



Train your ML models at scale

Gal Oshri

Product Manager
Amazon Web Services

Rise of large-scale models

“a picture of a very clean living room”



2017

StackGAN,
Zhang et al.

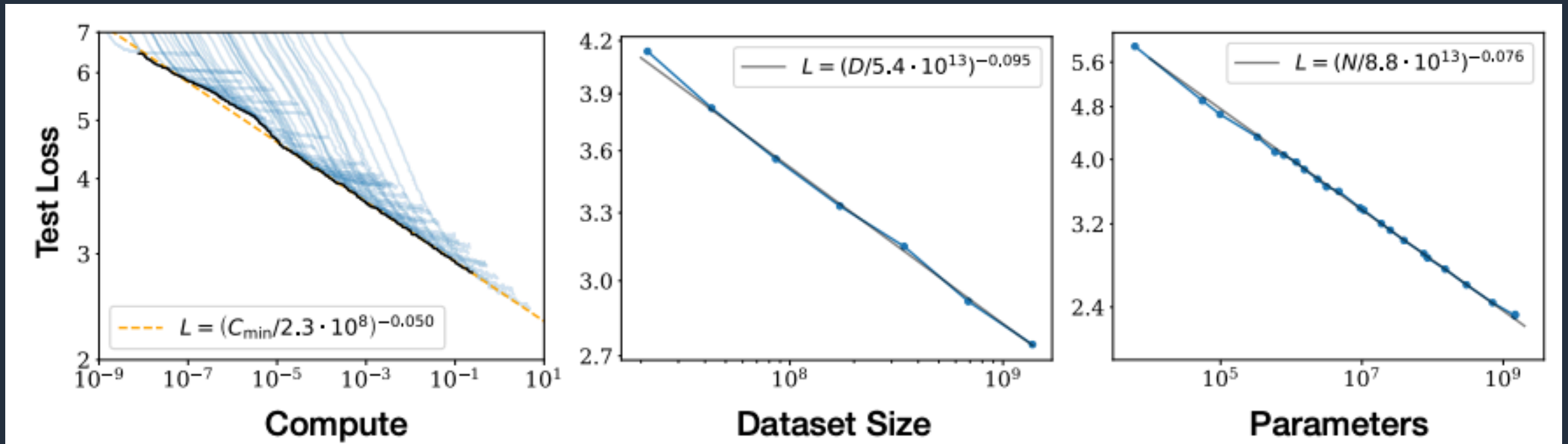
© 2023, Amazon Web Services, Inc. or its affiliates.



2022

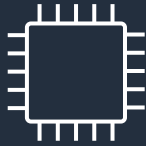
Stable Diffusion,
Rombach et al.

Large-scale models lead to better results



Scaling Laws for Neural Language Models
Kaplan et al., 2020

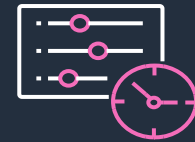
Challenges with training large-scale models



Hardware



Health checks



Orchestration



Data



Scaling up



Cost

SageMaker accelerates large-scale model training



Large-scale training on SageMaker

OPTIMIZED DISTRIBUTED TRAINING LIBRARIES & FRAMEWORKS



SageMaker Distributed
Training Libraries

Bring your own library (e.g.
DeepSpeed, Megatron)

AMAZON SAGEMAKER TRAINING

Large Scale Cluster
Orchestration

NCCL Health Checks

Resilient training

SageMaker
Compiler

Warm pools

SSH to container

Data loading

Debugger

Profiling

Experiment tracking

Hyperparameter
optimization

Pay for what
you use

ML COMPUTE INSTANCES & ACCELERATORS

NVIDIA GPUS
A100, V100, K80, T4, A10

AWS Nitro

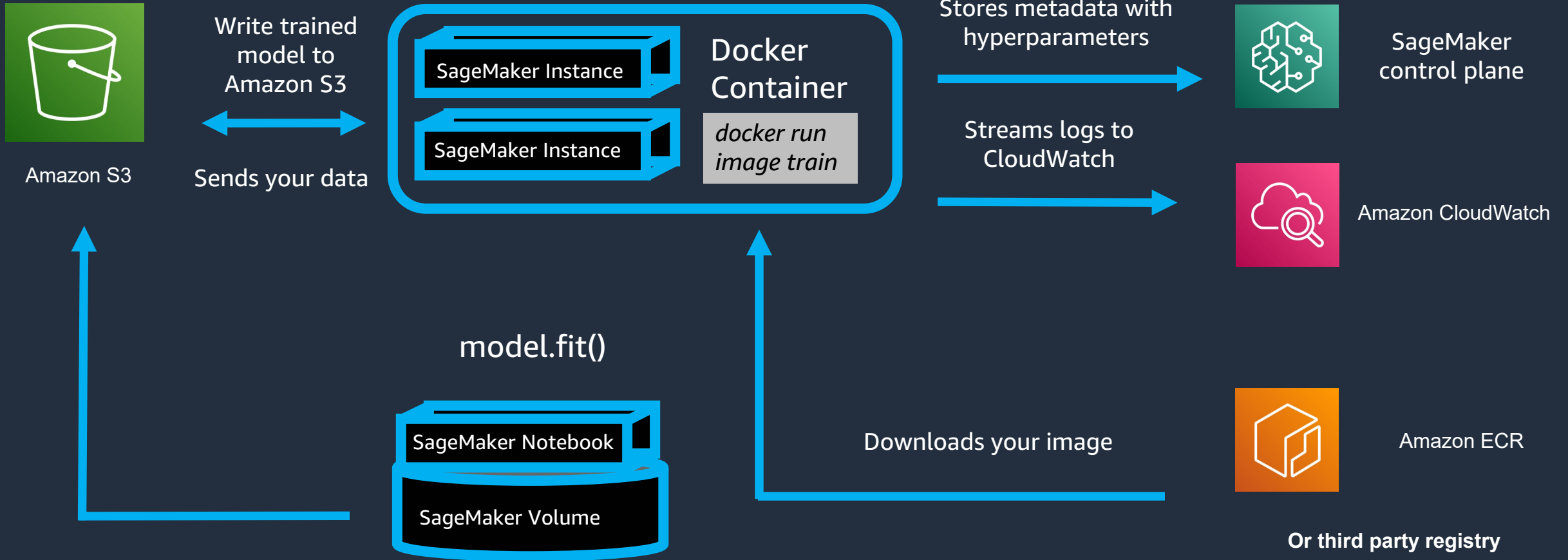
400/800 Gbps
EFA Networking

CPU instances

AWS Trainium



Amazon SageMaker ephemeral training clusters



Train with your own deep learning model

```
from sagemaker.pytorch import PyTorch

estimator = PyTorch(entry_point = './cifar10.py',
                    role = role,
                    framework_version = '1.13',
                    py_version = 'py38',
                    instance_count = 1,
                    instance_type = 'ml.g5.xlarge',
                    hyperparameters = {'epochs': 50, 'batch_size': 32},
                    metric_definitions = [{'Name': 'train:loss', 'Regex': 'loss: (.*)'}])

estimator.fit("s3://bucket/path/to/training/data")
```


Accelerate local ML code conversion to training jobs

```
from sagemaker.remote_function import remote

@remote(instance_type="ml.g4dn.xlarge", dependencies = "./environment.yml")
def train_hf_model(
    train_input_path, test_input_path, s3_output_path = None,
    *, epochs = 1, train_batch_size = 32, eval_batch_size = 64,
    warmup_steps = 500, learning_rate = 5e-5
):
    model_name = "distilbert-base-uncased"
    model = AutoModelForSequenceClassification.from_pretrained(model_name)
    ...
    return os.path.join(s3_output_path, model_dir), eval_result
```



Replicate experimental results by default

pytorch-training-2022-04-14-20-33-18-654 Clone Create model package Stop Create model

Job settings

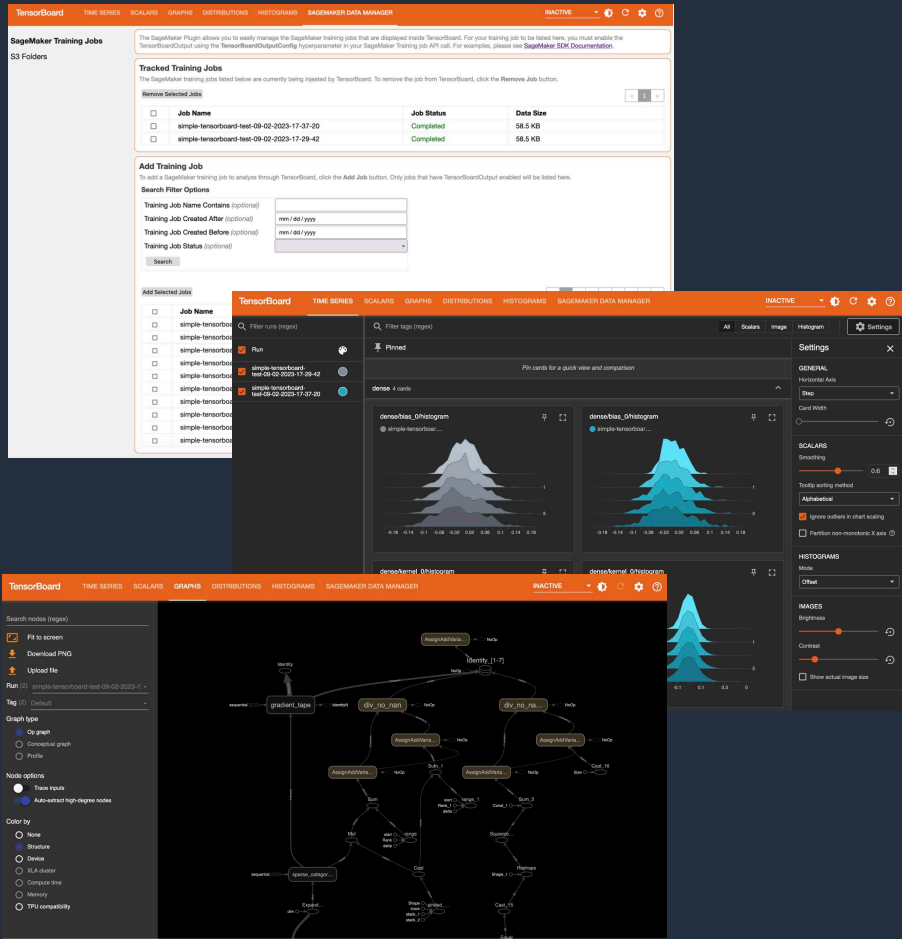
Job name pytorch-training-2022-04-14-20-33-18-654	Status Completed View history	SageMaker metrics time series Enabled	IAM role ARN arn:aws:iam::524898879256:role/service-role/AmazonSageMaker-ExecutionRole-20210323T152430
ARN arn:aws:sagemaker:us-west-2:524898879256:training-job/pytorch-training-2022-04-14-20-33-18-654	Creation time Apr 14, 2022 20:33 UTC	Training time (seconds) 464	Billable time (seconds) 464
	Last modified time Apr 14, 2022 20:42 UTC	Managed spot training savings 0%	Tuning job source/parent -

Algorithm

Algorithm ARN -	Instance type ml.g5.xlarge	Additional volume size (GB) 30	Volume encryption key -
Training image 763104351884.dkr.ecr.us-west-2.amazonaws.com/pytorch-training:1.10.0-gpu-py38	Instance count 1	Maximum runtime (s) 86400	Maximum wait time for managed spot training(s) -
Input mode File			



Hosted TensorBoard



Automated TensorBoard app management

provides a pre-configured and managed TensorBoard interface, which can save data scientists time by eliminating the need to install and configure TensorBoard on their own.



Scalable

designed to meet the needs of large-scale distributed machine learning workloads by having the UI automatically hosted on memory optimized r5 instances



Automated data management

easily configure TB data uploaded to S3 with the training job by passing an API argument (TensorBoardOutputConfig)

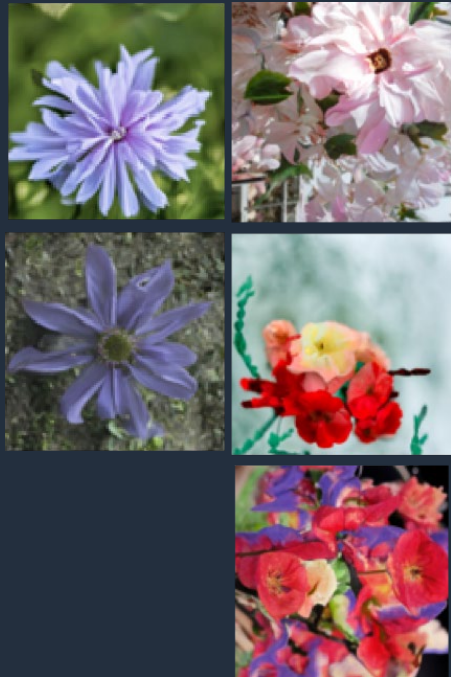


Security

provides a secure and reliable environment for storing and processing machine learning data



LG's Tilda, the AI artist powered by EXAONE



“... we could optimize distributed training and were able to train the model faster by 59% ...”

Seung Hwan Kim , Vice president and vision lab leader at LG AI Research

Sharded data parallelism with tensor parallelism

```
smp_parameters = {  
    "ddp": True,  
    "fp16": True,  
    "prescaled_batch": True,  
    "sharded_data_parallel_degree": 4,  
    "tensor_parallel_degree": 4  
}  
  
pytorch_estimator = PyTorch(  
    entry_point="your_training_script.py",  
    role=role,  
    instance_type="ml.p4d.24xlarge",  
    distribution={  
        "smdistributed": {  
            "modelparallel": {  
                "enabled": True,  
                "parameters": smp_parameters,  
            }  
        },  
        ...  
    },  
    ...  
)
```

Falcon

Technology Innovation Institute trains the state-of-the-art Falcon LLM 40B foundation model on Amazon SageMaker

by Dr. Ebtessam Almazrouei, Olivier Cruchant, and Will Badr | on 07 JUN 2023 | in [Amazon SageMaker](#), [Artificial Intelligence](#), [Intermediate \(200\)](#) | [Permalink](#) | [Comments](#) | [Share](#)

This blog post is co-written with Dr. Ebtessam Almazrouei, Executive Director–Acting Chief AI Researcher of the AI-Cross Center Unit and Project Lead for LLM Projects at TII.



Getting Started



Product page

aws.amazon.com/sagemaker/train/



Technical Documentation

docs.aws.amazon.com/sagemaker/latest/dg/how-it-works-training.html



SageMaker examples on GitHub

github.com/aws/amazon-sagemaker-examples



Training LLMs on Amazon SageMaker: Best Practices

<https://aws.amazon.com/blogs/machine-learning/training-large-language-models-on-amazon-sagemaker-best-practices/>



Thank you!

Gal Oshri

 @galoshri