

# GDP: Generalized Device Placement For Dataflow Graphs

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# Introduction

Neural networks have demonstrated remarkable scalability – improved performance can usually be achieved by training a larger model on a larger dataset. Training such large models efficiently while meeting device constraints, like memory limitations, necessitate partitioning of the underlying dataflow graphs for the models across multiple devices.

# Device Placement Using Reinforcement Learning

- ▶ **HDP** (Mirhoseini et al., 2018) uses feed forward NN to assign each op to a group and runs a seq-to-seq model to place each group to a device.
- ▶ **Spotlight** (Gao et al., 2018) heuristically groups nodes and generates placements with LSTM.
- ▶ **Placeto** (Addanki et al., 2019) uses GNN to encode the graph structure into embeddings, then uses feed forward NN to iteratively generate a placement for one node at each step.

# GDP

- ▶ An end-to-end deep RL method for device placement that can generalize to arbitrary and held-out graphs.
- ▶ The placement network is 15x faster than HDP without the need for explicit grouping.
- ▶ A new batch pre-training and fine-tuning strategy based on network superposition, which leads to improved transferability, better placements especially for large graphs, and huge reduction in policy search time.
- ▶ Superior performance over a wide set of workloads including graphs with over 50k nodes.

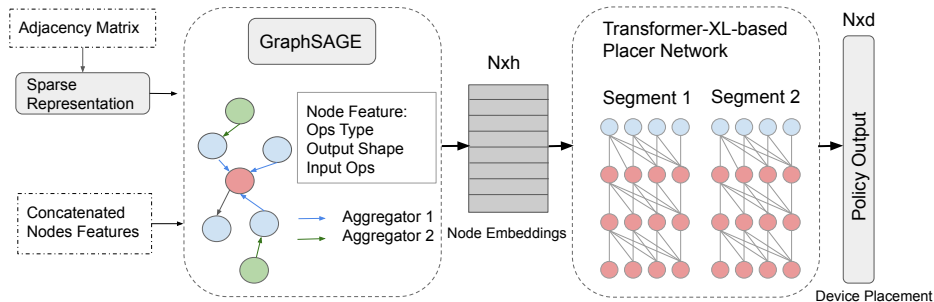
# Problem Formulation

Given a dataflow graph  $G(V, E)$  where  $V$  represents atomic computational operations (ops) and  $E$  represents the data dependency. The goal of GDP is to learn a policy  $\pi : \mathcal{G} \mapsto \mathcal{D}$  that maximizes reward  $r_{G,D}$  defined based on the run time. GDP represents policy  $\pi_\theta$  as a neural network parameterized by  $\theta$ .

$$J(\theta) = \mathbb{E}_{G \sim \mathcal{G}, D \sim \pi_\theta(G)}[r_{G,D}] \approx \frac{1}{N} \sum_G \mathbb{E}_{D \sim \pi_\theta(G)}[r_{G,D}]$$

We refer to the case when  $N = 1$  as *individual training* and the case when  $N > 1$  as *batch training*.

# System Overview



$N$ : Number of nodes,  $h$ : Hidden Size,  $d$ : Number of Devices

# Graph Embedding Network

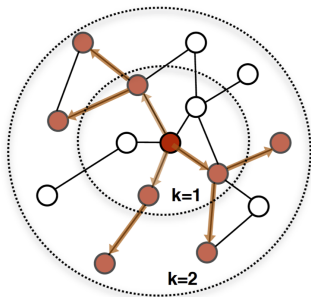
GDP adopts the feature aggregation scheme proposed in *GraphSAGE* as it shows better generalization.

$$h_{\mathcal{N}(v)}^{(l)} = \max(f_a^{(l)}(h_u^{(l)}), \forall u \in \mathcal{N}(v))$$
$$h_v^{(l+1)} = f_b^{(l+1)}(\text{concat}(h_v^{(l)}, h_{\mathcal{N}(v)}^{(l)}))$$

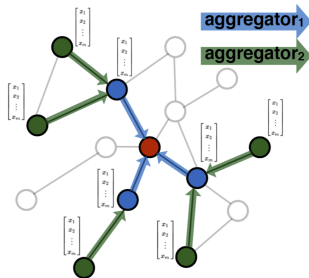
where  $h_v$  is the hidden feature of  $v$ ,  $f_a$  and  $f_b$  are dense layers,  $\mathcal{N}(v)$  represents the neighbors of  $v$ , and  $h_{\mathcal{N}(v)}$  stands for the aggregated feature from the neighbors of  $v$ .

Different from GraphSAGE, which is unsupervised, GDP trains the embeddings jointly with the placement network.

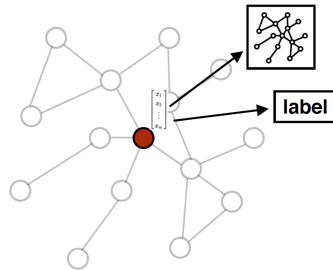
# GraphSAGE



1. Sample neighborhood



2. Aggregate feature information from neighbors



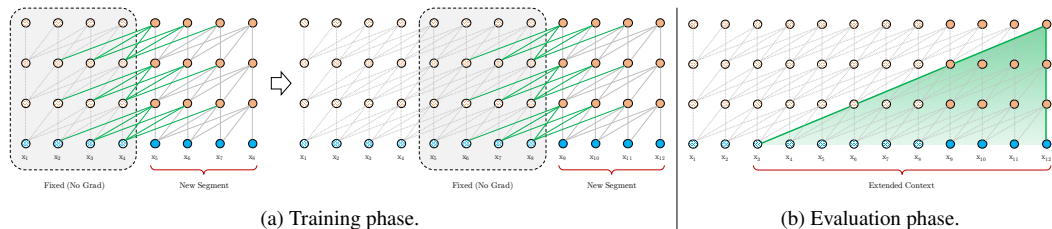
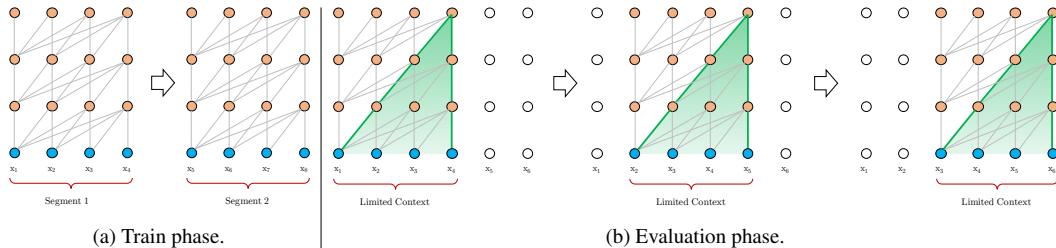
3. Predict graph context and label using aggregated information



# Placement Network

- ▶ Conventional seq-to-seq models usually target short sequences, which requires grouping beforehand.
- ▶ LSTM used in previous works is slower and more difficult to train than attention-based models.
- ▶ GDP adopts segment-level recurrence introduced in *Transformer-XL* to capture long-term dependencies. The key is to cache (with gradient flows disabled) and reuse the hidden states of previous segments.

# Transformer XL



# Batch Training

- ▶ Naive batch training is challenging because of the divergence of the dataflow graphs.
- ▶ GDP uses a feature conditioning mechanism similar to *parameter superposition*, implemented by replacing all dense layers in the placement network with:

$$x^{(l+1)} = g^{(l)}(c(x^{(0)}) \odot x^{(l)})$$

where  $g^{(l)}$  stands for a dense layer in the placement network,  $c$  stands for the feature conditioning layer, and  $x^{(0)}$  denotes the input feature generated by the graph-embedding network.

# Experiment Setup

- ▶ We compare GDP with human expert placement (**HP**), Tensorflow **METIS** placement (a general purpose graph partitioning tool), and **HDP** (Mirhoseini et al., 2018).
- ▶ 8 Nvidia P100
- ▶ We use negative square root of the run time as the reward, and subtract the average reward of all previous trials to calculate the advantage value. Invalid placements are given a large (-10) negative reward.

# Performance on Individual Graphs

Model (#devices)	GDP-one (s)	HP (s)	METIS (s)	HDP (s)	Run time speed up over HP / HDP	Search speed up
2-layer RNNLM (2)	0.234	0.257	0.355	0.243	9.8% / 4%	2.95x
4-layer RNNLM (4)	0.409	0.48	OOM	0.490	17.4% / 19.8%	1.76x
2-layer GNMT (2)	0.301	0.384	OOM	0.376	27.6% / 24.9%	30x
4-layer GNMT (4)	0.409	0.469	OOM	0.520	14.7% / 27.1%	58.8x
8-layer GNMT (8)	0.649	0.610	OOM	0.693	-6% / 6.8%	7.35x
2-layer Transformer-XL (2)	0.386	0.473	OOM	0.435	22.5% / 12.7%	40x
4-layer Transformer-XL (4)	0.580	0.641	OOM	0.621	11.4% / 7.1%	26.7x
8-layer Transformer-XL (8)	0.748	0.813	OOM	0.789	8.9% / 5.5%	16.7x
Inception (2)	0.405	0.418	0.423	0.417	3.2% / 3%	13.5x
AmoebaNet (4)	0.394	0.44	0.426	0.418	26.1% / 6.1%	58.8x
2-stack 18-layer WaveNet (2)	0.317	0.376	OOM	0.354	18.6% / 11.7%	6.67x
4-stack 36-layer WaveNet (4)	0.659	0.988	OOM	0.721	50% / 9.4%	20x
GEOMEAN	-	-	-	-	<b>16% / 9.2%</b>	<b>15x</b>

## Performance on Batch Training

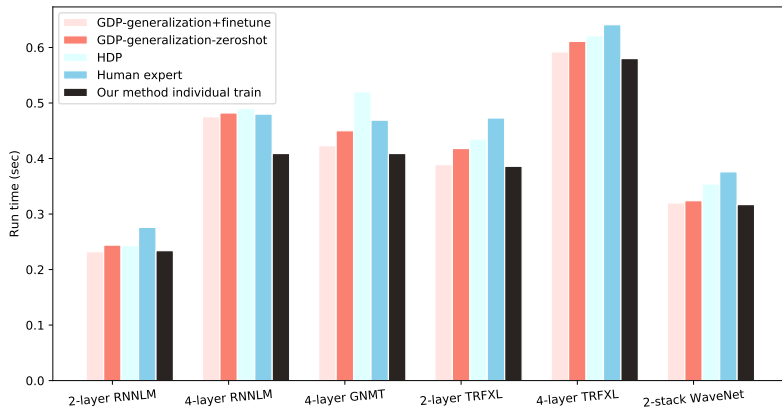
Run time comparing on GDP-batch vs. GDP-one

Model	Speed up	Model	Speed up
2-layer RNNLM	0	Inception	0
4-layer RNNLM	5%	AmoebaNet	-5%
2-layer GNMT	0	4-stack 36-layer WaveNet	3.3 %
4-layer GNMT	0	2-stack 18-layer WaveNet	15%
2-layer Transformer-XL	7.6%	8-layer Transformer-XL	1.5%
4-layer Transformer-XL	3%		

A possible explanation for the performance gain is the additional feature conditioning layer in the batch training effectively enlarged the model.

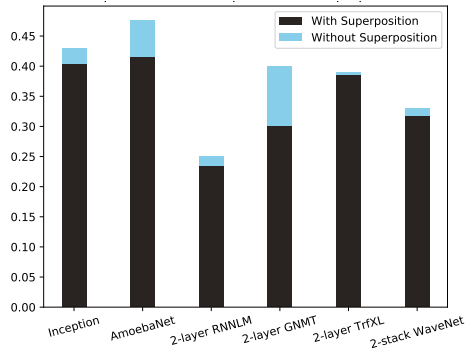
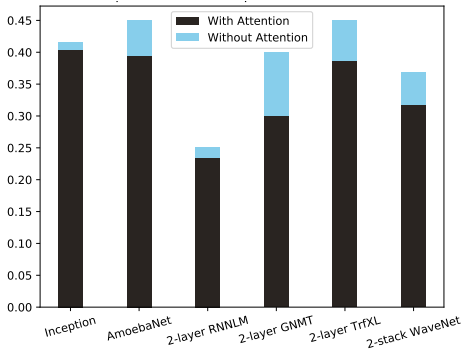
## Performance on Hold-out Graphs

We run GDP on unseen graphs with and without finetuning, called **GDP-generalization-finetune** and **GDP-generalization-zeroshot** respectively.



# Ablation Studies

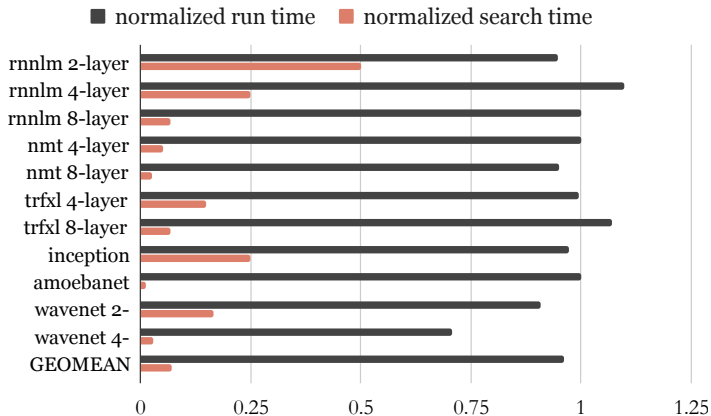
We did ablation studies on the attention and the superposition layer in the placement network. They improved the average run time by 18% and 6.5% respectively.





# Pre-training Graph Embeddings

We train GDP-batch like before, but then fine-tuning on each specific graphs. The run time and search time are reduced by 5% and 86% respectively, compared with GDP-one.



Thank you!