Table of Contents

4

8

9

20

21

22

24

26

26

Preface

Section 1 – Data Parallelism

Splitting Input Data

Single-node training is too slow

The mismatch between data loading bandwidth and model training bandwidth 5 Single-node training time on popular datasets 6

Accelerating the training process with data parallelism

Data parallelism – the high-level bits

Stochastic gradient descent	13
Model synchronization	14
Hyperparameter tuning	15
Global batch size	16
Learning rate adjustment	16
Model synchronization schemes	17
Summary	18

Technical requirements Parameter server architecture

Communication bottleneck in the parameter server architecture Sharding the model among parameter servers

Implementing the parameter server

Defining model layers

Defining the parameter server	27
Defining the worker	28
Passing data between the parameter	
server and worker	30

Issues with the parameter server

32

The parameter server architecture introduces a high coding complexity for practitioners

viii Table of Contents

All-Reduce architecture	34	Broadcast	40
Reduce	34	Gather	41
All-Reduce	36	All-Gather	42
Ring All-Reduce	37	Summary	43
Collective communication	40		

and and a

.

Building a Data Parallel Training and Serving Pipeline

Technical requirements 46 Single-machine multi-GPU 52

46

48

49

50

50

51

52

52

The data parallel training pipeline in a nutshell

Input pre-processing Input data partition Data loading Training Model synchronization Model update

Single-machine multi-GPUs and multi-machine multi-GPUs

Multi-machine multi-GPU	56	
Checkpointing and fault tolerance	64	
Model checkpointing Load model checkpoints	64 65	
Model evaluation and hyperparameter tuning Model serving in data parallelism	67 n 71	
Summary	73	

Bottlenecks and Solutions

Communication bottlenecks in

Tree All-Reduce

data parallel training 76

Analyzing the communication workloads 76Parameter server architecture77The All-Reduce architecture80The inefficiency of state-of-the-art83

Leveraging idle links and host resources

Hybrid data transfer over PCIe and NVLink	91
On-device memory bottlenecks	93
Recomputation and quantization	94
Recomputation	95
Quantization	98
Summary	99

85

Table of Contents ix

Section 2 – Model Parallelism

B

Splitting the Model

Technical requirements 104 Single-node training error – out of memory 10 Fine-tuning BERT on a single GPU 105

Trying to pack a giant model inside one

4	BERT	119
	GPT	121
5	Pre-training and fine-tuning	122

State-of-the-art hardware	123
P100, V100, and DGX-1	123

state-of-the-art GPU	107	P100, V100, and DGX-1
		NVLink
ELMo, BERT, and GPT	110	A100 and DGX-2
Basic concepts	110	NVSwitch

NVLink	124
A100 and DGX-2	125
NVSwitch	125
Cumpopari	125
Summary	125
	A100 and DGX-2

RNN ELMO

Pipeline Input and Layer Split

Vanilla model parallelism is inefficient

Forward propagation 130 **Backward** propagation 131 GPU idle time between forward and 132

Advantages of pipeline parallelism	141
Disadvantages of pipeline parallelism	142
Layer split	142
Notes on intra-layer model	
parallelism	145

backward propagation

Pipeline input Pros and cons of pipeline parallelism

F 145 Summary 137

141

128



x Table of Contents

Q

Implementing Model Parallel Training and Serving Workflows

Technical requirements	148	Fine-tuning transformers	162
Wrapping up the whole model parallelism pipeline	149	Hyperparameter tuning in model parallelism	163
A model parallel training overview	149	Balancing the workload among GPUs	163
Implementing a model parallel training		Enabling/disabling pipeline parallelism	164
pipeline Specifying communication protocol	150	NLP model serving	164
among GPUs	153	Summary	165
Model parallel serving	158		

Achieving Higher Throughput and Lower Latency

Technical requirements Freezing layers	169 169	Exploring memory and storage resources	177
Freezing layers during forward propagation	171	Understanding model decomposition and distillation	180
Reducing computation cost during forward propagation	173	Model decomposition Model distillation	180 183
Freezing layers during backward propagation	174	Reducing bits in hardware Summary	184 184

Section 3 – Advanced Parallelism Paradigms

A Hybrid of Data and Model Parallelism

Technical requirements Cross-machine for data parallelism 189 200 Case study of Megatron-LM 189 Implementation of Layer split for model parallelism 189 **Megatron-LM** 201 Row-wise trial-and-error approach 192 Case study of Column-wise trial-and-error approach 196 **Mesh-TensorFlow** 203

Implementation of Mesh-TensorFlow

	Pros and cons of Megatron-LM	
204	and Mesh-TensorFlow	204
	Summary	205

10

Federated Learning and Edge Devices

209

210

211

226

229

Technical requirements Sharing knowledge without sharing data

Recapping the traditional data parallel model training paradigm No input sharing among workers

- 209 Communicating gradients for collaborative learning
 - Case study: TensorFlow Federated

212

Federated	217
Running edge devices with	
TinyML	219
Case study: TensorFlow Lite	219
Summarv	220

11

Elastic Model Training and Serving

Technical requirements Introducing adaptive model training

Traditional data parallel training Adaptive model training in data parallelism

Adaptive model training (AllReducebased)

223	Traditional model-parallel model		
	training paradigm	231	
223	Adaptive model training in model parallelism	232	
here have be	Implementing adaptive model		
226	training in the cloud	235	

Adaptive model training (parameter server-based)

Elasticity in model inference	236	
Serverless	238	
Summary	238	



12

Advanced Techniques for Further Speed-Ups

Technical requirements Debugging and performance analytics

General concepts in the profiling results Communication results analysis Computation results analysis

241	Job migration and multiplexing	249
	Job migration	250
241	Job multiplexing	251
243	Model training in a heterogeneous environment	251
245		tanan egye u
246	Summary	252

Index

Other Books You May Enjoy

