IIT Kharagpur | IIT Madras | IIT Goa | IIT Palakkad

APPLIED ACCELERATED ARTIFICIAL INTELLIGENCE

Accelerated TensorFlow

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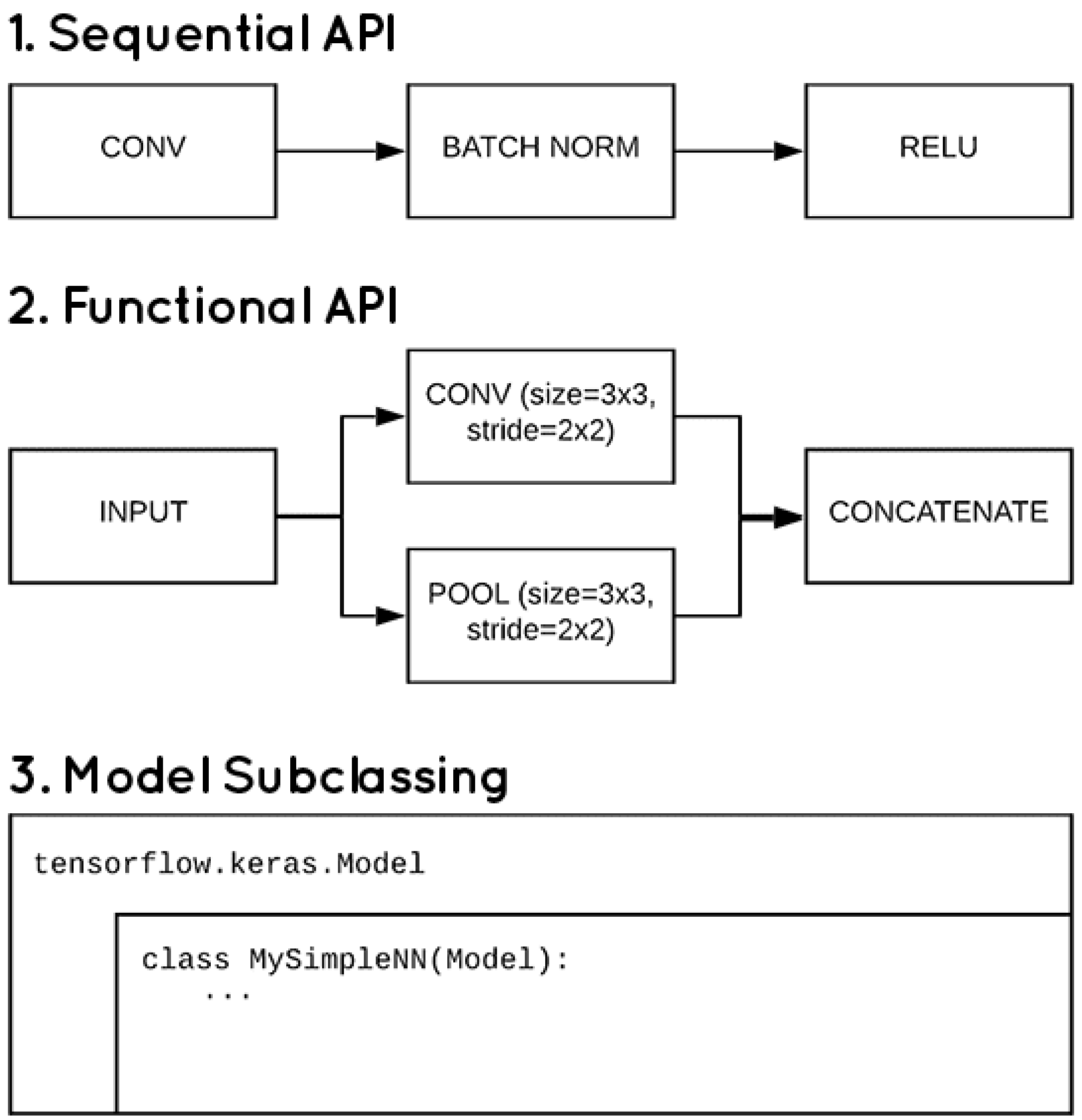
Topics

- 3 ways to create a model
- Accelerated data pipelining
- Distributed training

3 ways to create model



Quick overview

```
model = Sequential()

model.add(Dense(4,activation='relu')) ##<----- You don't have to specify input size.Just define the hidden layers
model.add(Dense(4,activation='relu’))
model.add(Dense(1))## defining the optimiser and loss function


model.compile(optimizer='adam',loss='mse')## training the model
model.fit(x=X_train,y=y_train, validation_data=(X_test,y_test), batch_size=128,epochs=400)
```

```
class WideAndDeepModel(keras.Model):
        def __init__(self, units=30, activation="relu", **kwargs):
        super().__init__(**kwargs) # handles standard aruments ( name, etc.)
       self.hidden1 = keras.layers.Dense(units, activation=activation)
       self.hidden2 = keras.layers.Dense(units, activation=activation)
       self.main_output = keras.layers.Dense(1)
       self.aux_output = keras.layers.Dense(1)

    def call(self, inputs):
        input_A, input_B = inputs
      hidden1 = self.hidden1(inputs_B)
      hidden2 = self.hidden2(hidden1)
      concat = keras.layers.Concatenate([input_A, hidden2])
      main_ouput = self.main_ouput(concat)
      aux_ouput = self.aux_ouput(hidden2)
      return main_ouput, aux_output

model = WideAndDeepModel()
```

```
## Creating the layers

input_layer = Input(shape=(3,))
Layer_1 = Dense(4, activation="relu")(input_layer)
Layer_2 = Dense(4, activation="relu")(Layer_1)
output_layer= Dense(1, activation="linear")(Layer_2)

##Defining the model by specifying the input and output layers

model = Model(inputs=input_layer, outputs=output_layer) ## defining the optimiser and loss function model.compile(optimizer='adam', loss='mse’)

## training the model model.fit(X_train, y_train,epochs=400, batch_size=128,validation_data=(X_test,y_test))
```

Why input pipeline is important

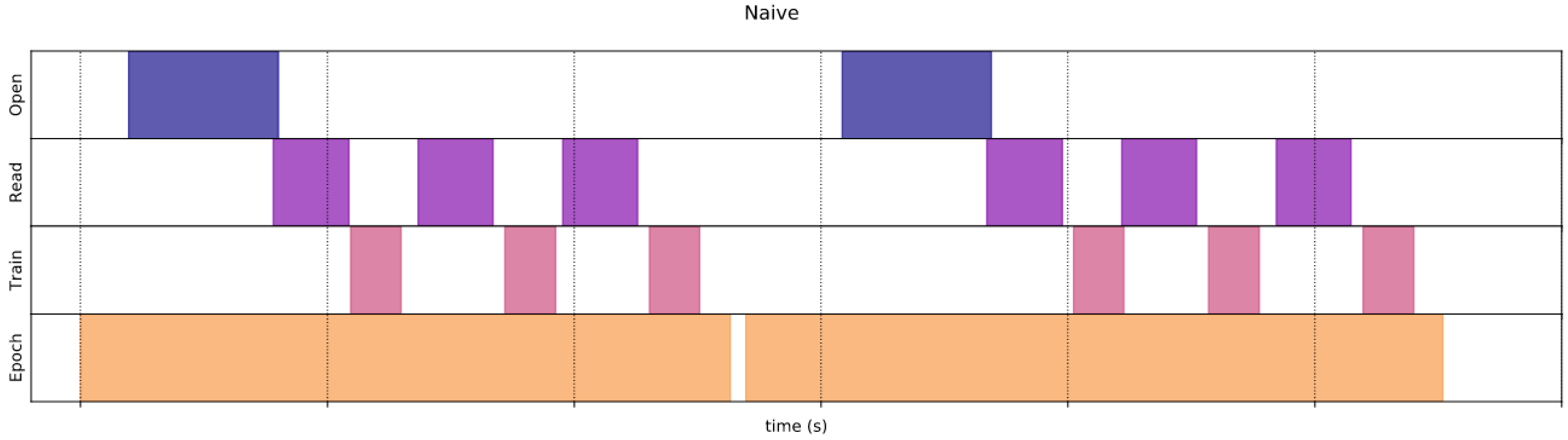
- data might not fit into memory
- data might require (randomized) pre-processing
- efficiently utilize hardware
- decouple loading + pre-processing from distribution

- Extract:
  - read data from memory / storage
  - parse file format
- Transform:
  - text vectorization
  - image transformations
  - video temporal sampling
  - shuffling, batching,...
- Load:
  - transfer data to the accelerator

The naive approach

```python
def benchmark(dataset, num_epochs=2):
    start_time = time.perf_counter()
    for epoch_num in range(num_epochs):
        for sample in dataset:
            # Performing a training step
            time.sleep(0.01)
    print("Execution time:", time.perf_counter() - start_time)
```

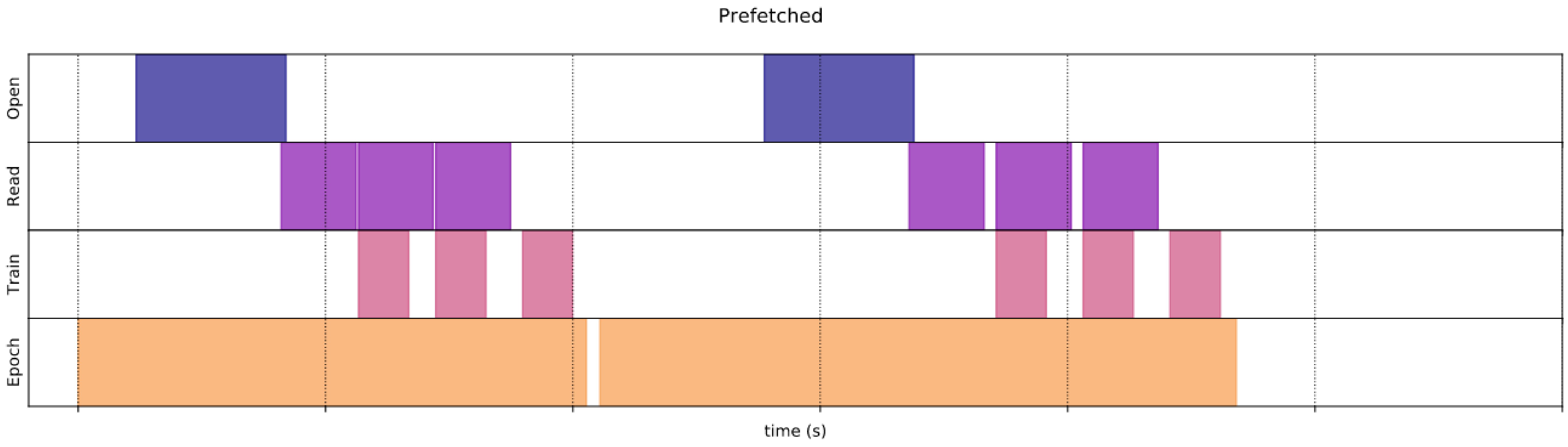
```python
benchmark(ArtificialDataset())
```



https://www.tensorflow.org/guide/data_performance

Prefetching

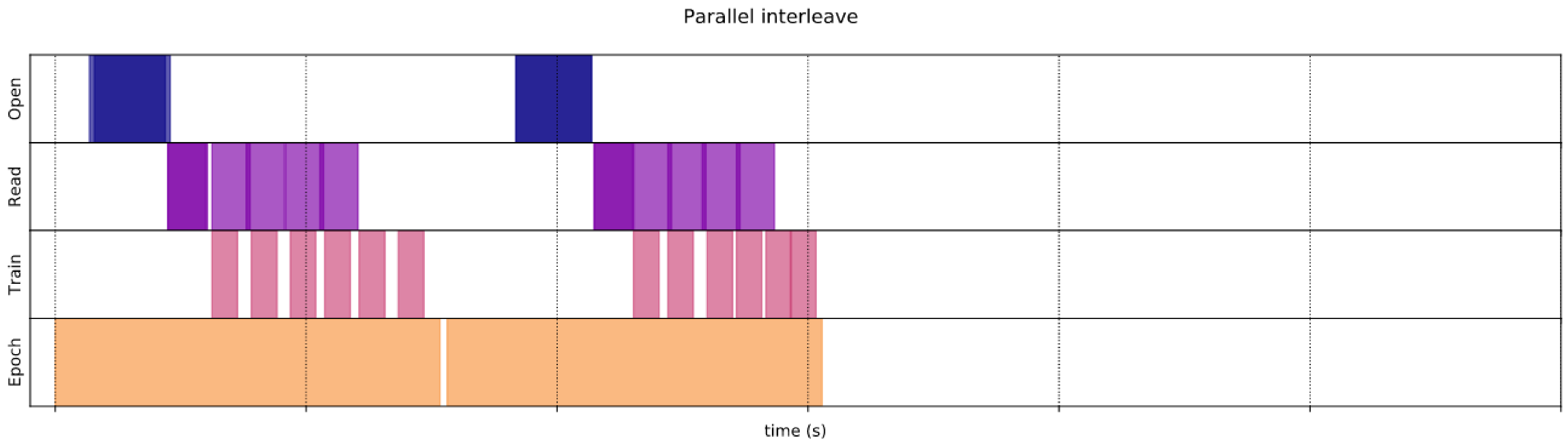
```
benchmark(
    ArtificialDataset()
    .prefetch(tf.data.AUTOTUNE)
)
```



https://www.tensorflow.org/guide/data_performance

Interleaving

```
benchmark(
    tf.data.Dataset.range(2)
    .interleave(
        lambda _: ArtificialDataset(),
        num_parallel_calls=tf.data.AUTOTUNE
    )
)
```

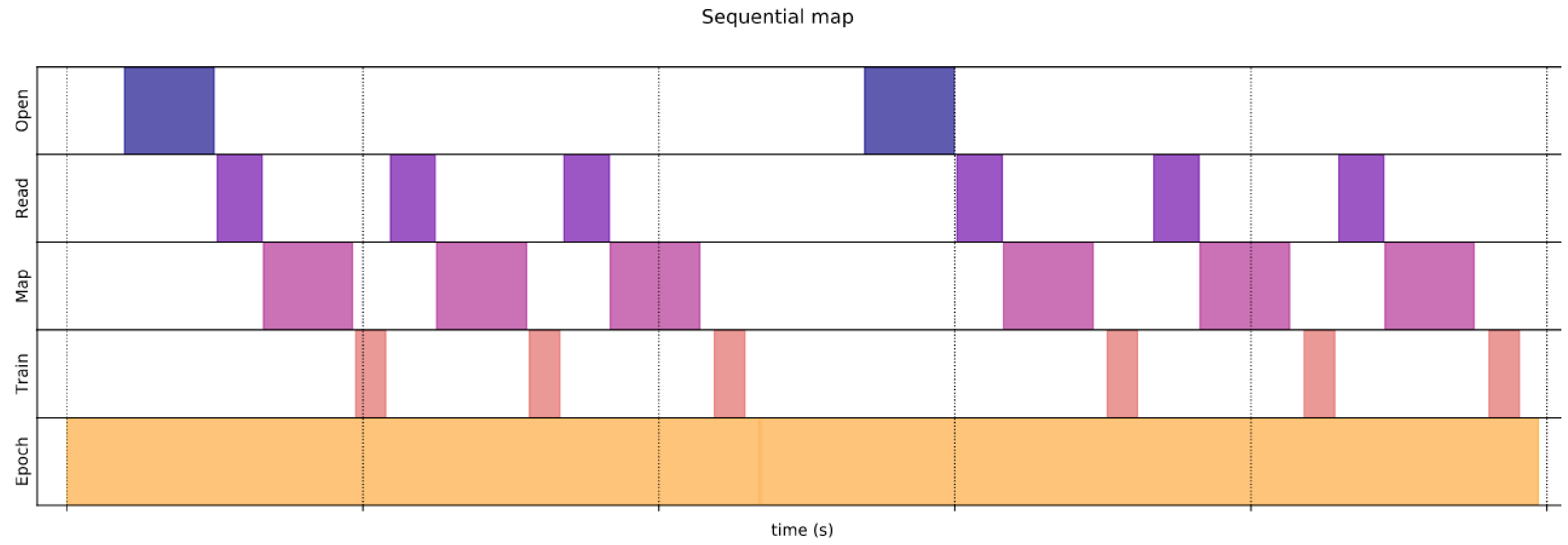


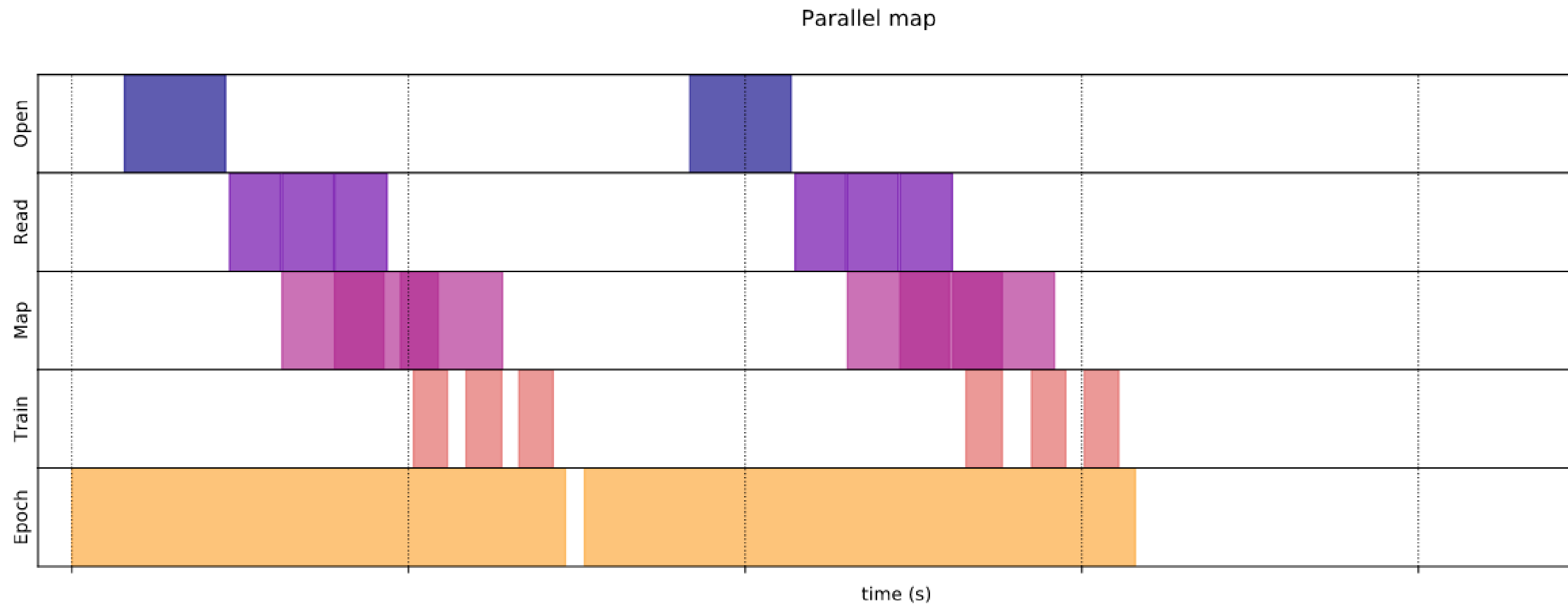
https://www.tensorflow.org/guide/data_performance

Sequential vs parallel mapping

```
benchmark(
    ArtificialDataset()
    .map(mapped_function)
)
```

```
benchmark(
    ArtificialDataset()
    .map(
        mapped_function,
        num_parallel_calls=tf.data.AUTOTUNE
    )
)
```



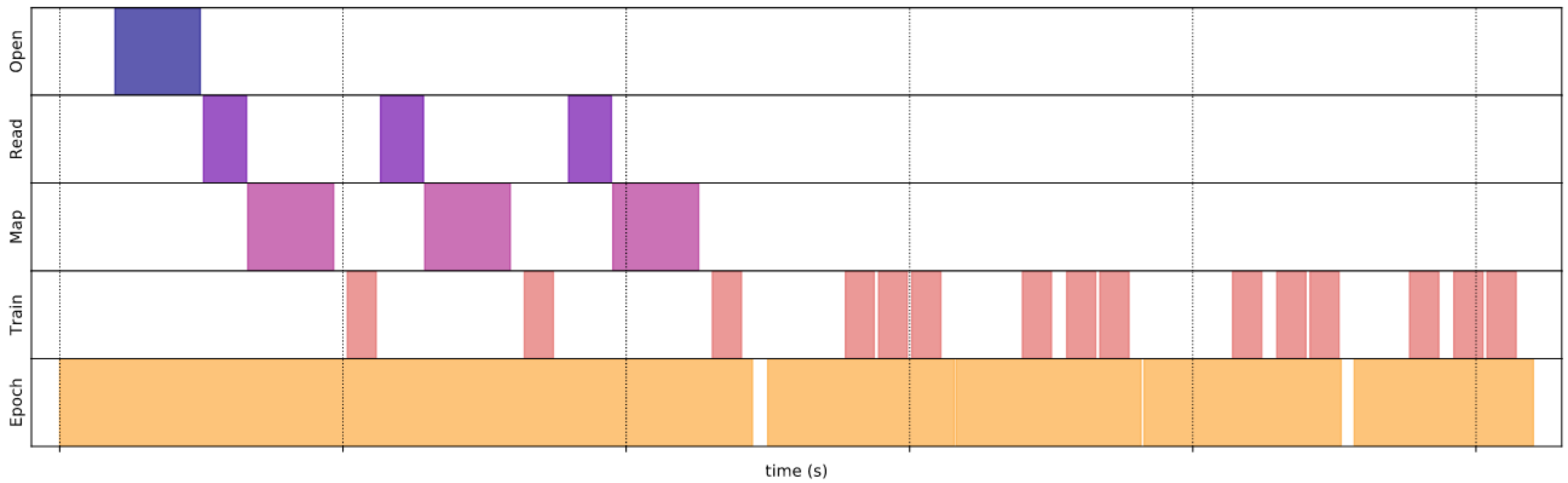


https://www.tensorflow.org/guide/data_performance

Caching

```
benchmark(
    ArtificialDataset()
    .map(  # Apply time consuming operations before cache
        mapped_function
    ).cache(
    ),
    5
)
```

Cached dataset

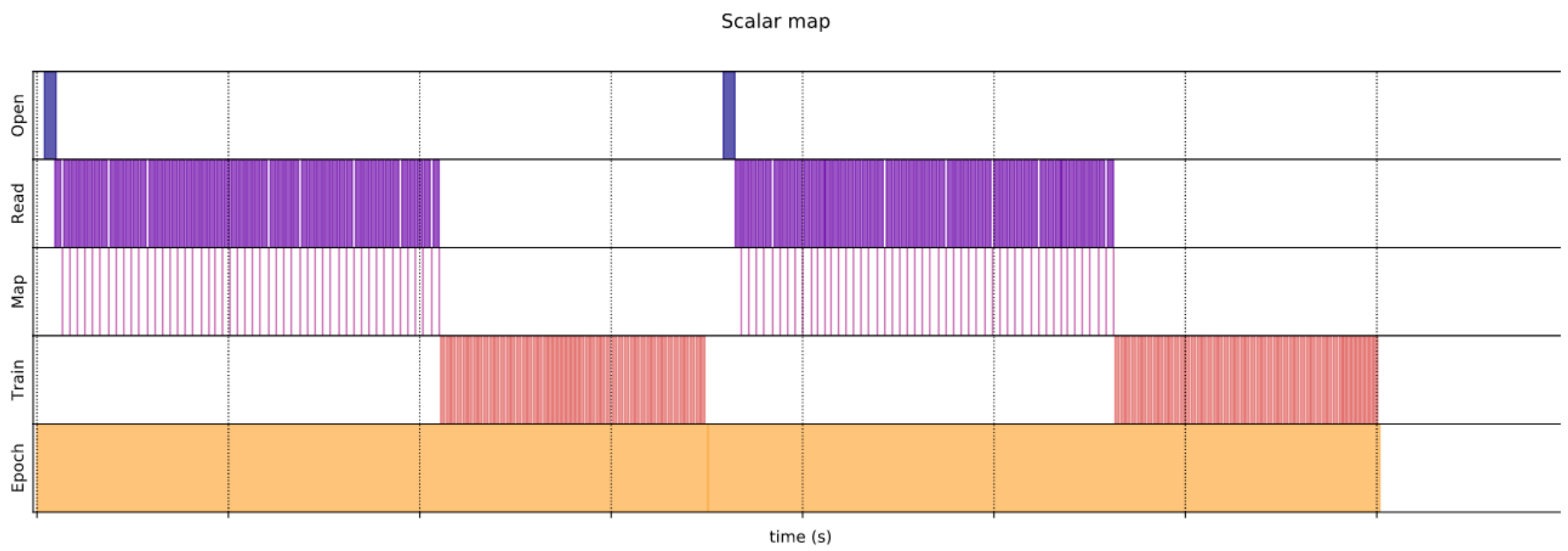


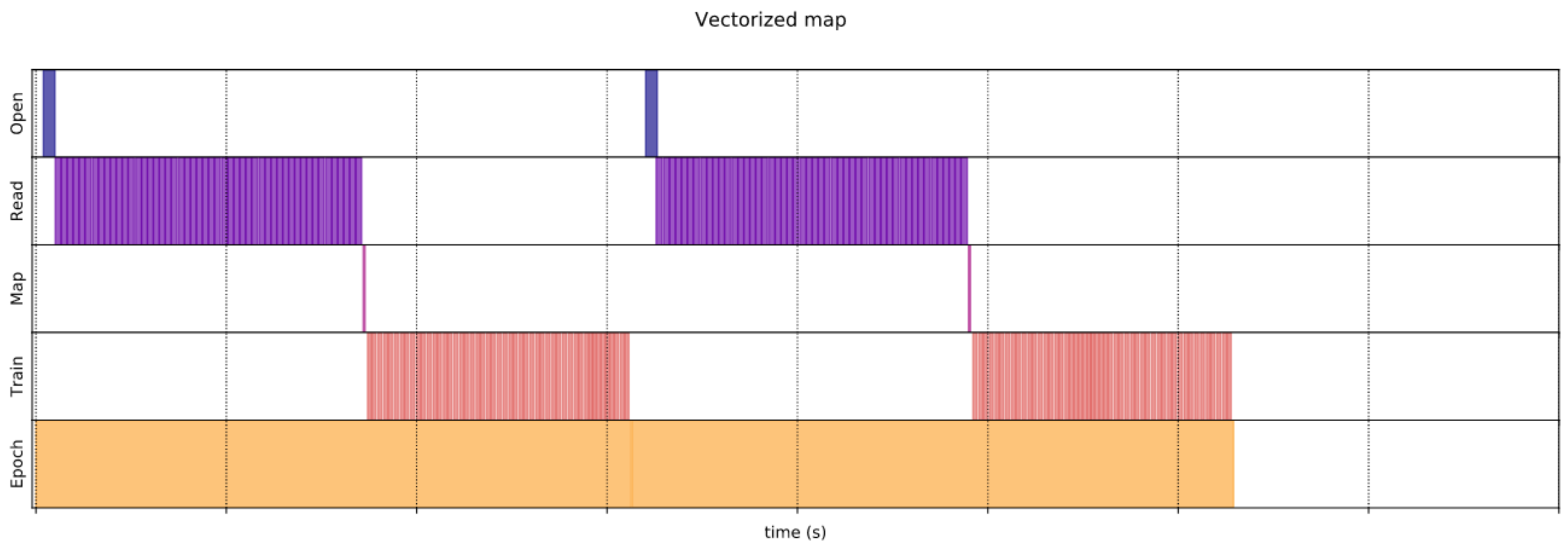
https://www.tensorflow.org/guide/data_performance

Scalar vs Vectorized mapping

```
fast_benchmark(
    fast_dataset
    # Apply function one item at a time
    .map(increment)
    # Batch
    .batch(256)
)
```

```
fast_benchmark(
    fast_dataset
    .batch(256)
    # Apply function on a batch of items
    # The tf.Tensor.__add__ method already handle batches
    .map(increment)
)
```





https://www.tensorflow.org/guide/data_performance

TfDS

```
import tensorflow_datasets as tfds

# Download the dataset and create a tf.data.Dataset
ds, info = tfds.load("mnist", split="train", with_info=True)

# Access relevant metadata with DatasetInfo
print(info.splits["train"].num_examples)
print(info.features["label"].num_classes)

# Build your input pipeline
ds = ds.batch(128).repeat(10)

# And get NumPy arrays if you'd like
for ex in tfds.as_numpy(ds):
  np_image, np_label = ex["image"], ex["label"]
```

https://colab.research.google.com/github/tensorflow/datasets/blob/master/docs/overview.ipynb

Why Distributed Training

- An easy way to distribute TensorFlow training.
- Goals:
  - Easy to use - minimal code changes
  - Great out-of-the-box performance
  - Versatile - works with different architectures, hardware and APIs

Credit: Jiri Simsa

Use cases of tf.distribute.strategy

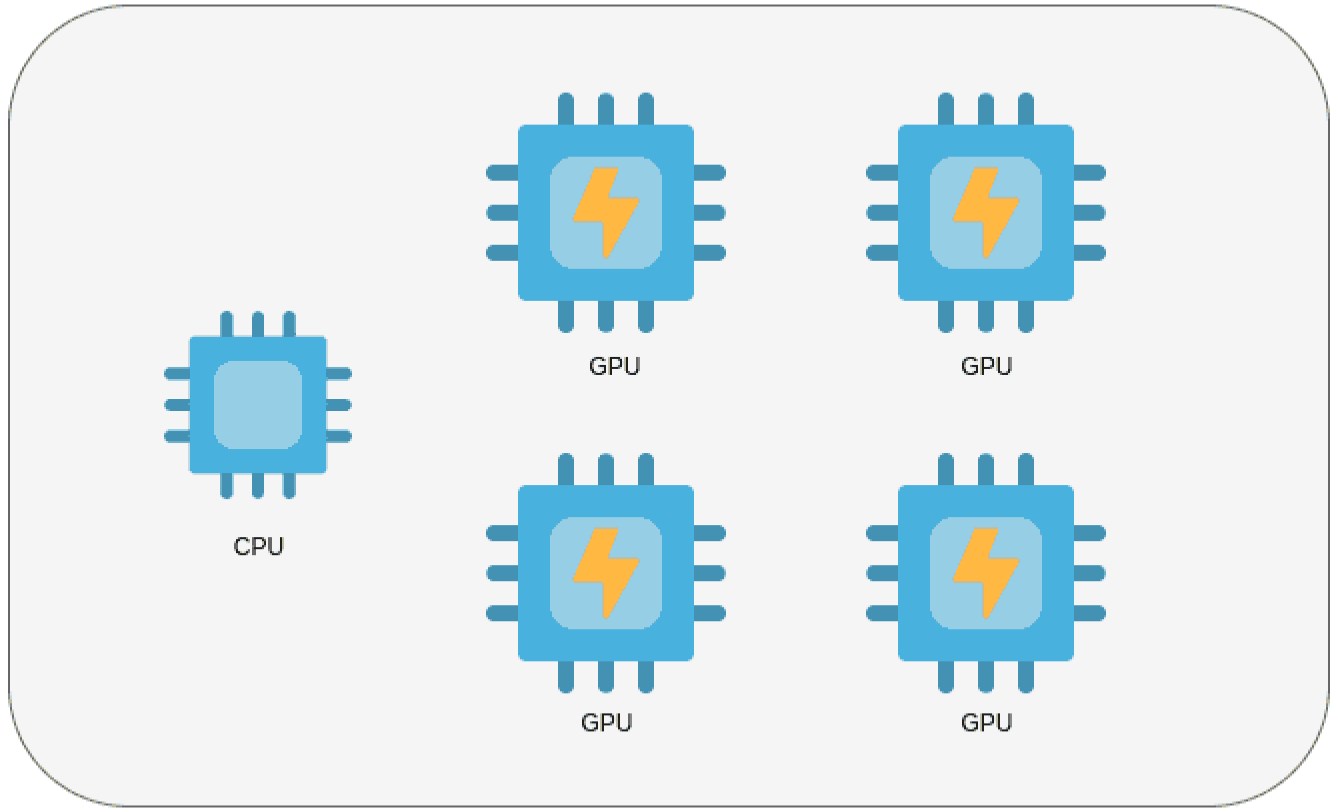
- Distribute my model using Keras / Estimator API
- Distribute my model using a custom training loop
- Make my layer / library / infrastructure distribute-aware
- Make a new strategy

Different API surfaces for each

https://www.tensorflow.org/guide/distributed_training

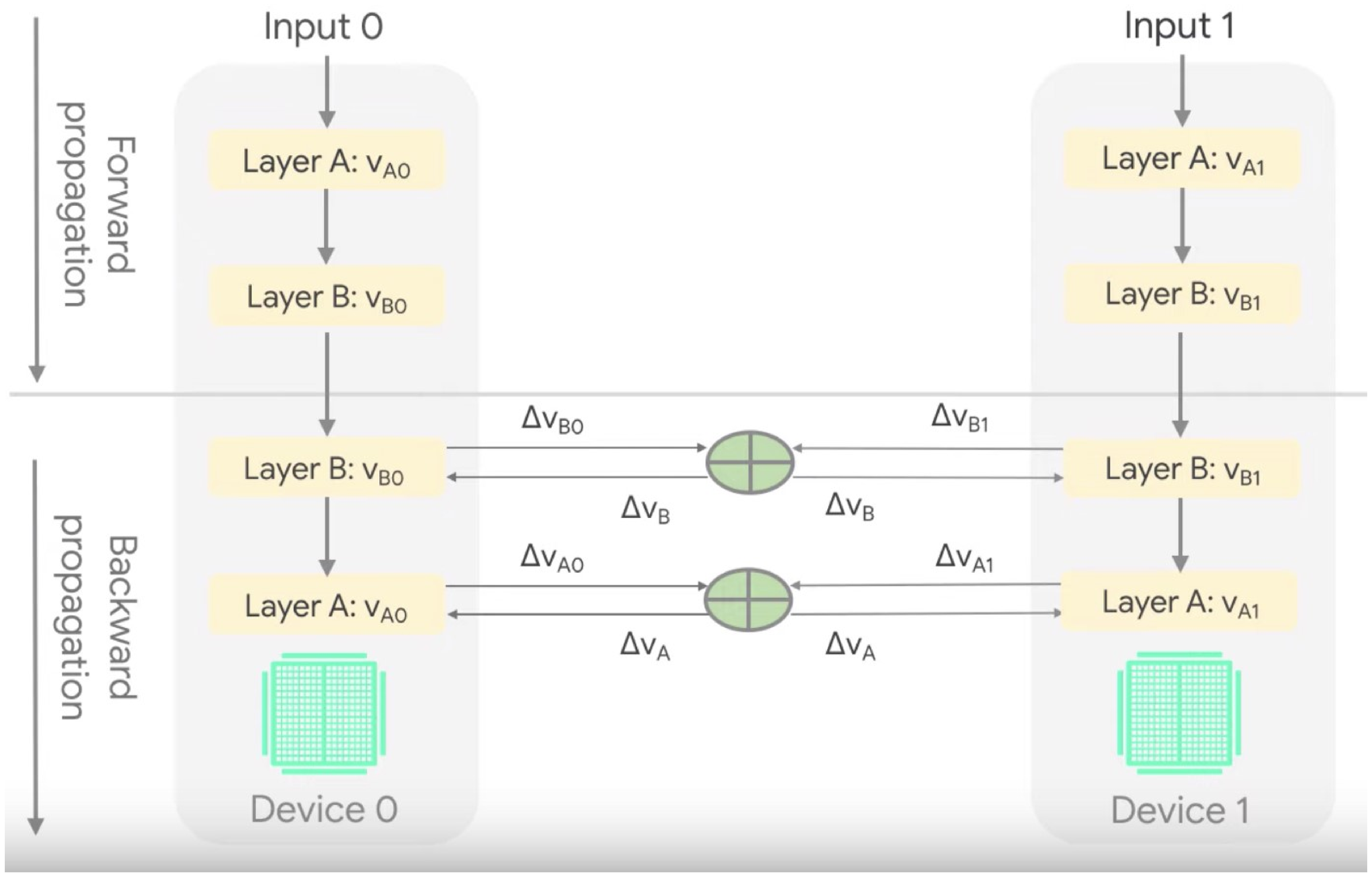
Multi-GPU All-reduce sync training

- All-reduce synchronous training for multi-GPU
  - replicas are run in lock-step, synchronizing gradients at each step
  - Variables are mirrored on each GPU
  - All-reduce: network efficient way to aggregate gradients



https://theaisummer.com/distributed-training/

Synchronous training



Credit: Jiri Simsa

MirroredStrategy

```
import tensorflow as tf


strategy = tf.distribute.MirroredStrategy()
strategy = tf.distribute.MirroredStrategy(devices=["gpu:0", "gpu:1"])
strategy = tf.distribute.MirroredStrategy(
    cross_device_op=tf.distribute.NcclAllReduce(num_packs=2))
```

Credit: Jiri Simsa

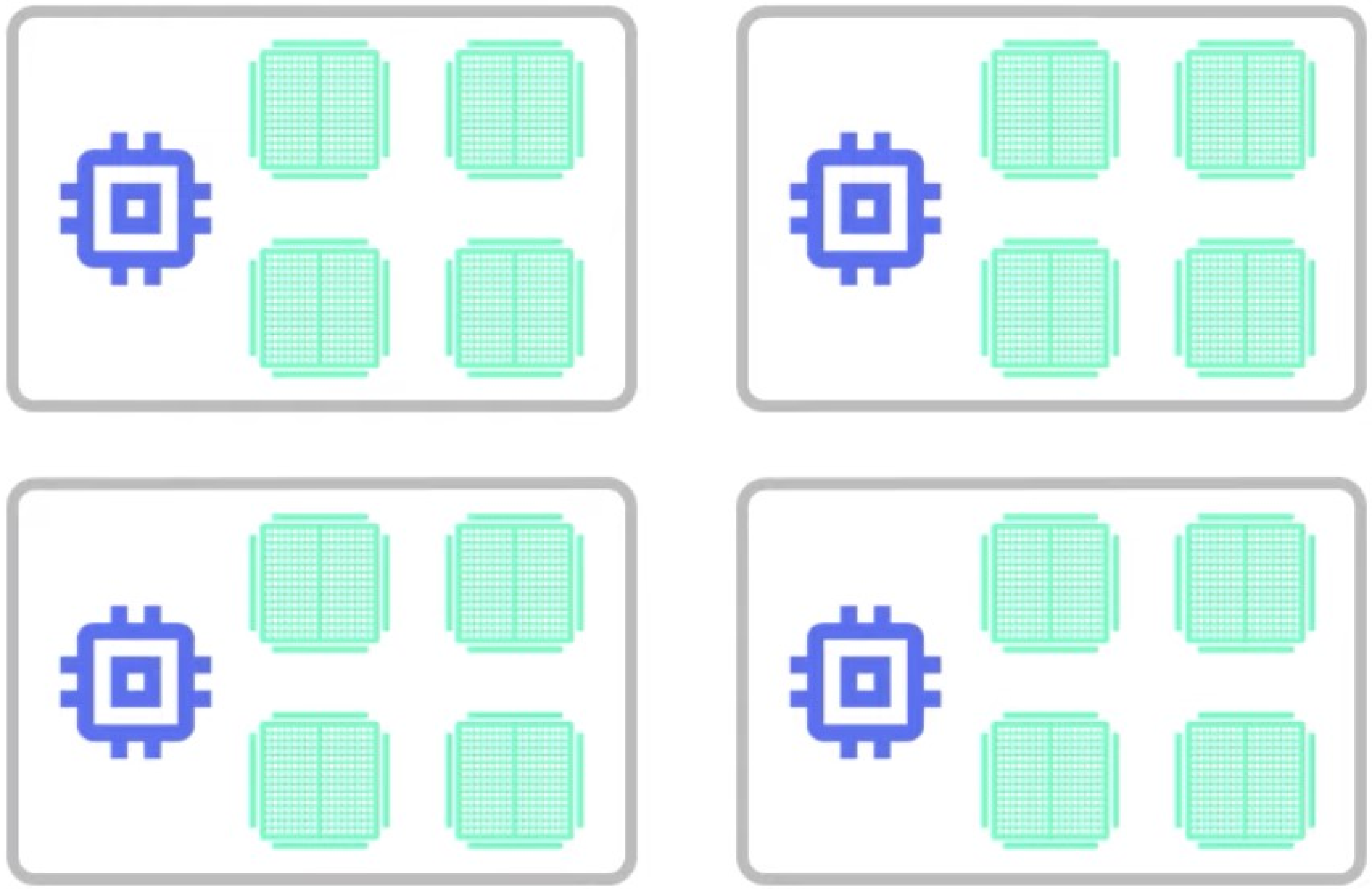
Use the strategy with Keras API

```
model = tf.keras.Sequential([
    tf.keras.layers.Conv2D(32, 3, activation='relu', input_shape=(28, 28, 1)),
    tf.keras.layers.MaxPooling2D(),
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(10)
])

model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              optimizer=tf.keras.optimizers.Adam(),
              metrics=['accuracy'])
```

Multi worker all-reduce sync training

- Uses new collective ops
- Workers are run in lock-step,
- synchronizing gradients at each step



Credit: Jiri Simsa

Multi worker all-reduce sync training

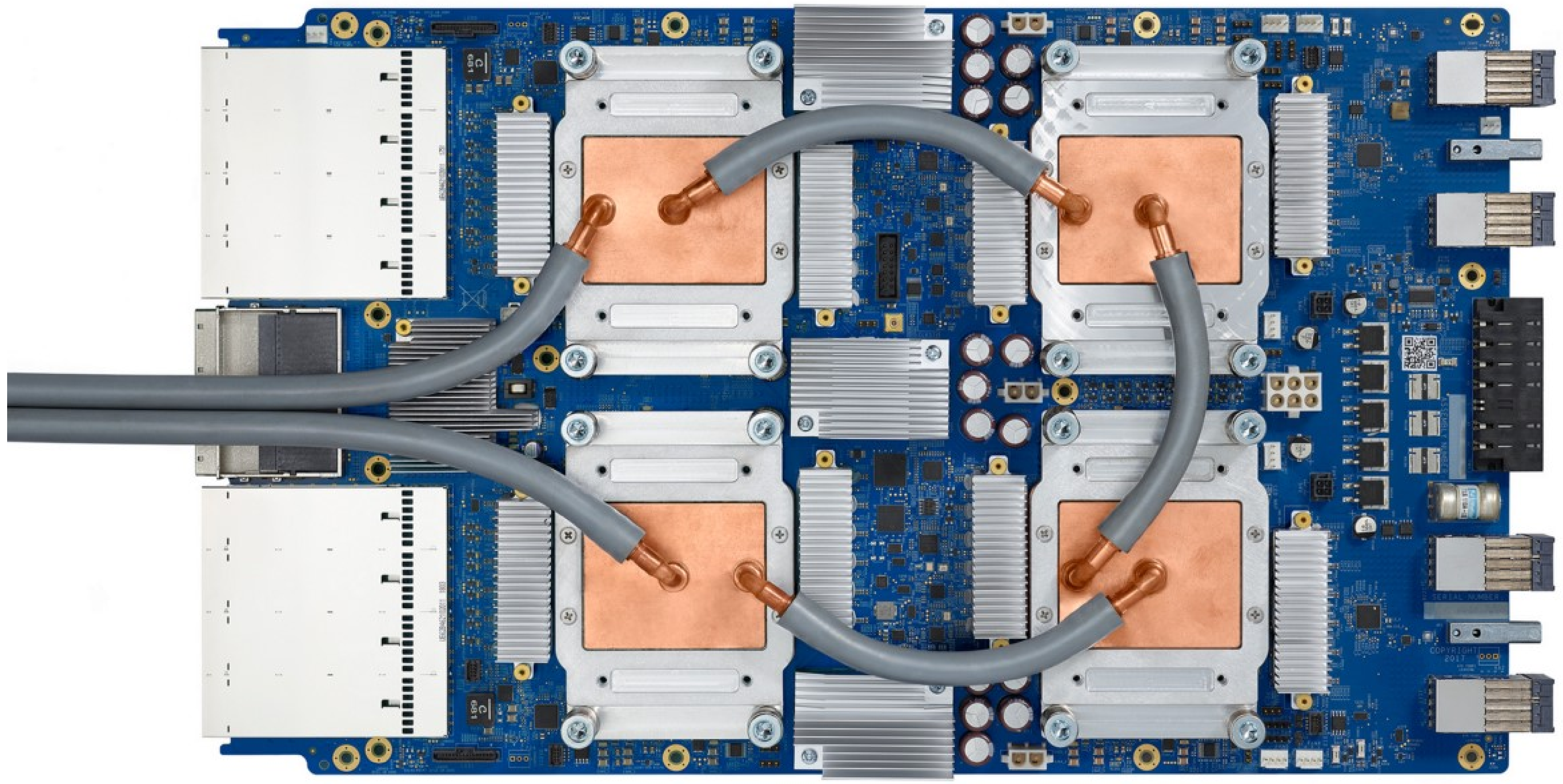
```
import tensorflow as tf


strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy()
strategy = tf.distribute.experimental.MultiWorkerMirroredStrategy(
    tf.distribute.experimental.CollectiveCommunication.NCCL)
```

Credit: Jiri Simsa

All-reduce sync training for TPUs

- Similar to MirroredStrategy
- Uses cross-replica-sum on TPUs to do all reduce

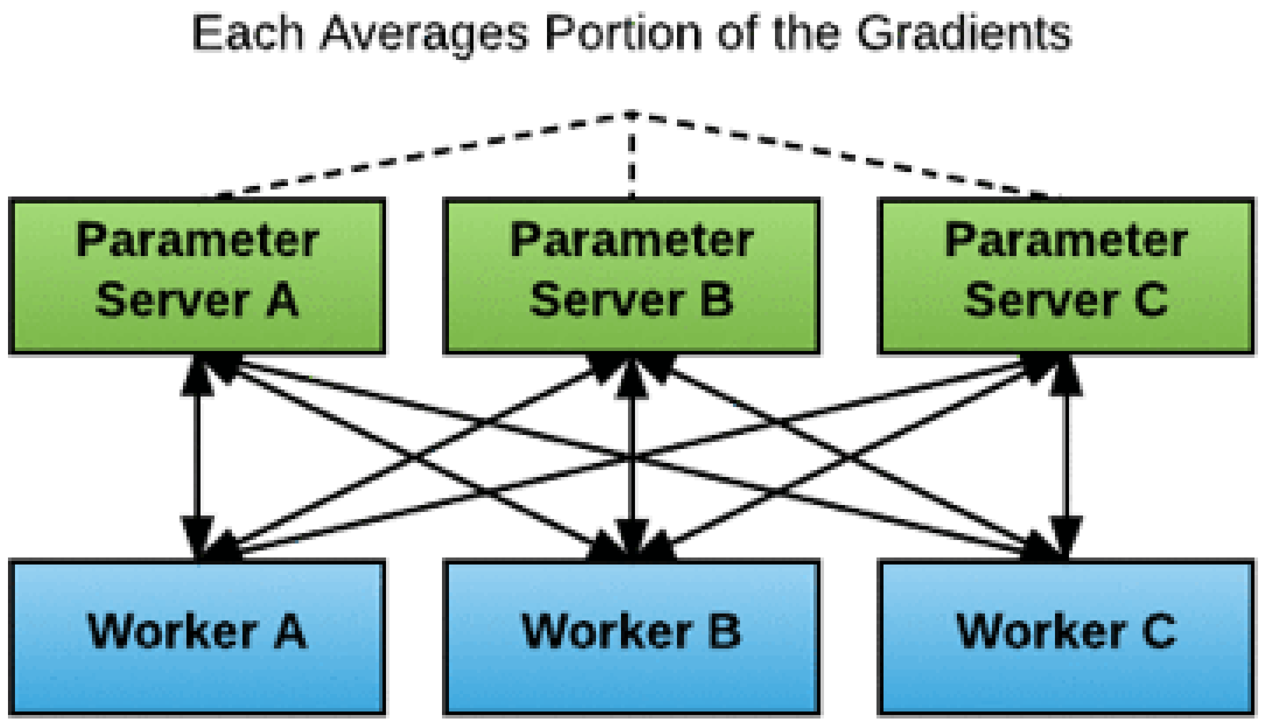


https://medium.com/@decoded_cipher/tensor-processing-units-both-history-and-applications-b3479d92a61d

```
resolver = tf.distribute.cluster_resolver.TPUClusterResolver(tpu='')
tf.config.experimental_connect_to_cluster(resolver)
tf.tpu.experimental.initialize_tpu_system(resolver)
strategy = tf.distribute.experimental.TPUStrategy(resolver)
```

Credit: Jiri Simsa

Parameter Servers and Workers

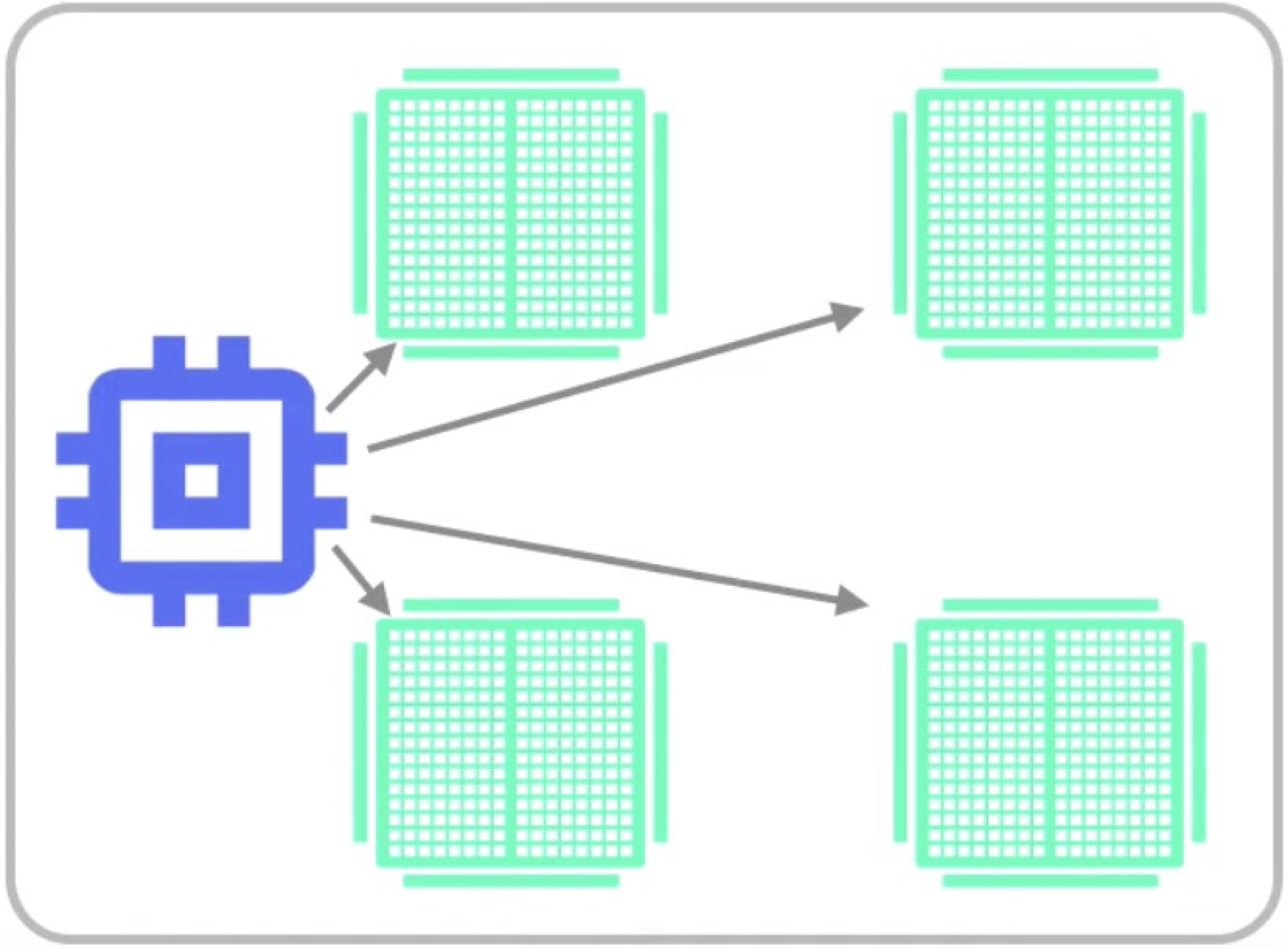



```
ps_strategy = tf.distribute.experimental.ParameterServerStrategy()
parameter_server_strategy = tf.distribute.experimental.ParameterServerStrategy()
```

Credit: AWS

Central storage

- 1-machine multi-GPU
  - one copy of each variable on CPU
  - one replica of the model per GPU
  - Can handle embeddings that wont fit on a GPU



```
import tensorflow as tf


strategy = tf.distribute.experimental.CentralStorageStrategy()
```

Credit: Jiri Simsa

Reference code

- https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/distribute/custom_training.ipynb
- https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/distribute/multi_worker_with_keras.ipynb
- https://github.com/python-engineer/tensorflow-course/blob/master/07_Functional_API_Project.ipynb

Thank You