PLACETO: LEARNING GENERALIZABLE DEVICE PLACEMENT ALGORITHMS FOR DISTRIBUTED MACHINE LEARNING

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Distributed training (GPU and CPU)

Human experts?

Problem



Reinforcement learning?





Sometimes tolerable.

Solutions do not generalize

Problem





The optimization is done for a single graph.

Single computational graph vs Class of computational graph

Placeto





Efficiency

Sequence of iterative placement improvements

Generalizability

NN architecture that uses graph embedding to encode the computation of graph structure in the placement policy.

Learning method

Markov Decision Process





POLICY NETWORK ARCHITECTURE



GRAPH EMBEDDING

Training Details





Deep learning models (Inception-V3, NASNet, NMT)

Experimentation



Synthetic data (cifar10, ptb, nmt)



Single GPU, Scotch, Human Expert, RNN based approach.

Result



	Placement runtime							Training time		Improvement	
	CPU	(Sec) CPU Single RNN-						(# placements sampled)		Runtime	Speedup
Model	only	GPU	#GPUs	Expert	Scotch	n Placeto	based	Placeto ł	based	Reduction	factor
Inception-V3	12.54	1.56	2	1.28	1.54	1.18	1.17	1.6 K	7.8 K	- 0.85%	4.8 ×
			4	1.15	1.74	1.13	1.19	5.8 K	35.8 K	5%	6.1 ×
NMT	33.5	OOM	2	OOM	OOM	2.32	2.35	20.4 K	73 K	1.3 %	3.5 ×
			4	OOM	OOM	2.63	3.15	94 K	51.7 K	16.5 %	0.55 ×
NASNet	37.5	1.28	2	0.86	1.28	0.86	0.89	3.5 K	16.3 K	3.4%	4.7 ×
			4	0.84	1.22	0.74	0.76	29 K	37 K	2.6%	1.3 ×

PLACETO VS RNN



GENERALIZABILITY



GENERALIZABILITY



Place deep dive

Critic

+ First attempt to generalize device placement using a graph embedding network

+ Really Impressive performance

- Only optimizes placement decisions

- It shows generalization to unseen graphs, but they are generated artificially by architecture search for a single learning task and dataset.

How does the framework handle failure. Evaluation protocol needs to be more explicit.