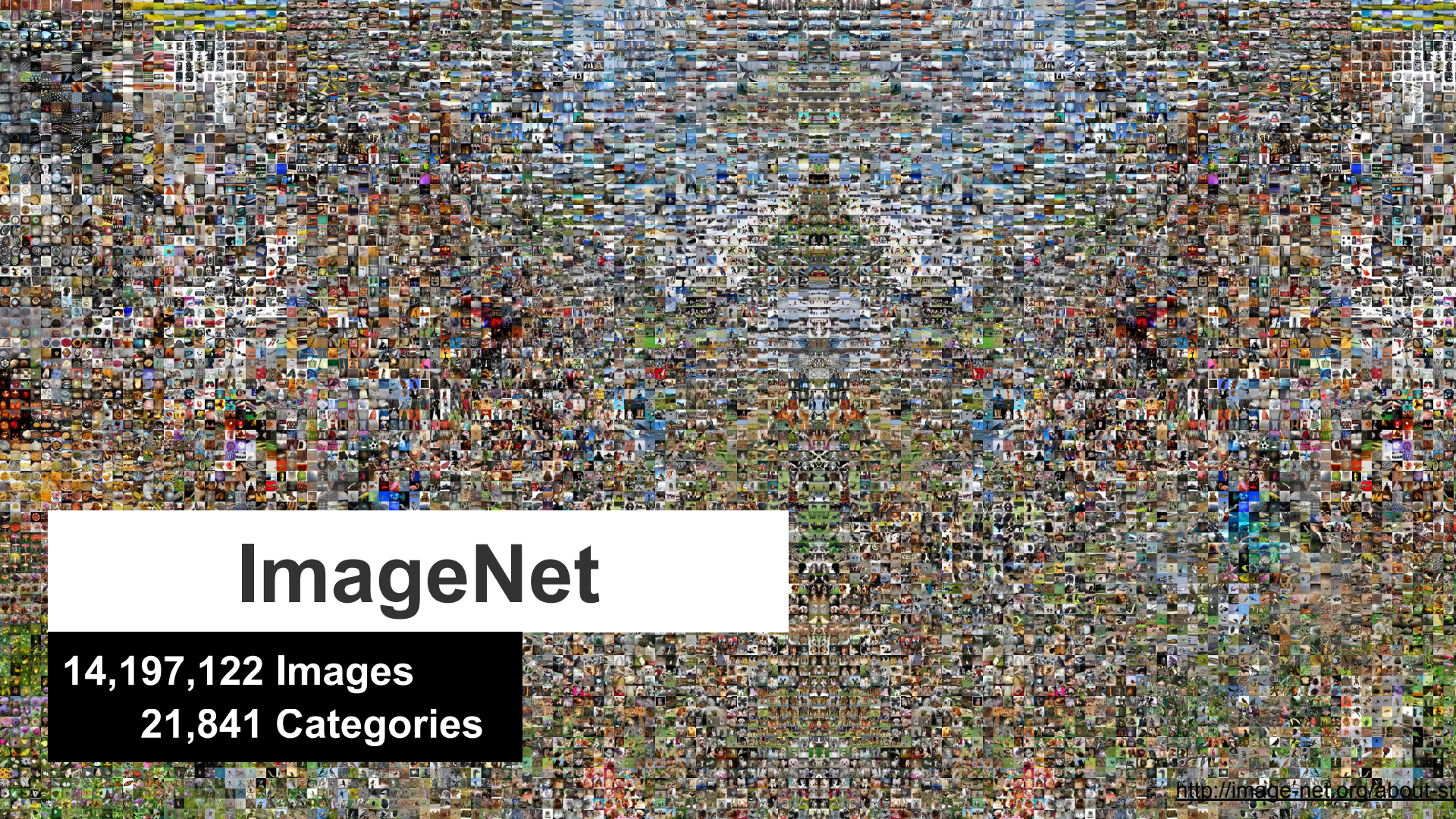
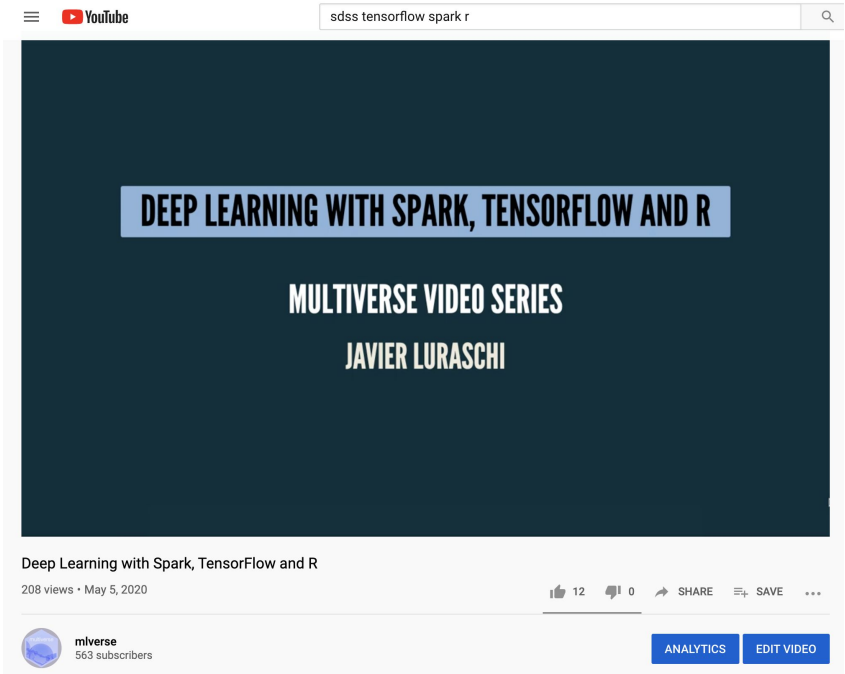
Training ImageNet using TensorFlow and R

@javierluraschi
DSSV 2020 / RStudio PBC


ImageNet
14,197,122 Images
21,841 Categories
http://image-net.org/about-st

Need to catch up?



[YouTube mlverse -- Deep Learning with Spark, TensorFlow and R]

fast.ai

Making neural nets uncool again

Home

About

Our MOOC

Now anyone can train Imagenet in 18 minutes

Written: 10 Aug 2018 by *Jeremy Howard*

This post extends the work described in a previous post, Training Imagenet in 3 hours for $25; and CIFAR10 for $0.26.

A team of fast.ai alum Andrew Shaw, DIU researcher Yaroslav Bulatov, and I have managed to train Imagenetto 93% accuracy in just 18 minutes, using 16 public AWScloud instances, each with 8 NVIDIA

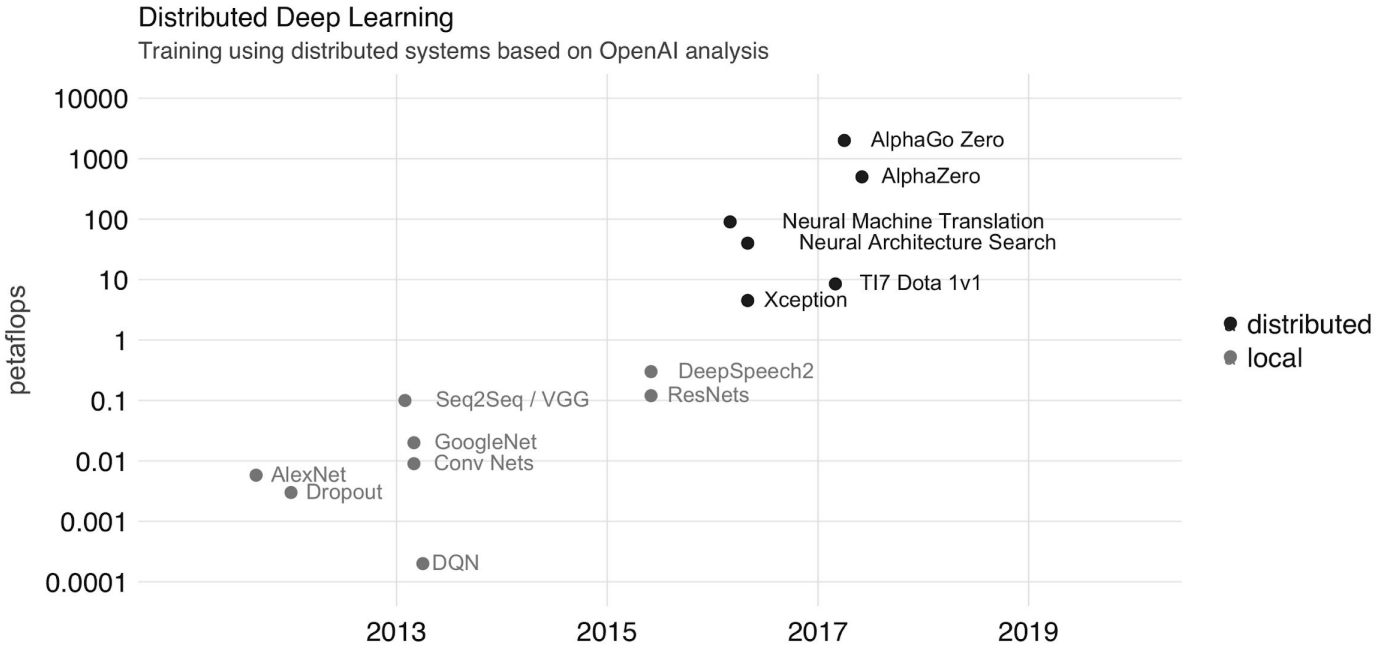
V100 GPUs, running the fastai and PyTorch libraries. This is a new speed record for training Imagenet to this accuracy on publicly available infrastructure, and is 40% faster than Google's DAWNBench record on their proprietary TPU Pod cluster. Our approach uses the same number of processing units as Google's benchmark (128) and costs around $40 to run.

DIU and fast.ai will be releasing software to allow anyone to easily train and monitor their own distributed models on AWS, using the best practices developed in this project. The main training methods we used (details below) are: fast.ai's progressive resizing for classification, and rectangular image validation; NVIDIA's NCCL with PyTorch's all-reduce; Tencent's weight decay tuning; a variant of Google Brain's dynamic batch sizes, gradual learning rate warm-up (Goyal et al 2018, and Leslie Smith 2018). We used the classic ResNet-50 architecture, and SGD with momentum.

https://www.fast.ai/2018/08/10/fastai-diu-imagenet/

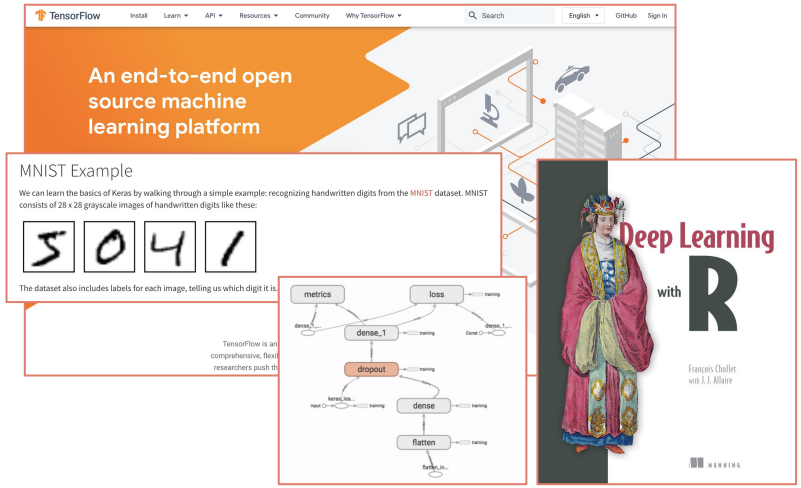
Distributed Deep Learning

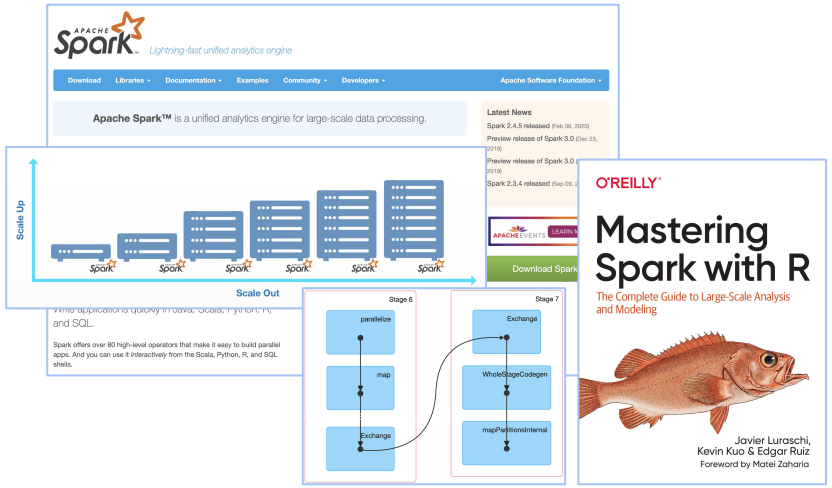
Recent state-of-the-art models require distributed training.



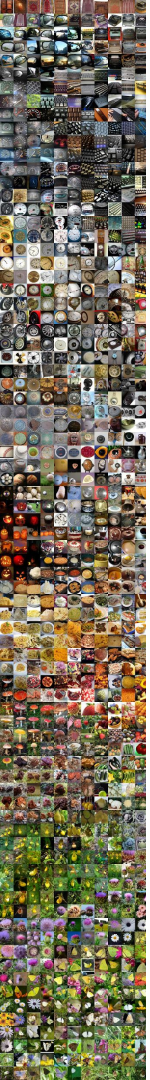
Overview

This talk assumes you are somewhat familiar with TensorFlow and Spark:





Talk Outline: **Distributed Deep Learning, TensorFlow** and **Spark.**



Distributed Deep Learning

Deep Learning Recap: AlexNet

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
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University of Toronto
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Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

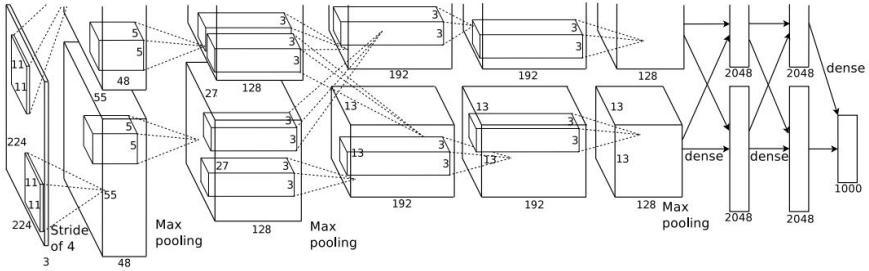
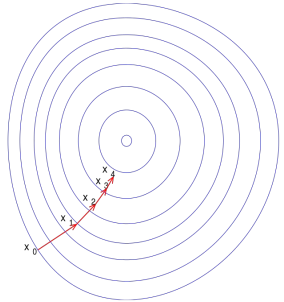


Figure 2: An illustration of the architecture of our CNN, explicitly showing the delineation of responsibilities between the two GPUs. One GPU runs the layer-parts at the top of the figure while the other runs the layer-parts at the bottom. The GPUs communicate only at certain layers. The network's input is 150,528-dimensional, and the number of neurons in the network's remaining layers is given by 253,440–186,624–64,896–64,896–43,264–4096–4096–1000.



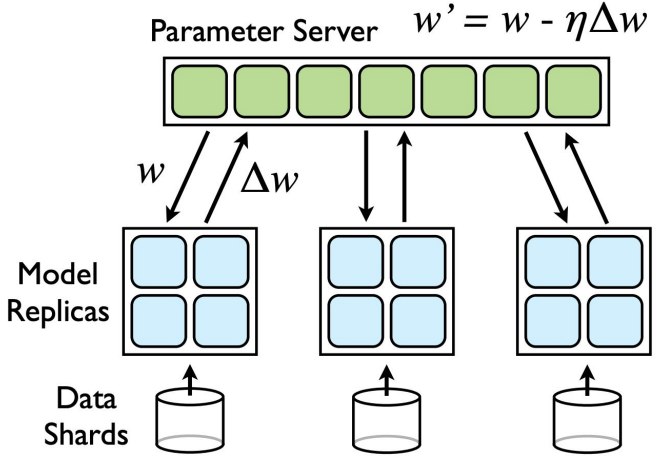
$$\mathbf{a}_{n+1} = \mathbf{a}_n - \gamma \nabla F(\mathbf{a}_n)$$

https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf

Parameter Server @Google

Large Scale Distributed Deep Networks

Jeffrey Dean, Greg S. Corrado, Rajat Monga, Kai Chen, Matthieu Devin, Quoc V. Le, Mark Z. Mao, Marc'Aurelio Ranzato, Andrew Senior, Paul Tucker, Ke Yang, Andrew Y. Ng
{jeff, gcorrado}@google.com
Google Inc., Mountain View, CA



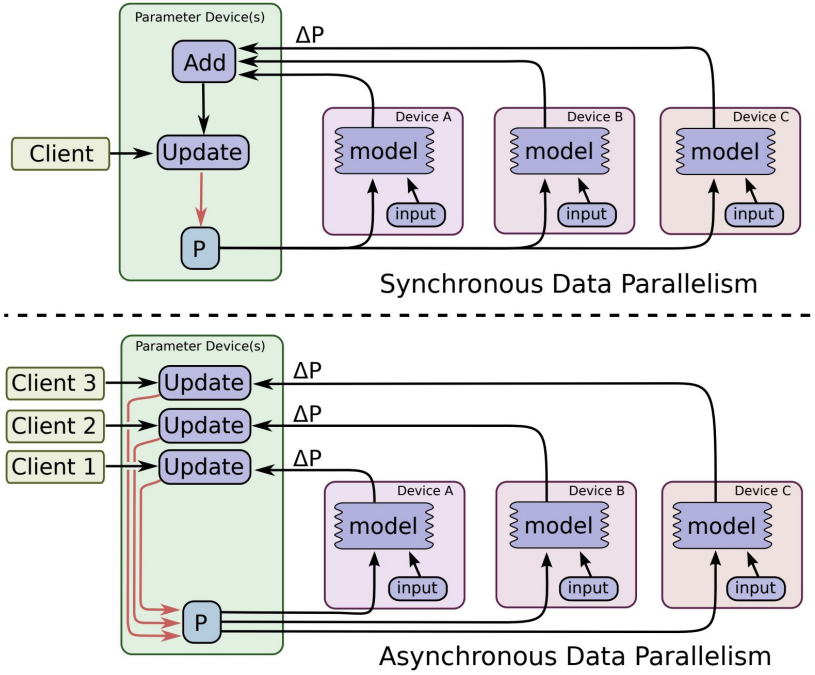
the same order. Moreover, because the model replicas are permitted to fetch parameters and push gradients in separate threads, there may be additional subtle inconsistencies in the timestamps of parameters. There is little theoretical grounding for the safety of these operations for nonconvex problems, but in practice we found relaxing consistency requirements to be remarkably effective.

http://papers.nips.cc/paper/4687-large-scale-distributed-deep-networks.pdf

Parameter Server @TensorFlow

TensorFlow:
Large-Scale Machine Learning on Heterogeneous Distributed Systems
(Preliminary White Paper, November 9, 2015)

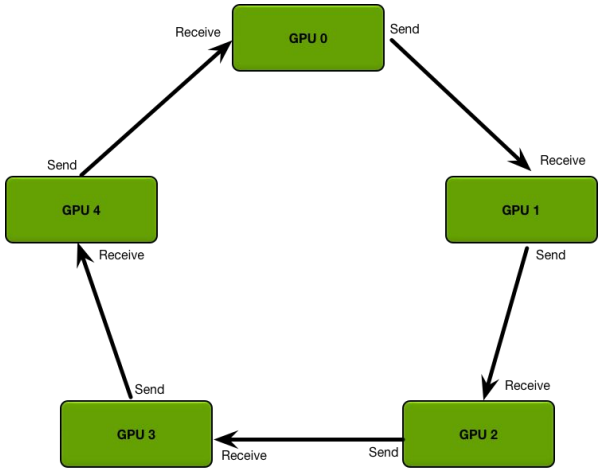
Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dan Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng
Google Research*



https://arxiv.org/pdf/1603.04467.pdf

Ring All-Reduce @Baidu

Two steps: First, a scatter-reduce, and then, an allgather.



https://andrew.gibiansky.com/blog/machine-learning/baidu-allreduce/

Ring All-Reduce @Horovod

Horovod: fast and easy distributed deep learning in TensorFlow

Alexander Sergeev
Uber Technologies, Inc.
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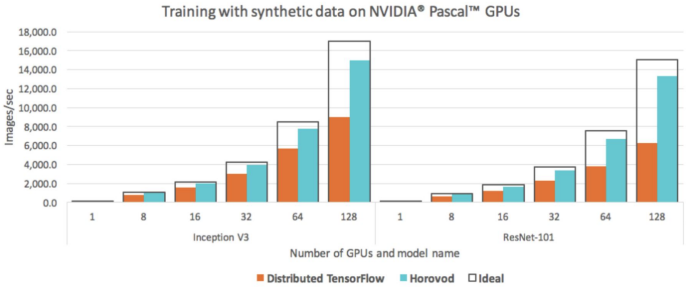
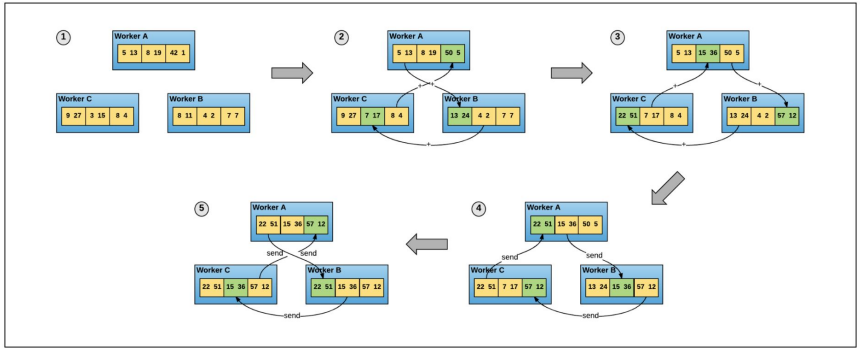
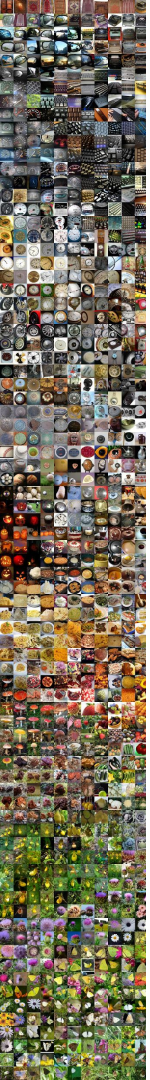
Mike Del Balso
Uber Technologies, Inc.
mdb@uber.com



In early 2017 Baidu published an article [8] evangelizing a different algorithm for averaging gradients and communicating those gradients to all nodes (Steps 2 and 3 above), called ring-allreduce, as well as a fork of TensorFlow through which they demonstrated a draft implementation of this algorithm. The algorithm was based on the approach introduced in the 2009 paper by Patarasuk and Yuan [9].

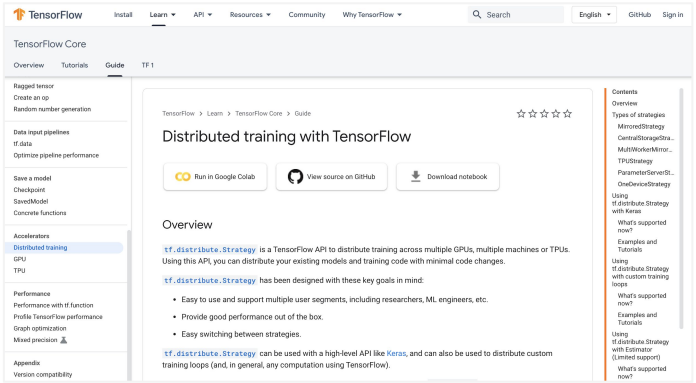


https://arxiv.org/pdf/1802.05799.pdf



TensorFlow

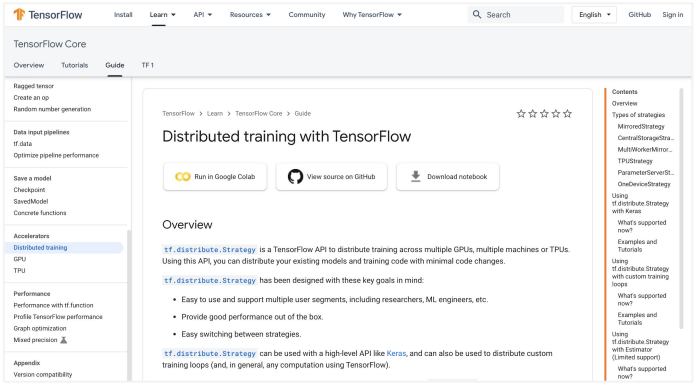
Distributed Training with TensorFlow



Training API	MirroredStrategy	TPUStrategy	MultiWorkerMirroredStrategy	CentralStorageStrategy	ParameterServerStrategy	OneDeviceStrategy
Keras API	Supported	Experimental support	Experimental support	Experimental support	Supported planned post 2.0	Supported
Custom training loop	Experimental support	Experimental support	Support planned post 2.0	Support planned post 2.0	No support yet	Supported
Estimator API	Limited Support	Not supported	Limited Support	Limited Support	Limited Support	Limited Support

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

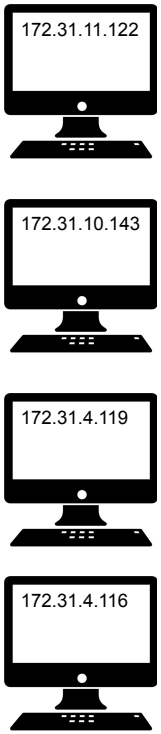
Distributed Training with TensorFlow



Training API	MirroredStrategy	TPUStrategy	MultiWorkerMirroredStrategy	CentralStorageStrategy	ParameterServerStrategy	OneDeviceStrategy
Keras API	Supported	Experimental support	Experimental support	Experimental support	Supported planned post 2.0	Supported
Custom training loop	Experimental support	Experimental support	Support planned post 2.0	Support planned post 2.0	No support yet	Supported
Estimator API	Limited Support	Not supported	Limited Support	Limited Support	Limited Support	Limited Support

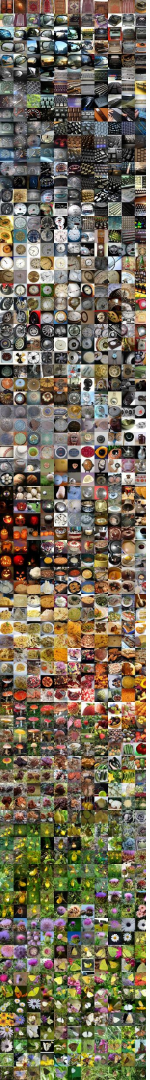
https://www.tensorflow.org/guide/distributed_training

Configuration File




```
# run in main worker
Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
    cluster = list(
        worker = c("172.31.11.122:10090", "172.31.10.143:10088", "172.31.4.119:10087", "172.31.4.116:10089")
    ),
    task = list(type = 'worker', index = 0)
), auto_unbox = TRUE))

# run in worker(1)
Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
    cluster = list(
        worker = c("172.31.11.122:10090", "172.31.10.143:10088", "172.31.4.119:10087", "172.31.4.116:10089")
    ),
    task = list(type = 'worker', index = 1)
), auto_unbox = TRUE))

# run in worker(2)
Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
    cluster = list(
        worker = c("172.31.11.122:10090", "172.31.10.143:10088", "172.31.4.119:10087", "172.31.4.116:10089")
    ),
    task = list(type = 'worker', index = 2)
), auto_unbox = TRUE))

# run in worker(3)
Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
    cluster = list(
        worker = c("172.31.11.122:10090", "172.31.10.143:10088", "172.31.4.119:10087", "172.31.4.116:10089")
    ),
    task = list(type = 'worker', index = 3)
), auto_unbox = TRUE))
```

https://github.com/mlverse/distributed



Distributed Pseudocode

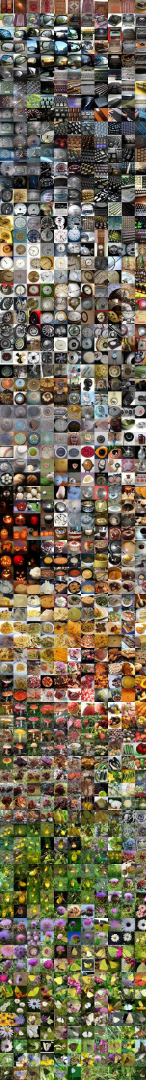
Local Model

```
library(tensorflow)
library(keras)

# create model
model ← keras_model_sequential() # %>% ...

# compile model
model %>% compile()

# fit model
model %>% fit()
```

Distributed Model

```
# define configuration
Sys.setenv(TF_CONFIG = "")

library(tensorflow)
library(keras)

# define strategy
strategy ← tf$distribute$experimental$MultiWorkerMirroredStrategy()
with (strategy$scope(), {
  # create model
  model ← keras_model_sequential() # %>% ...

  # compile model
  model %>% compile()
})

# fit model
model %>% fit()
```

https://github.com/mlverse/distributed



Distributed Code

Local Model

```
library(tensorflow)
library(keras)

batch_size <- 64L

mnist <- dataset_mnist()
x_train <- mnist$train$x
y_train <- mnist$train$y

x_train <- array_reshape(x_train, c(nrow(x_train), 28, 28, 1))
x_train <- x_train / 255

model <- keras_model_sequential() %>%
  layer_conv_2d(
    filters = 32,
    kernel_size = 3,
    activation = 'relu',
  input_shape = c(28, 28, 1)
  ) %>%
    layer_max_pooling_2d() %>%
    layer_flatten() %>%
    layer_dense(units = 64, activation = 'relu') %>%
    layer_dense(units = 10)

model %>% compile(
  loss = tf$keras$losses$SparseCategoricalCrossentropy(from_logits = TRUE),
  optimizer = tf$keras$optimizers$SGD(learning_rate = 0.001),
  metrics = 'accuracy')

model %>% fit(x_train, y_train, batch_size = batch_size, epochs = 3, steps_per_epoch = 5)
```

Distributed Model

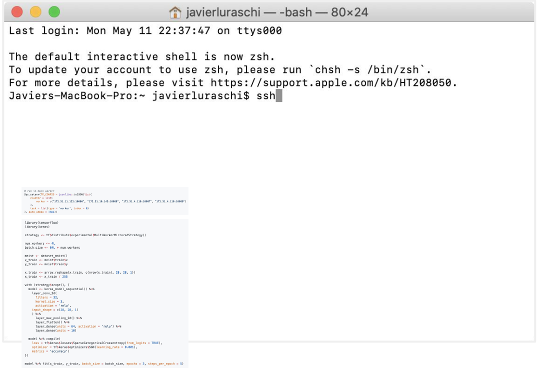
```
# run in main worker
Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
    cluster = list(
        worker = c("172.31.11.122:10090", "172.31.10.143:10088", "172.31.4.119:10087", "172.31.4.116:10089")
    ),
    task = list(type = 'worker', index = 0)
), auto_unbox = TRUE))
```

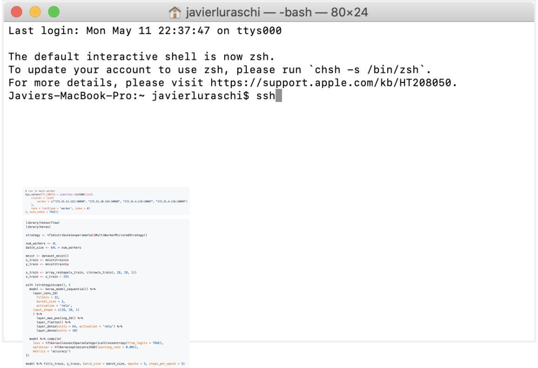
```
library(tensorflow)
library(keras)

strategy <- tf$distribute$experimental$MultiWorkerMirroredStrategy()

num_workers <- 4L
batch_size <- 64L * num_workers

mnist <- dataset_mnist()
x_train <- mnist$train$x
y_train <- mnist$train$y

x_train <- array_reshape(x_train, c(nrow(x_train), 28, 28, 1))
x_train <- x_train / 255

with (strategy$scope(), {
  model <- keras_model_sequential() %>%
    layer_conv_2d(
      filters = 32,
      kernel_size = 3,
      activation = 'relu',
    input_shape = c(28, 28, 1)
    ) %>%
      layer_max_pooling_2d() %>%
      layer_flatten() %>%
      layer_dense(units = 64, activation = 'relu') %>%
      layer_dense(units = 10)

  model %>% compile(
    loss = tf$keras$losses$SparseCategoricalCrossentropy(from_logits = TRUE),
    optimizer = tf$keras$optimizers$SGD(learning_rate = 0.001),
    metrics = 'accuracy')
})

model %>% fit(x_train, y_train, batch_size = batch_size, epochs = 3, steps_per_epoch = 5)
```

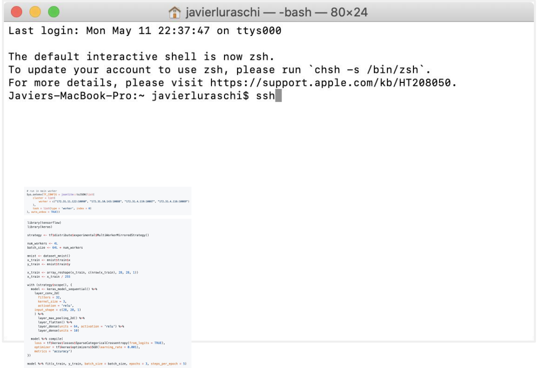
https://github.com/mlverse/distributed

Distributed Training

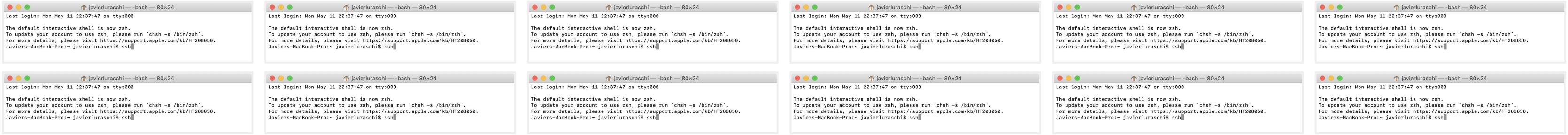
SSH to each machine, transfer **data subset**, run the code in each machine.

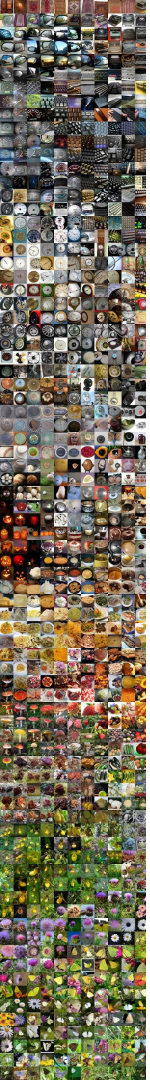






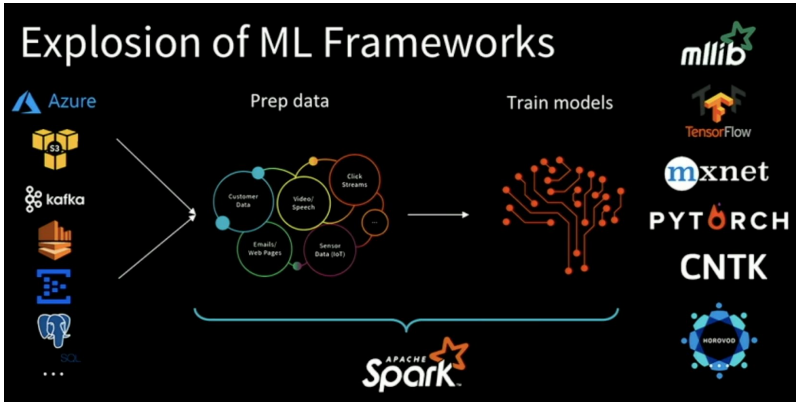
What if you need dozens of machines?

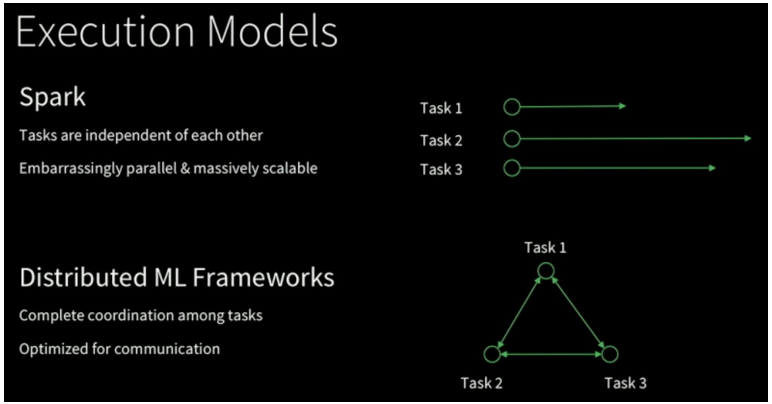


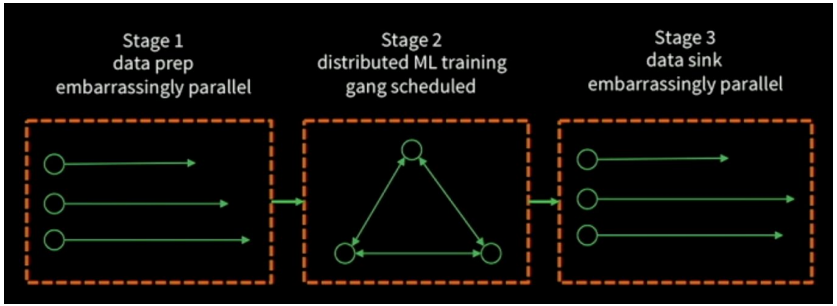


Spark

Deep Learning Frameworks and Spark



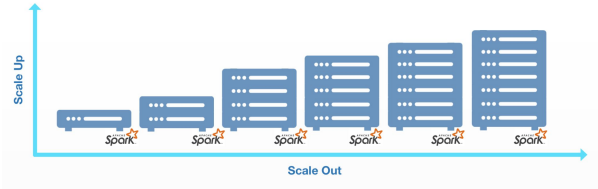


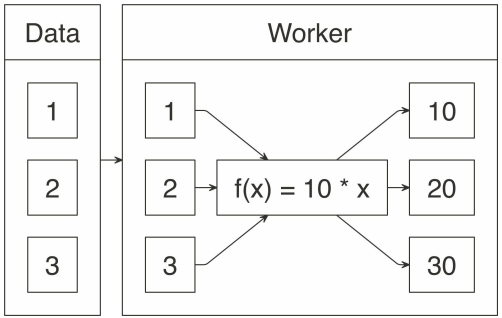


[Project Hydrogen: State-of-the-Art Deep Learning on Apache Spark Reynold Xin]

Spark Apply

You can use **spark_apply()** to apply an arbitrary transformation in R:

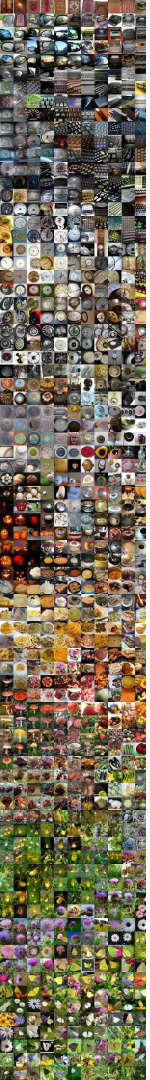





```
sdf_len(sc, 3) %>%
  spark_apply(~ 10 * .x)
```

```
# Source: spark<?> [?? x 1]
     id
* <dbl>
1    10
2    20
3    30
```

Can't we just use **spark_apply()** to run TensorFlow code?



Barrier Execution

Barrier Execution supported since sparklyr 1.1 and Spark 2.4. Used to schedule all-or-nothing resources, retrieve IP addresses and process data.

Barrier Execution

Barrier execution is a new feature introduced in Spark 2.4 which enables Deep Learning on Apache Spark by implementing an all-or-nothing scheduler into Apache Spark. This allows Spark to not only process analytic workflows, but also to use Spark as a high-performance computing cluster where other framework, like OpenMP or TensorFlow Distributed, can reuse cluster machines and have them directly communicate with each other for a given task.

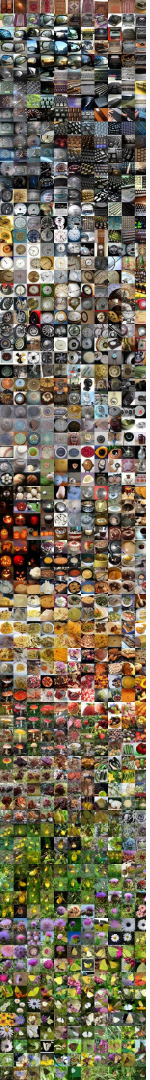
In general, we don't expect most users to use this feature directly; instead, this is a feature relevant to advanced users interested in creating extensions that support additional modeling frameworks. You can learn more about barrier execution in Reynold Xin's keynote.

To use barrier execution from R, set the `barrier = TRUE` parameter in `spark_apply()` and then make use of a new parameter in the R closure to retrieve the network address of the additional nodes available for this task. A simple example follows:

```
library(sparklyr)
sc <- spark_connect(master = "local", version = "2.4")

sdf_len(sc, 1, repartition = 1) %>%
  spark_apply(~ .y$address, barrier = TRUE, columns = c(address = "character")) %>%
  collect()
```

```
# A tibble: 1 x 1
  address
  <chr>
1 localhost:50693
```

https://blog.rstudio.com/2020/01/29/sparklyr-1-1/#barrier-execution



Spark and TensorFlow Pseudocode

```
library(sparklyr)
sc ← spark_connect(master = "local|yarn|etc")

# partition dataset
sdf_len(sc, 3, repartition = 3) %>%
  spark_apply(function(df, barrier) {
      library(tensorflow)
      library(keras)

      # define configuration from barrier
      Sys.setenv(TF_CONFIG = "")

      # define strategy and model
      strategy ← MultiWorkerMirroredStrategy()
      with (strategy$scope(), {
        model ← keras_model_sequential() # %>% ...
        model %>% compile()
      })

      # fit and retrieve model
      model %>% fit()
  }, barrier = TRUE) %>% collect()
```

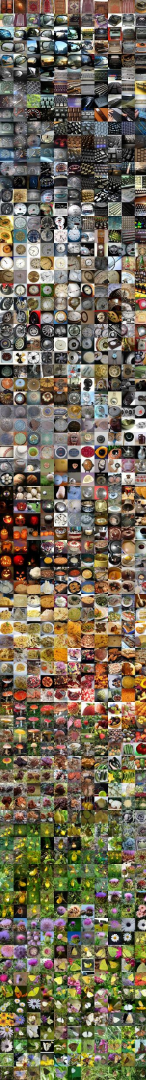
- ❏ Connect
- ❏ Partition Data
- ❏ Apply Transform
- ❏ Load Libraries
- ❏ Set Configuration
- ❏ Define Strategy
- ❏ Define Model
- ❏ Compile Model
- ❏ Fit Model
- ❏ Retrieve Model

https://github.com/mlverse/distributed

Example (1/2)

```
library(sparklyr)
sc <- spark_connect(master = "yarn", spark_home = "/usr/lib/spark/", config =
list(spark.dynamicAllocation.enabled= FALSE, `sparklyr.shell.executor-cores` = 8,
`sparklyr.shell.num-executors` = 3, sparklyr.apply.env.WORKON_HOME= "/tmp/.virtualenvs"))

sdf_len(sc, 3, repartition = 3) %>%
  spark_apply(function(df, barrier) {
    tryCatch({
      library(tensorflow)
      library(keras)

      Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
        cluster = list(worker = paste(gsub(":[0-9]+$", "", barrier$address), 8000 +
seq_along(barrier$address), sep = ":")),
        task = list(type = 'worker', index = barrier$partition)
      ), auto_unbox = TRUE))

      if (is.null(tf_version())) install_tensorflow()

      // << tensorflow model >>

    }, error = function(e) e$message)
  }, barrier = TRUE, columns = c(address = "character"), ) %>% collect()
```

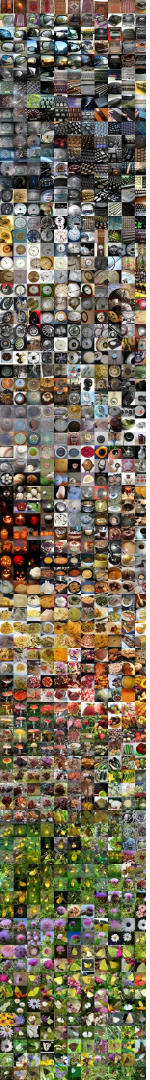
https://github.com/mlverse/distributed



Example (1/2)

```
strategy <- tf$distribute$experimental$MultiWorkerMirroredStrategy()
mnist <- dataset_mnist()

x_train <- mnist$train$x
y_train <- mnist$train$y
x_train <- array_reshape(x_train, c(nrow(x_train),28, 28, 1))
x_train <- x_train / 255

with (strategy$scope(), {
   model <- keras_model_sequential() %>%
     layer_conv_2d(filters = 32, kernel_size = 3, activation = 'relu', input_shape = c(28, 28, 1)) %>%
     layer_max_pooling_2d() %>%
     layer_flatten() %>%
     layer_dense(units = 64, activation = 'relu') %>%
     layer_dense(units = 10)

   model %>% compile(
     loss = tf$keras$losses$SparseCategoricalCrossentropy(from_logits = TRUE),
     optimizer = tf$keras$optimizers$SGD(learning_rate = 0.001),
     metrics = 'accuracy') })

model %>% fit(x_train, y_train, batch_size = 64L * 3L, epochs = 3, steps_per_epoch = 5)
```

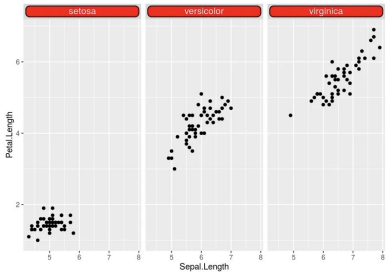
https://github.com/mlverse/distributed



Pins

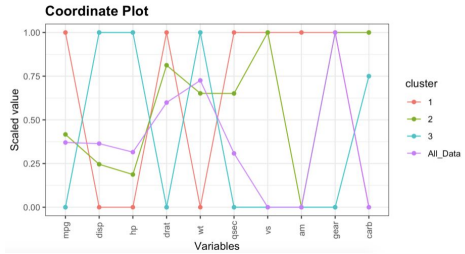
Data Workflows - Today

June 16th posts in R-bloggers use iris, mtcars, have missing data paths and require manually downloading datasets.




```
32. ###################################
    ### IMPORT RAW DATA
33.
34. log_info("Loading data")
35.
36. mydat = fread(data_path)
37.
```

```
coord_plot(data=mtcars2, group_var="cluster",
group_func=median, print_table=TRUE)
```

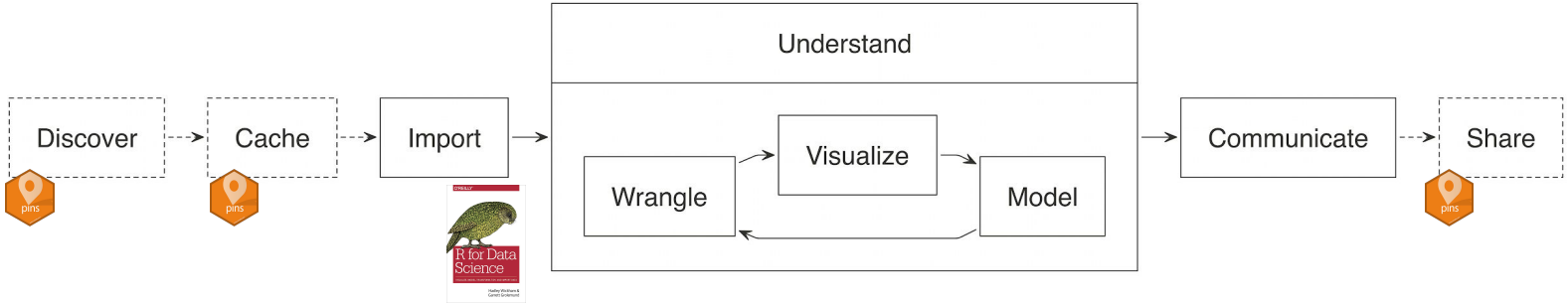



```
# https://www.data.gouv.fr/fr/datasets/donnees-
hospitalieres-relatives-a-lepidemie-de-covid-19/
fichier_covid <- "donnees/covid.csv"
```

https://r-bloggers.com

Data Workflows - In Data Science

We know from R for Data Science that in a typical project we usually need to import, tidy, understand and communicate knowledge.

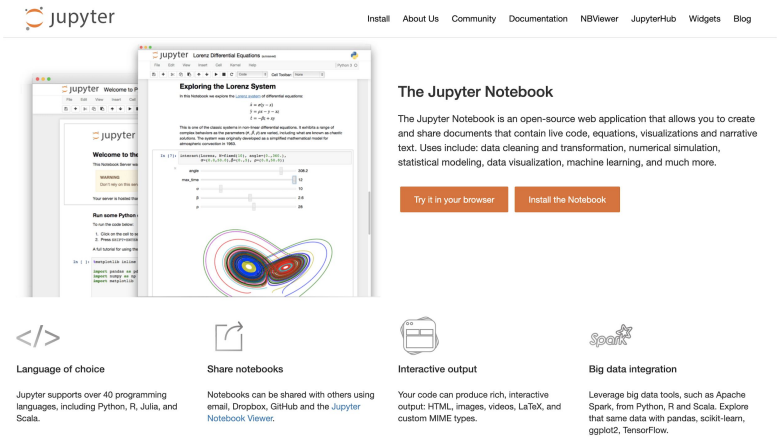


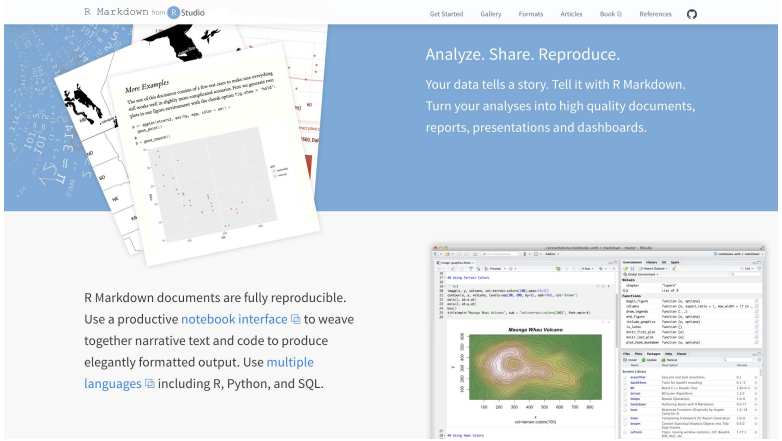
However, it is often also required for us to discover which dataset to use, cache it locally, and share our datasets with colleagues.

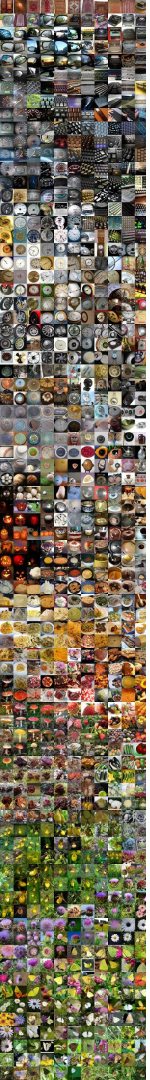
https://pins.rstudio.com

Data Workflows - Reproducibility

But more importantly, properly caching and sharing our datasets allows us to make Data Science more reproducible in tools like R Markdown and Jupyter.

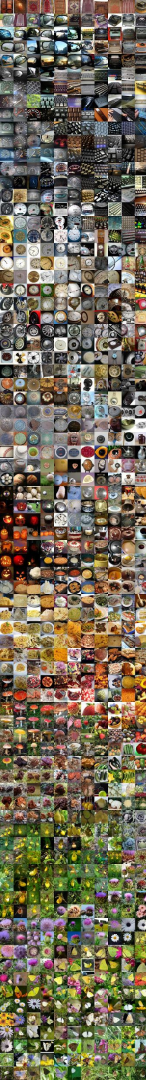






Data Workflows - Ideally

- Learn a **single tool** regardless of where data lives.
- Easy **switch storage** and share it anywhere.
- Easy to build **automated workflows**.
- Can share datasets of **any size**.
- Can easily use **interesting datasets**!
- Data loads **fast** and works **offline**.



What is the pins package?

- **Pin** remote resources locally with pin(), work offline and cache results.
- **Discover** new resources across different boards using pin_find().
- **Share resources** in local folders, GitHub, Kaggle, and RStudio Connect by registering new boards with board_register().

Links

Download from CRAN at
https://cloud.r-project.org/package=pins

Browse source code at
https://github.com/rstudio/pins

Report a bug at
https://github.com/rstudio/pins/issues

License

Apache License 2.0

Developers

Javier Luraschi
Author, maintainer

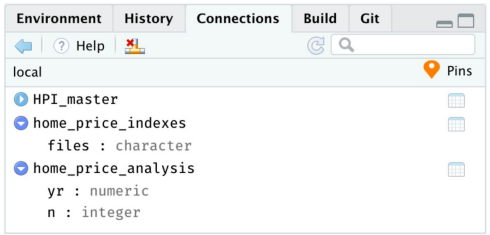
All authors...

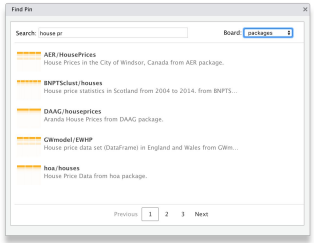
Dev status

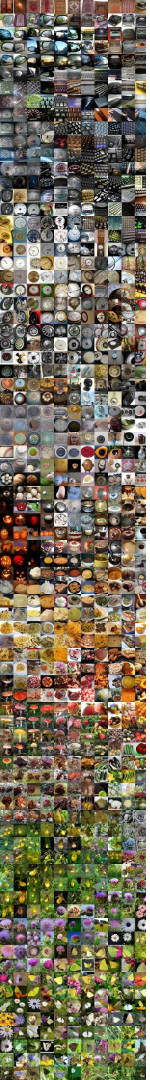
How can I use Pins?

Use pin() to save objects, pin_get() to retrieve them and pin_find() to search.

```
pin(1:10, name = "numbers")
pin_get("numbers")

pin("http://cs231n.stanford.edu/tiny-imagenet-200.zip ", name = "tinyimagenet")
pin_get("tinyimagenet")

pin_find()
```

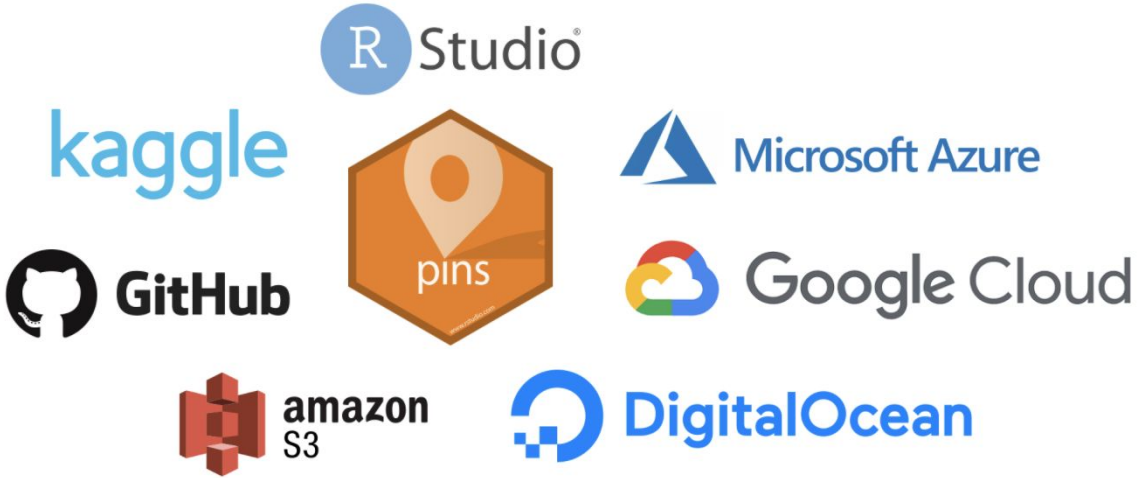


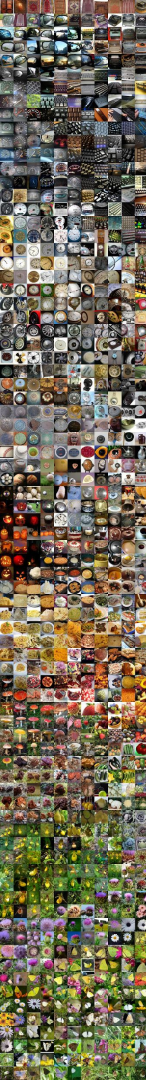




What are Boards?

A board is a storage location, like your local hard drive, but there are also many additional places where you can store your datasets like RStudio Connect, Microsoft Azure, Google Cloud, Digital Ocean, Amazon S3, GitHub and Kaggle.

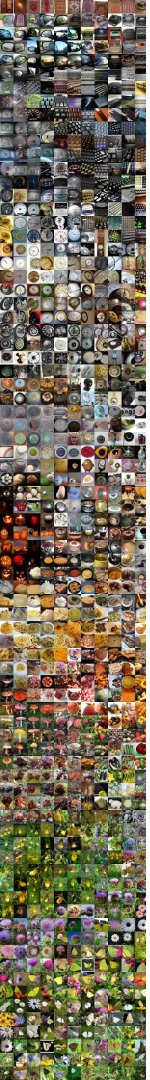




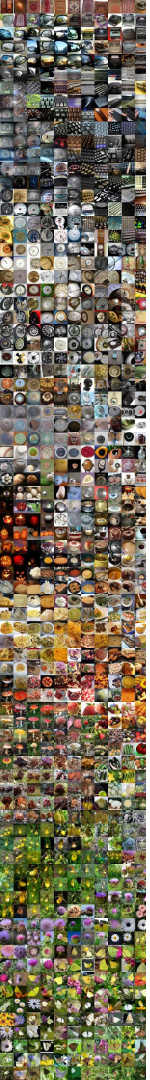
What are Boards?

To use pins with boards, first register the board, then specify the board in pin().

```
board_register("_____")

pin(1:10, name = "numbers", board = "_____")
pin_get("numbers")

pin("cs231n.stanford.edu/tiny-imagenet-200.zip ", "tinyimagenet", board = "_____")
pin_get("tinyimagenet")

pin_find()
```



ImageNet

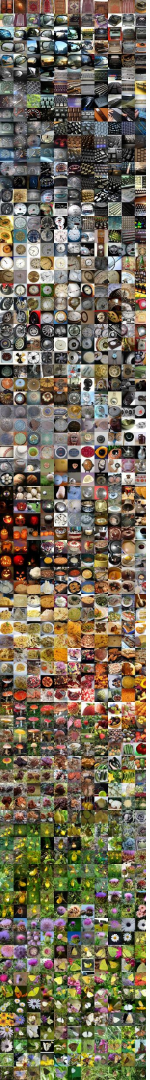


Retrieving ImageNet

Use pins and the Kaggle board to fetch ImageNet's 250GB dataset.

```
library(pins)
board_register("kaggle", "path/to/kaggle.json" )

imagenet <- pin_get("c/imagenet-object-localization-challenge" , board = "kaggle")
untar(imagenet[1], exdir = "imagenet/")
```

Which takes 60 minutes to download and 60 minutes to uncompress...

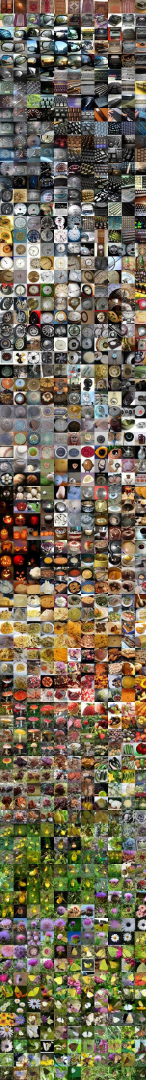


Using Local SSDs

n1-standard-8 (8 vCPUs, 30 GB memory) and 4 local SSDs

```
> system.time(pins::pin_get("imagenet", board = "https://storage.googleapis.com/imagenet-pins/"))
    user   system  elapsed
 211.937  512.572 1847.234

> system.time(untar(imagenet[1], exdir = "/localssd/imagenet/"))
    user   system  elapsed
1273.879  443.763 1360.702
```

Down to 30 minutes to download and 22 to uncompress...



More and Faster CPUs

c2-standard-16 (16 vCPUs, 64 GB memory)

```
> system.time(pins::pin_get("imagenet", board = "https://storage.googleapis.com/imagenet-pins/"))
    user   system  elapsed
 147.031  387.707 1522.945

> system.time(untar(imagenet[1], exdir = "/localssd/imagenet/"))
   user  system elapsed
887.538 284.525 961.746
```

Down to 25 minutes to download and 16 minutes to uncompress...

CPU Bottleneck? (top)

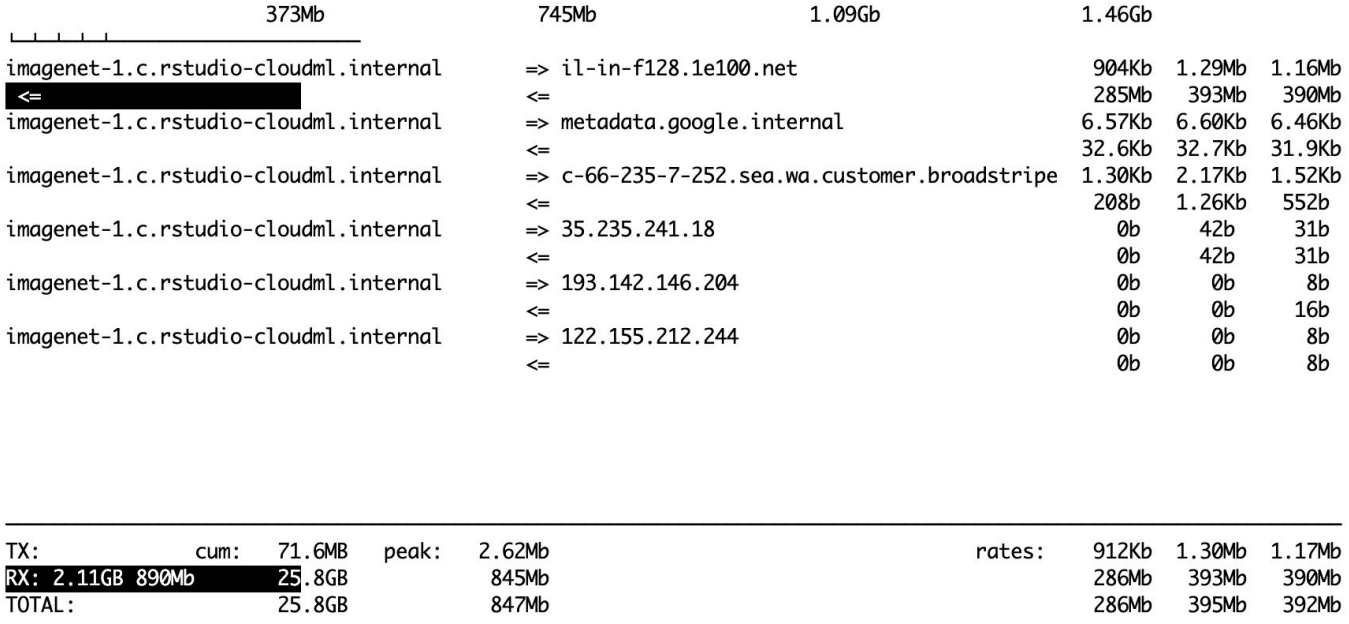
Use the **top** command to display CPU usage to diagnose bottlenecks.

```
top - 22:48:19 up 9 min,  0 users,  load average: 0.23, 0.63, 0.46
Tasks:   9 total,   1 running,   8 sleeping,   0 stopped,   0 zombie
%Cpu(s):  0.7 us,  0.9 sy,  0.0 ni, 98.0 id,  0.1 wa,  0.0 hi,  0.3 si,  0.0 st
KiB Mem : 65972836 total, 50130140 free,  1029696 used, 14813000 buff/cache
KiB Swap:        0 total,        0 free,        0 used. 64238656 avail Mem
```

PID	USER	PR	NI	VIRT	RES	SHR	S	%CPU	%MEM	TIME+	COMMAND
140	rstudio	20	0	1544424	228464	59368	S	28.7	0.3	0:25.61	rsession
3479	root	20	0	250608	5716	5292	S	0.3	0.0	0:00.22	iftop
1	root	20	0	20048	3436	3180	S	0.0	0.0	0:00.17	bash
7	root	20	0	6220	852	788	S	0.0	0.0	0:00.00	tail
16	rstudio+	20	0	268368	52276	8712	S	0.0	0.1	0:00.57	rserver
176	rstudio	20	0	21364	5076	3436	S	0.0	0.0	0:00.01	bash
3478	root	20	0	53676	3948	3512	S	0.0	0.0	0:00.00	sudo
3516	rstudio	20	0	21364	4924	3380	S	0.0	0.0	0:00.01	bash
3519	rstudio	20	0	38264	3596	3168	R	0.0	0.0	0:00.00	top

Network Bottleneck? (iftop)

Or iftop to troubleshoot network bottlenecks:



Disk Bottleneck? (dstat)

Or dstat to diagnose disk performance:

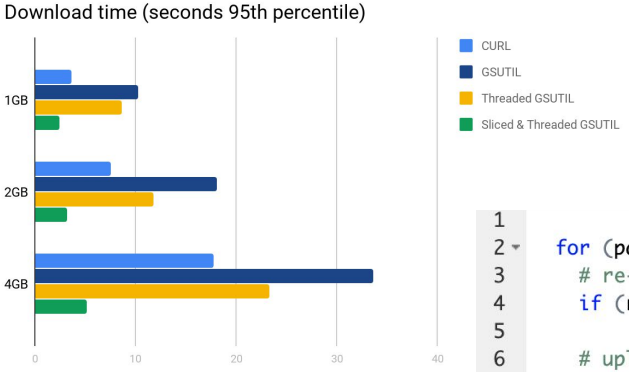
```
--total-cpu-usage-- -dsk/total- -net/total- ---paging-- ---system--
usr sys idl wai stl| read  writ| recv  send|  in   out | int   csw
  1   1  98   0   0|   0    32M| 141M  715k|   0     0 |  14k 3477
  1   2  97   0   0|   0    34M| 190M 1004k|   0     0 |  20k 5884
  1   1  98   0   0|   0    32M| 148M  778k|   0     0 |  15k 3734
  1   1  98   0   0|   0    32M| 110M  583k|   0     0 |  12k 3135
  1   1  98   0   0|   0    34M| 137M  720k|   0     0 |  14k 3560
  1   1  98   0   0|   0    32M| 105M  567k|   0     0 |  11k 3174
  1   1  98   0   0|   0    34M| 145M  780k|   0     0 |  16k 4376
  1   1  98   0   0|   0    32M| 129M  696k|   0     0 |  14k 3775
  1   3  92   5   0|   0  1171M| 143M  745k|   0     0 |  16k 3111
  1   2  89   8   0|4096B 1542M| 139M  718k|   0     0 |  15k 2048
  1   2  92   5   0|4096B 1519M|  80M  446k|   0     0 |  11k 3267
  1   1  97   0   0|   0   220M| 142M  738k|   0     0 |  14k 2376
  1   2  97   0   0|   0    34M| 190M  993k|   0     0 |  19k 3915
  1   1  98   0   0|   0    32M| 121M  621k|   0     0 |  12k 2530
  1   1  98   0   0|   0    34M| 144M  748k|   0     0 |  15k 2938
  1   1  98   0   0|   0    32M| 123M  641k|   0     0 |  13k 2715
  1   1  98   0   0|   0    32M| 153M  800k|   0     0 |  15k 3373
  1   1  97   0   0|   0    34M| 160M  816k|   0     0 |  16k 3114
  1   1  98   0   0|   0    32M| 123M  619k|   0     0 |  12k 1915
  1   1  99   0   0|   0    34M|  89M  455k|   0     0 |8891  1474
  0   1  99   0   0|   0    32M|  81M  412k|   0     0 |8171  1678
```

No Bottleneck?

Not the CPU, not the disk, not the network...

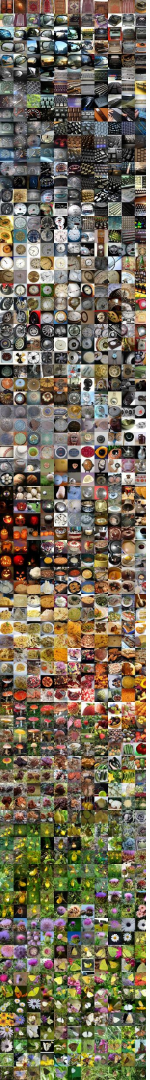
So now what?

a. Use faster tools (gsutil parallel, lbzip2).
b. Partition datasets.




```
1
2  for (path in dir("/localssd/imagenet/ILSVRC/Data/CLS-LOC/train/", full.names = TRUE)) {
3    # re-register board every 10 uploads to refresh authentication headers
4    if (runif(1) > 0.9) board_register("gcloud", name = "imagenet", bucket = "r-imagenet")
5
6    # upload imagenet partition
7    dir(path, full.names = TRUE) %>% pin(name = basename(path), board = "imagenet", zip = TRUE)
8  }
9
```

https://medium.com/@duhroach/gcs-read-performance-of-large-files-bd53cfca4410

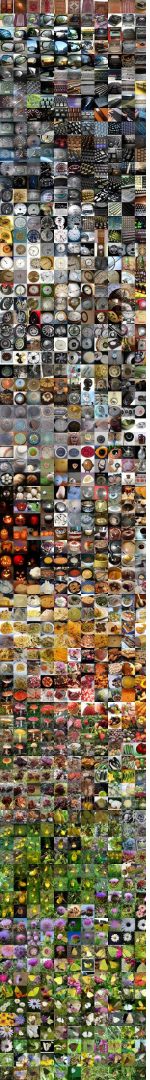


Partitioned Dataset

Assuming we train with 16 instances, we can test download/extraction with 1/16th of the data:

```
> pins::board_register_datatxt("https://storage.googleapis.com/r-imagenet/", "imagenet")
> categories <- pins::pin_get("categories", board = "imagenet")
> categories <- categories$id[1:(length(categories$id) / 16)]
> system.time({
+     procs <- lapply(categories, function(cat)
+         callr::r_bg(function(cat) {
+             pins::board_register_datatxt("https://storage.googleapis.com/r-imagenet/", "imagenet")
+             pins::pin_get(cat, board = "imagenet", extract = TRUE)
+         }, args = list(cat))
+     )
+
+     while (any(sapply(procs, function(p) p$is_alive()))) Sys.sleep(1)
+ })
   user  system elapsed
309.800  86.256  58.729
```

Nice improvement from 41 minutes down to 58 seconds.



Dry Run

We can train a subset using the [r-tensorflow/alexnet] package

```
pins::board_register_datatxt("https://storage.googleapis.com/r-imagenet/", "imagenet")
data <- list(
  image = unlist(lapply(categories, function(cat) {
    pins::pin_get(cat, board = "imagenet", download = FALSE)
  })),
  category = unlist(lapply(categories, function(cat) {
    rep(cat, length(pins::pin_get(cat, board = "imagenet", download = FALSE)))
  })),
  categories = categories
)

alexnet::alexnet_train(data = data)
```

```
    user   system  elapsed
1267.204  360.276  696.639
```

Although, still takes 11.6 minutes to train 1/16th epoch in a Tesla K80 GPU.

Dry Run (Multi GPU)

We can try instead with 4 GPUs,

```
> strategy <- tf$distribute$MirroredStrategy()
> alexnet::alexnet_train(data = data, strategy = strategy)
2020-07-30 03:06:39.958696: W tensorflow/core/framework/op_kernel.cc:1753] OP_REQUIRES failed at nccl_op
s.cc:104 : Internal: NCCL: unhandled system error. Set NCCL_DEBUG=WARN for detail.
2020-07-30 03:06:39.958863: W tensorflow/core/framework/op_kernel.cc:1753] OP_REQUIRES failed at nccl_op
s.cc:104 : Internal: NCCL: unhandled system error. Set NCCL_DEBUG=WARN for detail.
2020-07-30 03:06:39.958921: W tensorflow/core/framework/op_kernel.cc:1753] OP_REQUIRES failed at nccl_op
s.cc:104 : Internal: NCCL: unhandled system error. Set NCCL_DEBUG=WARN for detail.
2020-07-30 03:06:39.958986: W tensorflow/core/framework/op_kernel.cc:1753] OP_REQUIRES failed at nccl_op
s.cc:104 : Internal: NCCL: unhandled system error. Set NCCL_DEBUG=WARN for detail.
```

```
Error in py_call_impl(callable, dots$args, dots$keywords) :
  InternalError: 2 root error(s) found.
  (0) Internal:  NCCL: unhandled system error. Set NCCL_DEBUG=WARN for detail.
         [[node NcclAllReduce (defined at /keras/engine/training.py:66) ]]
  (1) Internal:  NCCL: unhandled system error. Set NCCL_DEBUG=WARN for detail.
         [[node NcclAllReduce (defined at /keras/engine/training.py:66) ]]
         [[GroupCrossDeviceControlEdges_1/SGD/SGD/update_0/Const/_135]]
0 successful operations.
2 derived errors ignored. [Op:__inference_train_function_10923]

Function call stack:
train_function -> train_function
```

Show Traceback

Rerun with Debug

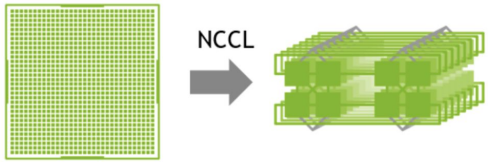
Ughh, NCCL errors, NCCL?

NVIDIA NCCL

NVIDIA NCCL

The NVIDIA Collective Communications Library (NCCL) implements multi-GPU and multi-node collective communication primitives that are performance optimized for NVIDIA GPUs. NCCL provides routines such as all-gather, all-reduce, broadcast, reduce, reduce-scatter, that are optimized to achieve high bandwidth and low latency over PCIe and NVLink high-speed interconnect.

Get Started



Performance

NCCL conveniently removes the need for developers to optimize their applications for specific machines. NCCL provides fast collectives over multiple GPUs both within and across nodes.

Ease of Programming

NCCL uses a simple C API, which can be easily accessed from a variety of programming languages.NCCL closely follows the popular collectives API defined by MPI (Message Passing Interface).

Compatibility

NCCL is compatible with virtually any multi-GPU parallelization model, such as: single-threaded, multi-threaded (using one thread per GPU) and multi-process (MPI combined with multi-threaded operation on GPUs).

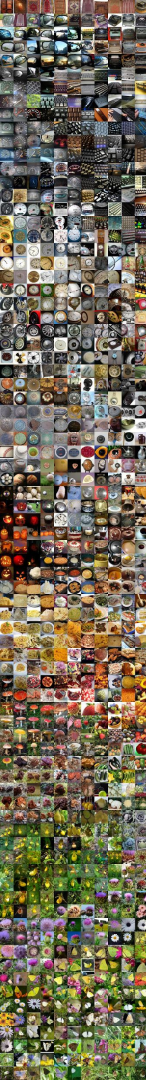
https://developer.nvidia.com/nccl

Dry Run (Multi GPU)

Or we can just disable NCCL by reducing in one device.

```
> system.time(alexnet::alexnet_train(data = data, strategy = strategy))
2020-07-30 03:44:39.084119: I tensorflow/stream_executor/platform/default/dso_loader.cc:44] Successfully
opened dynamic library libcublas.so.10
2020-07-30 03:44:40.058825: I tensorflow/stream_executor/platform/default/dso_loader.cc:44] Successfully
opened dynamic library libcudnn.so.7
Epoch 1/2
2067/2067 [==============================] - 375s 181ms/step - accuracy: 0.0383 - loss: nan
Epoch 2/2
2067/2067 [==============================] - 373s 181ms/step - accuracy: 0.0197 - loss: nan
    user   system  elapsed
1711.044  334.644  764.518
```

```
+-----------------------------------------------------------------------------+
| NVIDIA-SMI 418.152.00   Driver Version: 418.152.00   CUDA Version: 10.1     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  Tesla K80           Off  | 00000000:00:04.0 Off |                    0 |
| N/A   48C    P0    79W / 149W |  10936MiB / 11441MiB |     47%      Default |
+-------------------------------+----------------------+----------------------+
|   1  Tesla K80           Off  | 00000000:00:05.0 Off |                    0 |
| N/A   73C    P0    80W / 149W |  10936MiB / 11441MiB |     27%      Default |
+-------------------------------+----------------------+----------------------+
|   2  Tesla K80           Off  | 00000000:00:06.0 Off |                    0 |
| N/A   74C    P0    84W / 149W |  10936MiB / 11441MiB |     30%      Default |
+-------------------------------+----------------------+----------------------+
|   3  Tesla K80           Off  | 00000000:00:07.0 Off |                    0 |
| N/A   74C    P0    86W / 149W |  10936MiB / 11441MiB |     28%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
```

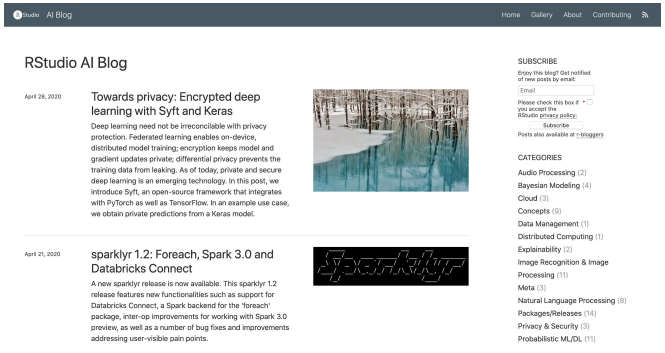


Multi Worker - Multi GPU

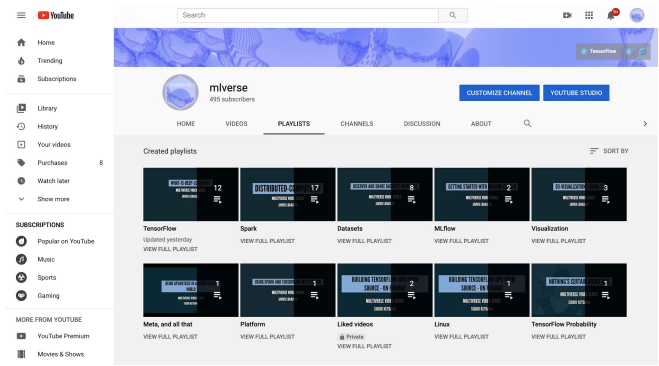
After configuring Spark, we can then run something like:

```
library(sparklyr)
sc <- spark_connect(master = "<master>")

sdf_len(sc, 3, repartition = 3) %>%
  spark_apply(function(df, barrier) {
    tryCatch({
      library(tensorflow)

      Sys.setenv(TF_CONFIG = jsonlite::toJSON(list(
        cluster = list(worker = paste(gsub(":[0-9]+$", "", barrier$address), 8000 + seq_along(barrier$address), sep = ":")),
        task = list(type = 'worker', index = barrier$partition)
      ), auto_unbox = TRUE))

      strategy <- tf$distribute$experimental$MultiWorkerMirroredStrategy()

      data <- alexnet::alexnet_imagenet(partition = barrier$partition, partitions = 16)
      alexnet::alexnet_train(data = data, strategy = strategy, parallel = 6)
    }, error = function(e) e$message)
  }, barrier = TRUE, columns = c(address = "character"), ) %>%
  collect()
```

Thanks!



blogs.rstudio.com/ai



youtube.com/c/mlverse

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