Model-based Reinforcement Learning in Computer Systems

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Declaration

I, Sean J. Parker of Clare Hall, being a candidate for the M.Phil in Advanced Computer Science, hereby declare that this report and the work described in it are my own work, unaided except as may be specified below, and that the report does not contain material that has already been used to any substantial extent for a comparable purpose.

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Acknowledgements

Abstract

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Background and Related Work

2.1 Introduction to Deep Learning Models

This section discusses the way in which machine learning models are represented for efficient execution on physical hardware devices. First, we discuss how the mapping of tensor operations to computation graphs is performed followed by an overview of recent approaches that optimise computation graphs to minimise execution time.

Over the past decade, there has been a rapid development of various deep learning architectures that aim to solve a specific task. Common examples include convolutional networks (popularised by AlexNet then ResNets, etc), transformer networks that have seen use in the modelling and generation of language. Recurrent networks that have shown to excel at learning long and short trends in data.

Importantly, the fundamental building blocks of the networks have largely remained unchanged. As the networks become more complex, it becomes untenable to manually optimise the networks to reduce the execution time on hardware. Therefore, there is extensive work in ways to both automatically optimise the models, or, alternatively apply a set of hand-crafted optimisations.

Computation graphs are a way to graphically represent both the individual tensor operations in a model, and the connections (or data-flow) along the edges between nodes in the graph. Figure 2.1 shows how the expression, $y = \texttt{ReLU}(\mathbf{w} \cdot \mathbf{x} + b)$, can be represented graphically in a computation graph.

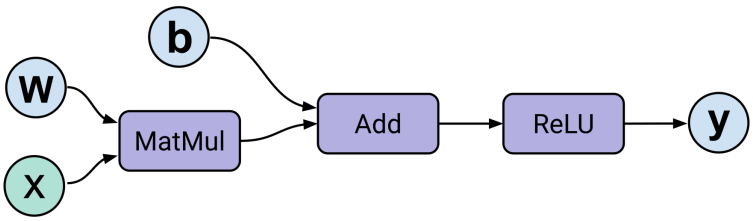

Figure 2.1: The operations shown in purple are the nodes of the computation graph which take an arbitraty number of inputs, performs a computation at the node and produces an output. The blue nodes represent the input nodes for tensors. The directed edges show the flow of tensors through the graph.

Similarly, the whole model can be converted into a stateful dataflow graph in this manner. By using a stateful dataflow (or computation) graph, we can use any optimisation technique for backpropagation of the model loss though the graph [TODO rewrite last sentence]. We consider two key benefits of this representation. First, we can execute the model on any hardware device as the models have a single, uniform representation. Secondly, it allows for pre-execution optimisations based on the host device, for example, we may perform different optimisations for executing on a GPU compared to a TPU.

2.1.1 Current approaches to optimising deep learning models

Due to the prevalence and importance of machine learning, especially deep networks, there is a focus on finding ways decrease the inference runtime and by extension, increasing the model throughput. All major frameworks such as TensorFlow [1], PyTorch [2], MXNet [3], and Caffe [4] have some level of support for performing pre-execution optimisations. However, the process of performing such optimisations is often time-consuming and cannot

be completed in real-time. Rather, it is common to use a deep learning optimisation library such as cuDNN [5] or cuBLAS [6] that instead directly optimise individual tensor operations.

Alternatively, TVM and TensorRT can be used to optimise deep learning models and offer greater performance gains compared to the more commonly used frameworks such as TensorFlow and PyTorch. They also use greedy rule-based optimisation approaches. TODO - either expand or remove

Rather than using a rule-based optimisation approach, it is possible to use more sophisticated algorithms to optimise deep learning models at the expense of computation time. Jia et al. used a cost-based backtracking search to iteratively search through the state space of possible graphs that are provably equivalent [7]. As opposed to using rule-based optimisation that applied hand-crafted optimisations, TASO generates the candidate subgraphs automatically and formally proves the transformations are equivalent using an automated theorem prover. Furthermore, Jia et al. showed that by jointly optimising both the data layout of the subgraph transformation, and the transformation itself, TASO achieves a speedup compared to performing the operations sequentially.

A key benefit of using a cost-based approach is that the search can take into account far more complex interactions between the transformed kernels. For example, if we apply a series of transformations $T_1, \cdots, T_i$, the runtime may increase, and, due to the first set of transformations, we can now apply $T_{i+1}, \cdots, T_{i+j}$, after all transformations have been applied, it is possible that we see a net decrease in runtime. By increasing the search space of transformations in this way, it is possible to increase the runtime of deep learning models by up to 3x [7, 8].

2.2 Reinforcement Learning

Reinforcement learning (RL) is a sub-field in machine learning, broadly, it aims to compute a control policy such that an agent can maximise its cu-

mulative reward from the environment. It has powerful applications in environments where a model that describes the semantics of the system are not available and the agent must itself discover the optimal strategy via a reward signal.

- TODO Can also mention POMDPs

Formally, RL is a class of learning problem that can be framed as a Markov decision processes (MDP) when the MDP that describes the system is not known [9]; they are represented as a 5-tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}_a, \mathcal{R}_a, \rho_0 \rangle$ where:

- $\mathcal{S}$, is a finite set of valid states
- $\mathcal{A}$, is a finite set of valid actions
- $\mathcal{P}_a$, is the transition probability function that an action a in state s_t leads to a state s'_{t+1}
- $\mathcal{R}_a$, is the reward function, it returns the reward from the environment after taking an action a between state s_t and s'_{t+1}
- ρ_0, is the starting state distribution

We aim to compute a policy, denoted by π, that when given a state $s \in \mathcal{S}$, returns an action $a \in \mathcal{A}$ with the optimisation objective being to find a control policy π^* that maximises the *expected reward* from the environment defined by 2.1. Importantly, we can control the 'far-sightedness' of the policy by tuning the discount factor $\gamma \in [0, 1)$. As γ tends to 1, the policy will consider the rewards further in the future but with a lower weight as the distant expected reward may be an imperfect prediction.

$$\pi^* = \arg\max_{\pi} \ \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t \ \mathcal{R}_t\right] \tag{2.1}$$

Classic RL problems are formulated as MDPs in which we have a finite state space, however, such methods quickly become inefficient with large state spaces that we consider with applications such as Atari and Go. Therefore, we take advantage of modern deep learning function approximators, such as

neural networks, that makes learning the solutions far more efficient in practise. We have seen many successfully applications in a wide range of fields, for example, robotic control tasks [10], datacenter power management, device placement, and, playing both perfect and imperfect information games to a super-human level. Reinforcement learning excels when applied to environments in which actions may have long-term, inter-connected dependencies that are difficult to learn or model with traditional machine learning techniques.

In the following sections we discuss the two key paradigms that exist in reinforcement learning and the current research in both areas and the application to systems tasks.

2.2.1 Model-Free and Model-Based RL

Model-free and model-based are the two main approaches to reinforcement learning, however, with recent work such as [11, 12, 13], the distinction between the two is becoming somewhat nebulous; it is possible to use a hybrid approach that aims to improve the sample efficiency of the agent by training model-free agents directly in the imagined environment.

The major branching point that distinguishes between model-free and model-based approaches is in what the agent learns during training. A model-free agent, in general, could learn a governing policy, action-value function, or, environment model. On the other hand, model-based agents commonly either learn an explicit representation of the policy $\pi_\theta(a|s)$ using planning, such as AlphaZero [14] or ExIt [15]. Alternatively, we can use use data augmentation methods to learn a representation of the underlying environment behaviour, and either only use fictitious model, or augment real experiences to train an agent in the domain [12, 16, 17].

Understandably, a relevant question is why one would prefer a model-free over model-based approach and what are the benefits of the respective methods. The primary benefit of model-based RL is that is has far greater sample

efficiency, meaning, the agent requires in total, less interactions with the real environment than the model-free counterparts. If we can either provide, or learn, a model of the environment it allows the agent to plan ahead, choosing from a range of possible trajectories its actions to maximise its reward.

Unfortunately, learning a model of the environment is not trivial. The most challenging problem that must be overcome is that if the model is imperfect, the agent may learn to exploit the models deficiencies, thus making it useless (or almost useless) in the real environment.

- Model-free has had more applications with greater success, e.g. in Atari, Go

- In systems environments, it can be costly for the agent to interact with the environment (which is the opposite of Atari emulators)

- Approaches for overcoming the same inefficiency, by almost brute force, by using massive amounts of compute via distributed training

- Model-based RL is concerned with learning a model of the underlying environment which it learns to simulate its dynamics – thereby agents can be cheaply and quickly trained in this 'imagined/dreamed/hallucinogenic' environment (famous example is AlphaZero where it was given an explicit model of the environment) : two options, learn a model, or be given a model

- Model-free, either policy optimisation (PPO) or Q-learning (and lots in between)

2.2.2 World Models

2.3 Graph Neural Networks

Algorithm 1: Steps of computation in a full GN block

for $k \in \{1 \dots N^e\}$ **do**
  $\mathbf{e}'_k \leftarrow \phi^e(\mathbf{e}_k, \mathbf{v}_{r_k}, \mathbf{v}_{s_k}, \mathbf{u})$
end
for $i \in \{1 \dots N^n\}$ **do**
  let $E'_i = \{(\mathbf{e}'_k, r_k, s_k)\}_{r_k=i, k=1:N^e}$
  $\bar{\mathbf{e}}'_i \leftarrow \rho^{e\to v}(E'_i)$
  $\bar{\mathbf{v}}'_i \leftarrow \phi^v(\bar{\mathbf{e}}'_i, \mathbf{v}_i, \mathbf{u})$
end
let $V' = \mathbf{v}'_{i=1:N^v}$
let $E' = (\mathbf{e}'_k, r_k, s_k)_{k=1:n^e}$
$\bar{\mathbf{e}}' \leftarrow \rho^{e\to u}(E')$
$\bar{\mathbf{v}}' \leftarrow \rho^{v\to u}(V')$
$\bar{\mathbf{u}}' \leftarrow \phi^u(\bar{\mathbf{e}}', \bar{\mathbf{v}}', \mathbf{u})$
return $(E', V', \mathbf{u}')$

- Form of neural network that has seen lots of active research recently

- Can be viewed in similar way to CNNs

- Graph network, Edge block -¿ Node block -¿ global block

- We use it to process the graphs and produce a latent tensor (from the global block) which we can learn using

Chapter 3

Title

Chapter 4

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Chapter 5

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