Achieving optimal speed on TF 2

Zebroid Meeting 2020-07-21

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Topics for today

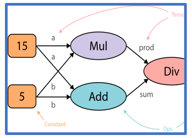
Relevant questions

A What are the major changes from TF1 to TF2?

B How does TF2 compare against TF1 and PyTorch?

C What are the most important TF APIs for performance?

APIs / Tools analyzed



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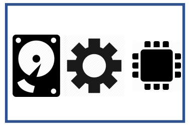

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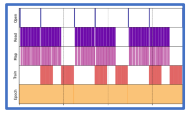

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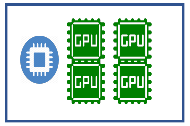


Distributed training (tf.distribute)

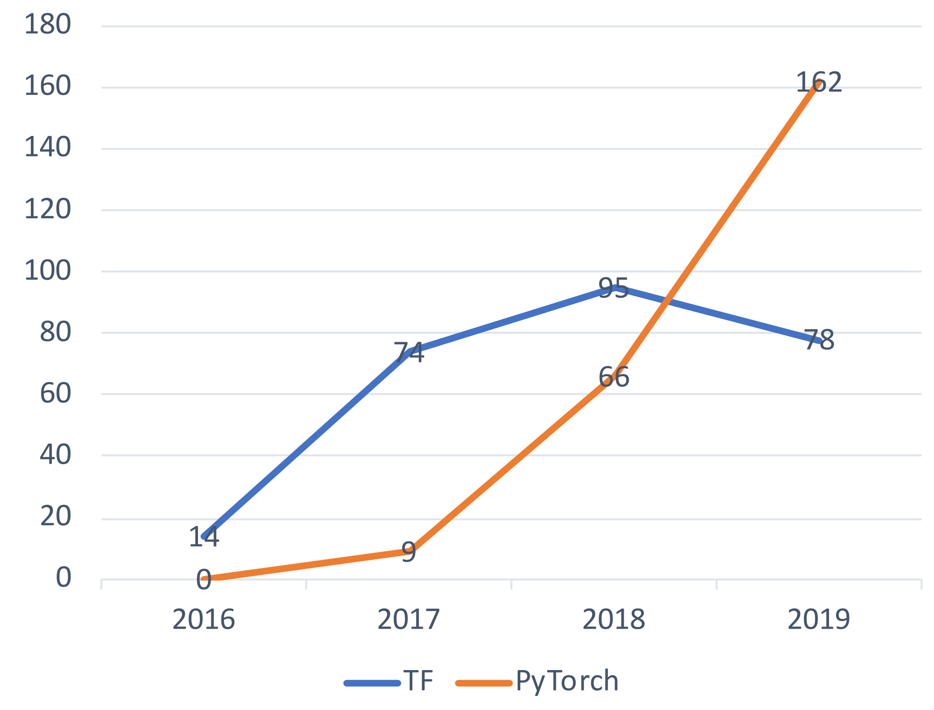
Preamble

Focus

A Similar to PyTorch, TF 2 is easier to debug and more pythonic

PyTorch has been gaining popularity in the community

of NeurIPs papers with implementations on a given framework*



From (TF 1)**

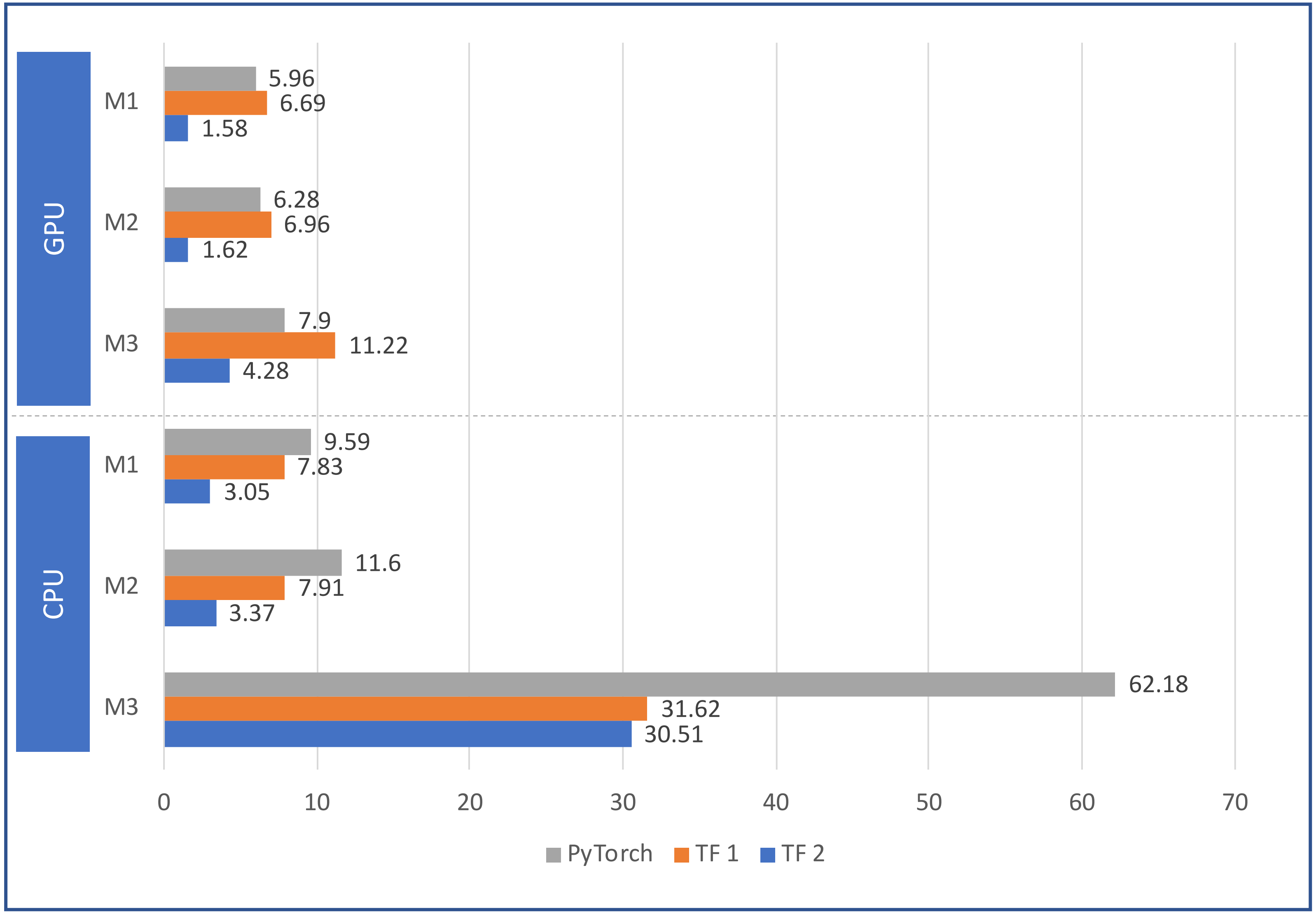
- Using graphs by default
- Defining nodes on a graph
- Constructing a graph with a fixed type in mind
- Using control dependencies to manage the execution
- Initializing variables manually
- Writing non-intuitive control flow statements and functions

To (TF 2)**

- Running code on eager execution (enables per step debugging)
- Selecting operations to run under tf.function
- Having functions that ”adapt” to different types
- Writing code imperatively to control order of execution
- Letting the variables be automatically initialized
- Using python syntax to define control flows (and letting Autograph do the translation)

* http://horace.io/pytorch-vs-tensorflow/, ** tf.function and Autograph (TF Dev Summit 2019) talk

B In principle, TF 2 should not be slower than TF 1 (VAEs)



Models on MNIST

M1 VAE (dense linear architecture)

- Encoder: Dense(784) - Dense(400) – Dense(64)
- Decoder: Dense(64) – Dense(400) – Dense(784)

M2 VAE (dense nonlinear architecture)

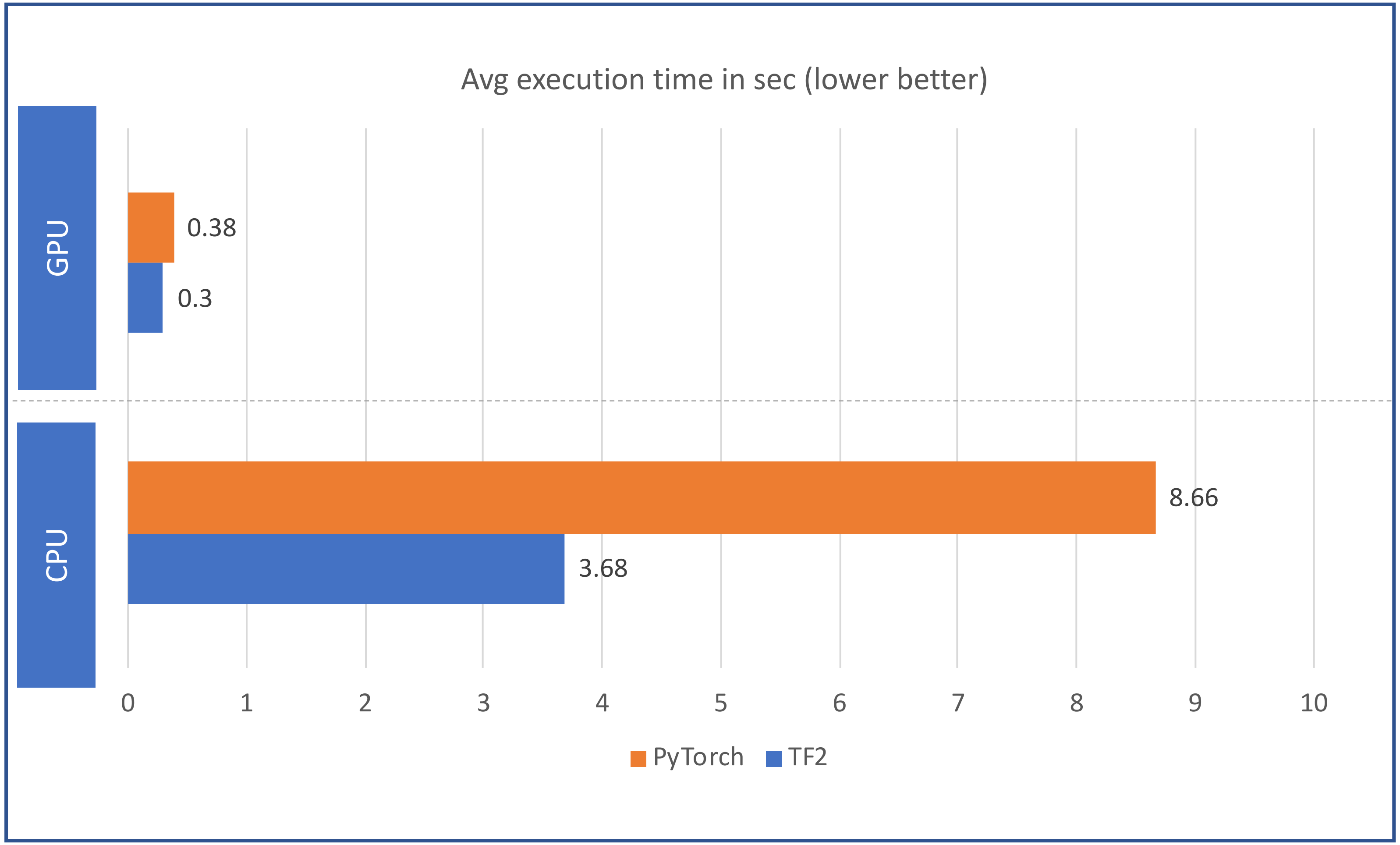
- Encoder: Dense(784) - Dense(400) – Dense (240) – Dense(64)
- Decoder: Dense(64) – Dense(240) – Dense(400) – Dense(784)

M3 VAE (convolutional architecture)

- Encoder: Conv2D(32, 3, 2) - Conv2D(64, 3, 2) – Dense(64).
- Decoder: Dense(1568) - Conv2DT(64, 3, 2) - Conv2DT(32, 3, 2) - Conv2DT(1, 3, 1)

All models ran with a batch size of 128 and latent dimension of 64. All GPUs runs were done in the custom Google Cloud images optimized for each framework

B And in some cases faster than PyTorch



Models

Generator

- 4 Conv2DTranspose layers with Batch Normalization and ReLU activations
- 1 Conv2DTranpose layer with Tanh at the end

Discriminator

- 4 Conv2D layers with Batch Normalization and LeakyReLU activations
- 1 Conv2D layer with Sigmoid at the end

C TF 2 encapsulates several APIs for different tasks

NOT EXHAUSTIVE

High-level DL APIs	tf.keras, tf.estimator
Low-level DL APIs	tf.nn, tf.losses, tf.metrics, tf.optimizers, tf.train, tf.initializers
Autodiff	tf.GradientTape, tf.gradients
I/O and Preprocessing	tf.data, tf.feature_column, tf.audio, tf.image, tf.io, tf.queue
Visualization	tf.summary, tf.profile
Deployment and optimization	tf.distribute, tf.saved_model, tf.autograph, tf.lite, tf.quantization, tf.tpu
Special data structures	tf.lookup, tf.ragged, tf.nest, tf.sparse
Mathematics	tf.math, tf.linalg, tf.signal, tf.random, tf.bitwise

Based on: Geron's *Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow (2019)*

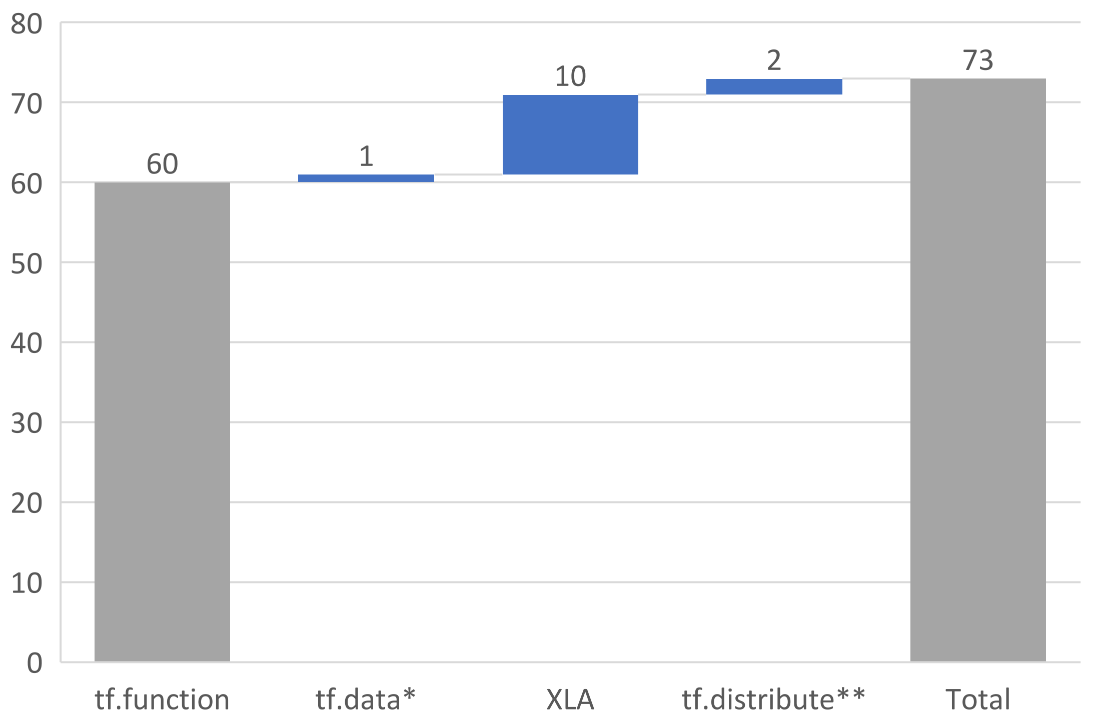
C We focus on the APIs that drive performance

Covered

Activity	API / Tool
• Ensure code is graph executable (optimize graph with XLA)	• tf.function
• Preprocess data efficiently	• tf.data
• Profile bottlenecks	• tf.profiler
• Distribute across GPUs	• tf.distribute
• Accelerate computation by reducing precision	• tf.keras.mixed_precision / tf.keras.quantize
• Shrink your models	• tf.keras.prune

Even small models can benefit from all the optimizations

M3 VAE on MNIST, % reduction in execution time over baseline



* Data optimization consists of caching and prefetching, ** Even for small models, tf.distribute yields some improvement despite its overhead. Distributed across 2 Tesla P4 GPUs

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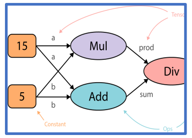

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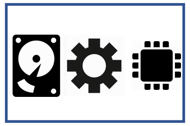

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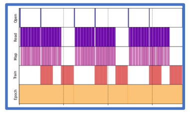

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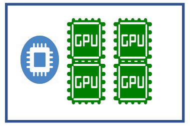
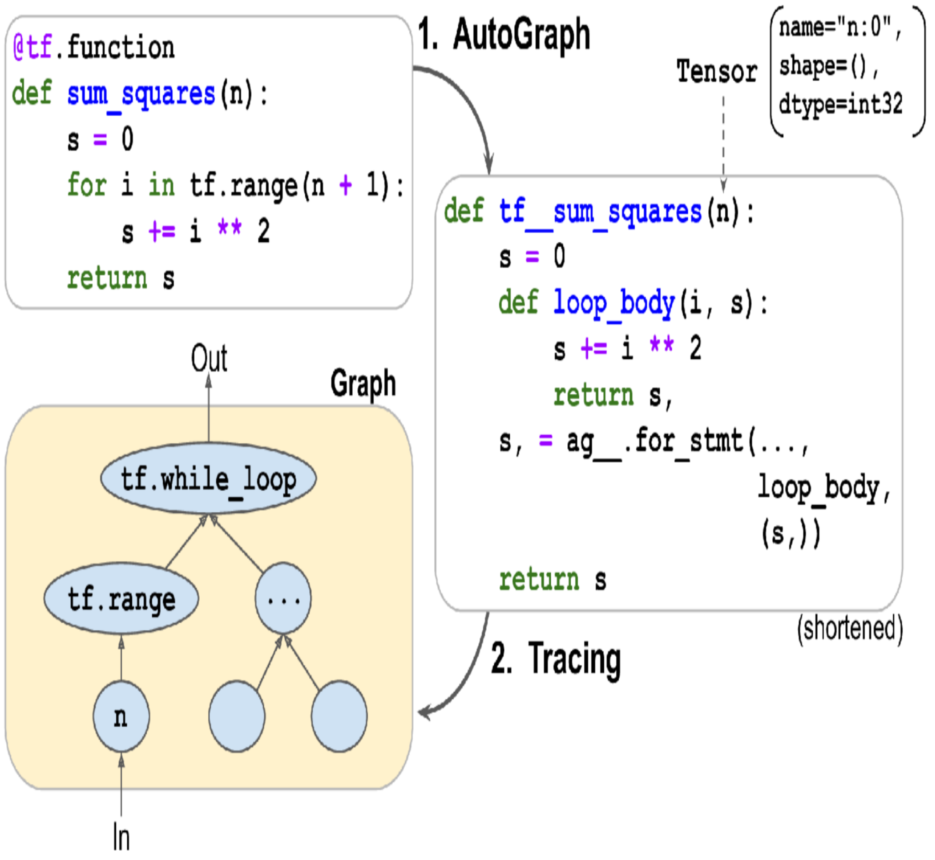


Distributed training (tf.distribute)

tf.function requires some rules to compile properly

Translation of python code to graph by decoration



Common mistakes

- Writing all the code and then trying to decorate it
- Calling external libraries (like NumPy)
- Multiple function retracing from feeding python objects
- Returning non tensor objects
- Creating variables on every call
- Using the tensor's shape value (specially batch size)
- Putting decorators on all functions

Lack of examples and documentation might be hampering the adoption of TF 2!

Based on: Geron's *Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow (2019)*, https://stackoverflow.com/search?q=tf.function

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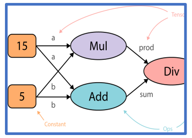

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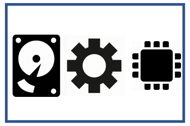

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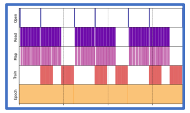

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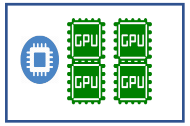

Distributed training (tf.distribute)

tf.data simplifies the input pipeline

Standard code example

Extract

```
files = tf.data.Dataset.list_files(file_pattern)
ds = tf.data.TFRecordDataset(files)
```

Transform

```
ds = ds.shuffle(buffer_size)
ds = ds.repeat(epochs)
ds = ds.map(pre_fn, num_parallel_calls=tf.data.experimental.AUTOTUNE)
ds = ds.batch(batch_size)
ds = ds.cache()
ds = ds.prefetch(tf.data.experimental.AUTOTUNE)
```

Load

```
iterator = ds.make_one_shot_iterator()
x = iterator.get_next()
```

* tf.data: Fast, flexible and easy-to-use input pipelines (https://www.youtube.com/watch?v=uIcqeP7MFH0&t=230s), Inside TensorFlow: tf.data (https://www.youtube.com/watch?v=kVEOCfBy9uY&list=WL&index=2&t=938s)

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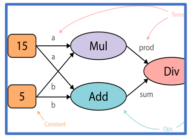

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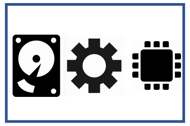

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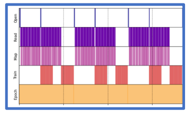

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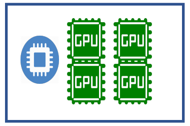

Distributed training (tf.distribute)

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tf.profiler helps your model execute faster

NOT EXHAUSTIVE

EXAMPLE

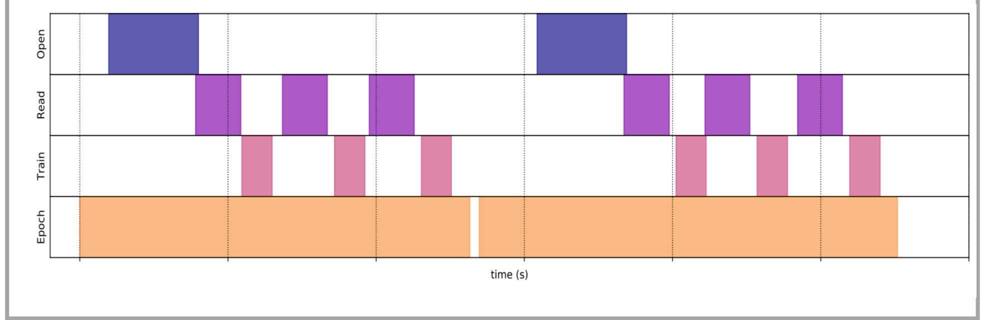
Benefits (tools)

- Shows input bottlenecks (input pipeline analyzer)
- Guides how to speed up parts of training by exhibiting the cost of their ops (TF Stats)
- Breaks down ops per device and exhibits if they are waiting for input

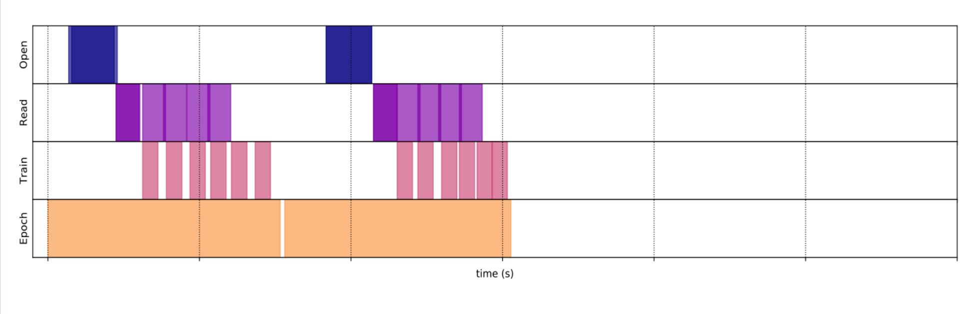
Best Practices*

- Use parallel calls on map, prefetch and cache input
- Utilize the devices more by increasing batch size
- Calculate metrics every few steps and reduce callbacks
- Reduce precision fp16 and make dimension divisible by 8
- Send data to multiple devices in parallel
- Use tf.name_scope to identify most costly ops in python construct

Inadequate trace



Optimized trace



Based on: https://www.tensorflow.org/tensorboard/tensorboard_profiling_keras, * https://www.tensorflow.org/guide/profiler, https://www.tensorflow.org/guide/data_performance_analysis

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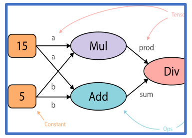

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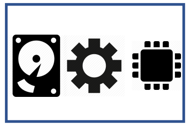

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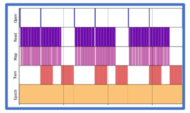

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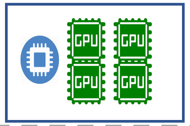
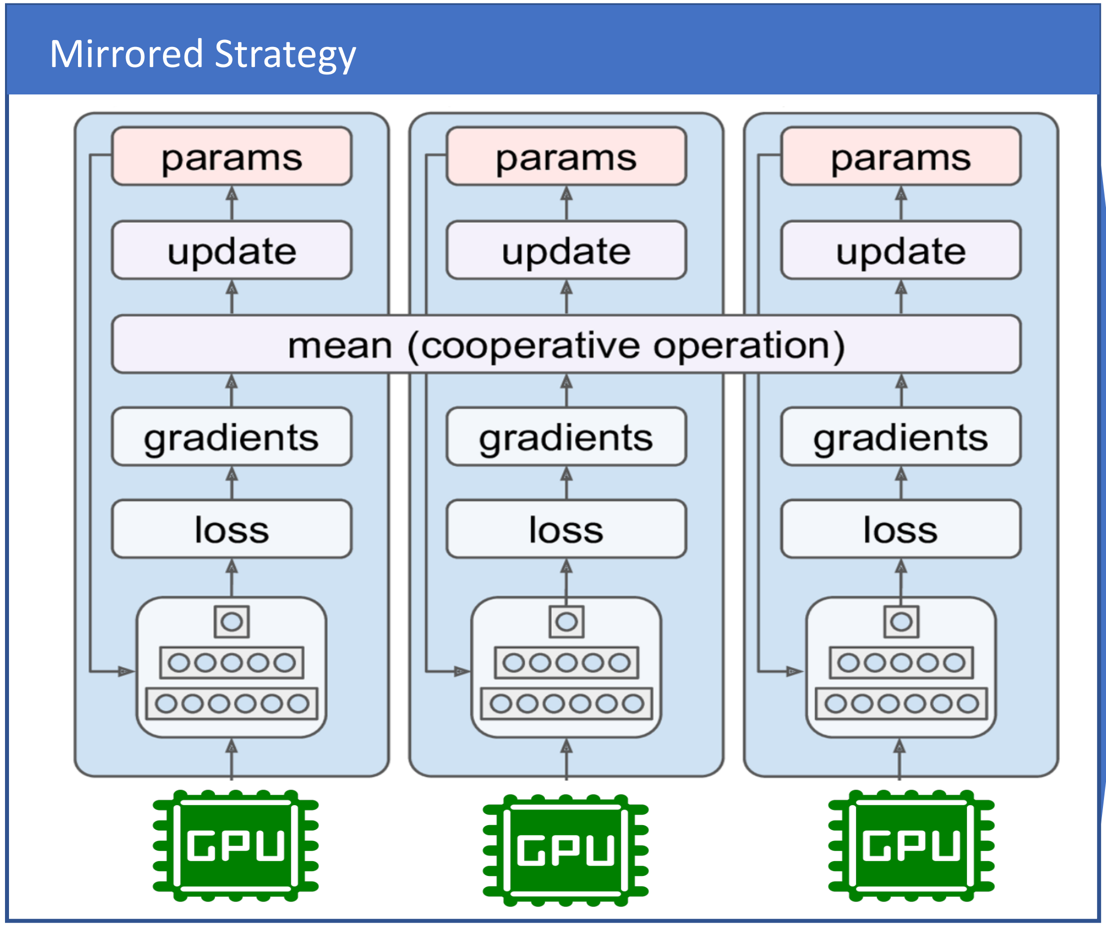


Distributed training (tf.distribute)

tf.distribute is easy to use since TF 2 is “strategy aware”



Code changes

- Change data pipeline by distributing it
- Create model and optimizer under the strategy scope
- Define loss on a per example basis, create distributed train step function and aggregate loss and gradients using global batch size