

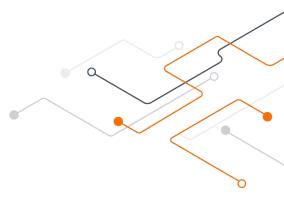


TensorFlow Lite

Lightweight cross-platform solution for mobile and embedded devices







Martin Andrews

Google Developer Expert, Machine Learning

Red Dragon Al



Why TensorFlow Lite?



ML runs in many places

- Access to more data
- Fast and closely knit interactions
- Privacy preserving







Creates many challenges

• Reduced compute power

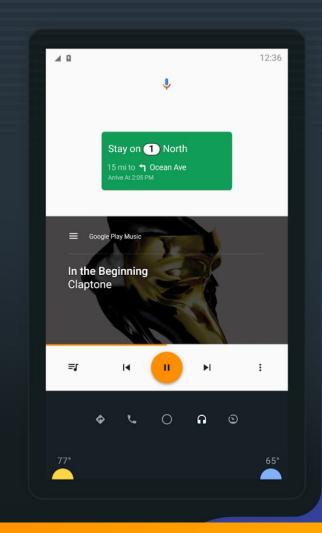






Creates many challenges

- Reduced compute power
- Limited memory







Creates many challenges

- Reduced compute power
- Limited memory
- Battery constraints







Simplifying ML on-device

TensorFlow Lite makes these challenges much easier!



What can I do with it?



Many use cases

Classification Prediction

Text

Speech Recognition Text to Speech OCR Speech to Text Facial modelling

Image

Segmentation

Compression

Super Resolution

Clustering

Object detection Object Location Gesture recognition

Translation

Voice Synthesis

Audio

Content

Video generation Text generation Audio generation



Who is using it?



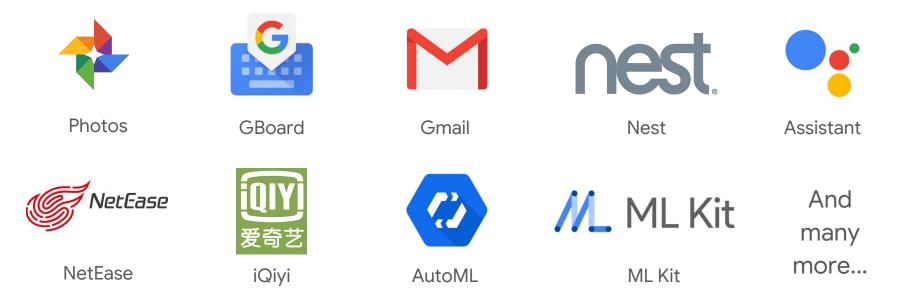
>2B mobile devices

Have TensorFlow Lite **deployed** on them **in production**





Some of the users ...

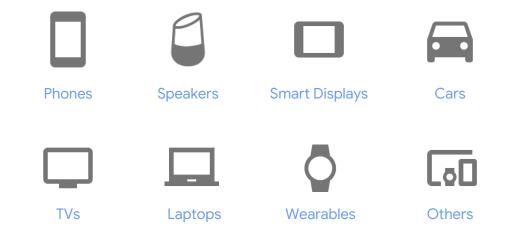






Google Assistant is on 1B+ devices

Wide range of devices: High/low end, arm, x86, battery powered, plugged in, many operating systems







Key Speech On-Device Capabilities

- "Hey Google" Hotword with VoiceMatch
 - Tiny memory and computation footprint, running continuously
 - Extremely latency sensitive
- On-device speech recognition
 - High computation running in shorter bursts





Online Education Brand with the largest numbers of users in China

800 million

Users in total

22 million

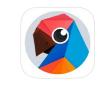
DAU



Youdao Applications with TensorFlow Lite



Youdao Dictionary



Youdao Translator



U-Dictionary





Youdao On-Device Al Translation & OCR

- Applied in Youdao dictionary and translator apps
- Offline photo translation speed improved 30-40%
- Support Realtime AR translation





The conversion flow to TensorFlow Lite is simple ...



Saved Model TF Lite Converter TF Lite Model





... however there are points of failure

- Limited ops
- Unsupported semantics (e.g. control-flow in RNNs)





TensorFlow Select

Available now

- Enables hundreds more ops from TensorFlow on CPU.
- Caveat: binary size increase (~6MB compressed).

In the pipeline

- Selective registration
- Improved performance





Control flow support

In the pipeline

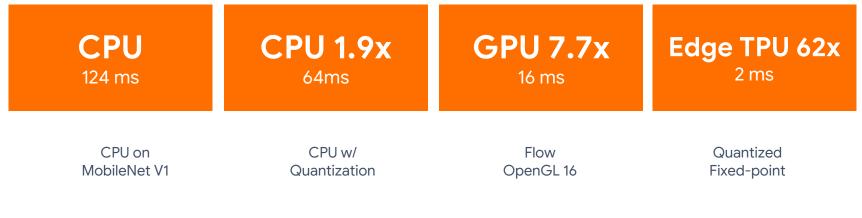
Control flow are core to many ops (e.g. RNNs) and graphs. Thus we are adding support for:

- Loops
- Conditions





Inference performance



MobileNet V1





Benchmarking

Benchmarking and profiling

Available

Improvements to the Model Benchmark tool:

- Support for threading
- Per op profiling
- Support for Android NN API





Benchmarking

Per-op profiling breakdown

======================================	n Order =======	=======================================	=====	
[node type]	[start]	[first]	[avg ms]	[%]
CONV_2D	0.000	4.269	4.269	0.107%
DEPTHWISE_CONV_2D	4.270	2.150	2.150	0.054%
CONV_2D	6.421	6.107	6.107	0.153%
DEPTHWISE_CONV_2D	12.528	1.366	1.366	0.034%
RESHAPE	79.440	0.002	0.002	0.000%
SOFTMAX	79.443	0.029	0.029	0.001%





Benchmarking

Profiling summary

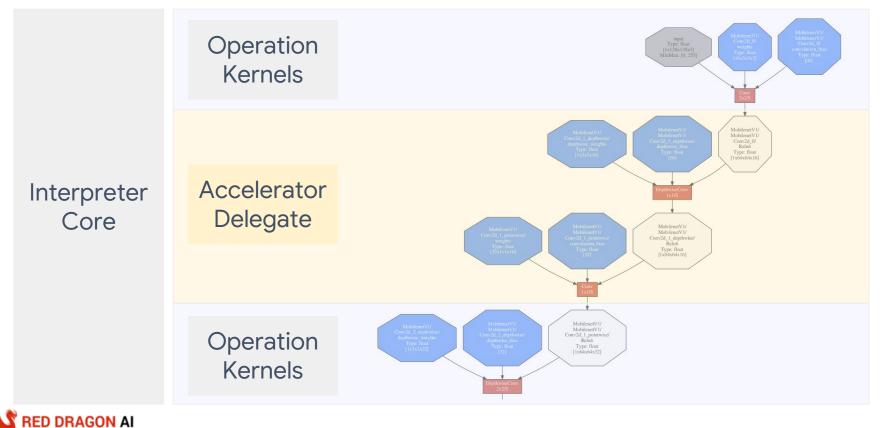
D DRAGON AI

by node type	=======================================	==========	
[count]	[avg ms]	[avg %]	[cdf %]
15	1.406	89.270%	89.270%
13	0.169	10.730%	100.000%
1	0.000	0.000%	100.000%
1	0.000	0.000%	100.000%
1	0.000	0.000%	100.000%
	[count] 15	[count] [avg ms] 15 1.406 13 0.169 1 0.000 1 0.000	[count] [avg ms] [avg %] 15 1.406 89.270% 13 0.169 10.730% 1 0.000 0.000% 1 0.000 0.000%

Timings (microseconds): count=50 first=79449 curr=81350 min=77385 max=88213 avg=79732 std=1929 Memory (bytes): count=0 31 nodes observed

Average inference timings in us: Warmup: 83235, Init: 38467, no stats: 79760.9







Android Neural Network API delegate

Enables hardware supported by the Android NN API

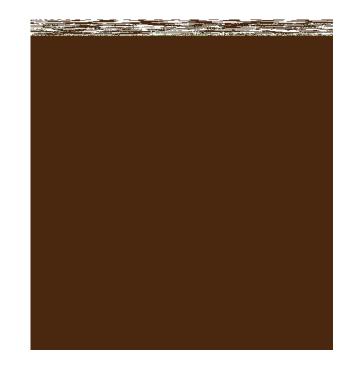




GPU delegate

Preview available!

- 2–7x faster than the floating point CPU implementation
- Adds ~250KB to binary size (Android/iOS).







GPU delegate

In the pipeline

- Expand coverage of operations
- Further optimize performance
- Evolve and finalize the APIs

Make it generally available!





Edge-TPU delegate

Enables next generation ML hardware!

- High performance
- Small physical and power footprint

Available in Edge TPU development kit









Make your models even smaller and faster.





1

Optimization

	Available	In the pipeline
Quantization	Post-training quantization (CPU)	Keras-based quantized training (CPU/NPU) Post-training quantization (CPU/NPU)
Other optimizations	Model optimization toolkit	Keras-based connection pruning





Quantization

New tools

- Post-training quantization with float & fixed point
- Great for CPU deployments!







Quantization

Benefits

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- 4x reduction in model sizes
- Models, which consist primarily of convolutional layers, get 10–50% faster execution (CPU)
- Fully-connected & RNN-based models get up to 3x speed-up (CPU)



Quantization

In the pipeline

- Training with quantization Keras-based API
- Post-training quantization with fixed point math only

Even better performance on CPU

Plus enable many NPUs!



Keras-based quantization API

```
(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)

Keras-based quantization API

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Keras-based quantization API

```
(x_train, y_train),(x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Flatten(),
    quantize.Quantize(tf.keras.layers.Dense(512, activation=tf.nn.relu)),
    tf.keras.layers.Dropout(0.2),
    quantize.Quantize(tf.keras.layers.Dense(10, activation=tf.nn.softmax))
])
model.compile(optimizer='adam',
        loss='sparse_categorical_crossentropy',
        metrics=['accuracy'])
```

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)



Quantization (post-training)



Saved Model

TF Lite Converter TF Lite Model





Quantization (post-training)



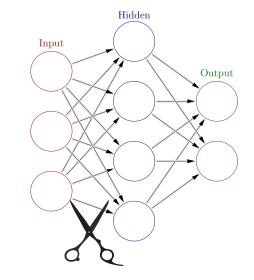




Connection pruning

What does it mean?

- Drop connections during training.
- Dense tensors will now be sparse (filled with zeros).



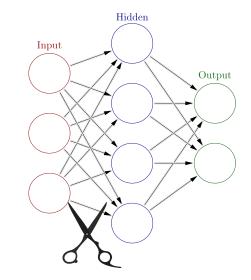




Connection pruning

Benefits

- Smaller models. Sparse tensors can be compressed.
- Faster models. Less operations to execute.







Connection pruning

Coming soon

• Training with connection pruning in Keras-based API (compression benefits)

In the pipeline

 Inference support for sparse models (speed-ups on CPU and selected NPUs)



1

Optimization

Pruning results

- Negligible accuracy loss at 50% sparsity
- Small accuracy loss at 75%

100.00% Top1 Accuracy 89.50% 89.50% 90.00% 84.70% 70.60% 69.50% 69.50% 67.70% 61.80%

0.6

53.60%

0.8

Mobilenet Top1&Top5 Accuracy vs. Sparsity

60.00%

50.00%

0

0.2

0.4





Model repository

Added new model repository

In depth sample applications & tutorials for:

- Image classification
- Object detection
- Pose estimation
- Segmentation
- Smart reply







TF Mobile Deprecated

- Provided 6+ months of notice
- Limiting developer support in favor of TensorFlow Lite
- Still available for training on Github



TensorFlow Lite for

Microcontrollers

Smaller, cheaper & wider range of devices



What am I talking about?

Tiny models on tiny computers!

- Microcontrollers are everywhere
- Speech researchers were pioneers
- Models just tens of kilobytes







Here's one I have in my pocket

Get ready for a live demo!

https://www.sparkfun.com/products/15170

384KB RAM, 1MB Flash, \$15 Low single-digit milliwatt power usage Days on a coin battery!





Why is this useful?

Running entirely on-device

Tiny constraints:

- It's using a 20KB model
- Runs using less than 100KB of RAM and 80KB of Flash





Coral

What is Coral?

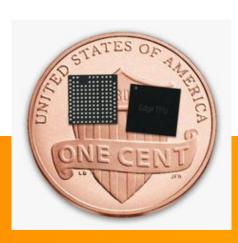
- Coral is a platform for creating products with on-device ML acceleration.
- Our first products feature Google's Edge TPU in SBC and USB accessory forms.





Edge TPU

A Google-designed ASIC that lets you run inference on-device:



- Very fast inference speed (object detection in less than 15ms)
- Enables greater data privacy
- No reliance on a network connection
- Runs inference with TensorFlow Lite

Enables unique workloads and new applications

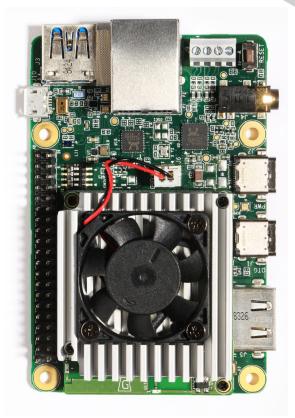




Coral Dev Board

CPU	i.MX 8M SoC w/ Quad-core A53
GPU	Integrated GC7000 Lite GPU
TPU	Google Edge TPU
RAM Memory	1GB LPDDR4 RAM
Flash Memory	8 GB eMMC
Security/Crypto	eMMC secure block for TrustZone MCHP ATECC608A Crypto Chip
Power	5V 3A via Type-C connector
Connectors	USB-C, RJ45, 3.5mm TRRS, HDMI
Supported OS	Mendel Linux (Debian derivative) Android
Supported ML	TensorFlow Lite

RED DRAGON AI





Coral Accelerator

TPU	Google Edge TPU
Power	5V 3A via Type-C connector
Connectors	USB 3.1 (gen 1) via USB Type-C
Supported OS	Debian 6.0 or higher Other Debian Derivatives
Supported Architectures	x86_64 ARMv8
Supported ML	TensorFlow Lite







These actually exist!



They're available now at coral.withgoogle.com



Get it. Try it.

Code: github.com/tensorflow/tensorflow Docs: tensorflow.org/lite/ Discuss: tflite@tensorflow.org mailing list



Deep Learning MeetUp Group

The Group:

- MeetUp.com / TensorFlow-and-Deep-Learning-Singapore
- > 3,500 members

The Meetings :

- Next = 16-April, hosted at Google
 - Something for Beginners
 - Something from the Bleeding Edge
 - Lightning Talks



Deep Learning JumpStart Workshop

This Saturday + (Tues & Thurs evening next week)

- Hands-on with real model code
- Build your own Project

Action points :

- http:// bit.ly / jump-start-march-2019
- Cost is heavily subsidised for SC/PR



Advanced Deep Learning Courses

Module #1: JumpStart (see previous slide)

Each 'module' will include :

- In-depth instruction, by practitioners
- Individual Projects
- 70%-100% funding via IMDA for SG/PR

Action points :

• Stay informed: http://bit.ly/rdai-courses-2019



Red Dragon Al : Intern Hunt

Opportunity to do Deep Learning "all day"

Key Features :

- Work on something cutting-edge (+ publish!)
- Location : Singapore (SG/PR FTW) and/or Remote

Action points :

- Need to coordinate timing...
- Contact Martin or Sam via LinkedIn

TensorFlow

DEV SUMMIT 2019