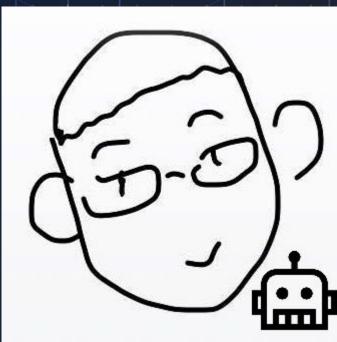


在云上运行机器学习工作负载

高策

关于我

- 高策,就职于才云科技

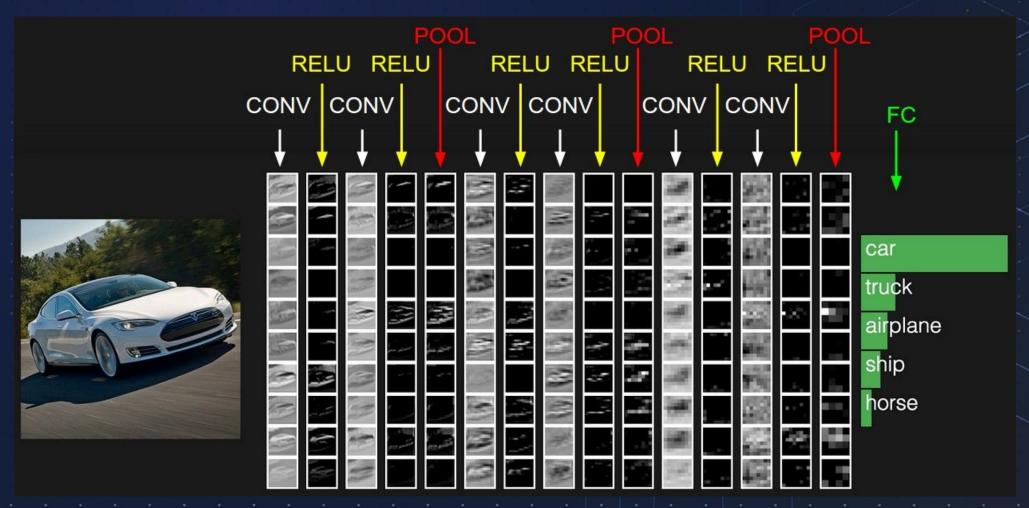


纲要

- 背景
- 问题
- 云上的资源管理问题
- 大规模分布式训练
- 可容错的模型训练



背景-VGG16



Credits: http://cs231n.github.io/convolutional-networks/



背景-VGG16,

```
# Block 1
x = layers.Conv2D(64, (3, 3),
                  activation='relu',
                  padding='same',
                  name='block1_conv1')(img_input)
x = layers.Conv2D(64, (3, 3),
                  activation='relu',
                  padding='same',
                  name='block1_conv2')(x)
x = layers.MaxPooling2D((2, 2), strides=(2, 2), name='block1_pool')(x)
# Block 2
x = layers.Conv2D(128, (3, 3),
                  activation='relu',
                  padding='same',
                  name='block2 conv1')(x)
x = layers.Conv2D(128, (3, 3),
                  activation='relu',
                  padding='same',
                  name='block2_conv2')(x)
x = layers.MaxPooling2D((2, 2), strides=(2, 2), name='block2 pool')(x)
```



背景-Behind the Scene

User API

High level Packages

Programming API

Gradient Calculation (Differentiation API)

System Components

Computational Graph Optimization and Execution

Runtime Parallel Scheduling

Architecture

GPU Kernels, Optimizing Device Code

Accelerators and Hardwares

Credits: http://dlsys.cs.washington.edu/pdf/lecture3.pdf



背景-分布式训练

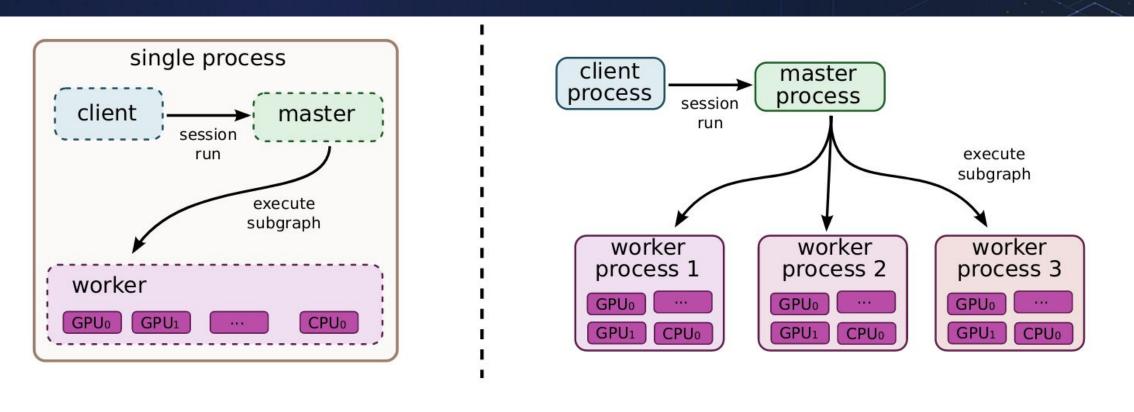


Figure 3: Single machine and distributed system structure



机器学习落地的问题

算法工程师的角度

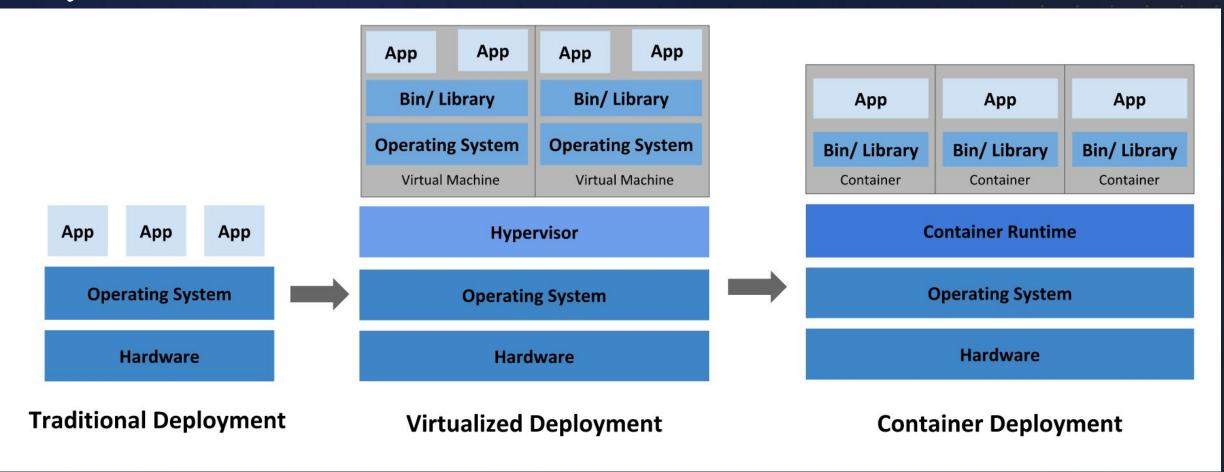
- 如何做好数据的准备与预处理
- 如何做好模型训练(单机/分布式)

基础架构工程师的角度

- 如何做好硬件资源的管理(隔离与共享)
- 如何做好大规模分布式训练的支持
- 如何保证集群资源的高利用率
- 如何容忍训练/推理过程中的错误



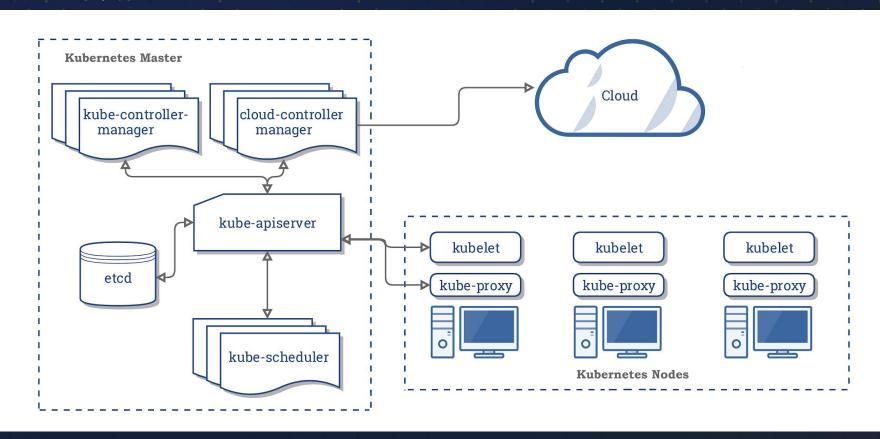
Why Kubernetes





Why Kubernetes

- 容器化, 方便管理
- 扩展性好,支持不同的存储方式,不同的运行时,不同的硬件
- 横向扩展性好, 节点可横向扩容
- 集群管理领域的事实标准





Why Kubernetes

```
apiVersion: v1
kind: Pod
metadata:
  name: myapp-pod
  labels:
    app: myapp
spec:
  containers:
  - name: myapp-container
    image: busybox
    command: ['sh', '-c', 'echo Hello Kubernetes! && sleep 3600']
```

为什么需要对硬件资源进行管理

- 隔离(CPU, Memory, GPU 等资源)
 - 保证训练与训练之间不会互相影响
 - 保证训练失败不会影响其他训练
 - 保证训练不会影响推理服务
- 共享
 - 在推理等单个服务用不完单个显卡算力的情况下,共享来提高资源利用率,节约成本



硬件资源的管理:隔离

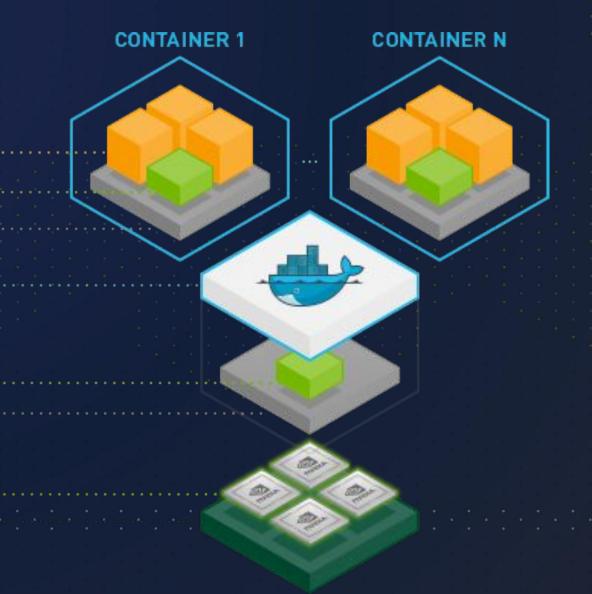
Applications

CUDA Toolkit

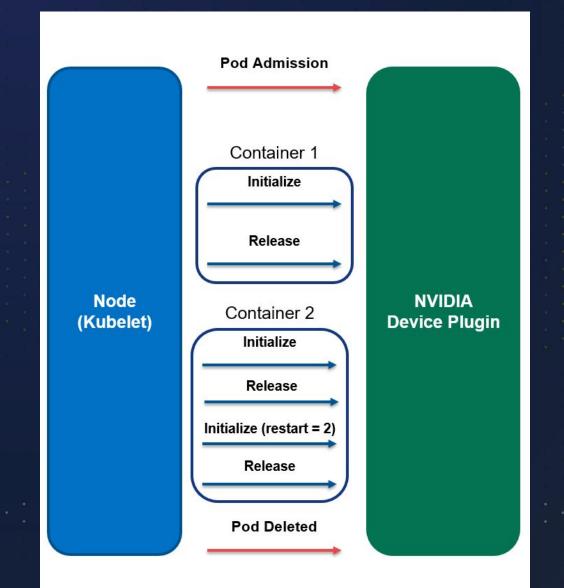
Docker Engine

NVIDIA GPUs

Container OS User Space

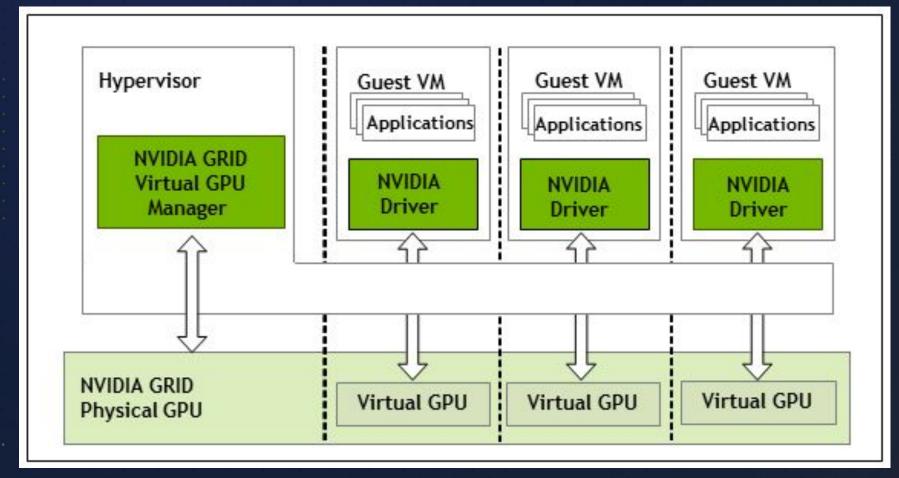


硬件资源的管理:隔离



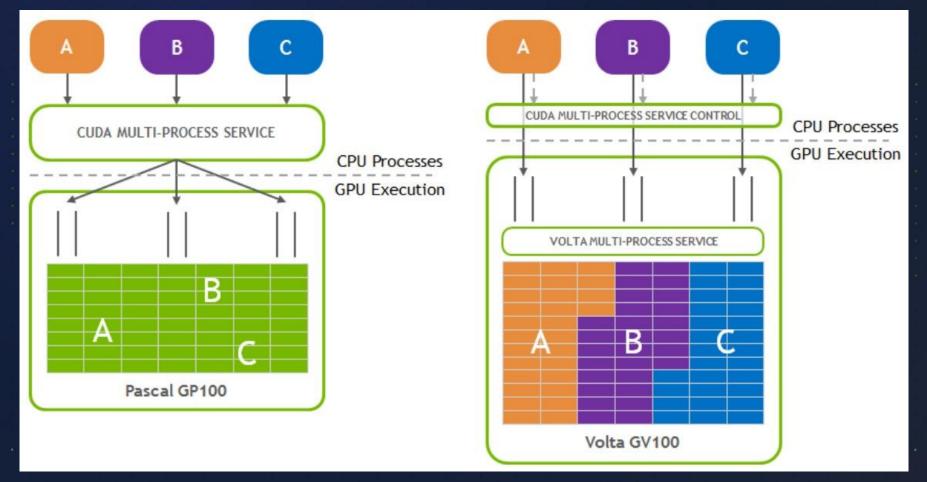


- 英伟达基于虚拟化的解决方案 Nvidia Grid



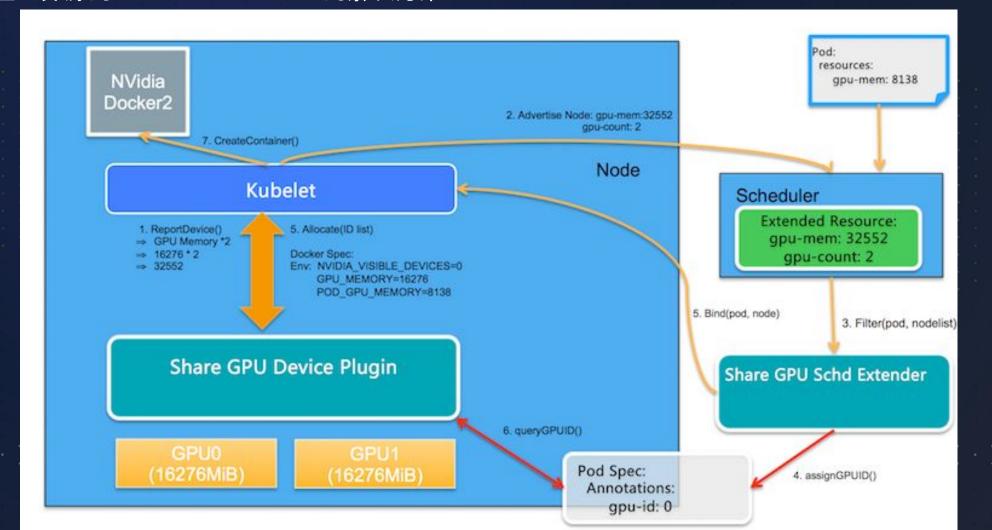


- 英伟达基于最新硬件(Volta)的解决方案 MPS



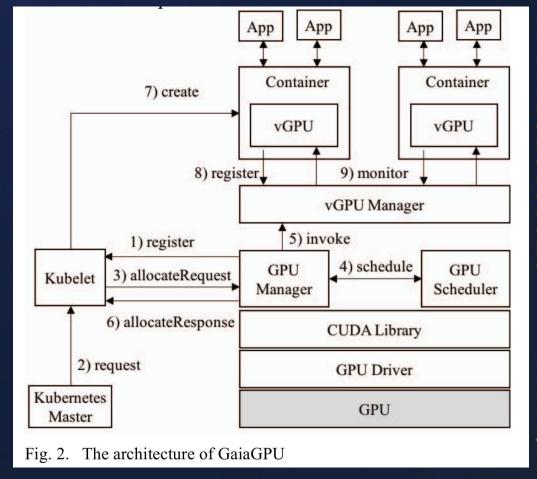


- 阿里云开源的 Kubernetes Native 的解决方案





- Intercept CUDA 调用的解决方案:以腾讯云开源的解决方案为例





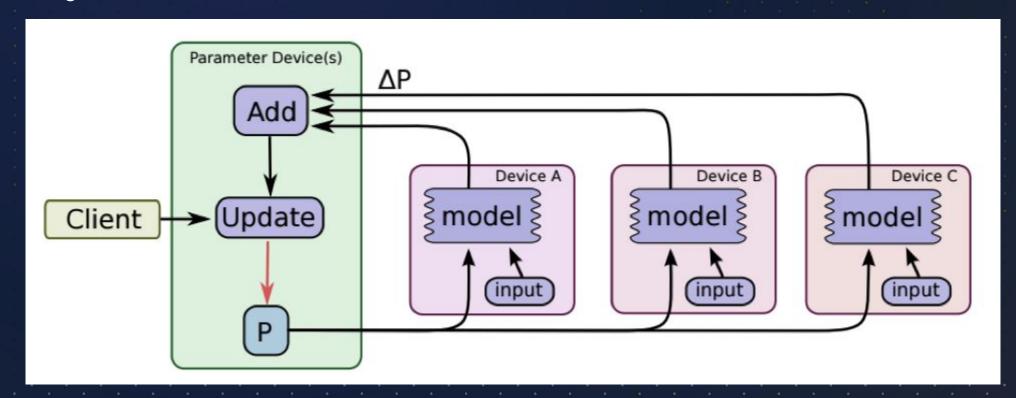
Credits: GaiaGPU: Sharing GPUs in Container Clouds

硬件资源的管理-总结

- 各有利弊
 - Nvidia Grid:基于虚拟机的解决方案
 - MPS:需要新硬件
 - Kubernetes Native 方案: 没有真正的隔离
 - Intercept CUDA: error prone

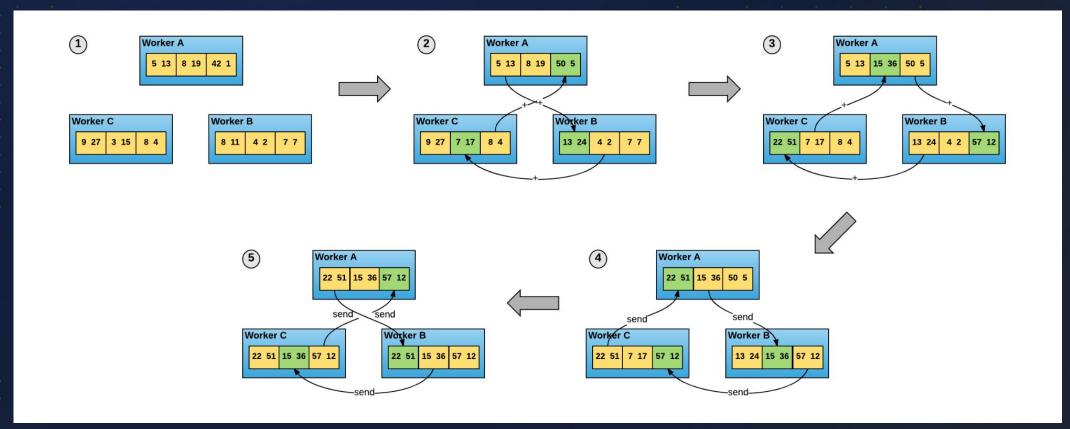


- 加快训练速度
 - PS-Worker
 - RingAllReduce





- 加快训练速度
 - PS-Worker
 - RingAllReduce





```
# On ps0.example.com:
$ python trainer.py \
     --ps_hosts=ps0.example.com:2222,ps1.example.com:2222 \
     --worker_hosts=worker0.example.com:2222,worker1.example.com:2222
     --job name=ps --task index=0
# On ps1.example.com:
$ python trainer.py \
     --ps_hosts=ps0.example.com:2222,ps1.example.com:2222 \
     --worker_hosts=worker0.example.com:2222,worker1.example.com:2222
     --job_name=ps --task_index=1
# On workerO.example.com:
$ python trainer.py \
     --ps_hosts=ps0.example.com:2222,ps1.example.com:2222 \
     --worker_hosts=worker0.example.com:2222,worker1.example.com:2222
     --job_name=worker --task_index=0
# On worker1.example.com:
$ python trainer.py \
     --ps_hosts=ps0.example.com:2222,ps1.example.com:2222 \
     --worker_hosts=worker0.example.com:2222,worker1.example.com:2222
     --job_name=worker --task_index=1
```



```
apiVersion: "kubeflow.org/v1beta1"
kind: "TFJob"
metadata:
  name: "dist-mnist"
spec:
  tfReplicaSpecs:
    PS:
      replicas: 2
      restartPolicy: Never
      template:
        spec:
          containers:
            name: tensorflow
              image: kubeflow/mnist:1.0
    Worker:
      replicas: 4
      restartPolicy: Never
      template:
        spec:
          containers:
            name: tensorflow
              image: kubeflow/mnist:1.0
```



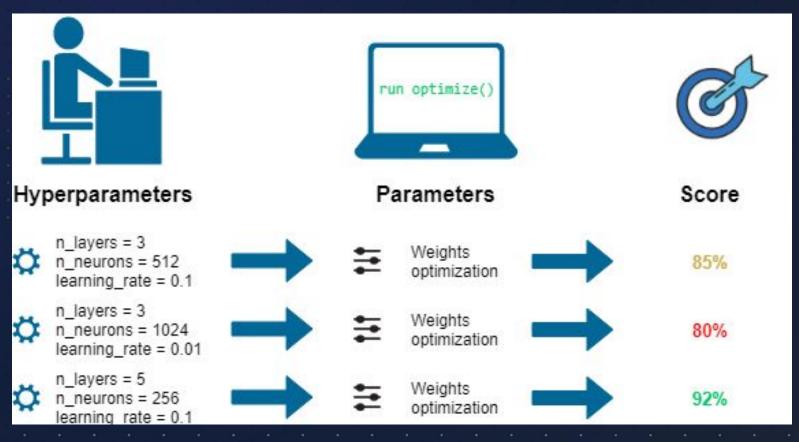
TF_CONFIG 的格式

TF_CONFIG 环境变量是一个 JSON 字符串,格式如下:

键	说明					
"cluster"	TensorFlow 集群描述。此对象的格式设置为 TensorFlow 集群规范,并且可以传递给 tf.train.ClusterSpec 🗹 的构造函数。					
"task"	描述运行代码的特定节点的任务。您可以使用此信息为分布式作业中的特定工作器编写代码。此条目 是一个含有以下键的字典:					
	"type" 此节点执行的任务类型。可能的值包括 master、worker 和 ps。					
	"index" 任务的索引(从零开始)。大多数分布式训练作业都有一个主任务、一个或多个参数服务器,以及一个或多个工作器。					
	"trial" 当前运行的超参数调节试验的标识符。为作业配置超参数调节时,可以设置多个要训练的试验。此值为您提供了一种区分代码中正在运行的试验的方法。标识符是一个包含试验编号的字符串值,从 1 开始。					
"job"	启动作业时使用的作业参数。在大多数情况下,您可以忽略此条目,因为其中包含的数据与通过命令行参数传递给应用的数据完全一致。					



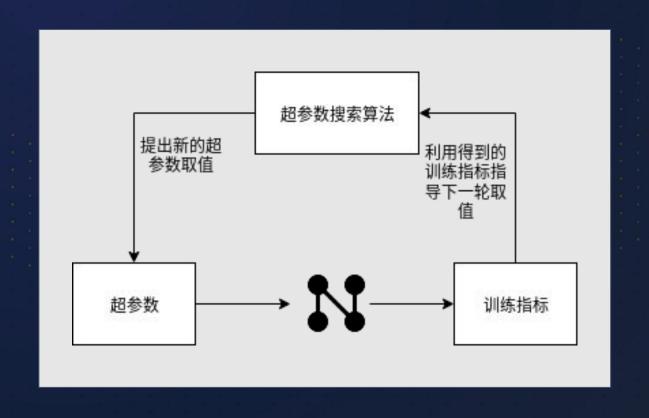
超参数:由用户在训练之前指定的参数,如神经网络中的 Learning Rate, Optimizer, Batch Size 等



Credits: https://towardsdatascience.com/hyperparameters-optimization-526348bb8e2d



经典的黑盒优化问题

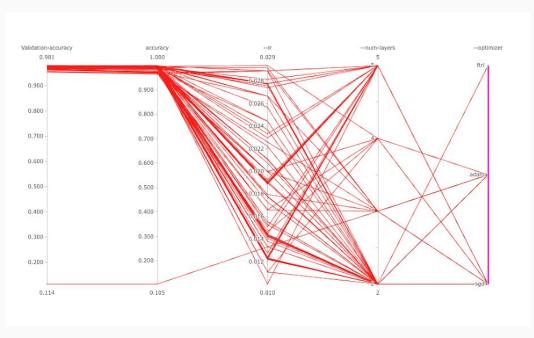




```
apiVersion: "kubeflow.org/v1alpha3"
kind: Experiment
metadata:
 name: example
spec:
 objective:
    type: maximize
    goal: 0.99
    objectiveMetricName: accuracy
    additionalMetricNames:
      accuracy
  algorithm:
    algorithmName: bayesianoptimization
  parallelTrialCount: 3
 maxTrialCount: 12
 maxFailedTrialCount: 3
 parameters:
    - name: --num-layers
      parameterType: int
      feasibleSpace:
       min: "2"
       max: "5"
    - name: --optimizer
      parameterType: categorical
      feasibleSpace:
        list:
        - sgd
        adam
        - ftrl
  trialTemplate:
```



Experiment Name: mnist-experiment



trialName	Validation-accuracy	accuracy	-lr	num-layers	optimizer
mnist-experiment-5p7tvdgn	0.979299	0.992031	0.01796154198777169	3	sgd
mnist-experiment-ccdgdp5v	0.981190	0.998906	0.014491188430762471	5	sgd
mnist-experiment-n24h6lwd	0.976712	0.992656	0.02915797314372763	3	sgd
mnist-experiment-lwf8dq49	0.962878	0.984062	0.017791967922146663	2	adam
mnist-experiment-2qv4mtsf	0.964869	0.974688	0.014689376618494194	4	adam
mnist-experiment-msdlqrjp	0.978603	0.994687	0.01775280397488328	2	sgd
mnist-experiment-pcr92pt2	0.957404	0.967969	0.022601601543350176	3	adam
mnist-experiment-njwhd2tr	0.977309	0.996719	0.029364679387401435	4	sgd







分布式训练总结

- 基于 Kubernetes 的大规模训练和超参数搜索可行,但资源利用率等问题仍有很大优化空间

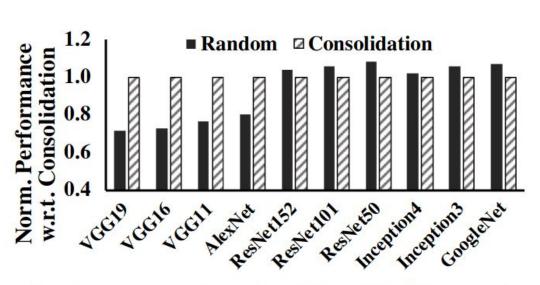
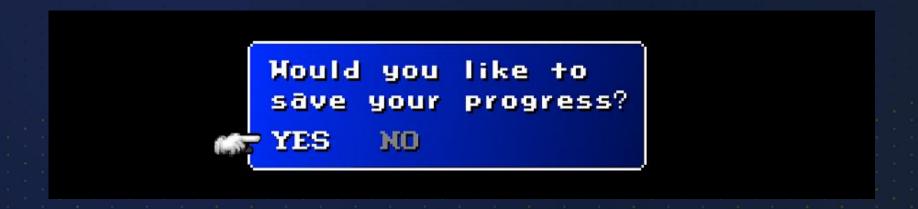


Figure 3: 4 concurrent 8-worker jobs with different placement schemes. The performance values are normalized by the value of the consolidation scheme. We use the median value from 10 (20) runs for consolidation (random) scheme.



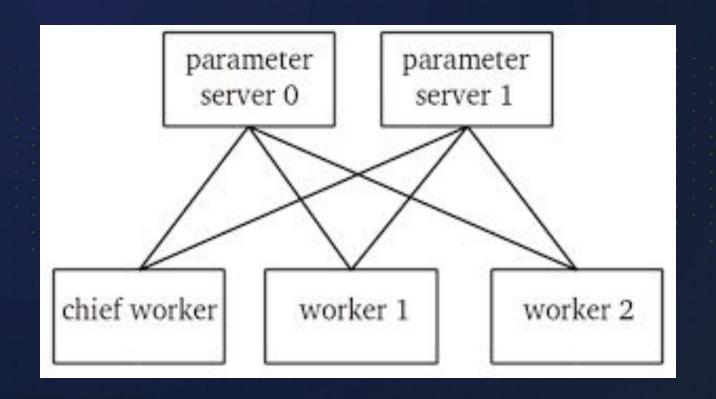


net.save_weights('easy_checkpoint')



```
tf.compat.v1.train.MonitoredTrainingSession(
   master='',
    is_chief=True,
    checkpoint_dir=None,
    scaffold=None,
   hooks=None,
    chief_only_hooks=None,
    save_checkpoint_secs=USE_DEFAULT,
    save_summaries_steps=USE_DEFAULT,
    save_summaries_secs=USE_DEFAULT,
    config=None,
    stop_grace_period_secs=120,
    log_step_count_steps=100,
   max_wait_secs=7200,
    save_checkpoint_steps=USE_DEFAULT,
    summary_dir=None
```

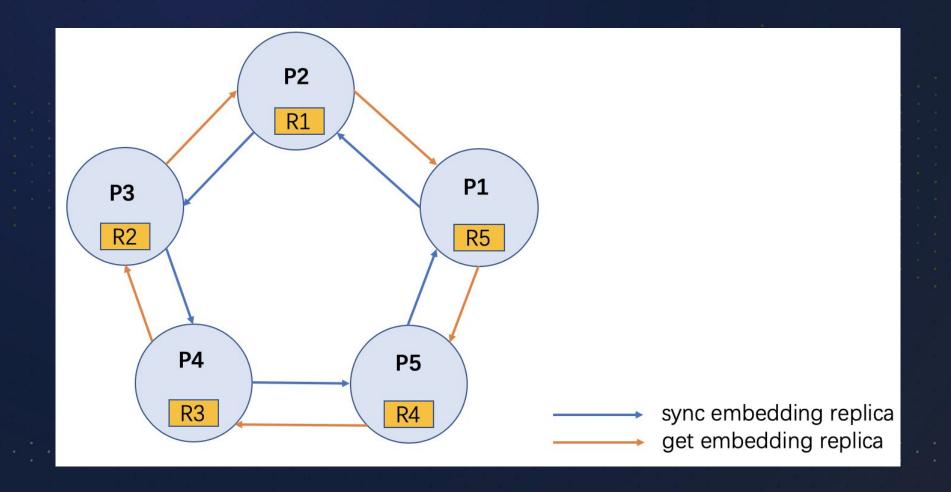






可容错的训练-PS/Worker

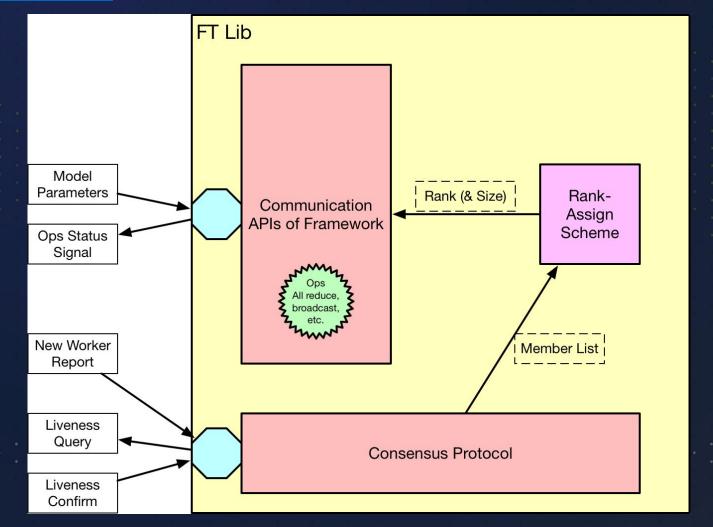
ElasticDL





可容错的训练-RingAllReduce

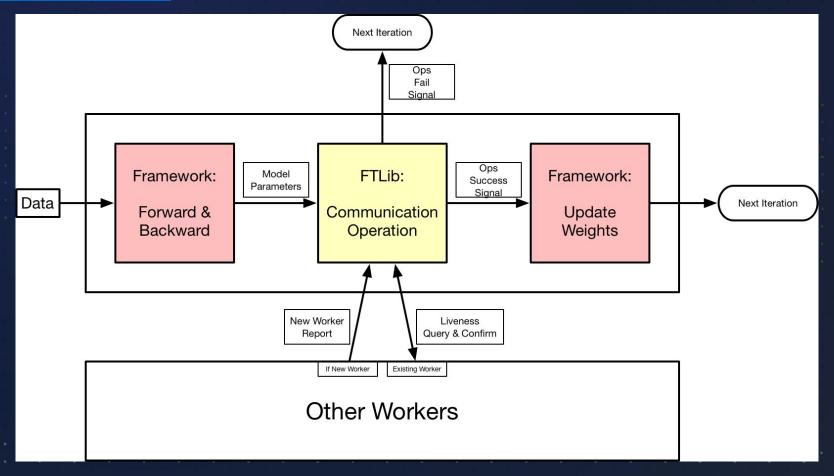
https://github.com/caicloud/ftlib/



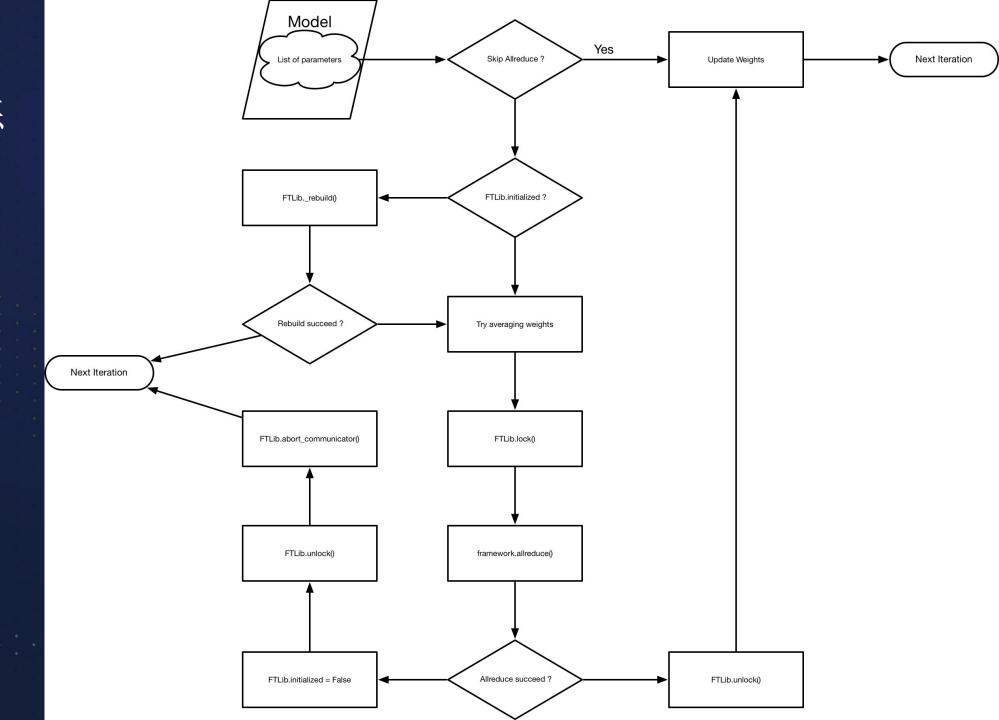


可容错的训练-RingAllReduce

https://github.com/caicloud/ftlib/







可容错的训练-RingAllReduce

一致性: SWIM-based Membership

A. Das, I. Gupta and A. Motivala, "SWIM: scalable weakly-consistent infection-style process group membership protocol," Proceedings International Conference on Dependable Systems and Networks, Washington, DC, USA, 2002, pp. 303-312.

doi: 10.1109/DSN.2002.1028914

URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=1028914&isnumber=22107



可容错的训练-总结

- 容错在大规模分布式训练中必不可少
- PS/Worker 和 RingAllReduce 需要不同的容错实现(?)
- 容错是弹性训练的前提



总结

- 硬件加速器资源的共享仍然是一个值得研究的领域
- 大规模,可容错的训练可行但具有侵入性
- 资源利用率的优化





THANK YOU!

Caicloud.io