation point, and as shown below, the installation is successful.



Note: Please reboot compute after installing driver.

4.2 Install RKNN-Toolkit

Before install RKNN-Toolkit, make sure python3.6 has been installed. This can be determined by executing python –version in cmd, as explained below. Python 3.6 is already installed on the system.

```
C:\Users\rk>python –version
Python 3.6.8
```

Get RKNN-Toolkit SDK package, then perform the following steps:

1. Enter directory: rknn-toolkit-v1.7.0/packages

```
D:\workspace\rknn-toolkit-v1.7.0>cd packages
```

2. Install Python dependency.

```
pip install tensorflow==1.14.0
pip install torch==1.6.0+cpu torchvision==0.7.0+cpu -f
https://download.pytorch.org/whl/torch_stable.html --user
pip install mxnet==1.5.0
pip install gluoncv
```

Note: gluoncv are used in example.

3. Install RKNN-Toolkit.

```
pip install rknn_toolkit-1.7.0-cp36-cp36m-win_amd64.whl
```

4. Check if RKNN-Toolkit is installed successfully or not.

```
D:\workspace\rknn-toolkit-v1.7.0\packages>python
Python 3.6.8 (tags/v3.6.8:3c6b436a57, Dec 24 2018, 00:16:47) [MSC v.1916 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license" for more information.
>>> from rknn.api import RKNN
>>>
```

4.3 Example running on RK1808

Take mobilenet_v1 as an example, which is a Tensorflow Lite model for image classification。

The running steps are as below:

1. Enter examples/lite/mobilenet_v1 directory.

```
D:\workspace\rknn-toolkit-v1.7.0\packages>cd ..\

D:\workspace\rknn-toolkit-v1.7.0>cd examples\lite\mobilenet_v1
```

2. Modify the parameter of initializing environment variable in test.py script.

```
#Befor modifying:
ret = rknn.init_runtime()
#After modifying:
ret = rknn.init_runtime(target='rk1808')
```

3. Run test.py script

```
D:\workspace\rknn-toolkit-v1.7.0\examples\lite\mobilenet_v1>python test.py
```

4. Get the TOP5 and performance after the script execution as below:

```
--> config model
done
--> Loading model
```

```
done
--> Building model
done
--> Export RKNN model
done
--> Init runtime environment
done
--> Running model
mobilenet_v1
-----TOP 5-----
[156]: 0.8828125
[155]: 0.06768798828125
[188 205]: 0.0086669921875
[188 205]: 0.0086669921875
[263]: 0.006366729736328125

done
--> Begin evaluate model performance
================================================
                                Performance
================================================
Total Time(us): 6032
FPS: 165.78
================================================

done
```

The main operations of this example include: create RKNN object, model configuration, load TensorFlow Lite model, structure RKNN model, export RKNN model, load pictures and infer to get TOP5 result, evaluate model performance, release RKNN object.

Other demos in the examples directory are executed the same way as mobilenet_v1. These models are mainly used for classification, target detection and image segmentation.

Note:

1. Simulator can not run on Windows platform. Therefore, Rockchip NPU devices must be connected to the Windows platform to use functions such as inference, performance evaluation and memory evaluation.

4.4 Example running on RV1126

When using RV1126 to run the example on the Windows platform, the modifications and the running steps are the same as the Ubuntu platform, so it won’t be repeated here.

5 Mac OS X platform Quick Start Guide

This chapter introduces how to use RKNN-Toolkit on Mac OS X platforms with python 3.6.

5.1 Environmental preparations

- One pc with MacOS High Sierra.
- One RK1808 or RV1126 EVB board.
- Connect RK1808 (or RV1126) EVB board to PC through USB(OTG), execute program 'npu_transfer_proxy' in directory 'platform-tools/ntp/mac-osx-x86_64', check weather EVB board has connected. Result should looks like below:

```
macmini:ntp rk$ ./npu_transfer_proxy devices
List of ntb devices attached
515e9b401c060c0b        2bed0cc1        USB_DEVICE
```

Note: The red line is the RK1808 EVB board. Device id is "515e9b401c060c0b".

5.2 Install RKNN-Toolkit

Get RKNN-Toolkit SDK package, then perform the following steps:

1. Enter directory: rknn-toolkit-v1.7.0/packages

```
cd packages/
```

2. Install Python dependency.

```
pip3 install tensorflow==1.14.0
pip3 install mxnet==1.5.0
pip3 install torch==1.6.0 torchvision==0.7.0
pip3 install gluoncv
```

Note: gluoncv are used in example.

3. Install RKNN-Toolkit.

```
pip3 install rknn_toolkit-1.7.0-cp36-cp36m-macosx_10_15_x86_64.whl
```

4. Check if RKNN-Toolkit is installed successfully or not.

```
(rknn-venv)macmini:rknn-toolkit-v1.7.0 rk$ python3
>>> from rknn.api import RKNN
>>>
```

5.3 Running the sample attached in the installation package

Take mobilenet_v1 as an example, which is a Tensorflow Lite model for image classification

The running steps are as below:

1. Enter examples/lite/mobilenet_v1 directory.

```
(rknn-venv)macmini:rknn-toolkit-v1.7.0 rk$ cd examples/lite/mobilenet_v1
```

2. Modify the parameter of initializing environment variable in test.py script.

```
#Befor modifying:
ret = rknn.init_runtime()
#After modifying:
ret = rknn.init_runtime(target='rk1808')
```

3. Run test.py script

```
(rknn-venv)macmini:mobilenet_v1 rk$ python3 test.py
```

4. Get the TOP5 and performance after the script execution as below:

```
--> config model
done
--> Loading model
done
--> Building model
done
--> Export RKNN model
done
--> Init runtime environment
done
--> Running model
mobilenet_v1
-----TOP 5-----
```

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

done
--> Begin evaluate model performance
========================================================
                               Performance
========================================================
Total Time(us): 6046
FPS: 165.40
========================================================

done
```

The main operations of this example include: create RKNN object, model configuration, load TensorFlow Lite model, structure RKNN model, export RKNN model, load pictures and infer to get TOP5 result, evaluate model performance, release RKNN object.

Other demos in the examples directory are executed the same way as mobilenet_v1. These models are mainly used for classification, target detection and image detection.

Note:

1. Simulator can not run on Mac OS X platform. Therefore, Rockchip NPU devices must be connected to the Windows platform to use functions such as inference, performance evaluation and memory evaluation.

5.4 Example running on RV1126

When using RV1126 to run the example on the Mac OS platform, the modifications and the running steps are the same as the Ubuntu platform, so it won't be repeated here.

6 ARM64 platform (Python 3.5) Quick Start Guide

This chapter introduces how to use RKNN-Toolkit on ARM64 platforms (Debian 9.8 systems) with python3.5.

6.1 Environmental preparations

- An RK3399Pro with Debian 9.8 operating system. Make sure that the remaining space of the root partition is greater than 5GB.
- If can not find npu_transfer_proxy or npu_transfer_proxy.proxy in /usr/bin directory, we need copy the npu_transfer_proxy in rknn-toolkit-v1.7.0\platform-tools\ntp\linux_aarch64 directory to /usr/bin/ directory, and go to the directory and execute the following command (you have to start the program after each reboot, so please add it to boot script):

```
sudo ./npu_transfer_proxy &
```

6.2 Install RKNN-Toolkit

1. Execute the following command to update the system packages which will be used later when installing Python dependencies.

```
sudo apt-get update
sudo apt-get install cmake gcc g++ libprotobuf-dev protobuf-compiler
sudo apt-get install liblapack-dev libjpeg-dev zlib1g-dev
sudo apt-get install python3-dev python3-pip python3-scipy
```

2. Execute the following command to update pip.

```
pip3 install --upgrade pip
```

3. Install Python package tool.

```
pip3 install wheel setuptools
```

4. Install dependency package h5py.

```
sudo apt-get build-dep python3-h5py && \
pip3 install h5py
pip3 install gluoncv
```

5. Install TensorFlow. Since there is no corresponding source on the debian9 system, you need to search for the wheel package on the Internet and install it.
6. Install torch and torchvision. Since there is no corresponding source on the debian9 system, you need to search for the wheel package on the Internet and install it.
7. Install mxnet. Since there is no corresponding source on the debian9 system, you need to search for the wheel package on the Internet and install it.
8. Install opencv-python. Since there is no corresponding source on the debian9 system, you need to search for the wheel package on the Internet and install it.
9. Install RKNN-Toolkit and the corresponding wheel package is in the rknn-toolkit-v1.7.0\packages directory

```
pip3 install rknn_toolkit-1.7.0-cp35-cp35m-linux_aarch64.whl --user
```

Note: Since some libraries that RKNN-Toolkit relies on need compile and install on the ARM64 platform after downloading the source code, this step will take a long time.

6.3 Running the sample attached in the installation package

Take mobilenet_v1 as an example, which is a Tensorflow Lite model for image classification.

The running steps are as below:

1. Enter examples/lite/mobilenet_v1 directory

```
linaro@linaro-alip:~/rknn-toolkit-v1.7.0/ $ cd examples/lite/mobilenet_v1
```

2. Run test.py script

```
linaro@linaro-alip: ~/rknn-toolkit-v1.7.0/examples/lite/mobilenet_v1$ python3 test.py
```

3. Get the results after the script execution as below:

```
--> config model
done
--> Loading model
done
--> Building model
done
--> Export RKNN model
done
--> Init runtime environment
done
--> Running model
mobilenet_v1
-----TOP 5-----
[156]: 0.85107421875
[155]: 0.09173583984375
[205]: 0.01358795166015625
[284]: 0.006465911865234375
[194]: 0.002239227294921875

done
--> Begin evaluate model performance
==============================================
                                    Performance
==============================================
Total Time(us): 5761
FPS: 173.58
==============================================

done
```

The main operations of this example include: create RKNN object, model configuration, load TensorFlow Lite model, structure RKNN model, export RKNN model, load pictures and infer to get TOP5 result, evaluate model performance, release RKNN object.

Other demos in the examples directory are executed the same way as mobilenet_v1. These models are mainly used for classification, target detection and image detection.

Note:

1. Simulator can not run on ARM64 platform, these models in example are running on built-in NPU of RK3399Pro.

7 Reference Document

For more detailed usage and interface descriptions of RKNN-Toolkit, please refer to <Rockchip_User_Guide_RKNN_Toolkit_V1.7.0_EN.pdf >.