Device Placement Optimization with Reinforcement Learning

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What is device placement

- Consider a TensorFlow computational graph G, which consists of M operations $\{o_1, o_2, \ldots, o_M\}$, and a list of D available devices.

- A placement $P = \{p_1, p_2, \ldots, p_M\}$ is an assignment of an operation o_i to a device p_i.

Why device placement

- Trend toward many-device training, bigger models, larger batch sizes

- Growth in size and computational requirements of training and inference

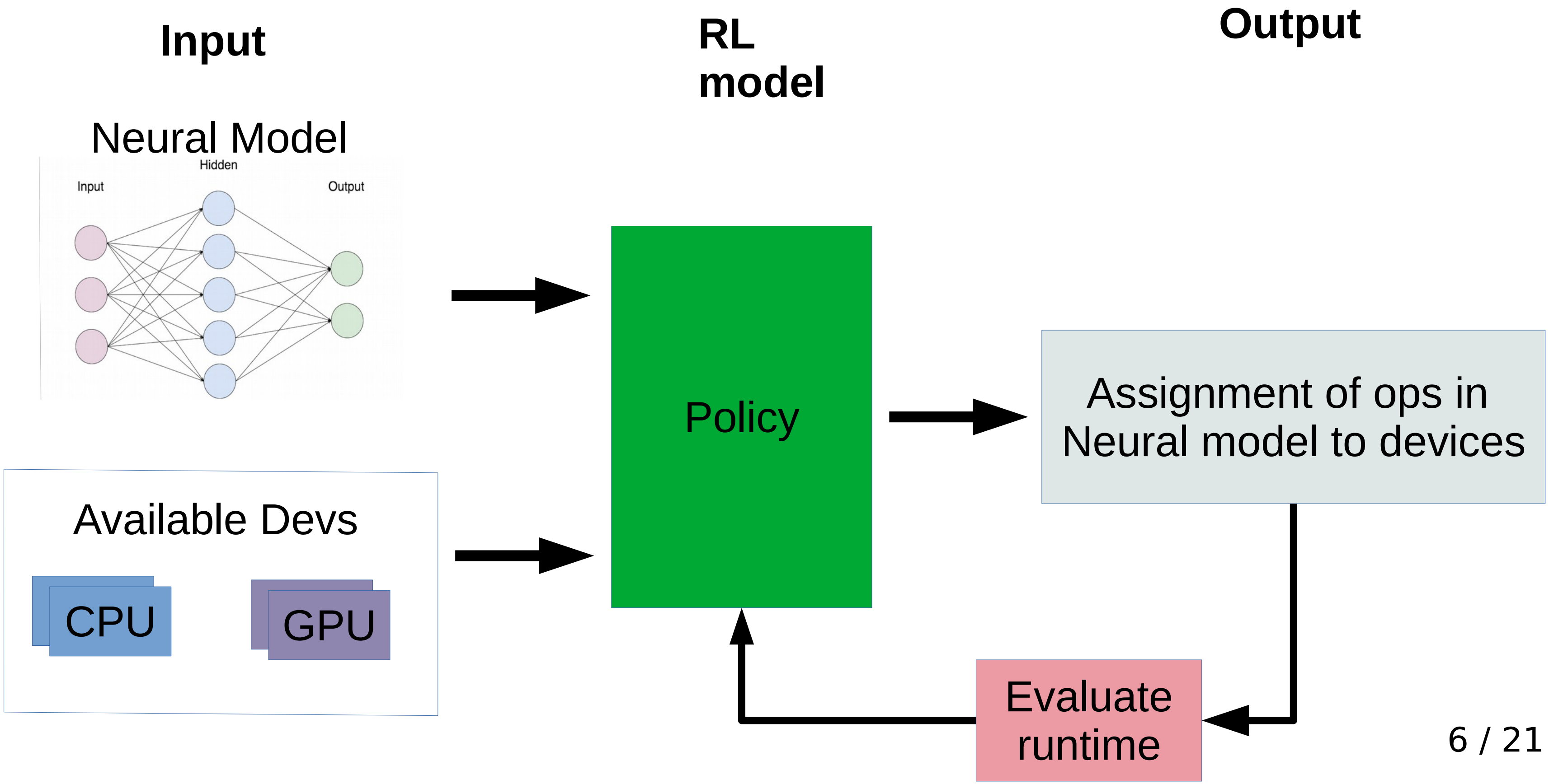
Typical approaches

- Use a heterogeneous distributed environment with a mixture of many CPUs and GPUs
- Often based on greedy heuristics
- Require deep understanding of devices: bandwidth, latency behavior
- Are not flexible enough and does not generalize well

ML for device placement

- ML is repeatedly replacing rule based heuristics
- RL can be applied to device placement
  - Effective search across large state and action spaces to find optimal solution
  - Automatic learning from underlying environment only based on reward function

RL based device placement



Problem formulation

$$J(\theta) = \mathbf{E}_{\mathcal{P} \sim \pi(\mathcal{P}|\mathcal{G};\theta)} \left[R\left(\mathcal{P}\right) | \mathcal{G} \right]$$

$J(\theta)$: expected runtime

θ : trainable parameters of policy

R : runtime

$\pi(P|G;\theta)$: policy

P : output placements

Training with REINFORCE

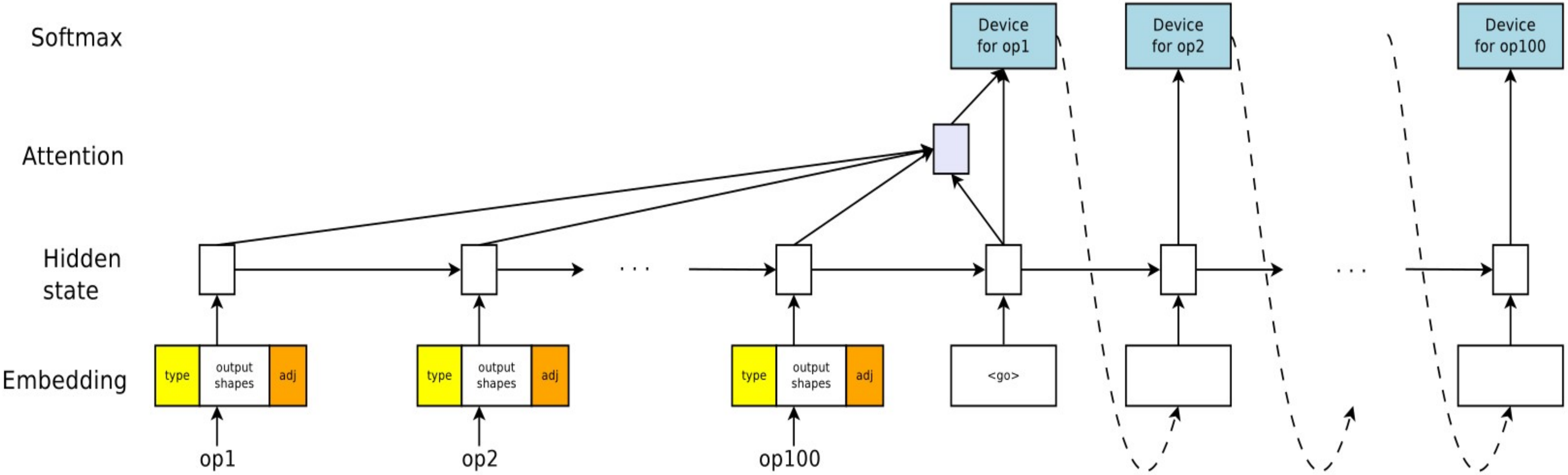
- Learn the network parameters using Adam optimizer based on policy gradients computed via the REINFORCE equation:

$$\nabla_\theta J(\theta) = \mathbf{E}_{\mathcal{P} \sim \pi(\mathcal{P}|\mathcal{G};\theta)} \left[R\left(\mathcal{P}\right) \cdot \nabla_\theta \log p\left(\mathcal{P}|\mathcal{G};\theta\right) \right]$$

- Use K placement samples to estimate policy gradients & use a baseline term B to reduce variance:

$$\nabla_\theta J(\theta) \approx \frac{1}{K} \sum_{i=1}^{K} \left(R\left(\mathcal{P}_i\right) - B \right) \cdot \nabla_\theta \log p\left(\mathcal{P}_i|\mathcal{G};\theta\right)$$

Model architecture

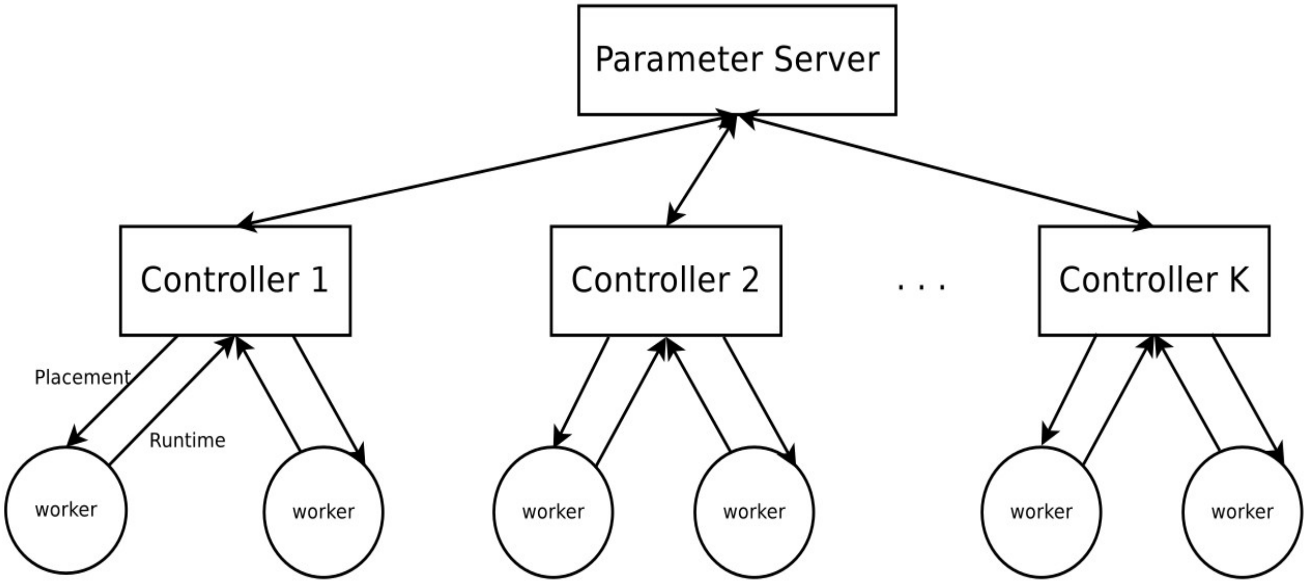


Challenges

- Vanishing
- Exploding gradient issue
- Large memory footprints

Model	#operations	#groups
RNNLM	8943	188
NMT	22097	280
Inception-V3	31180	83

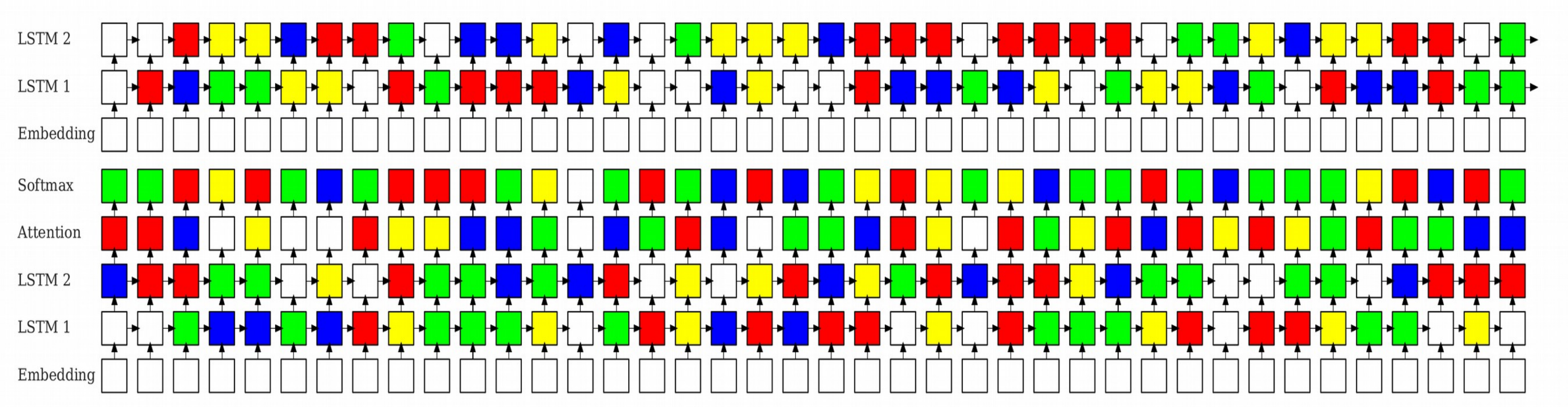
Distributed training



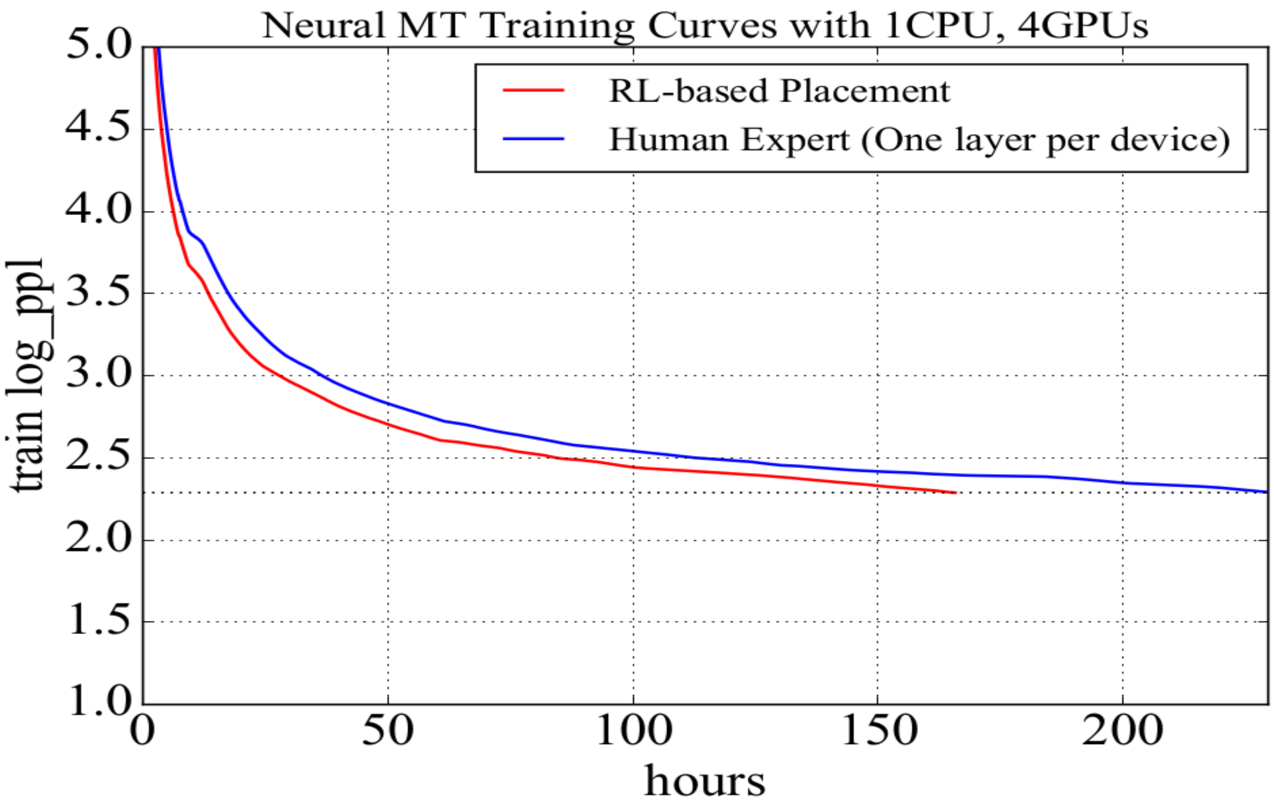
Experiments

- Recurrent Neural Language Model (RNNLM)
- Neural Machine Translation with attention mechanism(NMT)
- Inception-V3

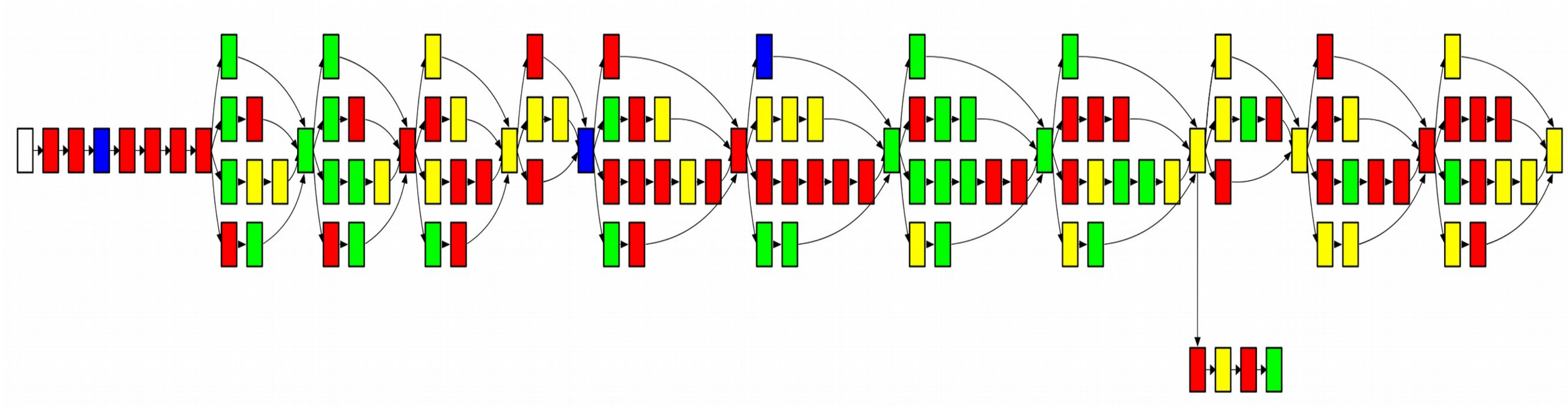
Learned placement on NMT



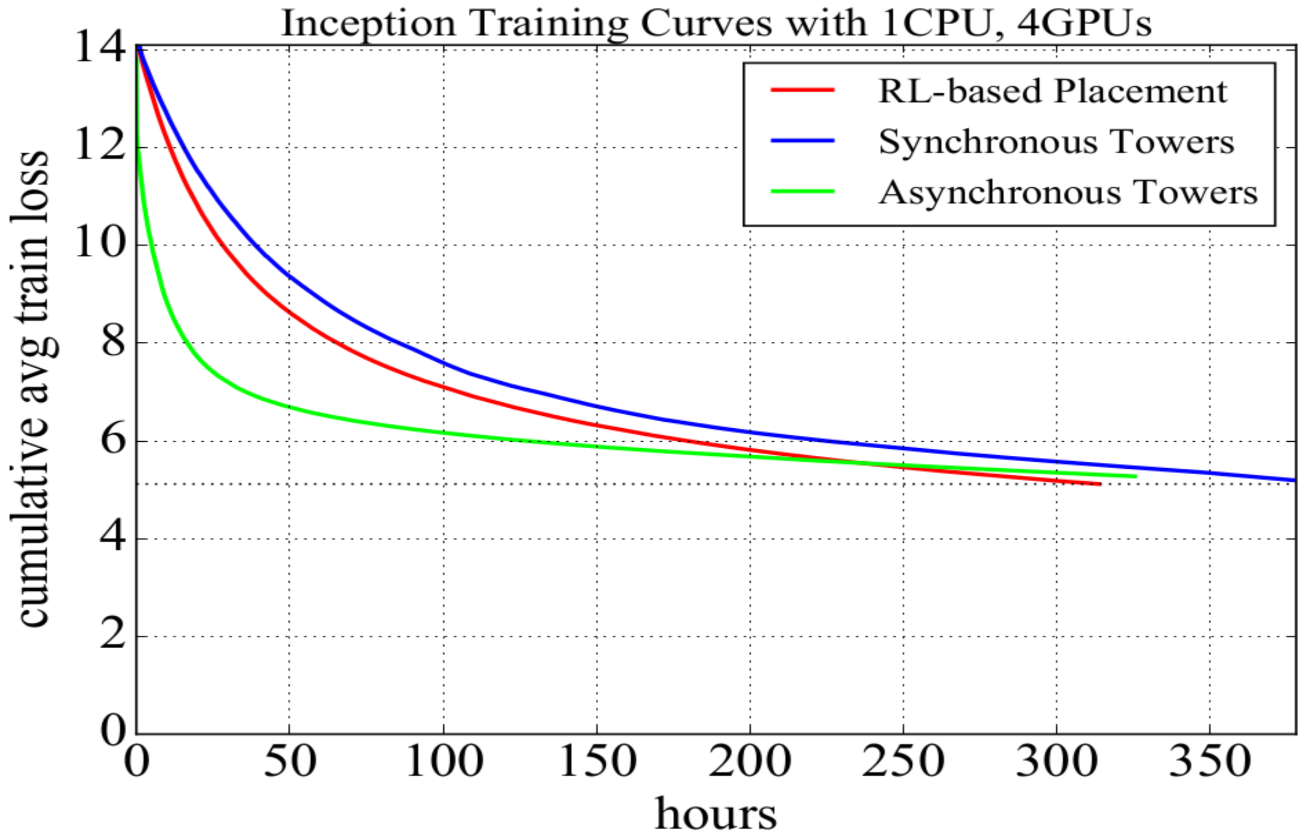
NMT end-to-end runtime



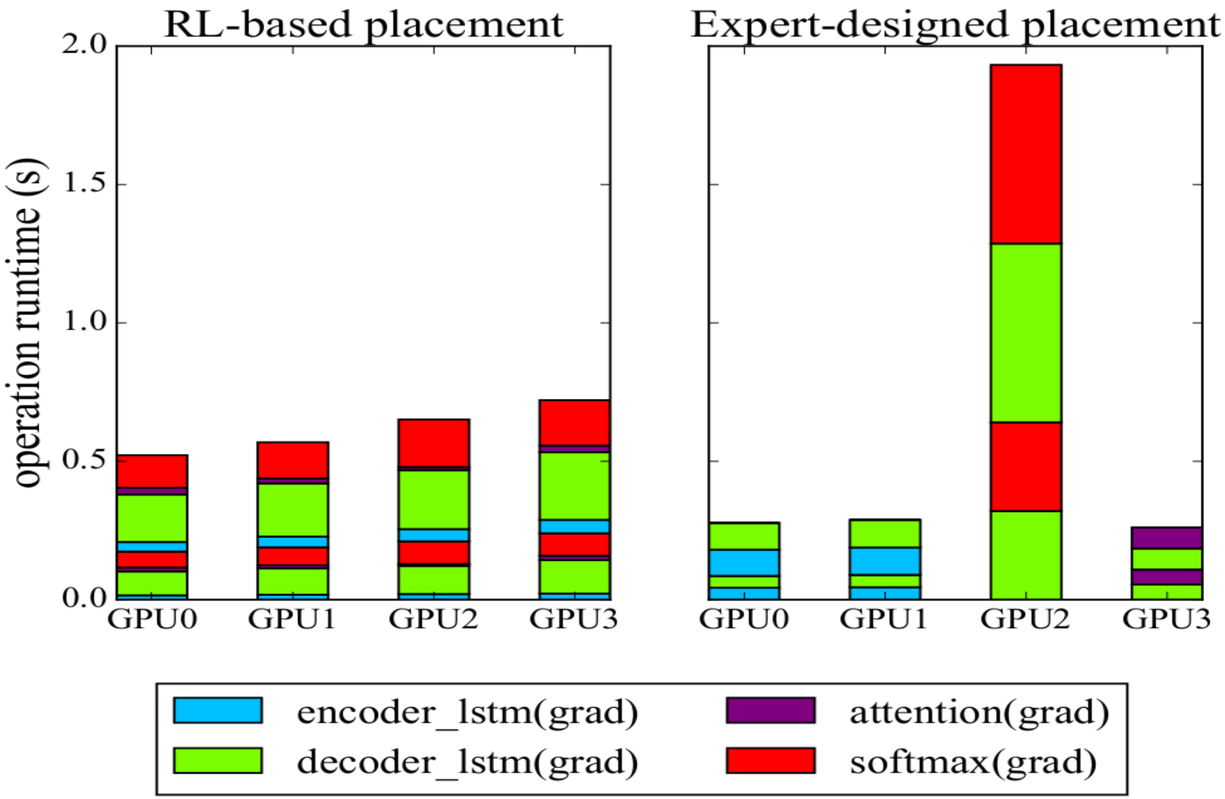
Learned placement on Inception-V3



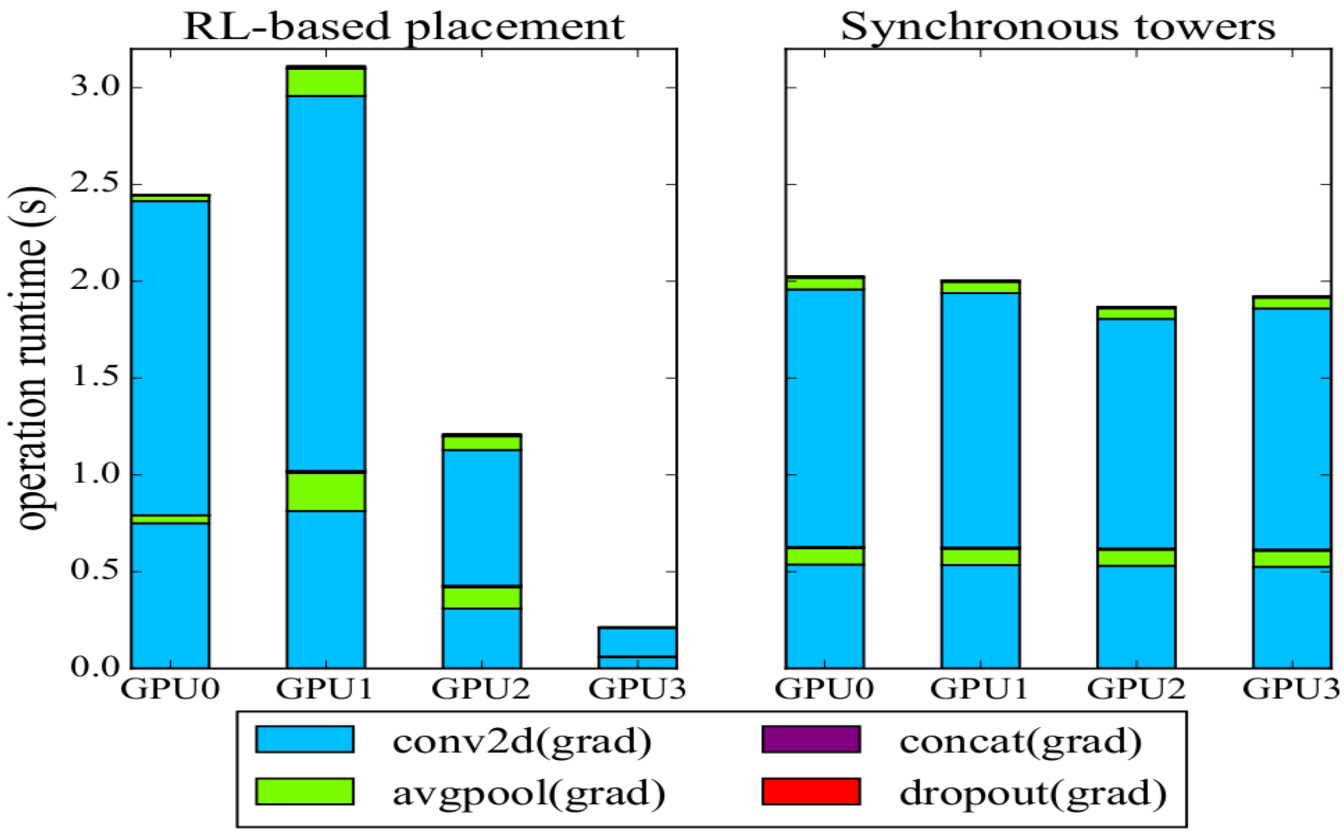
Inception-V3 end-to-end runtime



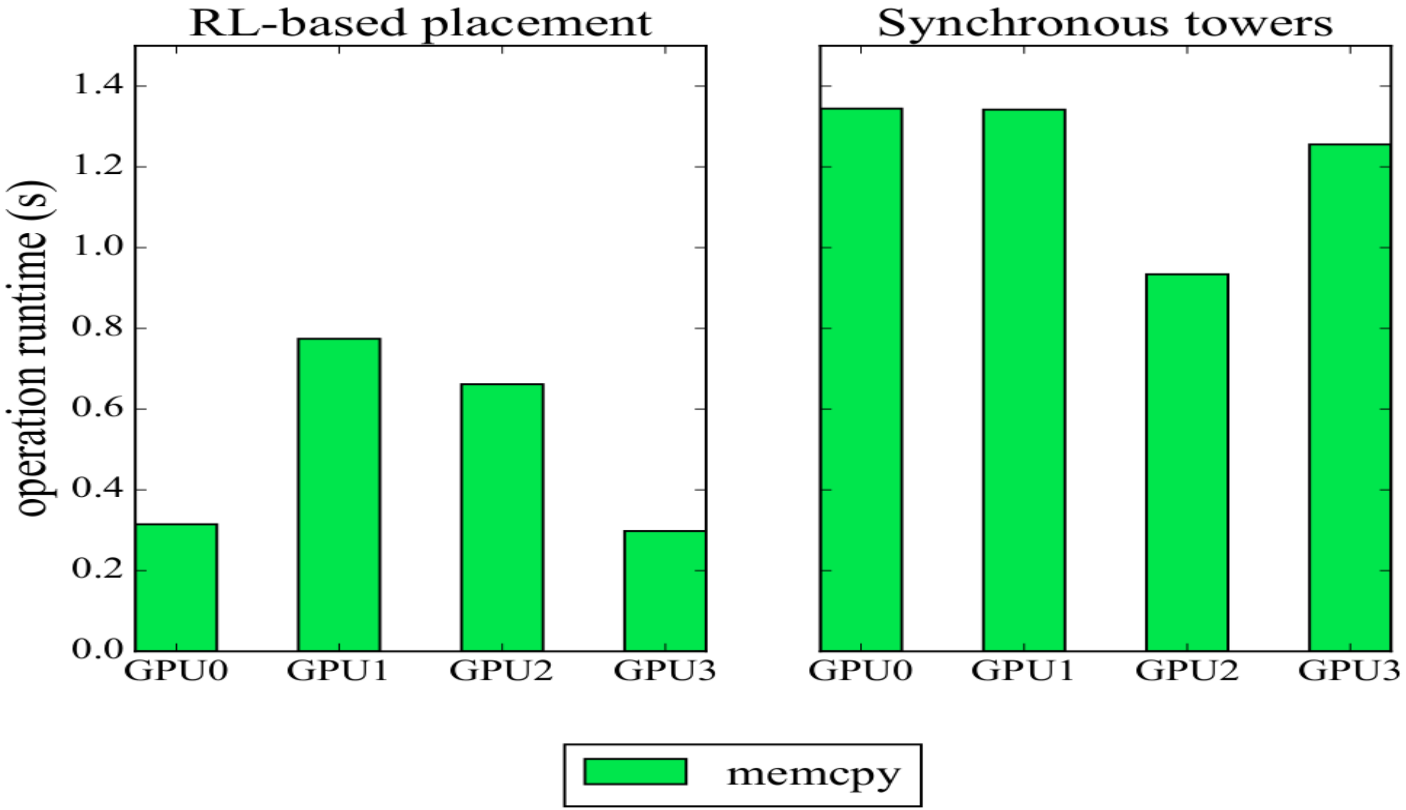
Profling on NMT



Profling on Inception-V3



Profling on Inception-V3



Running times (in seconds)

Tasks	Single-CPU	Single-GPU	#GPUs	Scotch	MinCut	Expert	RL-based	Speedup
RNNLM (batch 64)	6.89	**1.57**	2	13.43	11.94	3.81	**1.57**	0.0%
			4	11.52	10.44	4.46	**1.57**	0.0%
NMT (batch 64)	10.72	OOM	2	14.19	11.54	4.99	**4.04**	23.5%
			4	11.23	11.78	4.73	**3.92**	20.6%
Inception-V3 (batch 32)	26.21	**4.60**	2	25.24	22.88	11.22	**4.60**	0.0%
			4	23.41	24.52	10.65	**3.85**	19.0%

Summary

- Propose a RL model to optimize device placements for neural networks
- Use policy gradient to learn parameters
- Policy finds non-trival assignment of operations to devices that outperform heuristic approaches
- Profiling of results show policy learns implicit trade-offs between computation and communication in hardware