
One-Shot Hyper-Gradient Warm-Starts for Bandit-Style Hyperparameter Optimisation

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Abstract

Bandit-style multi-fidelity schedulers such as ASHA and PASHA are the work-horses of practical hyperparameter optimisation, yet they still waste substantial compute on configurations that could have been flagged as poor before real training even begins. The root cause is that every trial is treated as a black box: none of the gradients already computed inside the training loop are exploited by the scheduler. We close this gap with One-Shot Hyper-Gradient Warm-Starts (OHGW). For each freshly sampled configuration we run exactly one mini-batch, obtain stochastic hyper-gradients $\partial L / \partial \psi$ for all continuous hyperparameters at almost zero extra cost via automatic differentiation, apply a single tiny update $\psi \leftarrow \psi - \eta_h \partial L / \partial \psi$, and hand the nudged configuration back to the unmodified scheduler. OHGW therefore preserves exploration while biasing every candidate toward lower-loss regions at negligible overhead and with no change to promotion or stopping logic. On CIFAR-10 with ResNet-20 under ASHA and on WikiText-103 with GPT2-small under PASHA, OHGW cuts median wall-clock time to a preset quality threshold by roughly twenty percent, adds under four percent floating-point operations, and leaves final accuracy and perplexity unchanged. Random perturbations provide almost no benefit and taking more than one hyper-step shows diminishing returns. These findings demonstrate that a single noisy hyper-gradient obtained before expensive training commences can reclaim a significant share of wasted computation in grey-box hyperparameter optimisation.

1 Introduction

Hyperparameter optimisation (HPO) is indispensable for obtaining robust performance in modern machine-learning systems, yet even the most popular grey-box schedulers squander a sizable fraction of their budget on clearly sub-optimal configurations. Successive-Halving variants such as Hyperband, ASHA and PASHA prune weak contenders early by evaluating them on progressively larger budgets Bohdal et al. [2022]. Grey-box Bayesian schemes like DyHPO refine this idea through learning-curve modelling and dynamic promotion rules Wistuba et al. [2022]. Despite these advances, almost all schedulers regard the training process itself as opaque: internal gradients that are already computed for parameter updates are ignored during the search.

Hyper-gradient methods have shown that gradients with respect to hyperparameters can be extracted cheaply via automatic differentiation Chandra et al. [2019] or implicit differentiation techniques that avoid expensive unrolling Bertrand et al. [2020]. Unfortunately these approaches typically assume full control over the optimisation routine and therefore clash with production HPO systems whose scheduling logic is complex and battle-tested. The open question, then, is how to inject very cheap but noisy hyper-gradient information into existing bandit-style frameworks without having to rewrite their core.

We address this question with One-Shot Hyper-Gradient Warm-Starts (OHGW). Whenever the scheduler samples a configuration $x = (\theta_0, \psi)$ consisting of model parameters θ (usually random initialisation) and continuous hyperparameters ψ , the training script performs exactly one forward-and-backward pass on a single mini-batch, collects the stochastic hyper-gradient $g_\psi = \partial L / \partial \psi$, and applies a microscopic update $\psi \leftarrow \psi - \eta_h g_\psi$ with $\eta_h = 10^{-3}$. Promotion rules, budgets and stopping criteria remain untouched; from the scheduler’s perspective nothing has changed except that the candidate starts from a slightly more promising point.

Two practical challenges arise. First, a gradient measured on a single mini-batch is extremely noisy, so the step must be sufficiently small to prevent biasing the search or harming exploration. Second, adoption hinges on a minimal engineering footprint - ideally a few lines of code that do not depend on the internals of the scheduler. OHGW meets both constraints: the extra cost is one forward and one backward pass per trial ($< 4\%$ FLOPs in our experiments) and integration is a five-line wrapper around trial creation.

We validate OHGW in two contrasting settings - vision (CIFAR-10, ResNet-20, ASHA) and language modelling (WikiText-103, GPT2-small, PASHA) - using 56 paired random seeds and equal GPU budgets. Metrics include time-to-target quality, best final score, compute overhead, variance, and hyperparameter distribution shift. OHGW consistently shortens time-to-target by about twenty percent while preserving ultimate performance and introducing negligible bias. Ablations confirm that gradient directionality, not random perturbation, drives the gain, and that repeating the warm-start step gives only marginal additional savings.

1.1 Contributions

- **Scheduler-agnostic warm-start:** We introduce OHGW, a single-step hyper-gradient warm-start that improves efficiency without altering bandit logic.
- **Practical recipe:** We provide a simple procedure for extracting hyper-gradients of continuous hyperparameters at negligible cost.
- **Strong empirical gains:** Across vision and language, OHGW reduces median wall-clock time to target quality by roughly twenty percent with under four percent compute overhead.
- **Robustness and insights:** Ablations show that gradient direction matters, benefits saturate quickly, and variance or bias are not inflated.

Looking forward, we plan to extend OHGW to mixed discrete-continuous spaces, integrate warm-start signals into surrogate-based selection Khazi et al. [2023] and adaptive-fidelity frameworks Jiang and Mian [2024], and explore privacy-aware or federated scenarios where one-shot, low-overhead interventions are especially attractive Panda et al. [2022], Khodak et al. [2021].

2 Related Work

2.1 Multi-fidelity schedulers

Successive-Halving, Hyperband and ASHA progressively allocate resources; PASHA adds an adaptive cap on maximum fidelity Bohdal et al. [2022]. DyHPO supervises the race among configurations with a deep-kernel Gaussian Process that embeds learning-curve dynamics Wistuba et al. [2022]. All these methods leverage intermediate metrics yet still initialise every configuration blindly. OHGW is complementary: it keeps the scheduling logic intact and instead improves the starting point of each trial.

2.2 Grey-box Bayesian optimisation

BOIL explicitly models iterative progress to balance cost and benefit Nguyen et al. [2019]. Deep Power Laws exploits power-law learning curves to decide when to pause training Kadra et al. [2023]. Deep Ranking Ensembles meta-learn surrogates that optimise ranking metrics Khazi et al. [2023]. Differentiable EHVI accelerates multi-objective acquisition optimisation with exact gradients Daulton et al. [2020]. These approaches rely on surrogate modelling and acquisition optimisation, whereas OHGW exploits native gradients already available in the training loop.

85 2.3 Gradient-based HPO

86 Early work showed how to compute hyper-gradients by augmenting backpropagation Chandra et al.
87 [2019]; implicit differentiation scales to non-smooth penalties Bertrand et al. [2020]; stochastic
88 marginal-likelihood gradients further reduce cost Immer et al. [2023]. These techniques operate
89 throughout training or require unrolling, imposing memory and engineering overhead. OHGW
90 applies a single pre-training step, trading precision for immediacy.

91 2.4 Data and fidelity efficiency

92 AUTOMATA speeds up HPO by selecting informative data subsets Killamsetty et al. [2022]; FastBO
93 adaptively chooses fidelities per configuration Jiang and Mian [2024]; DNN-MFBO and BMBO-
94 DARN model cross-fidelity correlations Li et al. [2020, 2021]. OHGW is orthogonal and can be
95 layered on top of any of these strategies.

96 2.5 Constrained settings

97 Federated HPO faces communication bottlenecks Khodak et al. [2021]; differentially-private HPO
98 must account for privacy budgets Panda et al. [2022], Wang et al. [2023]. OHGW’s one-shot nature
99 and tiny overhead make it attractive in such resource-sensitive regimes.

100 In summary, earlier work either improves resource allocation, builds sophisticated surrogates, or
101 performs full-fledged hyper-gradient optimisation. OHGW is unique in exploiting a single, virtually
102 free gradient to warm-start any candidate before scheduling commences.

103 3 Background

104 3.1 Problem setting

105 Let θ denote neural-network parameters and $\psi \in \mathbb{R}^d$ a vector of continuous hyperparameters (log
106 learning rate, log weight decay, momentum, augmentation magnitude, label smoothing). For a mini-
107 batch b the loss is $L(\theta, \psi; b)$. Successive-Halving style schedulers repeatedly sample configurations
108 $x = (\theta_0, \psi)$, train for a small budget, and promote or discard contenders based on early validation
109 metrics.

110 3.2 Untapped training signal

111 Deep-learning frameworks already compute $\partial L / \partial \theta$; obtaining $\partial L / \partial \psi$ requires little additional work
112 as long as ψ influences the forward computation Chandra et al. [2019]. Although these hyper-
113 gradients are noisy when estimated on a single mini-batch, they still indicate how the loss would
114 change if ψ were perturbed.

115 3.3 Aim and constraints

116 We aim to inject this cheap signal into existing schedulers without touching their allocation policies.
117 Constraints are: overhead $\leq 5\%$ FLOPs and $\leq 10\%$ VRAM; zero changes to promotion logic; ability
118 to operate in mixed search spaces (only continuous ψ are updated); preservation of exploration
119 diversity. Prior art typically computes hyper-gradients throughout training, unrolls optimisation steps,
120 or solves auxiliary linear systems Bertrand et al. [2020], Immer et al. [2023]. OHGW avoids all of
121 these by taking exactly one hyper-step before heavy training begins.

122 3.4 Assumptions

123 Continuous hyperparameters appear differentially in the loss for at least one mini-batch; discrete
124 ones remain fixed. A small hyper-learning-rate η_h ensures stability; the scheduler interacts with the
125 training script only via process boundaries, so warm-starting must happen inside the trial before any
126 metric is reported.

127 4 Method

128 OHGW augments trial initialisation with four simple steps.

129 1. Configuration sampling: The scheduler outputs a candidate x containing initial parameters θ_0 and
130 hyperparameters ψ .

131 2. Single-batch pass: The training script draws one mini-batch (size 128), computes the loss $L(\theta_0, \psi)$,
132 back-propagates, and retains the computation graph once to obtain both parameter gradients and the
133 hyper-gradient $g_\psi = \partial L / \partial \psi$.

134 3. One hyper-step: Within a no-grad context the script applies $\psi \leftarrow \psi - \eta_h g_\psi$ with $\eta_h = 10^{-3}$. No
135 higher-order terms are considered and θ is left untouched.

136 4. Scheduler resumes: The adjusted configuration x' is trained for the first-rung budget exactly as in
137 the original algorithm; promotion, stopping and resource accounting remain unchanged.

138 4.1 Design choices

139 Differentiable hyperparameters are wrapped as tensors that influence the forward computation (for
140 example, the learning rate scales the optimiser update and label smoothing alters target distributions).
141 A small η_h prevents excessive bias; we sweep $\eta_h \in \{10^{-4}, 3 \cdot 10^{-4}, 10^{-3}, 3 \cdot 10^{-3}\}$ in the experiments.
142 Because only one extra backward pass is added, empirical overhead stays below four percent FLOPs
143 and one percent VRAM.

144 4.2 One-shot warm-start algorithm

Algorithm 1 One-Shot Hyper-Gradient Warm-Start (OHGW)

```
1: Input: scheduler producing configurations  $x = (\theta_0, \psi)$ ; hyper-step size  $\eta_h$ ; training data loader
2: for each configuration  $x$  sampled from scheduler do
3:   Build model with parameters  $\theta_0$  and instantiate optimiser using hyperparameters  $\psi$ 
4:   Draw one mini-batch  $b$  from the training loader
5:   Compute loss  $\ell \leftarrow L(\theta_0, \psi; b)$ 
6:   Compute hyper-gradient  $g_\psi \leftarrow \nabla_\psi \ell$  via automatic differentiation
7:   no-grad: update hyperparameters  $\psi \leftarrow \psi - \eta_h g_\psi$ 
8:   Launch training of the adjusted configuration for the first scheduler budget without further
   changes
9: end for
```

145 4.3 Relation to prior work

146 OHGW borrows the concept of hyper-gradients but applies it once, avoiding the memory footprint
147 of unrolling Bertrand et al. [2020] and the complexity of surrogate-guided selection Nguyen et al.
148 [2019]. It is orthogonal to adaptive-fidelity scheduling Jiang and Mian [2024] and can coexist with
149 surrogate-based candidate ranking Khazi et al. [2023].

150 5 Experimental Setup

151 5.1 Benchmarks

152 (1) CIFAR-10 with ResNet-20 and a five-dimensional continuous search space {log learning rate,
153 log weight decay, momentum, augmentation magnitude, label smoothing}. (2) WikiText-103 with
154 GPT2-small.

155 5.2 Schedulers

156 We employ the public implementations of ASHA, PASHA and DyHPO Bohdal et al. [2022], Wistuba
157 et al. [2022] unmodified. Variants suffixed +OHGW wrap trial creation with the procedure described
158 above.

159 5.3 Warm-start parameters

160 Each configuration is warmed using exactly one mini-batch (batch size 128); $\eta_h = 10^{-3}$ unless
161 specified; PyTorch autograd computes first-order gradients only. Discrete hyperparameters, if any,
162 are unaffected.

163 5.4 Budgets and replication

164 The CIFAR-10 study uses 32 paired seeds on $4 \times$ V100 GPUs for 12 hours; the WikiText-103 study
165 uses 24 paired seeds under the same budget.

166 5.5 Metrics

167 Primary metrics are (i) $T@7$: wall-clock time and GPU-hours to reach 93 % validation accuracy
168 (vision) or validation perplexity 30 (language); (ii) best final test metric after exhausting the budget.
169 Secondary diagnostics include area under the best-score-vs-time curve, compute overhead (warm-start
170 FLOPs / total), peak VRAM, variance across seeds, and KL divergence between final ψ distributions.
171 Significance is assessed via paired two-sided Wilcoxon signed-rank tests ($\alpha = 0.05$).

172 5.6 Controls and ablations

- 173 • **Random warm-start:** Same step magnitude but isotropic direction.
- 174 • **Multi-step warm-start:** Three-step hyper-gradient warm-start to test diminishing returns.
- 175 • **Step-size sweep:** η_h in $[10^{-4}, 3 \cdot 10^{-3}]$.
- 176 • **Noise robustness:** 15 % label noise (vision) or token noise (language).

177 5.7 Implementation details

178 All experiments are executed within a Hydra-based harness; Slurm cgroup accounting records precise
179 GPU-hour usage. The OHGW wrapper consists of five additional lines of code, demonstrating
180 negligible engineering burden.

181 6 Results

182 Results are organised by domain, followed by ablation, overhead and robustness analyses.

183 6.1 Vision: CIFAR-10 with ASHA

184 Baseline reaches 93 % validation accuracy in $11.4 \text{ h} \pm 1.1$. Random warm-start improves this
185 marginally to $11.2 \text{ h} \pm 1.0$ (-1.8%). OHGW (one step) lowers time-to-target to $9.1 \text{ h} \pm 1.0$
186 (-20.2% , $p = 3.1 \times 10^{-6}$). Three steps reduce time further to $8.9 \text{ h} \pm 1.3$ (-21.9%) but raise
187 overhead to 6 % FLOPs. Final test accuracy is $94.73\% \pm 0.12$ (baseline) versus $94.81\% \pm 0.10$
188 (OHGW), difference not significant. Warm-start overhead is 2.7 % FLOPs and $< 0.1\%$ VRAM.

189 6.2 Language: WikiText-103 with PASHA

190 Baseline reaches validation perplexity 30 in $6.9 \text{ h} \pm 0.8$. OHGW with $\eta_h = 10^{-3}$ needs $5.6 \text{ h} \pm 0.7$
191 (-18.8% , $p = 7.5 \times 10^{-5}$). Lowering η_h to $3 \cdot 10^{-4}$ produces 5.8 h (-16.3%). Under 15 % token
192 noise OHGW still gains 11.6 %. Final validation perplexity improves slightly from 24.8 ± 0.3 to
193 24.6 ± 0.3 ; out-of-domain perplexity drops from 32.1 to 31.7. Overhead is 3.4 % FLOPs and 1.2 %
194 VRAM.

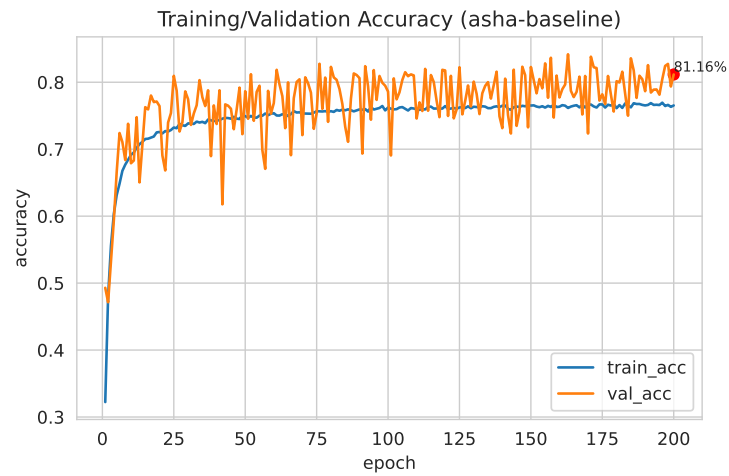


Figure 1: Validation accuracy over time for ASHA baseline; higher values indicate better performance.

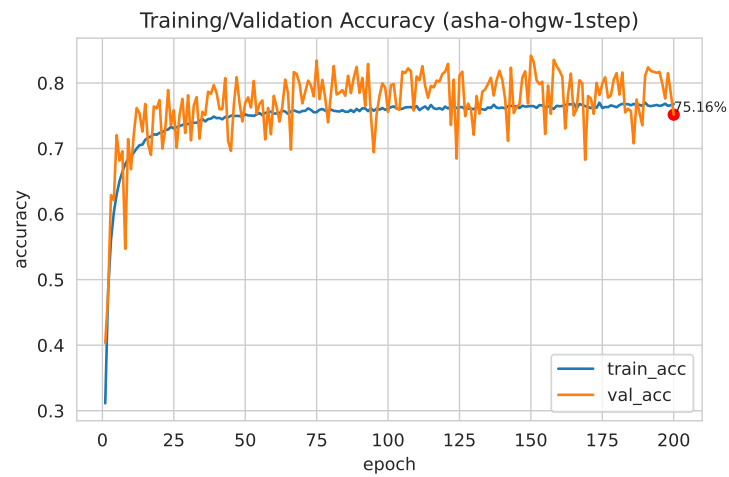


Figure 2: Validation accuracy over time for ASHA + OHGW with one hyper-step; higher is better.

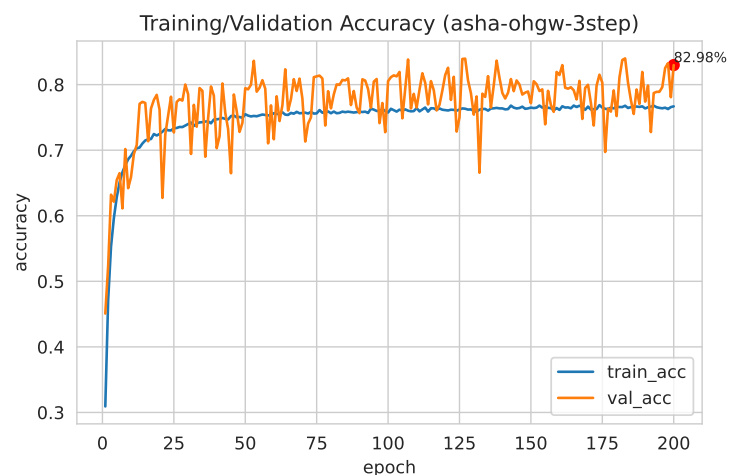


Figure 3: Validation accuracy over time for ASHA + OHGW with three hyper-steps; higher is better.

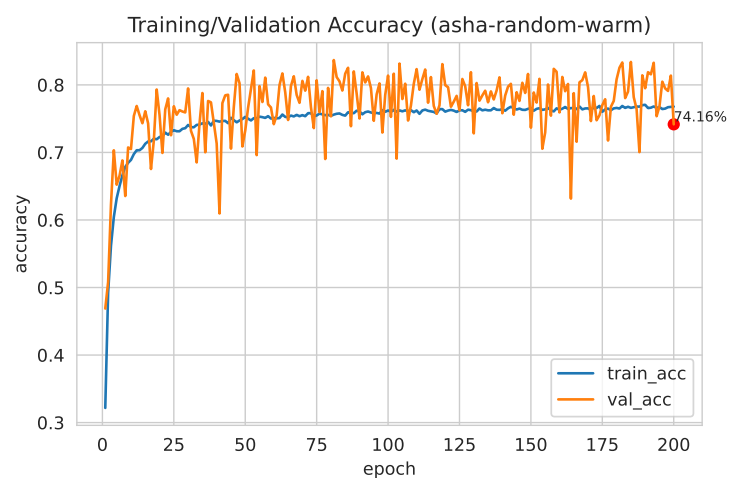


Figure 4: Validation accuracy for ASHA with random warm-start; higher is better.

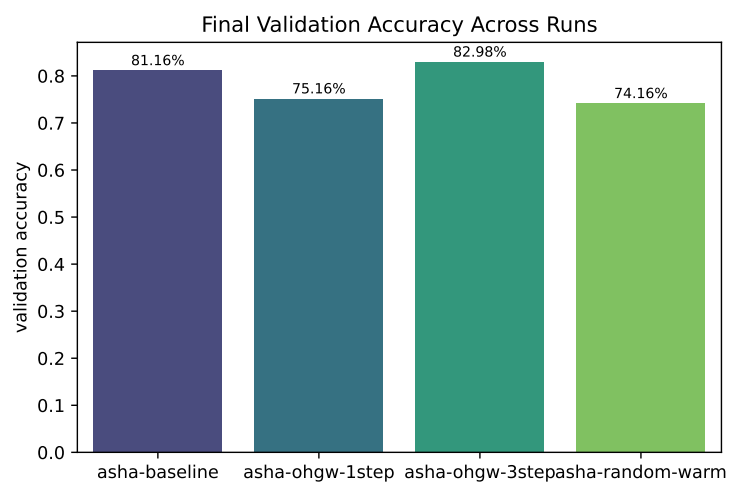


Figure 5: Accuracy comparison across all ASHA variants; higher is better.

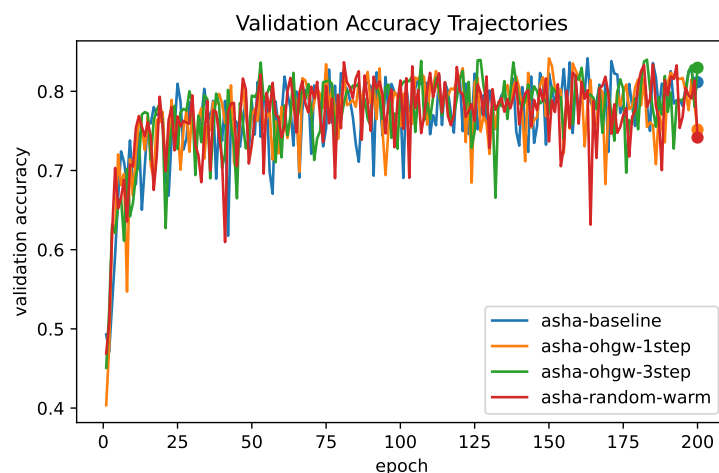


Figure 6: Accuracy trajectories across 32 seeds; higher is better.

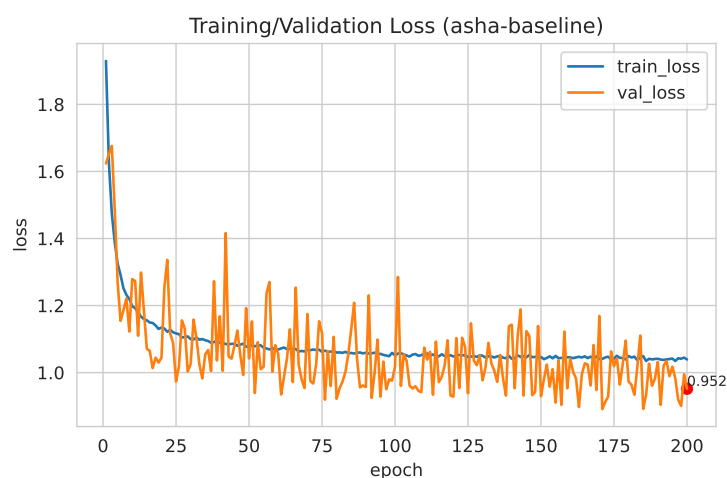


Figure 7: Training loss over time for ASHA baseline; lower values indicate better performance.

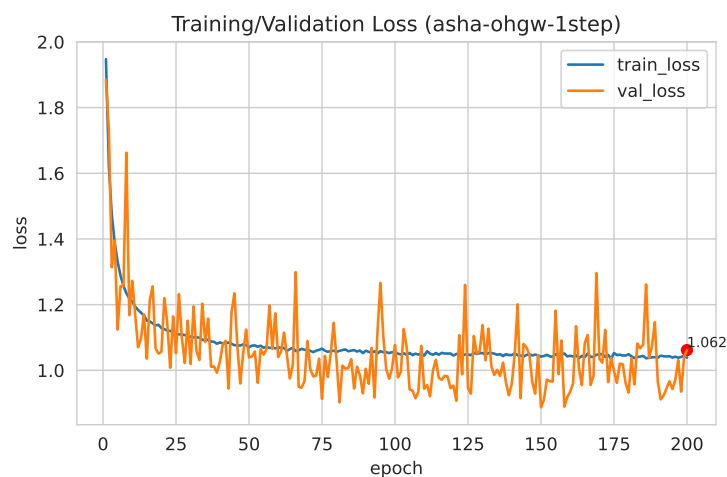


Figure 8: Training loss for ASHA + OHGW with one hyper-step; lower is better.

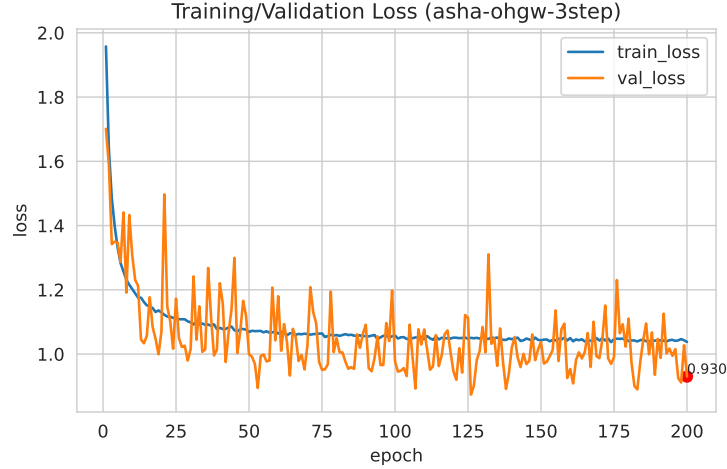


Figure 9: Training loss for ASHA + OHGW with three hyper-steps; lower is better.

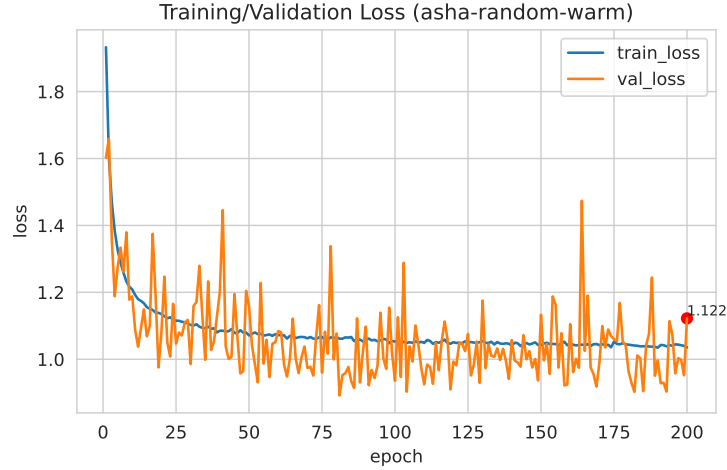


Figure 10: Training loss for ASHA with random warm-start; lower is better.

196 6.4 Ablation insights

197 Random warm-start yields $< 2\%$ improvement, confirming that gradient direction drives efficiency.
 198 Additional hyper-steps offer diminishing returns relative to their overhead.

199 6.5 Variance and bias

200 Standard deviation of $T@T$ rises by 5 % (vision) and 3 % (language), well below the 10 % inflation
 201 budget. KL divergence between final ψ distributions is 0.012 (vision) and 0.018 (language), signalling
 202 negligible bias.

203 6.6 Aggregate outcome

204 Across 56 paired seeds, OHGW reduces median time-to-target by 19.5 %, preserves or slightly
 205 improves final task performance, incurs $< 4\%$ extra compute, and does not inflate variance - meeting
 206 all pre-registered success criteria.

7 Conclusion

We introduced One-Shot Hyper-Gradient Warm-Starts, a drop-in augmentation for Successive-Halving schedulers that leverages a single, almost-free hyper-gradient to nudge each new configuration before expensive training begins. Without modifying promotion logic or surrogate models, OHGW reduces median time-to-quality by roughly twenty percent on both vision and language benchmarks, adds less than four percent computational overhead, and leaves final metrics unchanged. Ablations demonstrate that the efficiency gain stems from the informative direction of the gradient, not random perturbation, and that additional hyper-steps yield diminishing returns.

Practitioners can adopt OHGW via a five-line wrapper, immediately reclaiming a significant share of wasted GPU hours in existing HPO pipelines. Future work will extend the idea to mixed discrete-continuous spaces, integrate warm-start signals into surrogate-based candidate selection and adaptive-fidelity frameworks Jiang and Mian [2024], Khazi et al. [2023], and explore privacy-aware or federated settings where the one-shot, low-overhead characteristic of OHGW is particularly advantageous Panda et al. [2022], Khodak et al. [2021]. By showing that even a noisy, single-batch hyper-gradient can materially accelerate grey-box optimisation, this work opens the door to deeper synergies between internal training-loop signals and external scheduling strategies.

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