Distributed Learning - Model Parallelization

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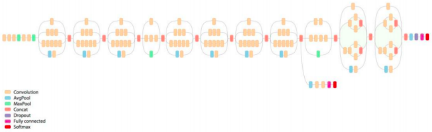
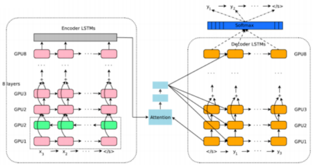
The Course Web Page

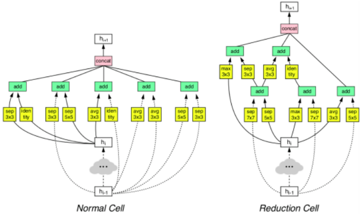
`https://fid3024.github.io`



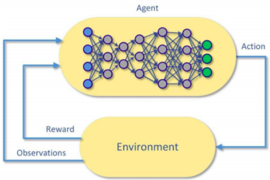
Convolutional Neural Networks



Recurrent Neural Networks



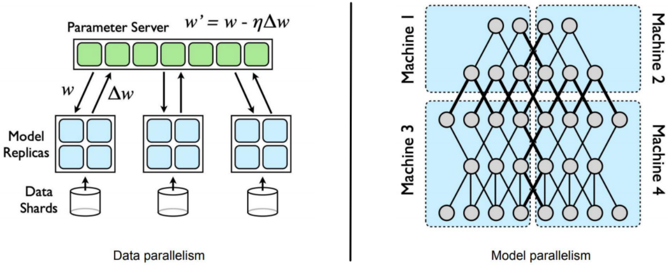
Neural Architecture Search



Reinforcement Learning

- Train large deep learning models with huge amounts of training data.
- Parallelization and distribution are essential.

Popular Parallelization Methods

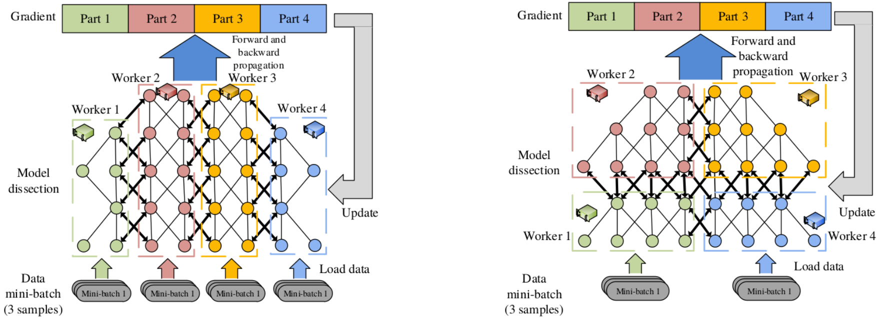


[Dean et al., Large Scale Distributed Deep Networks, 2012]

Model Parallelization

Model Parallelization

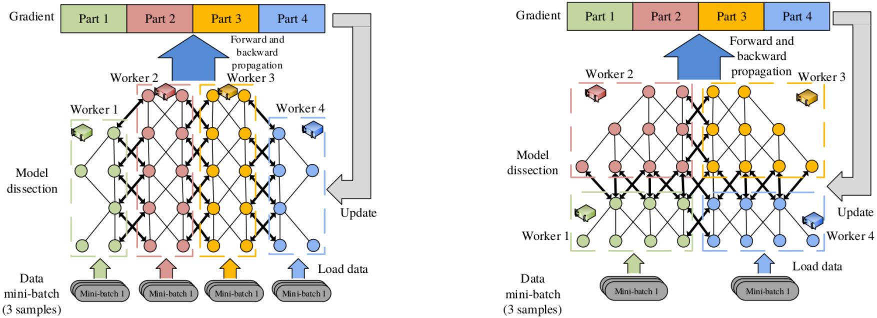
- The model is split across multiple devices.



[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

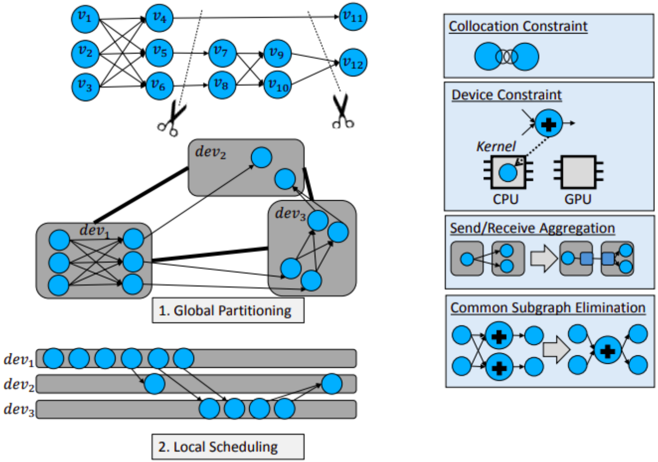
Model Parallelization

- The model is split across multiple devices.
- Depends on the architecture of the NN.



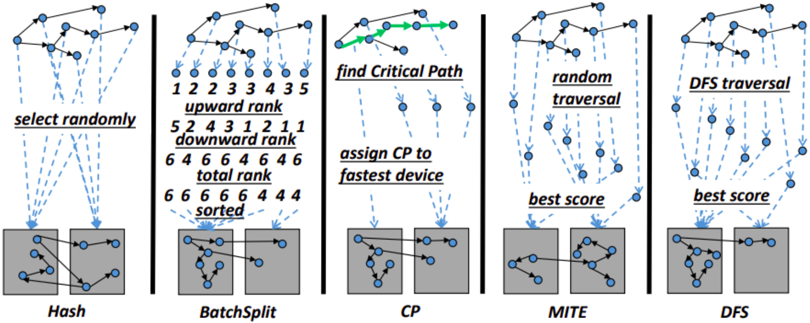
[Tang et al., Communication-Efficient Distributed Deep Learning: A Comprehensive Survey, 2020]

NP-Completeness



[Mayer, R. et al., The TensorFlow Partitioning and Scheduling Problem, 2017]

Partitioning Approaches



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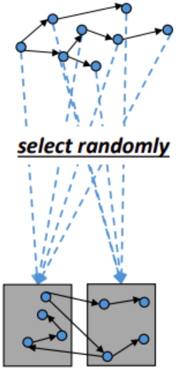
Model Parallelization - Hash Partitioning

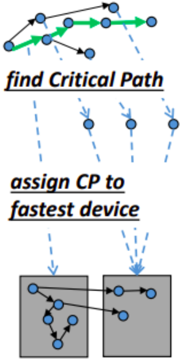
- Randomly assign vertices to devices proportionally to the capacity of the devices by using a hash function.



[Mayer, R. et al., The TensorFlow Partitioning and Scheduling Problem, 2017]

Model Parallelization - Critical Path

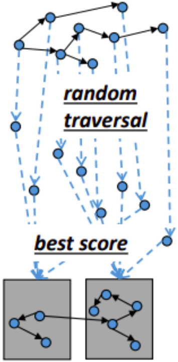
- Assigning the complete critical path to the fastest device.
- Critical path: the path with the longest computation time from source to sink vertex.



[Mayer, R. et al., The TensorFlow Partitioning and Scheduling Problem, 2017]

Model Parallelization - Multi-Objective Heuristics

- Different objectives, e.g., memory, importance, traffic, and execution time



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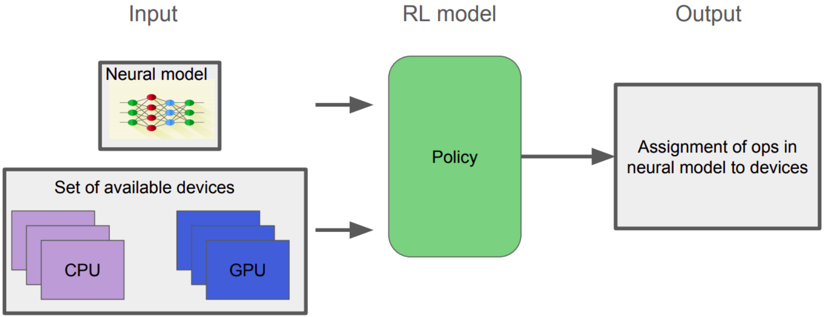
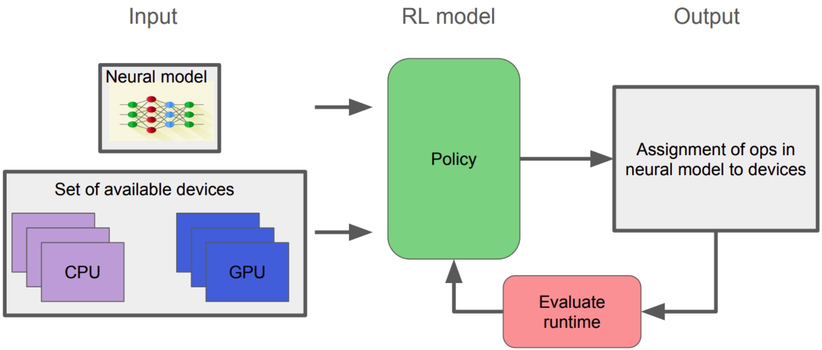
ML for Model Parallelization

Device Placement using Reinforcement Learning (1/3)



[Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017]

Device Placement using Reinforcement Learning (2/3)



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Device Placement using Reinforcement Learning (3/3)

- $\mathtt{J}(\mathtt{w}) = \mathbb{E}_{\mathcal{P} \sim \pi(\mathcal{P}|\mathcal{G},\mathtt{w})}[\mathtt{R}(\mathcal{P})|\mathcal{G}]$
- Objective: $\arg\min_{\mathtt{w}} \mathtt{J}(\mathtt{w})$

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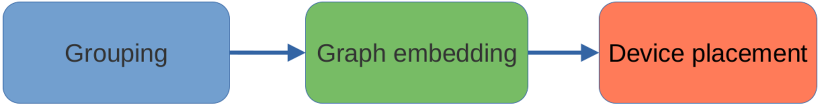
- $\mathtt{J}(\mathtt{w})$: expected runtime
- $\mathtt{w}$: parameters of the RL policy
- $\mathcal{G}$: input neural graph
- $\mathtt{R}$: runtime
- $\mathcal{P}$: output placements
- $\pi(\mathcal{P}|\mathcal{G},\mathtt{w})$: the RL policy (device placement policy)

Device Placement Policy

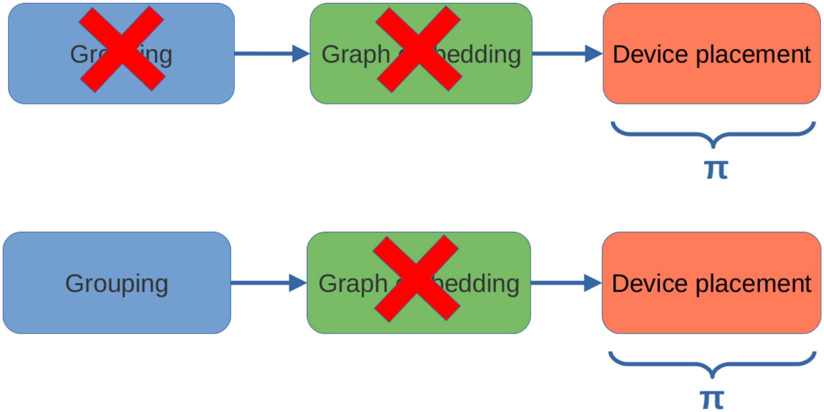


Solution 1

Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017
Mirhoseini et al., A Hierarchical Model for Device Placement, 2018

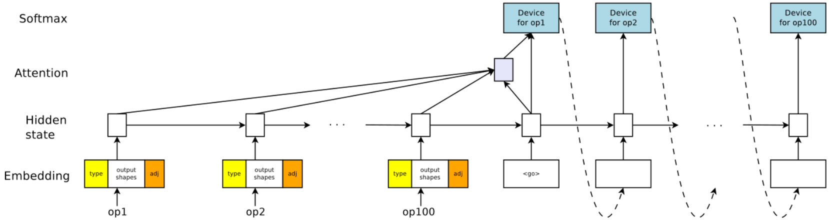
Device Placement Policy

Device Placement Policy



System Overview

- The RL policy is defined as a attentional seq-to-seq model.



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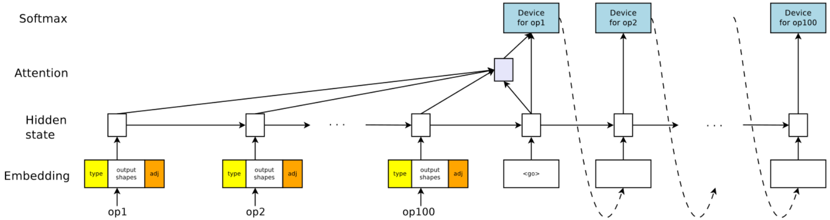
- RNN Encoder receives sequence of embedding for each operation.



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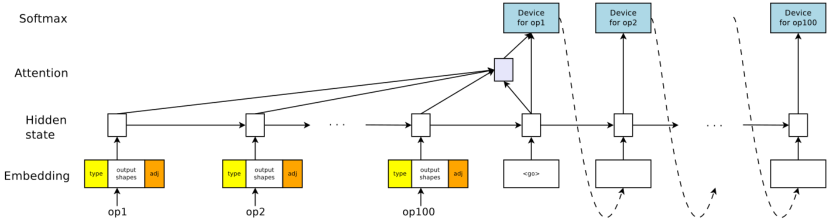
System Overview

- The RL policy is defined as a attentional seq-to-seq model.
- RNN Encoder receives sequence of embedding for each operation.
- RNN Decoder predicts a device placement for each operation.



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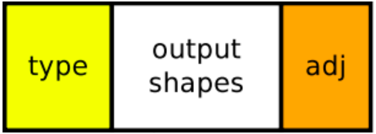
Operation Embedding

- The embedding of each operation is the concatenation of its type, its output shape, and its one-hot encoded adjacency information.



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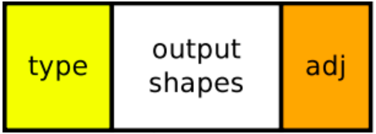

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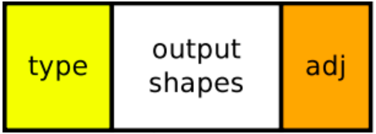
- The size of each operation's list of output tensors (the output shape).



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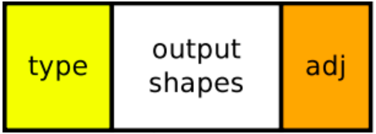
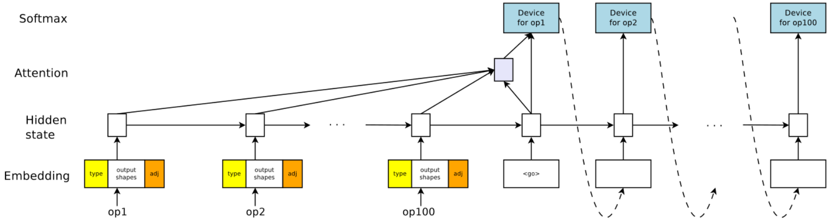
- Type of the operations, e.g., `MatMul` or `conv2d`.
- The size of each operation's list of output tensors (the output shape).
- The one-hot encoding vector that represents the operations that are direct inputs and outputs to each operation.



RNN Decoder

- The decoder is an attentional LSTM with a fixed number of time steps.



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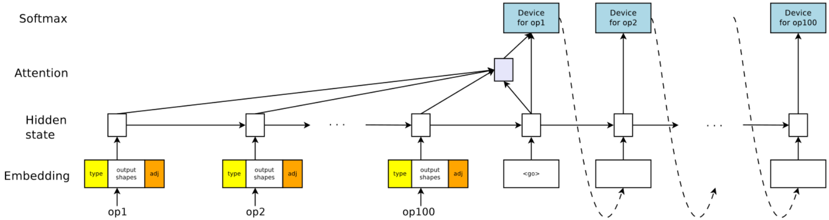

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RNN Decoder

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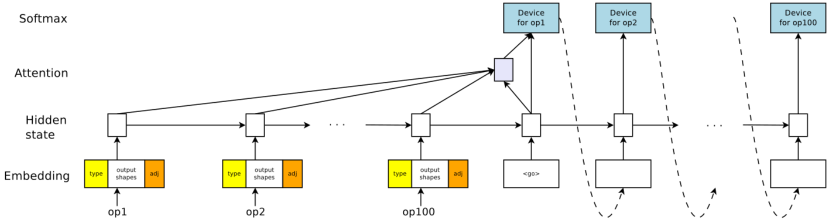
- At each step, the decoder outputs the device for the operation.



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- Estimate $\nabla_{\mathtt{w}}\mathtt{J}(\mathtt{w})$ by drawing $\mathtt{K}$ placement samples using $\mathcal{P} \sim \pi(.|\mathcal{G}, w)$.

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- $\nabla_{\mathtt{w}}\mathtt{J}(\mathtt{w}) = \frac{1}{\mathtt{K}}\sum_{\mathtt{i}=1}^{\mathtt{K}}[\mathtt{R}(\mathcal{P}_{\mathtt{i}} - \mathtt{B}).\nabla_{\mathtt{w}}\mathtt{log}_{\mathtt{p}}(\mathcal{P}|\mathcal{G},\mathtt{w})]$

Training with REINFORCE

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- Estimate $\mathtt{B}$: a baseline term to reduce the variance of the policy gradient.

Shortcomings of the Proposed Model

- Seq-to-seq models cannot be unrolled for more than few hundred steps.

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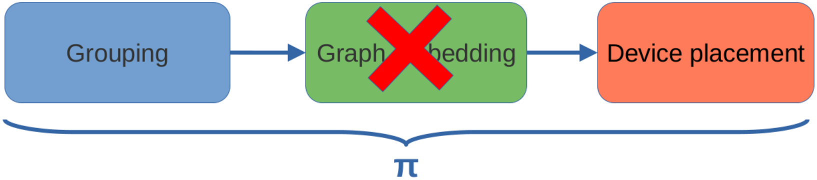
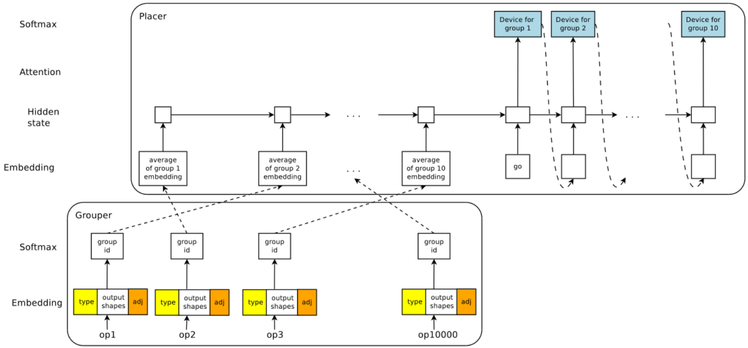
- Most TensorFlow graphs contain tens of thousands of operations.
- Manual grouping of operations hampers scalability.

Device Placement Policy



An End-to-End Hierarchical Placement Model

- Grouping operations.
- Prediction is for group placement, not for a single operation.



[Mirhoseini et al., A Hierarchical Model for Device Placement, 2018]

Hierarchical Device Placement Optimization (1/2)

- $J(\mathtt{w_g}, \mathtt{w_d}) = \mathbb{E}_{\mathcal{P}(\mathtt{d}, \mathtt{w_g}, \mathtt{w_d})}[\mathtt{R_d}] = \sum_{\mathtt{g} \sim \pi_\mathtt{g}} \sum_{\mathtt{d} \sim \pi_\mathtt{d}} \mathtt{p}(\mathtt{g}, \mathtt{w_g})\mathtt{p}(\mathtt{d}|\mathtt{g}, \mathtt{w_g})\mathtt{R_d}$
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- Objective: $\arg\min_{\mathtt{w}} \mathtt{J}(\mathtt{w})$
- $\mathcal{G}$: input neural graph

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- $J(w_g, w_d) = \mathbb{E}_{\mathcal{P}(d, w_g, w_d)}[R_d] = \sum_{g \sim \pi_g} \sum_{d \sim \pi_d} p(g, w_g) p(d|g, w_g) R_d$
- Objective: $\arg\min_w J(w)$

- $\mathcal{G}$: input neural graph
- R: runtime

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- $\mathcal{G}$: input neural graph
- $\mathtt{R}$: runtime
- $\mathtt{J}(\mathtt{w_g}, \mathtt{w_d})$: expected runtime

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- $\mathcal{G}$: input neural graph
- $\mathtt{R}$: runtime
- $\mathtt{J}(\mathtt{w_g}, \mathtt{w_d})$: expected runtime
- $\mathtt{w_g}$: parameters of the grouper

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- $\mathcal{G}$: input neural graph
- R: runtime
- $J(w_g, w_d)$: expected runtime
- w_g: parameters of the grouper
- w_d: parameters of the placer

Hierarchical Device Placement Optimization (2/2)

- $J(w_g, w_d) = \mathbb{E}_{\mathcal{P}(d, w_g, w_d)}[R_d] = \sum_{g \sim \pi_g} \sum_{d \sim \pi_d} p(g, w_g) p(d | g, w_g) R_d$

Hierarchical Device Placement Optimization (2/2)

- $J(w_g, w_d) = \mathbb{E}_{\mathcal{P}(d, w_g, w_d)}[R_d] = \sum_{g \sim \pi_g} \sum_{d \sim \pi_d} p(g, w_g) p(d|g, w_g) R_d$
- $p(g, w_g)$: the probability of a sample group assignment g drawn from the Grouper softmax distribution π_g.

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- $p(g, w_g)$: the probability of a sample group assignment g drawn from the Grouper softmax distribution π_g.
- $p(d|g, w_g)$: the probability of a sample device placement d drawn from the Placer softmax distribution π_d.

Training with REINFORCE

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- $J(w_g, w_d) = \mathbb{E}_{\mathcal{P}(d, w_g, w_d)}[R_d] = \sum_{g \sim \pi_g} \sum_{d \sim \pi_d} p(g, w_g) p(d|g, w_g) R_d$
- $\nabla_{w_g} J(w_g, w_d) = \sum_{g \sim \pi_g} \nabla_{w_g} p(g, w_g) \sum_{d \sim \pi_d} p(d|g, w_g) R_d$

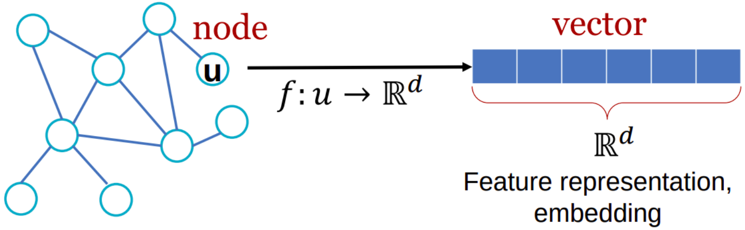
Training with REINFORCE

- $J(w_g, w_d) = \mathbb{E}_{\mathcal{P}(d, w_g, w_d)}[R_d] = \sum_{g \sim \pi_g} \sum_{d \sim \pi_d} p(g, w_g) p(d|g, w_g) R_d$
- $\nabla_{w_g} J(w_g, w_d) = \sum_{g \sim \pi_g} \nabla_{w_g} p(g, w_g) \sum_{d \sim \pi_d} p(d|g, w_g) R_d$
- $\nabla_{w_d} J(w_g, w_d) = \sum_{d \sim \pi_d} \sum_{g \sim \pi_g} p(g, w_g) \nabla_{w_d} p(d|g, w_g) R_d$

A Few Words About Graph Embedding

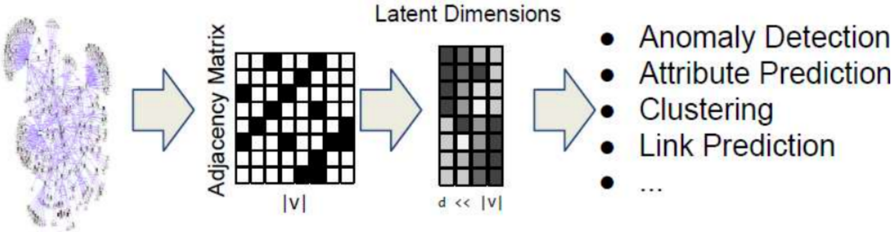
The slides of this part were derived from Jure Leskovec's slides - Stanford University

Feature Learning in Graphs



Why Learn Embedding?

- The goal is to map each node into a low-dimensional space.



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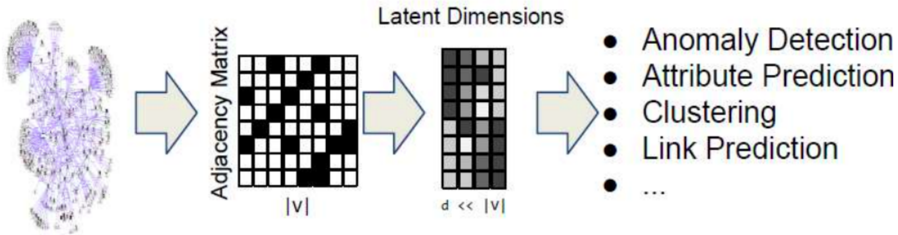

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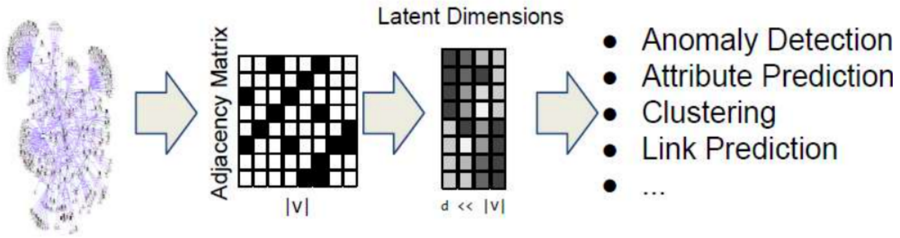
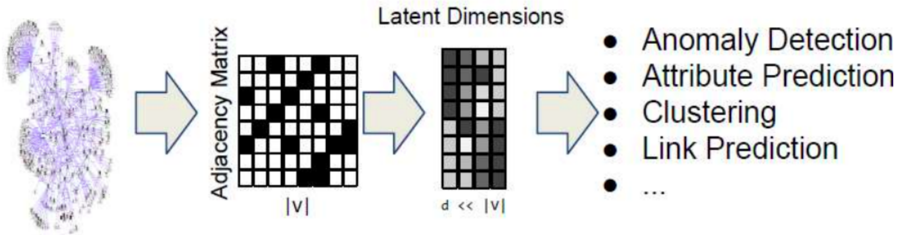
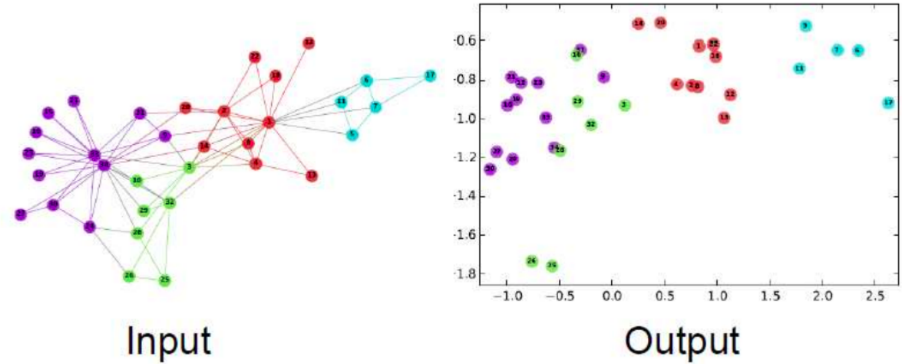


Why Learn Embedding?

- The goal is to map each node into a low-dimensional space.
  - Representation for nodes.
  - Similarity between nodes indicates link strength.
  - Encodes network information and generate node representation.



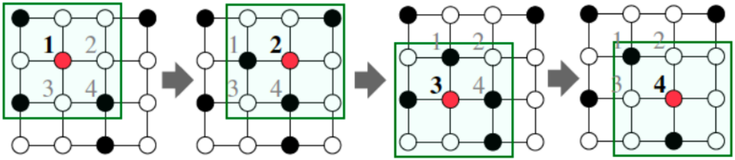
Example

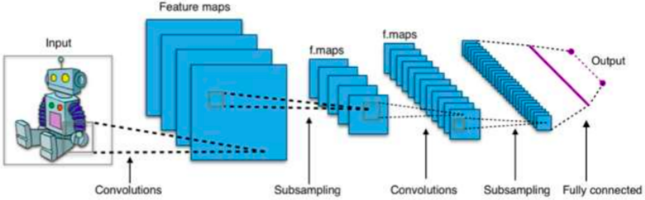


[Perozzi et al., DeepWalk: Online Learning of Social Representations, 2014]

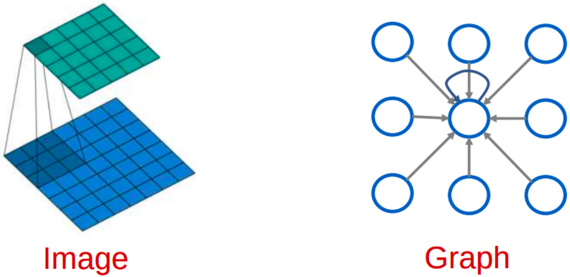
Idea: Convolutional Networks

- Goal is to generalize convolutions beyond simple lattices.
- Leverage node features/attributes (e.g., text, images).





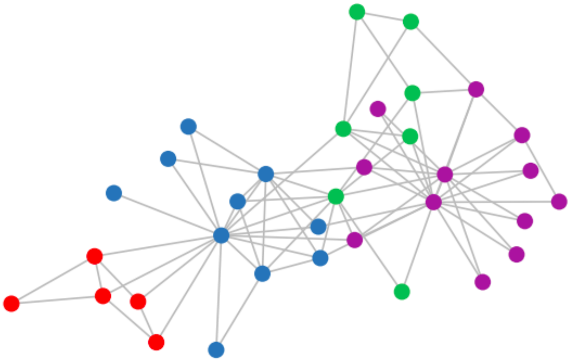
- Transform information at the neighbors and combine it:
  - Transform messages $\mathtt{h_i}$ from neighbors: $\mathtt{w_i h_i}$
  - Add them up: $\sum_i \mathtt{w_i h_i}$



Single CNN layer with 3×3 filter

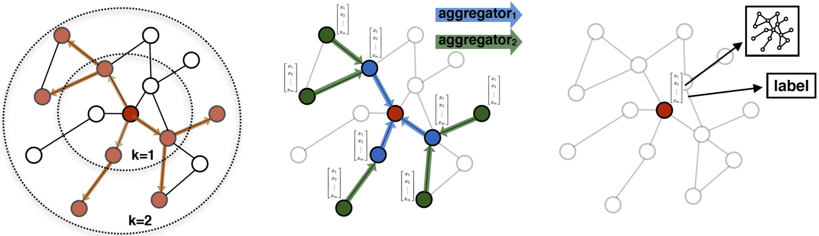
Real-World Graphs

- But what if your graphs look like this?



GraphSAGE (1/3)

- GraphSAGE aggregates neighbouring node embeddings for a given node.



1. Sample neighborhood

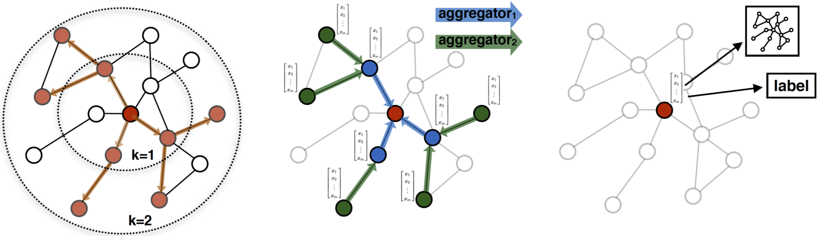
2. Aggregate feature information from neighbors

3. Predict graph context and label using aggregated information

[http://snap.stanford.edu/graphsage]

GraphSAGE (1/3)

- GraphSAGE aggregates neighbouring node embeddings for a given node.
- The output of one round of GraphSAGE: new node representation for every node in the graph.



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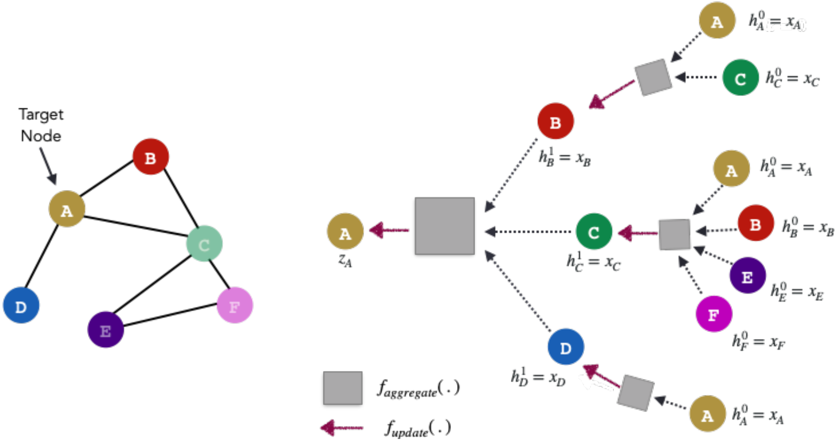
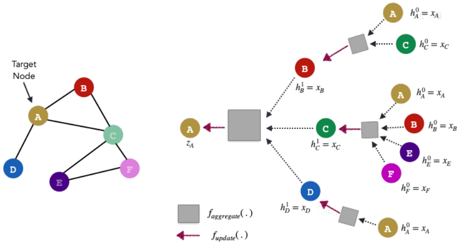
GraphSAGE (2/3)



[https://mc.ai/ohmygraphs-graphsage-and-inductive-representation-learning-2]

GraphSAGE (3/3)

- $\mathtt{h}^{\mathtt{l}}_{\mathcal{N}(\mathtt{v})} = \mathtt{max}(\mathtt{f}^{\mathtt{i}}_{\mathtt{a}}(\mathtt{h}^{\mathtt{l}}_{\mathtt{u}}), \forall \mathtt{u} \in \mathcal{N}(\mathtt{v}))$



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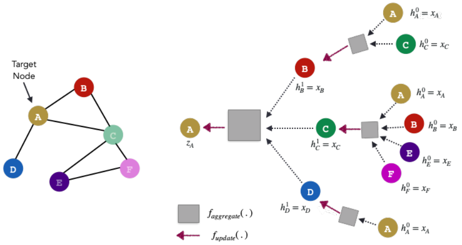

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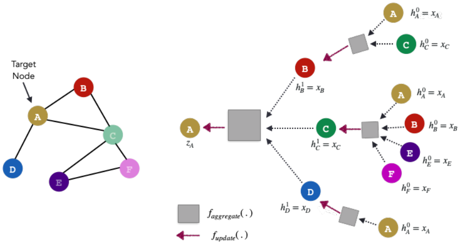
- $\mathtt{h}_{\mathtt{v}}$: the hidden feature of $\mathtt{v}$



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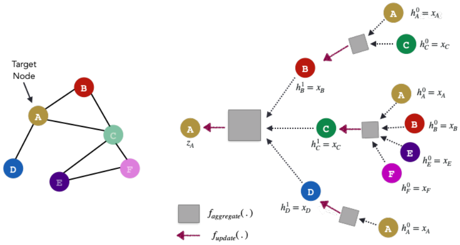

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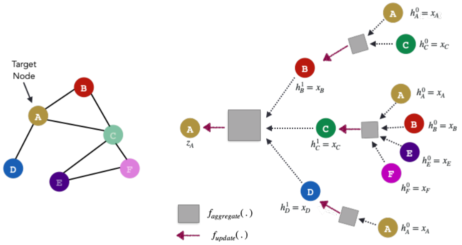

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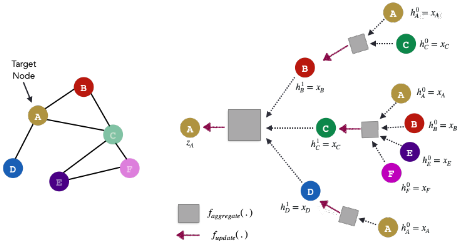
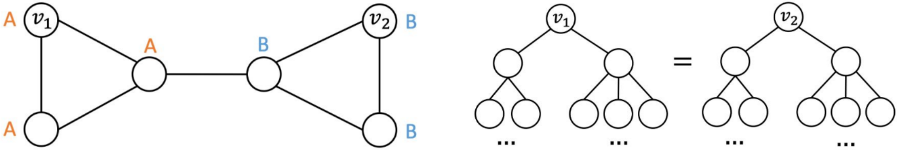
- $\mathtt{h}_{\mathcal{N}(\mathtt{v})}$: the aggregated feature from the neighbors of $\mathtt{v}$



GraphSAGE Shortcoming

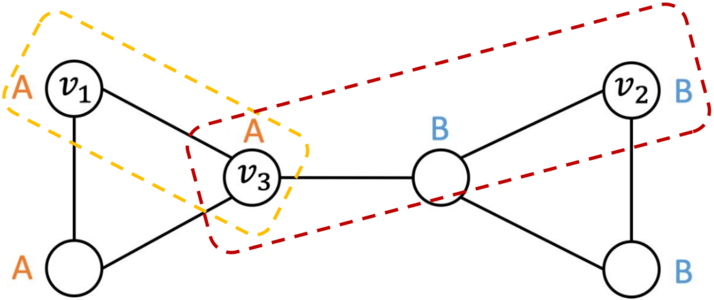
- Nodes with the same neighborhoods have the similar embeddings, regardless of their location in the graph?



[You et al., Position-aware Graph Neural Networks, 2019]

Position-aware Graph Neural Networks

- By adding anchor sets - we bypass that problem.

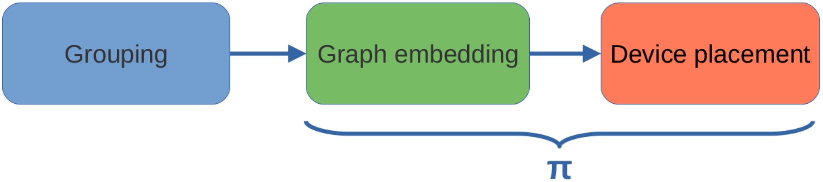


[Figure by Milko Mitropolitsky]

Solution 2

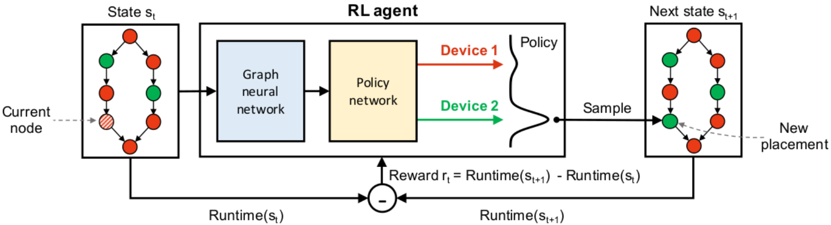
Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019

Device Placement Policy



Placeto System Overview

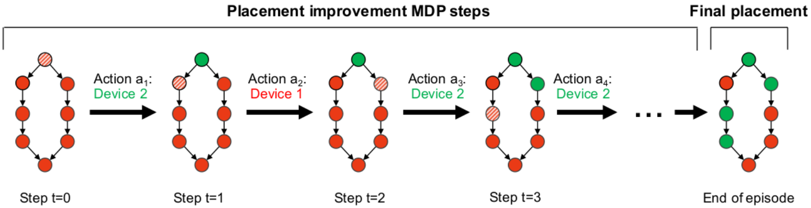
- Graph embedding
- Placement policy network



[Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019]

MDP Formulation (1/2)

- Model the device placement as Markov Decision Process (MDP).
- Initial state s_0, consists of $\mathcal{G}$ with an arbitrary device placement for each node group.



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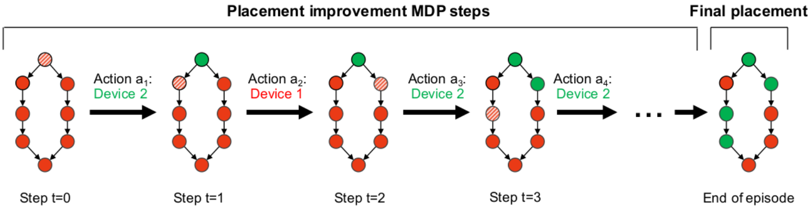

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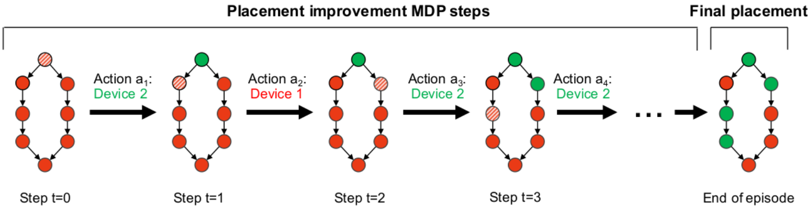
- Action in step $\mathtt{t}$ outputs a new placement for the $\mathtt{t}$th node in $\mathcal{G}$ based on $\mathtt{s}_{\mathtt{t}-1}$.
- Episode ends in $|\mathtt{V}|$ steps ($\mathtt{V}$: set of nodes in $\mathcal{G}$).



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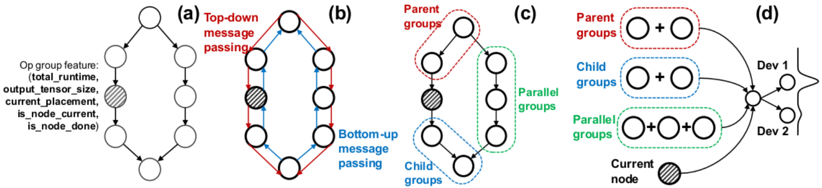
- Approach 2: assign intermediate rewards $r_t = R(\mathcal{P}_{s_{t+1}}) - R(\mathcal{P}_{s_t})$

Graph Embedding

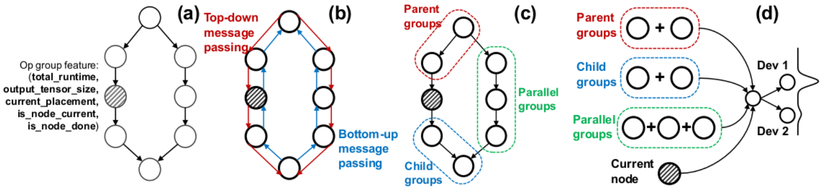
- Computing per-group attributes (a)



[Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019]

Graph Embedding

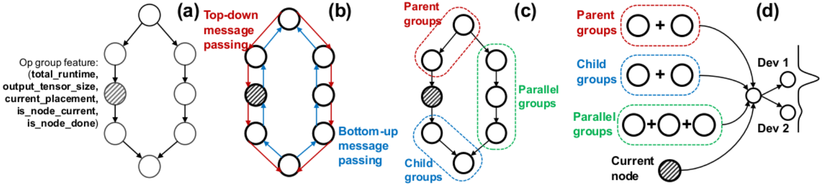
- Computing per-group attributes (a)
- Local neighborhood summarization (b)



[Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019]

Graph Embedding

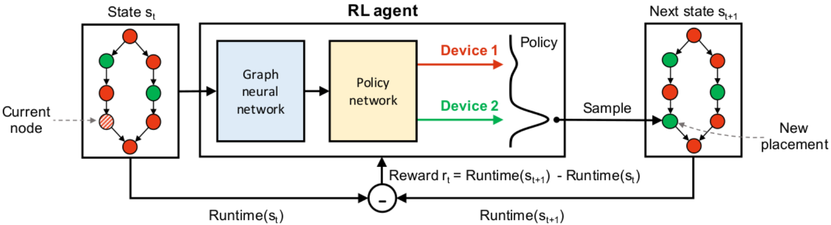
- Computing per-group attributes (a)
- Local neighborhood summarization (b)
- Pooling summaries (c)



[Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019]

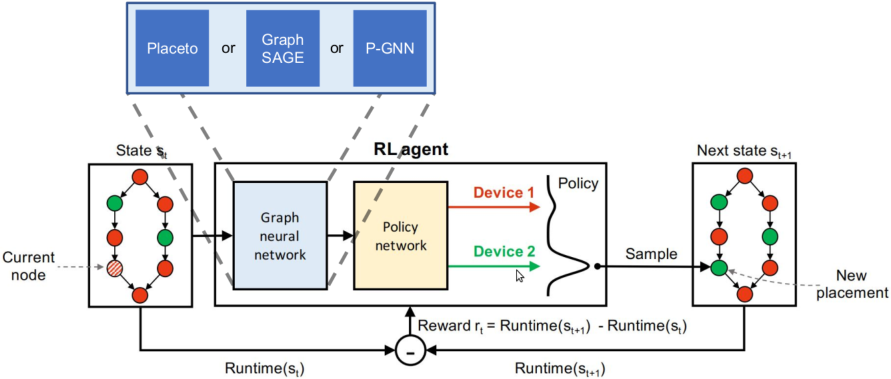
Placement Policy Network

- Implements the MDP policy using a three-layer fully connected neural network.
- Trains it using the REINFORCE policy-gradient algorithm.



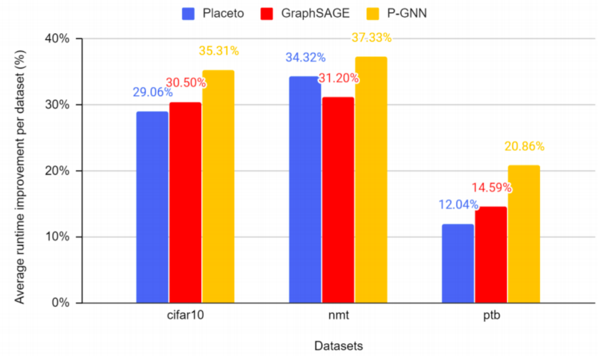
[Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019]

Graph Representation Matters in Device Placement (1/2)



[Mitropolitsky et al., Graph Representation Matters in Device Placement, 2020]

Graph Representation Matters in Device Placement (2/2)

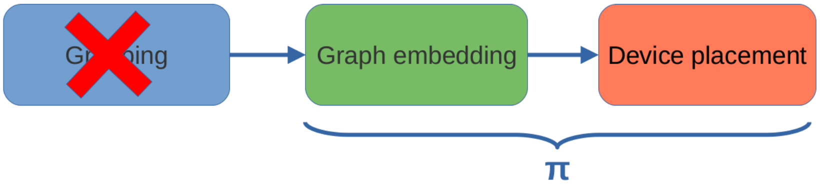


[Mitropolitsky et al., Graph Representation Matters in Device Placement, 2020]

Solution 3

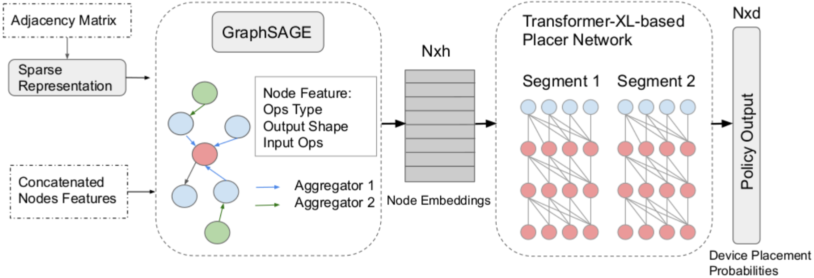
Zhou et al., A Single-Shot Generalized Device Placement for Large Dataflow Graphs, 2020

Device Placement Policy



GDP System Overview

- Uses a deep RL approach with graph embeddings and a Transformer.



N: number of nodes, h: hidden Size, d: number of devices

[Zhou et al., GDP: Generalized Device Placement for Dataflow Graphs, 2019]

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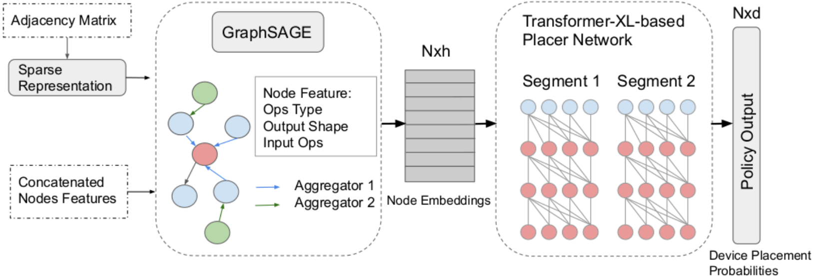

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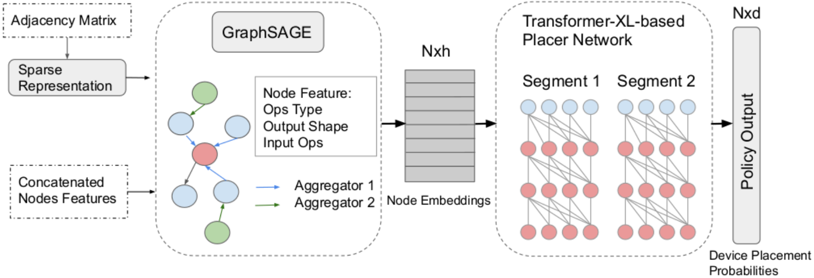
[Zhou et al., GDP: Generalized Device Placement for Dataflow Graphs, 2019]

GDP System Overview

- Uses a deep RL approach with graph embeddings and a Transformer.
- Generalize to unseen graphs.
- Generates placement for the whole graph in one step, reducing training time.



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- 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.

Placement Policy Network (2/2)

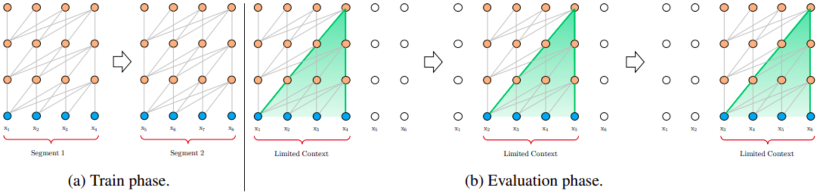
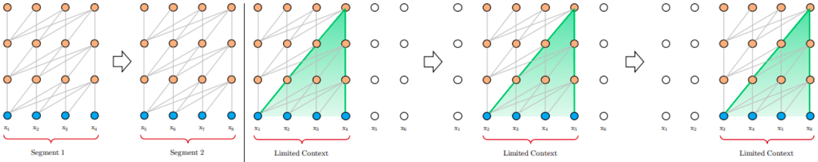


Figure 1: Illustration of the vanilla model with a segment length 4.

Placement Policy Network (2/2)



(a) Train phase. (b) Evaluation phase.

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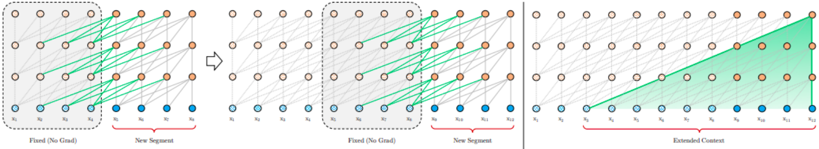

(a) Training phase. (b) Evaluation phase.

Figure 2: Illustration of the Transformer-XL model with a segment length 4.

[Z. Dai et al., Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context, 2019]

Batch Training

- Prior works focus on a single graph only.

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Summary

Summary

- Model parallelization and device placement
- Hierarchical device placement
- Placeto
- GDP

Reference

- Mayer, R. et al., The TensorFlow Partitioning and Scheduling Problem, 2017
- Mirhoseini et al., Device Placement Optimization with Reinforcement Learning, 2017
- Mirhoseini et al., A Hierarchical Model for Device Placement, 2018
- Addanki, et al., Placeto: Learning Generalizable Device Placement Algorithms for Distributed Machine Learning, 2019
- Zhou et al., GDP: Generalized Device Placement for Dataflow Graphs, 2019

Questions?