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Generalisable Agents for Neural Network Optimisation

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Abstract

Optimising deep neural networks is a challenging task due to complex training dynamics, high computational requirements, and long training times. To address this difficulty, we propose the framework of Generalisable Agents for Neural Network Optimisation (GANNO)—a multi-agent reinforcement learning (MARL) approach that learns to improve neural network optimisation by dynamically and responsively scheduling hyperparameters during training. GANNO utilises an agent per layer that observes localised network dynamics and accordingly takes actions to adjust these dynamics at a layerwise level to collectively improve global performance. In this paper, we use GANNO to control the layerwise learning rate and show that the framework can yield useful and responsive schedules that are competitive with handcrafted heuristics. Furthermore, GANNO is shown to perform robustly across a wide variety of unseen initial conditions, and can successfully generalise to harder problems than it was trained on. Our work presents an overview of the opportunities that this paradigm offers for training neural networks, along with key challenges that remain to be overcome.

1. Introduction

Existing strategies for choosing hyperparameters struggle to simultaneously satisfy the requirements of performance, efficiency, and generalisability. Methods like grid-search and Bayesian optimisation [10], though straightforward, are tuned to a particular problem and are unlikely to generalise. Expert-derived heuristics, such as Google's Deep Learning Playbook [12], are also often problem-specific, requiring reconsideration with each new context. Certain newer methods are instead data-driven, with the intention to generalise beyond their trained setting. One instance of this approach is to train an entirely new optimiser by meta-learning the weight-update rules for optimisation, based on the performance over a distribution of tasks (e.g. [2, 5, 19, 22, 31]). Though performant and generalisable, these methods carry a significant computational burden. Consider, for example, the VeLO optimiser [22], which required four-thousand TPU-months to train.

A more compute-efficient approach, which remains data-driven, is to instead learn an optimisation schedule, rather than the optimiser itself. That is, employ an existing optimisation algorithm

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(e.g., SGD [26]), but learn how to evolve its hyperparameters over time. Scheduling has widely been acknowledged for its potential to provide significant improvements in performance, especially when applied to the learning rate [4, 30], and it has been shown that it is possible to learn such schedules using reinforcement learning (RL). However, previous works using RL (e.g. [1, 35]) have taken a single-agent approach, and thus were constrained to learning an identical learning rate schedule for all layers, based on global network information, such as the training loss. Elsewhere though, it has been shown that setting layerwise learning rates is valuable [36, 37], and therefore, this global constraint naturally limits the overall effectiveness of learning dynamic schedules for deep networks.

In this work, we build on the success of RL as a sequential decision-making paradigm for optimisation. We use the knowledge that operating at a layerwise level is useful, while avoiding problem-specific heuristics and remaining relatively computationally friendly. Hence, we propose Generalisable Agents for Neural Network Optimisation (GANNO): a novel, multi-agent reinforcement learning (MARL) approach to optimisation. GANNO leverages layerwise information to learn adaptive layerwise learning rate schedules, as depicted in Figure 4. We show that GANNO can learn competitive schedules when compared to other leading approaches and demonstrates robustness across a wide range of unseen initial conditions. Importantly, this robustness removes the need to know the optimal values for these parameters *a priori*. We further demonstrate generalisation, where GANNO can be used successfully in problems that are more complex than what it was trained on. Finally, we outline the core challenges in this paradigm and some avenues for future work.

2. Methodology

GANNO is a general framework that uses MARL to train agents to observe aspects of a neural network f_θ during supervised learning, and develop a policy for selecting the optimiser hyperparameters dynamically during the learning process. Figure 4 provides a high-level illustration of how GANNO works: each layer passes observations to its corresponding agent; agents make decisions on how to adjust the hyperparameters; the neural network f_θ is trained for τ steps; and a reward is yielded from the performance of supervised learning. Although GANNO currently controls the learning rate, the framework can extended to other hyperparameters such as the weight decay coefficient. We describe below the details of our MARL formulation.

Timescale. Each timestep t in the MARL environment corresponds to τ steps of training in the underlying neural network, f_θ. Empirically, we find that acting with $\tau = 100$ (i.e. every 100 gradient updates of f_θ) performs well.

Environments. We make an important delineation between train and evaluation environments. The former is a neural network $f_{\boldsymbol{\theta}}$, dataset D, and optimiser ϕ, which is used when our MARL agents are training. The latter, in contrast, is only run *after* the MARL agents have been trained. We are particularly interested in evaluating generalisation, which is when the evaluation environment ($f_{\boldsymbol{\theta}}$ or D) differs from the training environment and is more complex.

Observations. Each agent receives a shared global observation along with a set of local observations specific to that agent's own layer. Details of all observations can be found in Appendix D.

Actions. Our agents operate in a discrete action space, taking actions to modify the current learning rate. Each action consists of a mathematical operation $\oplus$ with a corresponding value x. The modification to the learning rate is then $\alpha \oplus x$. For example, with the action $\{\oplus = +; x = 0.001\}$, the agent adds 0.001 to the current learning rate.

Reward. For the reward, we use the classification accuracy on a hold-out validation dataset used in the training environment,[1] to encourage the learning of generalisable behaviour. Importantly, when using solely this metric as a reward, our agents cannot tell if their actions directly resulted in a change in reward, or if the neural network's performance simply changed as a result of progress in the training of $f_{\boldsymbol{\theta}}$. To handle this problem, we leverage difference rewards [25, 32], where instead of using a reward signal $r^{(t)} = \mathcal{R}(s^{(t)}, a^{(t)}, s^{(t+1)})$, we shape the reward $r^{(t)} = \mathcal{R}(s^{(t)}, a^{(t)}, s^{(t+1)}) - \mathcal{R}(s^{(t)}, \tilde{a}, s^{(t+1)})$, where $\tilde{a}$ is the action of no modification to the current learning rate (often referred to as a 'no-op' action). [2]

Initial conditions. We aim for GANNO to have competitive performance across a wide range of initial conditions. Accordingly, we sample different values for the initial learning rate α_{init} and weight decay λ used in the training environment. Specifically, we use a log-uniform distribution to yield samples uniformly across different orders of magnitude. In evaluation, we use a fixed set of reasonable initial values for the problem, to robustly assess the performance of different approaches.

Agent policies. We use independent proximal policy optimisation (IPPO) [8, 27][3], where each agent's policy is parameterised by a recurrent neural network, with parameters ξ_i. We use weight sharing for efficient training by setting $\xi = \xi_1 = \cdots = \xi_N$. We still enable agent specialisation by conditioning each agent's policy on information local to that agent as well as an embedding of the agent's depth in the network. Note that this shared-parameter formulation naturally enables depth generalisation: we can train on a network with L_1 layers, yet evaluate on a network with $L_2 > L_1$ layers, while avoiding an observation-dimension mismatch due to having more layers in evaluation.

3. Results

We perform several experiments to validate our approach. We find that GANNO produces useful schedules which are responsive and robust, while being capable of generalising to more difficult problems. In Appendix G.1, we further show that our MARL formulation is crucial for such capabilities. We use the Adam [16] optimiser and unless otherwise stated, the hyperparameters used are those listed in Appendix D. Values in tables are given with one standard deviation over three seeds, and boldface indicates the largest value in a column.

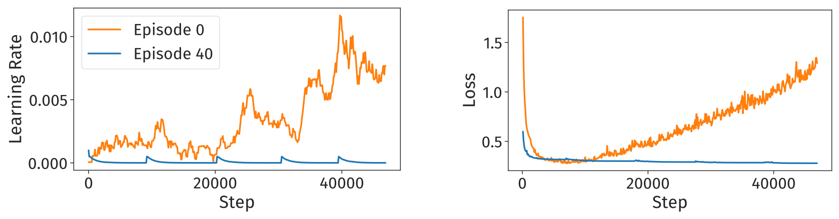
Useful and responsive schedules are generated. We first consider the simplest case of GANNO, without any notion of generalisation. Here we train and evaluate our MARL system on identical environments. We use a two-layered convolutional neural network (CNN), applied to `Fashion-MNIST` [33]. Figure 1 shows two instances of the learning rate that GANNO yields in this setting, at episode zero at the beginning of training, and then later in training at episode 40, along with their corresponding loss curves.

We highlight several interesting insights. Firstly, we observe clear learning taking place. GANNO outputs a random learning rate schedule during the first episode, which results in an undesirable loss curve; yet later in training, it yields a much improved dynamic schedule, resulting in a more desirable loss curve. Secondly, this dynamic schedule is reminiscent of some of the leading handcrafted schedules in the literature. We see similarity to exponential decay in the early stages of learning, and cyclical patterns akin to SGDR [20] as training progresses.

[1]Since we aim to generalise to unseen datasets during evaluation, there is no chance of dataset contamination.

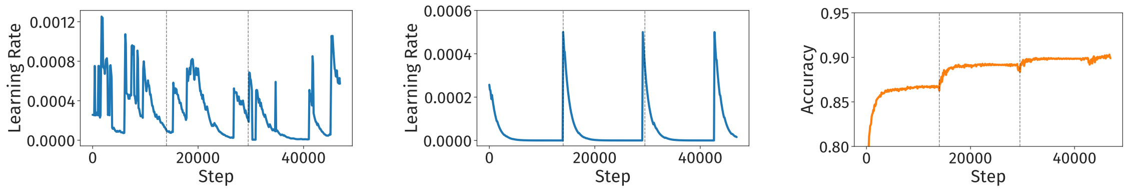
[2]This modification requires two steps of training the neural network $f_{\boldsymbol{\theta}}$ (one with each action, a and $\tilde{a}$) at each MARL timestep t, but this extra step only occurs during training and is not necessary during evaluation.

[3]Implemented using Mava [24], a MARL framework.



(*a*) Learning rate schedule. (*b*) Classification loss.

Figure 1: *GANNO's dynamic learning rate and corresponding training loss on* `Fashion-MNIST`*, shown at episodes 0 and 40.* The first episode of MARL training is shown in orange and in later training, at episode 40, in blue. Both training and evaluation use a two-layered CNN. We observe clear evidence of a useful schedule being learned, which improves the classification loss.



(*a*) First layer schedule. (*b*) Second layer schedule. (*c*) Test accuracy.

Figure 2: *GANNO's learning rate schedule dynamically escaping local optima during training for a two-layer CNN on* `Fashion-MNIST`. In both layers at key moments (around 14 000 and 29 000 training steps), GANNO spikes the learning rate and thereby escapes a local optima and improves performance.

Lastly, GANNO seems to instil in the learning rate schedule the ability to escape local optima in the loss landscape dynamically during training. To demonstrate this, we plot Figure 2, which shows another instance of training and evaluating on `Fashion-MNIST` with a two-layered CNN. We show the two layers' learning rate curves and the corresponding test accuracy. Here, the learned strategy for scheduling, particularly in Layer 1, is not as refined as seen in Figure 1. However, we draw attention to the two significant jumps in training accuracy at around 14 000 and 29 000 training steps—corresponding to spikes in the learning rate: firstly in Layer 2, and then in Layer 1. At this point in training, GANNO shows clear evidence of helping the neural network escape local optima, improving the test accuracy by several percentage points each time. Moreover, we observe how the layerwise learning rates coordinate to achieve this. This observation demonstrates the power of a responsive, layerwise scheduling algorithm. We see how GANNO can do more than simply yield a schedule akin to the handcrafted schedules from the literature, by acting dynamically based on the the layerwise information it observes.

Signs of generalisation and robustness. An important aim of GANNO is to generalise to problems of different levels of complexity. For example, to train on a simpler, shallower neural network, and still capture the dynamics well enough to be evaluated zero-shot on a more complex, deeper network. To investigate GANNO's ability to generalise in this way, we experiment by training on a two-layered CNN as before, but now evaluating on a five-layered CNN. Furthermore, we train on `Fashion-MNIST`, but evaluate on `CIFAR-10` [18], with the latter being a more complex dataset. We compare these methods across a range of initial learning rates during evaluation, with

Table 1: *Test accuracy (%) when generalising to a five-layered CNN on* `CIFAR-10`*, using manual, learned schedules and learned optimisers.* We compare GANNO to several manual learning rate schedules and two learned optimisers. This comparison is done across various initial learning rates, except for VeLO which does not take a learning rate parameter. All experiments are done with a weight decay of $\lambda = 0.1$, with additional experiments using $\lambda = 0.01$ for VeLO and Lion since they failed to generalise when using $\lambda = 0.1$. We find that GANNO performs competitively compared to the baselines and on average, is the third most performant approach across initial learning rates. We find this to be consistent across smaller λ values as shown in Table 3 in Appendix F.

	Initial learning rate					
Method	0.0001	0.0003	0.001	0.003	0.01	Average
Constant	71.99 ± 0.38	71.33 ± 0.20	71.95 ± 0.43	73.25 ± 0.73	62.34 ± 0.45	70.17 ± 0.21
Linear decay	71.27 ± 0.58	72.51 ± 0.52	72.77 ± 0.13	73.19 ± 0.39	69.87 ± 0.72	71.92 ± 0.23
Exponential decay	69.67 ± 0.59	72.99 ± 0.52	72.55 ± 0.24	72.47 ± 0.54	68.97 ± 0.74	71.33 ± 0.25
SGDR [20]	70.72 ± 0.28	72.90 ± 0.36	73.79 ± 0.50	**74.83 ± 0.09**	71.36 ± 2.44	72.72 ± 0.51
LAMB [37] w/ cosine decay	62.43 ± 0.38	69.65 ± 0.18	71.5 ± 0.15	72.58 ± 0.13	**75.48 ± 0.33**	70.33 ± 0.11
VeLO [22], $\lambda = 0.1$	/	/	/	/	/	10.00 ± 0.00
Lion [6], $\lambda = 0.1$	71.53 ± 0.28	**73.82 ± 0.14**	55.34 ± 17.27	10.00 ± 0.00	10.00 ± 0.00	44.14 ± 3.54
VeLO [22], $\lambda = 0.01$	/	/	/	/	/	**76.16 ± 0.25**
Lion [6], $\lambda = 0.01$	71.46 ± 0.13	73.25 ± 0.12	44.90 ± 8.44	10.00 ± 0.00	10.00 ± 0.00	41.96 ± 1.74
GANNO	**72.93 ± 0.21**	72.88 ± 0.80	**74.32 ± 0.16**	73.79 ± 0.26	67.12 ± 2.05	72.21 ± 0.70

the results given in Table 1. To benchmark our performance, we include the results of using various manual learning rate baselines from the literature, initialised across the same learning rate values, as well as two meta-learned optimisers, VeLO [22] and Lion [6].

When comparing GANNO to manual schedules, we see that although GANNO is not the best-performing schedule, it performs well across initial learning rate conditions, thus indicating robustness, while remaining competitive with popular expertly handcrafted schedules. In Appendix E, we show depictions of various manual schedules in Figure 5 and provide a full set of results for these schedules in Table 2. These results also highlight that expert-derived learning rate schedules, notably SGDR, are competitive baselines.

Competing with learned optimisers. We also compare GANNO to VeLO [22] and Lion [6]. We see in Table 1 that while GANNO performs better than Lion, it remains worse than VeLO on this benchmark. VeLO's impressive performance indicates that it has learned useful parameter update rules distinctively different from Adam. Even with the promise of VeLO, it has some challenges. Notably, we see that it performs poorly using a weight decay of $\lambda = 0.1$, hinting that it is sensitive to λ values. This could be problematic in compute-intensive tasks since sensitive values of λ are often unknown before evaluating on a task. Furthermore, meta-learned optimisers like VeLO require exceptionally more compute to train. We discuss this in more detail in Section 4 and Appendix H.3.

Generalising to deeper networks. We now consider GANNO's generalisation ability in a more complex setting: training on a residual network [15] that is 9 layers deep (ResNet-9) on `Fashion-MNIST`, and evaluating on one that is 18 layers deep (ResNet-18) on `CIFAR-10`. We compare GANNO to VeLO, the best-performing method from our smaller-scale experiments, along with simply using random layerwise agents. This comparison is done across two weight decay values, $\lambda = \{0.01, 0.1\}$. These results are shown in Figure 3 (we include results for SGDR, the best-performing manual schedule, in Figure 6 in Appendix F).

We see that GANNO performs competitively with VeLO. Furthermore, we find that it is more robust across the weight decay conditions compared to VeLO—which struggles to learn with a higher weight decay value, which is consistent with the results presented on a five-layer CNN.

Moreover, the poor performance of the random agent demonstrates the difficulty of this problem (i.e. learning a responsive learning rate schedule for 18 layers), and thus the significance of GANNO's performance.

It is promising that our framework can successfully generalise and control the hyperparameters of a network with vastly different dynamics than it was trained on. We see this evidence as a signal that GANNO is able to generalise to harder problem contexts (different layer depth, dataset difficulty), with robustness across unseen starting states (initial learning rate and weight decay values).

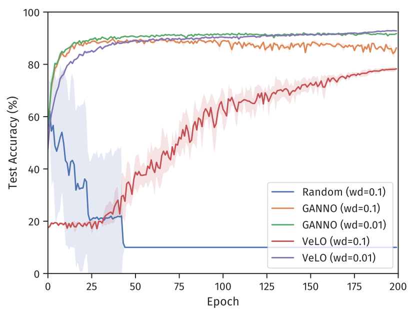


Figure 3: *Robustness of GANNO on ResNet-18.* Test accuracy across epochs for a random agent, VeLO and GANNO, evaluated on ResNet-18 on `CIFAR-10`, with an initial learning rate of 0.001 for GANNO and the random agent. We see that GANNO produces robust and competitive schedules better able to handle different weight decay values.

4. Challenges and Opportunities

We believe our results indicate that the GANNO formulation for controlling network dynamics is a powerful one, which opens up promising research directions. Nonetheless, we briefly identify several key challenges in this section. Firstly, *agent foresight*—our agents struggle to learn warmup schedules due to the tricky balance between venturing into high learning rate regions while maintaining learning stability (see Appendix H.1). Secondly, in a non-stationary environment understanding agent success and crafting an *effective reward signal* is challenging, as we discuss in Appendix H.2. Finally, there are *computational challenges*. We aim to balance the slow speeds for an environment step (we require τ i.e. 100 gradient updates from a supervised learning setting) and create a method that is viable without access to large compute. Methods like VeLO [22] are trained using a computational budget on the order of thousands of TPU months. Despite being 'once-off' after training is complete, subsequent development of similar methods is impossible for most of the machine learning community. GANNO's results were achieved in just under six hours on a single NVIDIA A100 GPU. This lower barrier to entry enables greater access, and thus more development opportunities (discussed in more detail in Appendix H.3).

5. Conclusion

We introduced GANNO, a MARL approach that is used to control the training of a neural network. We described the salient details of our solution—the observations, actions, and rewards. We then enumerated the strengths of our proposed framework, supported by empirical results: that responsive and robust schedules can be generated; that the framework demonstrates signs of generalisation ability, where we can perform well on environments more complex than we trained on; and that observing layerwise neural dynamics is important, thus validating our choice of utilising MARL. We also presented the core challenges and opportunities for this framework to flourish: in particular, the need for agent foresight, a good reward signal and computational challenges. In sum, this paper offers a novel paradigm for tackling neural network optimisation—one which demonstrates strong signs of viability. However, challenges remain, and with them, many avenues for exciting future work.

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Appendix A. GANNO's Training Process.

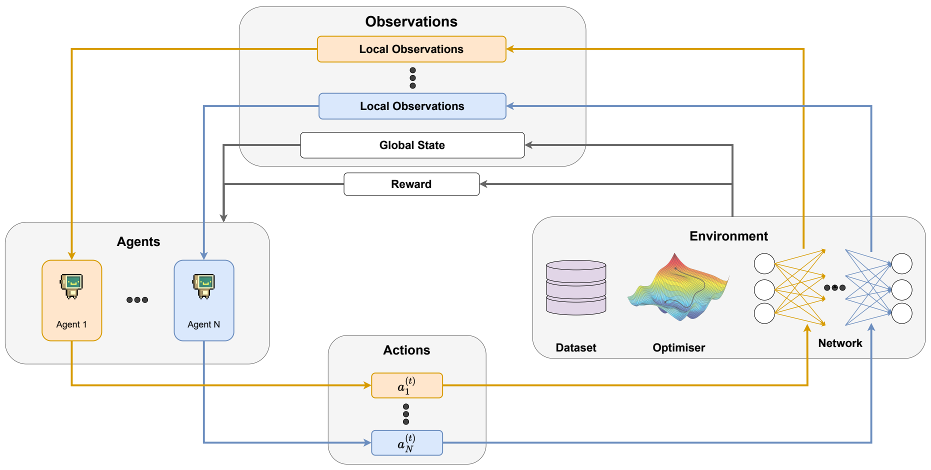

Figure 4: *GANNO's training process.* There is an agent per layer of a neural network. Each agent receives a set of global and layer-specific observations about the environment and uses this information to select an action, which is applied to a corresponding layer. Then, training in the environment progresses for some time, after which a reward signal is returned and this loop continues.

Appendix B. Background

Neural network optimisation. We consider a neural network $f_{\boldsymbol{\theta}}$, parameterised by learnable weights $\boldsymbol{\theta}$. Given a training dataset $D = \left\{\left(x^{(m)}, y^{(m)}\right)\right\}_m^M$ containing M examples, we aim to minimise the objective, $J(\boldsymbol{\theta}; \lambda) = \mathbb{E}_{\boldsymbol{x},y\sim\hat{p}_{\text{data}}(\boldsymbol{x},y)}[L(f(\boldsymbol{x}; \boldsymbol{\theta}), y; \lambda)]$, where L is a loss function evaluated using the predictions from the model $f(\boldsymbol{x}^{(m)}; \boldsymbol{\theta})$ and the true labels from the dataset $y^{(m)}$. We notate $\hat{p}_{\text{data}}$ as the empirical distribution over the training set, and λ as the weight decay coefficient.

To minimise this objective, we consider optimisation methods that adopt an update rule of the form, $\boldsymbol{\theta}^{(\tau+1)} \leftarrow \boldsymbol{\theta}^{(\tau)} - \phi\left(\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}^{(\tau)}; \lambda^{(\tau)}), \boldsymbol{\theta}^{(\tau)}; \alpha^{(\tau)}\right)$, where $\boldsymbol{\theta}^{(\tau)}$ are the current parameters at step τ and $\boldsymbol{\theta}^{(\tau+1)}$ are the updated parameters. ϕ is the chosen optimiser (e.g. Adam [16]) and is parameterised by $\alpha^{(\tau)}$ (e.g. the learning rate) and is a function of the gradient of the loss with respect to the parameters, $\nabla_{\boldsymbol{\theta}} J(\boldsymbol{\theta}^{(\tau)}; \lambda^{(\tau)})$ and the parameters themselves, $\boldsymbol{\theta}^{(\tau)}$.

Multi-agent reinforcement learning (MARL). We consider the case of common-reward co-operative MARL, which can be formulated as a decentralised partially-observable Markov decision process [3] with a set of N agents, $\mathcal{N} = \{1, \ldots, N\}$, a state space $\mathcal{S}$, a joint-observation space $\mathcal{O} = (\mathcal{O}_1 \times \cdots \times \mathcal{O}_N) \subseteq \mathcal{S}$, and a joint-action space $\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_N$. At each discrete timestep t, the agents exist in a state $s^{(t)} \in \mathcal{S}$, where each agent i perceives its own observation $o_i^{(t)} \in \mathcal{O}_i$ and accordingly takes its own action $a_i^{(t)} \in \mathcal{A}_i$. Based on the joint action, the agents transition to a next state $s^{(t+1)} \in \mathcal{S}$, with probabilities defined by a transition distribution $\mathcal{P} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$, and receive a shared scalar reward, $r^{(t)}$ from the reward function $\mathcal{R} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$. The agents' return is defined by their discounted cumulative rewards, $G = \sum_t^T \gamma^t r^{(t)}$, where T is the number of time steps in an episode, and $\gamma \in (0, 1]$ is a discounting factor. Each agent's policy is given by $\pi_i(a_i|o_i)$, with the set of all agents' policies as $\pi = \{\pi_1, \ldots, \pi_N\}$. The objective in cooperative MARL is to find a policy π_i for each agent i such that the return is maximised with respect to the other agents' policies, $\pi_{-i} := \{\pi \backslash \pi_i\}$. That is, $\forall i : \pi_i \in \arg\max_{\hat{\pi}_i} \mathbb{E}\left[G|\hat{\pi}_i, \pi_{-i}\right]$.

Notions of generalisation in RL. Along with Metz et al. [21] and Almeida et al. [1], we assert that generalisation is a critical component of learned optimisers. Yet generalisation, particularly in the context of reinforcement learning, can often lack a consistent definition. Here, we adopt an environment categorisation introduced by Kirk et al. [17], where environments may be (1) singleton, (2) independent and identically distributed (IID), or (3) out-of-distribution (OOD). When learning optimisers with this categorisation, environment generalisation can occur across various axes of the environment components, such as generalisation across various combinations of $f_{\boldsymbol{\theta}}$, D, L, and ϕ. In this work, we focus on IID generalisation of the neural network $f_{\boldsymbol{\theta}}$ and OOD generalisation of the dataset D. We consider it important to keep the specific area of generalisation clear and encourage future work into more complex levels of generalisation to do so as well.

Appendix C. Related Work

Our work primarily relates to three key insights from the literature on neural network optimisation.

Scheduling is useful. Using a schedule for hyperparameters has been recommended in training neural networks for several decades [7], and many subsequent works have sought to find good schedules via a wide variety of strategies [20, 28, 29]. Importantly, many of these scheduling approaches are based on simple heuristics, developed using the observations of practitioners with experience in the field (e.g. [12]). We aim to employ the power of scheduling in our work, but in a dynamic and responsive way, avoiding the need for handcrafted functions.

Layerwise information is important. The Layerwise Adaptive Rate Scaling (LARS) method [36] adapts stochastic gradient descent (SGD) to have layerwise learning rates, where a defined global rate is scaled for each layer by the ratio between the norm of that layer's weights and the norm of the gradient updates, referred to as the trust ratio. LAMB [37] extends this approach to use Adam [16] and additionally considers weight decay. These techniques demonstrate faster convergence times showing that layerwise information is useful. However, the trust ratio fundamentally remains a handcrafted heuristic, which happens to work well in certain domains and not necessarily in others [37]. We aim to leverage the layerwise information in a network while avoiding handcrafted heuristics, with the end goal of generalisation.

RL is effective for learning schedules. Most closely related to our work are methods which learn data-driven optimisation schedules using RL [1, 34, 35]. These works highlight the potential usefulness of such a strategy; however, none of them operate in a layerwise manner—considering layer-specific dynamics and taking layer-specific actions. Thus, we aim to extend these RL approaches to a multi-agent setting using a separate agent per layer.

Additionally, we acknowledge a growing body of work on directly learning gradient update rules using meta-learning techniques [2, 5, 19, 31]. These methods usually come at a high computational cost, which limits the researchers that are able to make progress in this direction. We thus avoid this approach.

Appendix D. Hyperparameters

We list below the hyperparameters used for all GANNO results, unless otherwise stated.

Observations:

- At a global level:
  - Train and test classification accuracy
  - Train and test classification loss
  - Boolean flag indicating if the loss is undefined or infinite
  - Training progress (current number of epochs/total epochs)
  - Ratio between the train and test loss (following Almeida et al. [1])
  - Initial learning rate
  - Initial weight decay
- At a layerwise level:
  - Current learning rate
  - Previous action taken
  - Layer type (linear, convolutional, or attention)
  - Layer depth (an embedding which indicates if the current layer is first, intermediate, or final layer)
  - LAMB trust ratio [37] ($\frac{||\theta_l^{(t)}||}{||u_l{}^{(t)}||}$, where θ_l is the weights for layer l and u_l is the Adam update term)
  - Norm of gradients for the layer $||g_l{}^{(t)}||$
  - Norm of the updates $||u_l{}^{(t)}||$
  - Mean and variance of the weights $\theta_l^{(t)}$
  - Norm of the layer weights $||\theta_l^{(t)}||$

Actions:

Current learning rate ... $\{+\,0.00, \times\,1.01, \times\,1.10, \div\,1.01, \div\,1.10, +\,0.0005, -\,0.0005, +\,0.001, -\,0.001\}$

PPO Details:

- Number of executors/parallel copies of the environment = 4
- Max executor steps/number of training timesteps = 50 000
- Layer norm? = False
- Policy layer sizes = [128,128]
- Critic layer sizes = [64,64]
- Policy recurrent layer size = 64
- Policy layer size after recurrent layer = 64
- Epoch batch size = 32
- Sequence length = 8

- Number of epochs = 2
- Number of mini-batches = 4
- Normalise advantage? = True
- Normalise target values? = True
- Clip value? = True
- Normalise observations? = True

Supervised learning of f_θ:

- Optimiser: Adam [16]
- Weight decay: $\lambda = 0.1$

Initial conditions:

- Learning Rate, α_{init}: Log-uniform distribution with bounds $[10^{-5}, 10^{-2}]$.
- Weight Decay, λ: Log-uniform distribution with bounds $[10^{-5}, 10^{-1}]$.

Appendix E. Manual Schedules

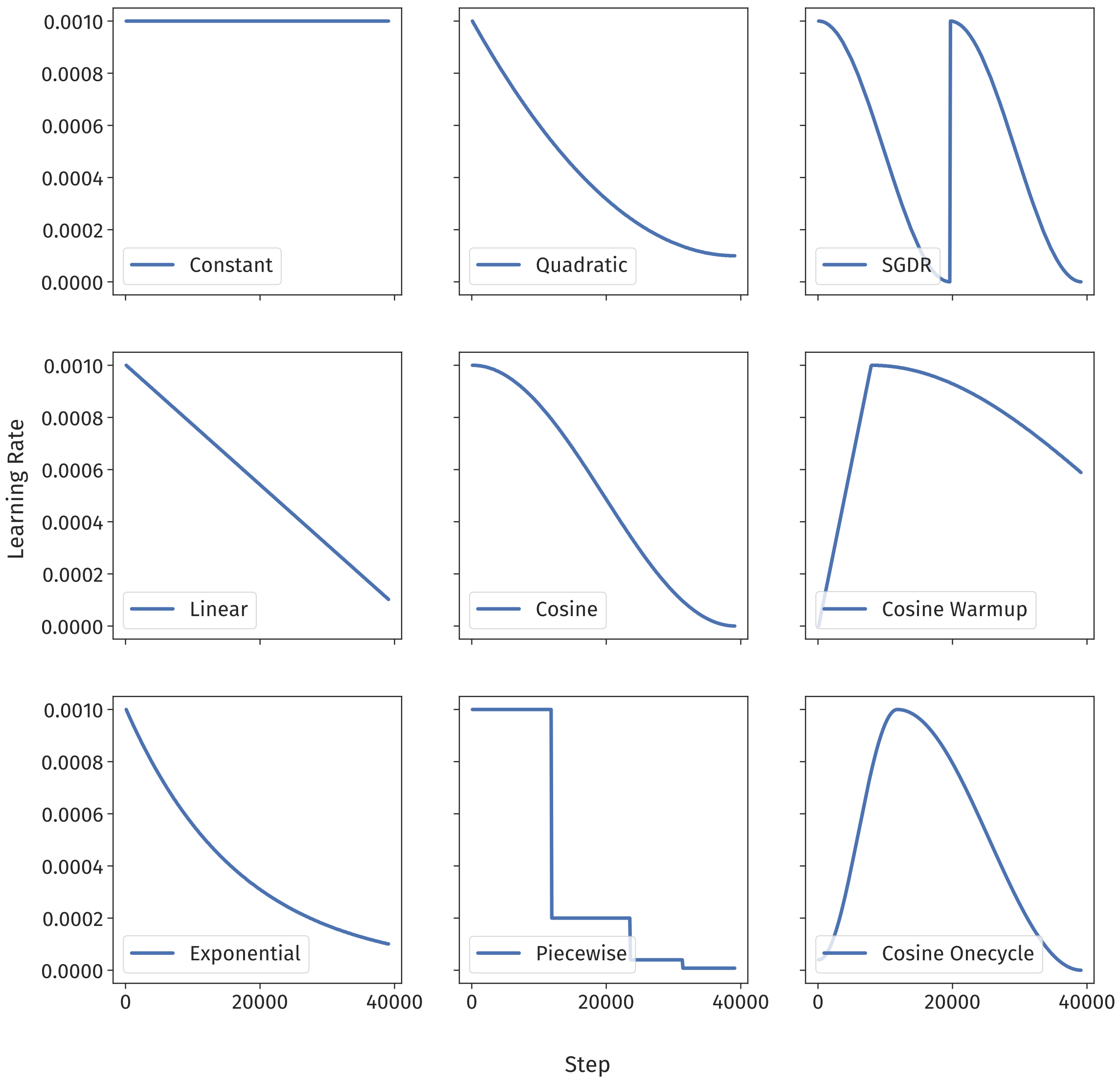

Figure 5: *Nine common handcrafted learning rate schedules used at various points in the paper.*

Appendix F. Extended Results

Table 2: *Classification accuracies (%) achieved by GANNO, along with several simple learning rate schedules, using a five-layered CNN on* `CIFAR-10`*, across various initial learning rates, with* $\lambda = 0.1$. We see that GANNO performs competitively with the best manual schedules.

	Initial Learning Rate					
Simple schedules	0.0001	0.0003	0.001	0.003	0.01	Average
Constant	71.99 ± 0.38	71.33 ± 0.20	71.95 ± 0.43	73.25 ± 0.73	62.34 ± 0.45	70.17 ± 0.21
Linear	71.27 ± 0.58	72.51 ± 0.52	72.77 ± 0.13	73.19 ± 0.39	69.87 ± 0.72	71.92 ± 0.23
Quadratic	69.71 ± 0.50	73.12 ± 0.50	72.07 ± 0.83	72.63 ± 0.26	69.58 ± 1.42	71.42 ± 0.36
Cosine	70.85 ± 0.41	72.83 ± 0.35	73.26 ± 0.23	73.74 ± 0.69	69.82 ± 0.72	72.10 ± 0.23
Exponential	69.67 ± 0.59	72.99 ± 0.52	72.55 ± 0.24	72.47 ± 0.54	68.97 ± 0.74	71.33 ± 0.25
Piecewise	69.83 ± 0.44	**73.56 ± 0.42**	73.14 ± 0.24	73.42 ± 0.09	69.96 ± 0.71	71.98 ± 0.19
SGDR	70.72 ± 0.28	72.90 ± 0.36	**73.79 ± 0.50**	**74.83 ± 0.09**	**71.36 ± 2.44**	**72.72 ± 0.51**
GANNO	**72.14 ± 0.77**	73.44 ± 0.86	72.99 ± 1.37	73.08 ± 0.21	68.15 ± 2.35	71.96 ± 1.11

Table 3: *Classification accuracies (%) achieved by GANNO, along with several simple learning rate schedules, using a five-layered CNN on* `CIFAR-10`*, across various initial learning rates, with* $\lambda = 0.0001$. We see that GANNO remains competitive with the other schedules, even at a lower weight decay value.

	Initial Learning Rate					
Simple schedules	0.0001	0.0003	0.001	0.003	0.01	Average
Constant	70.72 ± 0.55	70.08 ± 0.81	69.95 ± 0.81	66.60 ± 0.26	57.88 ± 1.30	67.05 ± 0.37
Linear	70.43 ± 0.52	70.35 ± 0.37	72.33 ± 0.09	69.90 ± 0.79	59.67 ± 2.68	68.54 ± 0.57
Quadratic	69.67 ± 0.57	71.90 ± 0.95	71.97 ± 0.25	70.94 ± 0.74	59.40 ± 1.33	68.78 ± 0.38
Cosine	70.50 ± 0.38	70.70 ± 0.38	72.51 ± 0.22	70.29 ± 0.38	58.33 ± 2.24	68.47 ± 0.47
Exponential	69.33 ± 0.41	70.73 ± 0.34	72.10 ± 0.53	70.93 ± 0.14	57.98 ± 1.51	68.21 ± 0.34
Piecewise	69.85 ± 0.59	71.97 ± 0.44	72.08 ± 0.27	70.28 ± 0.54	60.04 ± 1.86	68.84 ± 0.42
SGDR	70.55 ± 0.41	70.91 ± 0.40	**72.78 ± 0.43**	70.54 ± 0.36	61.48 ± 1.48	69.25 ± 0.34
VeLO	/	/	/	/	/	**74.86 ± 0.31**
LION	71.49 ± 0.23	**73.16 ± 0.27**	36.02 ± 11.00	10.00 ± 0.00	10.00 ± 0.00	40.13 ± 2.30
GANNO	**72.45 ± 0.32**	71.14 ± 0.49	72.09 ± 0.65	**71.08 ± 0.83**	**62.61 ± 1.25**	69.87 ± 0.35

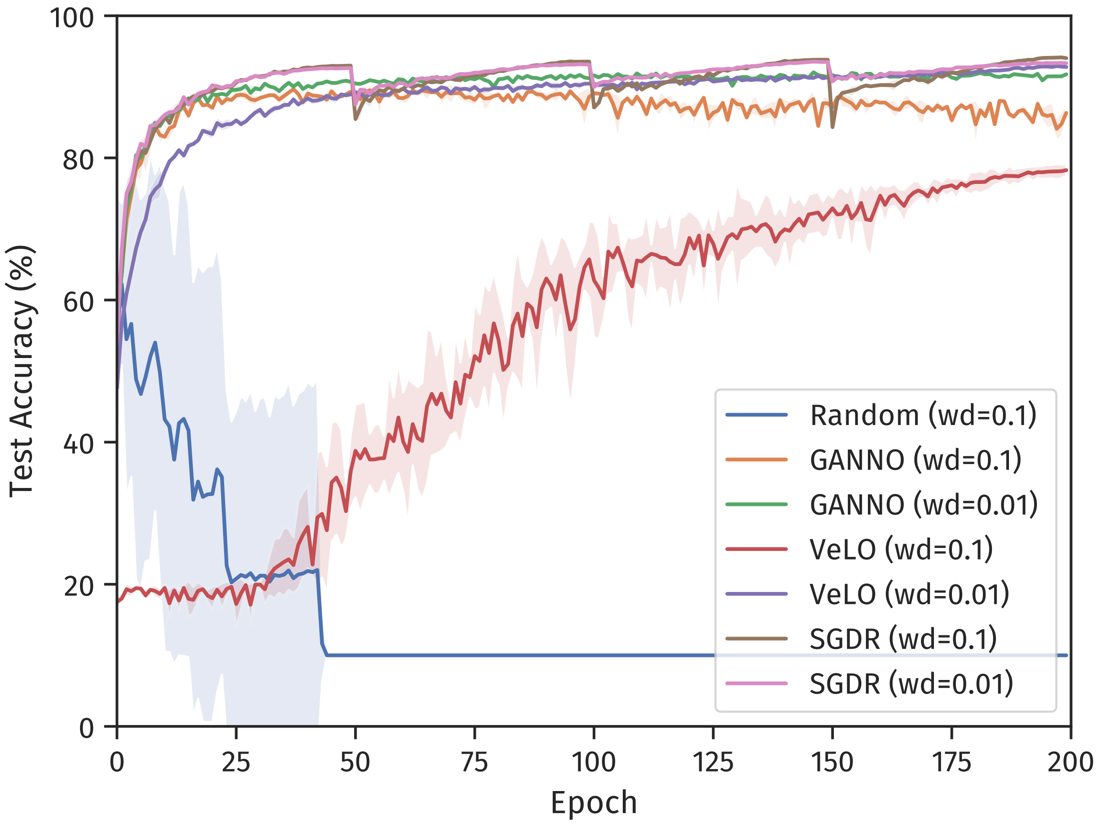

Figure 6: *Robustness of GANNO on ResNet-18.* Test accuracy across epochs for different schedules and learned optimisers on ResNet-18 trained on `CIFAR-10`, with an initial learning rate of 0.001 for GANNO and the random agent. We see that GANNO produces robust and competitive schedules better able at handling different weight decay values. Note this is the same as 3 but it includes SGDR as an extra set of results.

Appendix G. Ablations

G.1. The necessity of MARL.

In our results, we see early signs that GANNO is able to generate useful schedules and generalise to harder problem contexts. We now consider two further questions: is GANNO actually making use of the neural network dynamics to develop its control strategy? And is it important to observe such dynamics at a layerwise level? Accordingly, we study three ablated versions of GANNO: (1) `GANNO-LR-only`, where only the current learning rate is included in the observation, (2) `GANNO-timestep-only`, where only the training progress (current epoch count / total epoch count) is included in the observation, and (3) `GANNO-single-agent`, a single-agent version of GANNO where only global information (e.g. classification loss) is included in the observation and the agent learns a global learning rate schedule.[4] Table 4 shows the outcome of these experiments, with the same simplified problem configuration as used previously: training on a two-layered CNN with `Fashion-MNIST` and evaluating on a five-layered CNN with `CIFAR-10`.

Firstly, we notice that `GANNO-LR-only` performs well with some of the initial learning rates, specifically 0.003, but deteriorates at other values. Notably, with an initial learning rate of 0, it achieves a poor accuracy of just 35%. Studying the schedules that `GANNO-LR-only` yields, we find that agents often learn to simply decay the learning rate directly to zero, irrespective of the impact of this on the network dynamics. With an appropriate initial value, this strategy actually works reasonably well; but it is evidently not generalisable whatsoever, since it is not truly adaptive, leading to poor results across initial conditions.

For `GANNO-timestep-only`, we see that the training stage is indeed a useful observation, achieving relatively good performance across a fairly wide range of initial conditions. Nonetheless, we see again that this version of GANNO underperforms compared to the original, thus motivating the inclusion of network dynamics in our observations. Moreover, we witness much higher variance in the performance of `GANNO-timestep-only`, making the approach less reliable and robust.

Finally, we find that `GANNO-single-agent` significantly underperforms the layerwise version, and also fails to learn a generalisable schedule across initial conditions. This outcome clearly

[4]Note this version would be comparable to work by Almeida et al. [1], Xu et al. [35]. We were unable to find working code implementations for these methods so we implemented our own single-agent PPO agent with the same hyperparameters as our GANNO MARL agent.

Table 4: *An ablation study showing the necessity of GANNO's MARL formulation for learning dynamic schedules.* We show classification accuracies (%) using a five-layered CNN on `CIFAR-10` achieved by GANNO, along with the three ablations, all trained with a two-layered CNN on `Fashion-MNIST`, across various initial learning rates. We see that our GANNO formulation performs better than the ablated iterations, showing the necessity of observing layerwise dynamics and taking layerwise actions.

	Initial learning rate						
Ablations	0	0.0001	0.0003	0.001	0.003	0.01	Average
GANNO-LR-only	35.80 ± 0.69	62.85 ± 0.55	70.13 ± 0.30	64.64 ± 0.91	74.27 ± 0.65	63.48 ± 2.83	61.54 ± 0.65
GANNO-timestep-only	57.81 ± 15.29	68.99 ± 4.51	73.04 ± 2.11	72.37 ± 3.88	**74.39 ± 0.97**	63.69 ± 2.48	68.38 ± 6.84
GANNO-single-agent	9.74 ± 0.11	51.32 ± 0.46	60.37 ± 0.74	69.24 ± 0.30	73.63 ± 0.37	64.10 ± 1.29	54.73 ± 0.54
GANNO	**69.38 ± 1.47**	**72.93 ± 0.21**	**72.88 ± 0.80**	**74.32 ± 0.16**	73.79 ± 0.26	**67.12 ± 2.05**	**71.74 ± 0.83**

supports the usefulness of observing dynamics at a layerwise granularity and layerwise learning scheduling, as suggested in previous work [36, 37].

Appendix H. Challenges, Opportunities, and Future Work

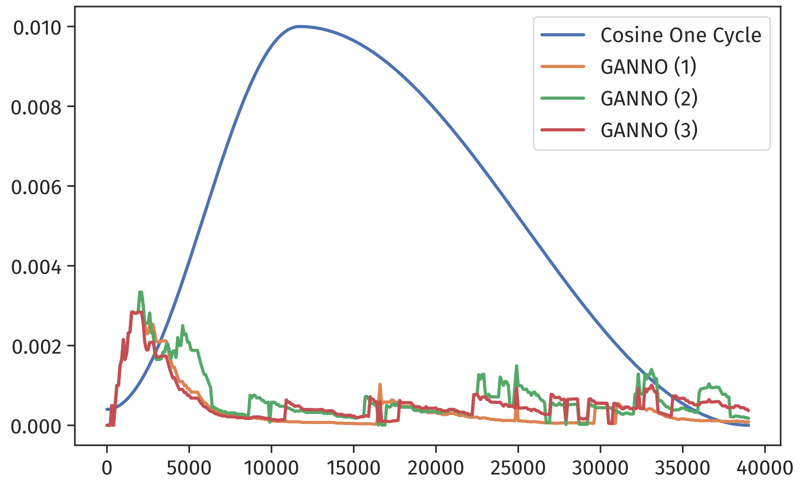

Figure 7: *Comparison of the manual learning rate schedule* `cosine-one-cycle` *with three instances of schedules from GANNO*. Notice how the GANNO agents act more conservatively in their scheduling to avoid the potential instability of a high learning rate.

We believe our results indicate that the GANNO formulation for controlling network dynamics is a powerful one, which opens up promising research directions. Nonetheless, there remain several key challenges which we identify in this section. We specifically enumerate three primary dimensions: (1) agent foresight, (2) understanding agent success, and (3) computational requirements.

H.1. Agent foresight is necessary for great performance.

It is both common and useful in supervised learning to 'warm up' the learning rate hyperparameter during training—that is, use lower values when starting training, increase them in some way, and thereafter proceed with a scheduling strategy like exponential decay [12, 13, 15]. In Table 5, we show the results of two such approaches when evaluating with a five-layered CNN on `CIFAR-10`: a simple strategy with linear warm-up and cosine decay, and the 'cosine one-cycle' schedule [29]. We compare these schedules to GANNO's performance in this evaluation environment, setting its initial learning rate to zero to induce warm-up behaviour, after training it with a two-layered CNN on `Fashion-MNIST`.

We see in these results that the warm-up schedules, particularly with a good peak learning rate selection, are the most performant, achieving up to 77% in this classification task—the best results on this evaluation environment in this paper. In contrast, when we evaluate GANNO using an initial learning rate of zero, we see inferior performance.

The challenge here rests in the tricky balance between venturing into high learning rate regions while maintaining learning stability. We know from Table 1 that a constant learning rate at a high value performs poorly, yet we now observe in Table 5 that a great strategy is to increase up to this

Table 5: *GANNO compared to warm-up schedules.* We show classification accuracies (%) achieved using a five-layered CNN on `CIFAR-10` by GANNO, trained with a two-layered CNN on `Fashion-MNIST`, along with two leading warm-up schedules, across various peak learning rates. We see that the warm-up schedules achieve higher accuracies than GANNO.

	Peak learning rate					
Warm-up schedules	0.0001	0.0003	0.001	0.003	0.01	Average
Linear warm-up, cosine decay	70.77 ± 0.45	72.36 ± 0.45	**73.61 ± 0.06**	**75.84 ± 0.26**	77.24 ± 0.32	73.96 ± 0.15
Cosine one-cycle [29]	**70.80 ± 0.16**	**72.71 ± 0.51**	73.29 ± 0.11	75.80 ± 0.35	**77.62 ± 0.60**	**74.04 ± 0.18**
GANNO from LR = 0	/	/	/	/	/	69.38 ± 1.47

high value and thereafter decrease it. Notice that for an agent to replicate this effective schedule, it must have the foresight to move into a potentially unstable state of learning, but only do so temporarily. Though recurrent policies can help with the longer-term planning required here [14], we find that agents tend to be more conservative to avoid this potential instability altogether (see Figure 7 for an example of such behaviour). A promising direction for this problem is to use existing manual schedules as demonstrations: e.g. to generate offline data from the successful handcrafted routines, and use this data in an offline MARL pre-training step [11], thereby showing the agents the benefits of warm-up-like schedules.

H.2. Understanding agent success.

The reward signal is a vital component of reinforcement learning, though one which is often considered as a given, simply as a part of the environment definition. Yet designing a reward signal for a particular goal may be an important task in itself [9]. Consider the challenge of defining a meaningful reward signal when the underlying environment is itself a supervised learning problem. Ultimately, we want to optimise some final metric, e.g. maximise classification accuracy. Thus, suppose we used the training accuracy of the supervised loop as our reward; we are faced with the question discussed earlier in this paper: is our agent receiving a 'good' reward because of its own 'good' actions, or simply because of progress in the underlying training loop? Indeed, to illustrate this point empirically, notice that the agent could yield a constant learning rate (by taking 'no-op' actions, leaving the value unchanged), and in Table 1, we see that such a schedule yields a decent performance of around 70%. Instead, we want our agents to find a schedule that can squeeze out the extra performance—e.g., reach scores of 77%, as seen in Table 5.

Various directions for future work could extend from this point, such as reward shaping (as was done in the 'difference' rewards, discussed earlier) or using a centralised critic to improve multi-agent credit assignment [38].

H.3. Computational Requirements.

In RL, it often takes millions of timesteps to train effective agents [23, 27]. In the case of GANNO, we train our agents for 50 000 timesteps. This shorter timespan is a result of two considerations. Firstly, for each training step, we require τ (e.g. 100) gradient updates from a supervised learning setting, which makes each environment step relatively slow compared to other RL environments. Secondly, we want our approach to be viable without access to large compute. In contrast, methods like VeLO [22] are trained using a computational budget on the order of thousands of TPU months.

This immense computational requirement, despite being ‘once-off’ after training is complete, makes subsequent development of similar methods impossible for most of the machine learning community. GANNO’s formulation is comparably much cheaper, with the above results yielded in just under six hours on a single NVIDIA A100 GPU. This lower barrier to entry enables greater access, and thus more development opportunities.