

# Cornell Bowers C-IS

## College of Computing and Information Science

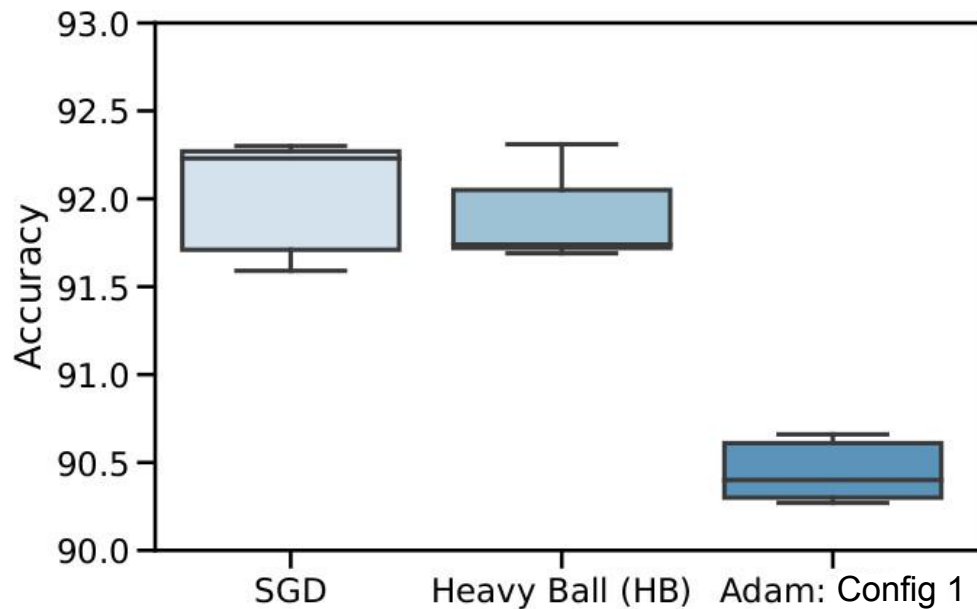
# Hyperparameter Optimization Is Deceiving Us, and How to Stop It

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# It is well-known that Hyperparameter Optimization (HPO) greatly impacts algorithm performance

Using **grid search**, we find the best hyperparameter configuration for each optimizer

and **conclude that non-adaptive optimizers outperform adaptive optimizers**

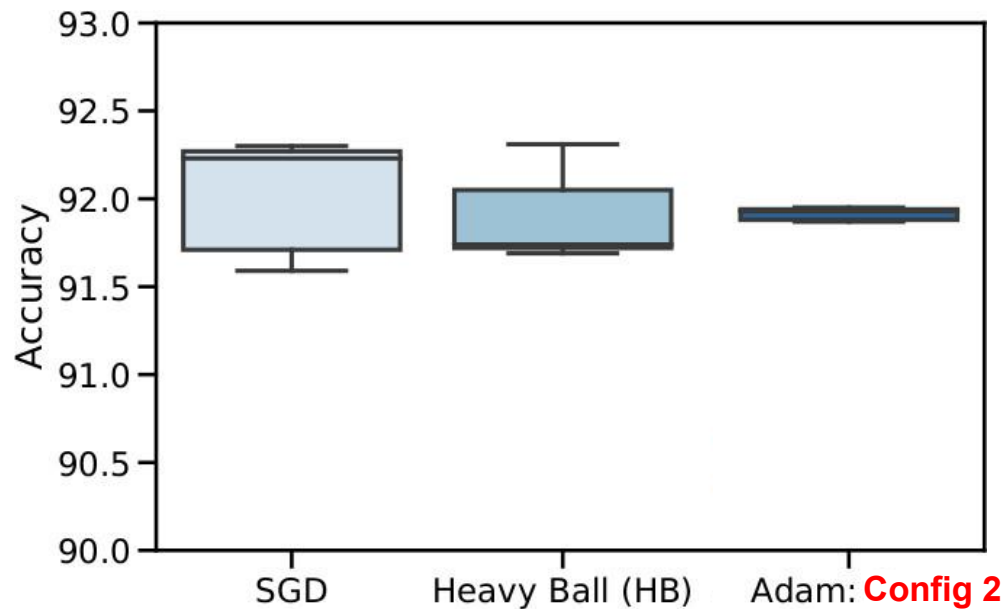


Optimizer test accuracy for VGG16 trained on CIFAR-10;  
n = 5 for each optimizer

# It is well-known that Hyperparameter Optimization (HPO) greatly impacts algorithm performance

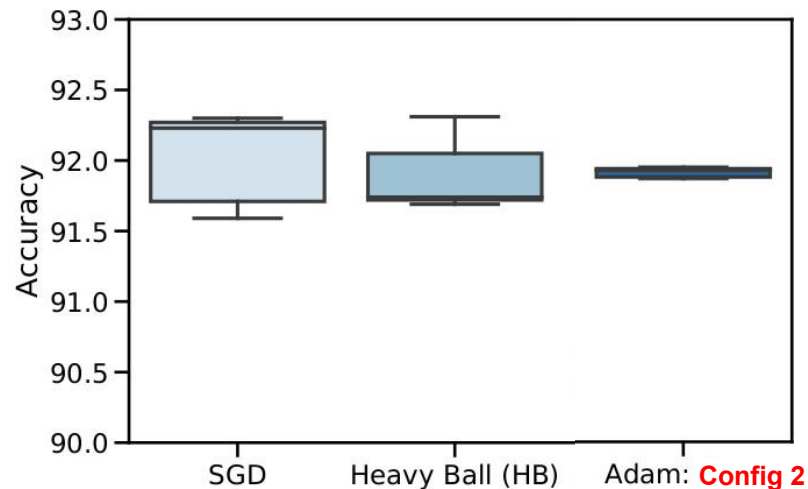
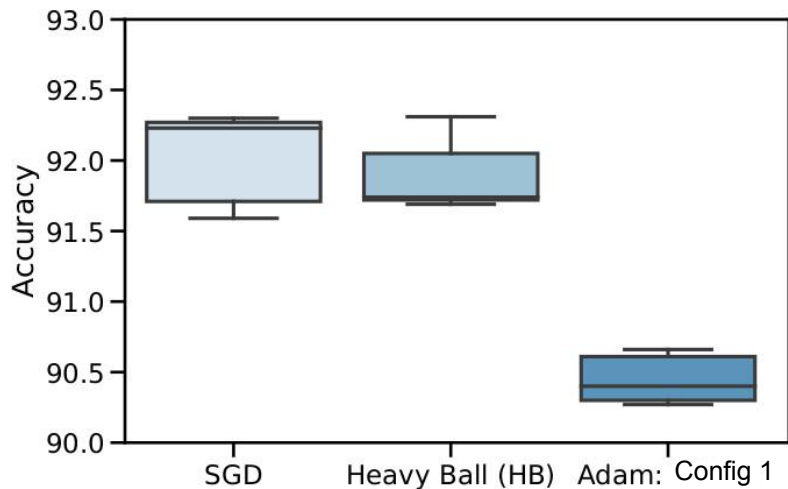
Changing HPO configuration can change our conclusions

We instead **conclude that non-adaptive optimizers do not outperform adaptive optimizers**



Optimizer test accuracy for VGG16 trained on CIFAR-10;  
n = 5 for each optimizer

# We want to prevent conclusions from depending on the underlying configuration of the HPO we perform

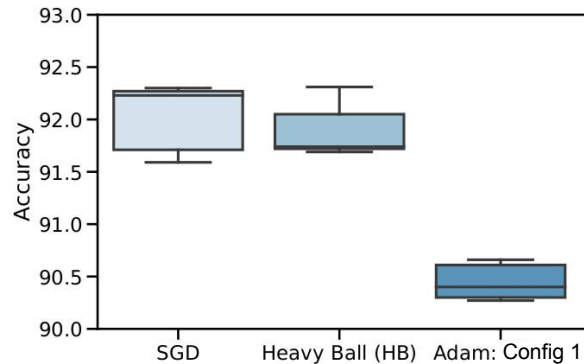


# We therefore formalize the process of drawing conclusions from empirical studies using HPO

## An **HPO procedure**

runs a **randomized algorithm** (e.g., grid search), with a particular **configuration** (e.g., grid points), to test a **set of hyperparameters** by running a **training algorithm** (e.g., SGD) to train a **model** (e.g., VGG16) on a **dataset**, using a **pseudorandom number generator**

and outputs the **chosen hyperparameter values** and a **log** documenting the run (which enables reproducibility)

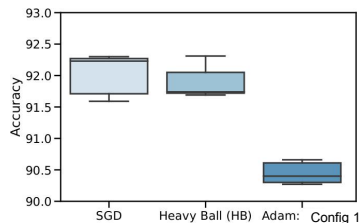


3 HPO procedures;  
Each box plot corresponds to a **log**

# We therefore formalize the process of drawing conclusions from empirical studies using HPO

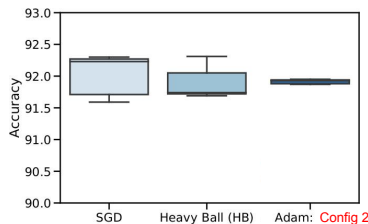
Epistemic Hyperparameter Optimization (EHPO) takes a set of HPO procedures and a function  $F$ , which maps a set of HPO procedure logs to conclusions about algorithm performance

Log set **L1**  
( $|L1| = 3$ )



$F(L1) \rightarrow$  “Non-adaptive optimizers outperform adaptive ones”

Log set **L2**  
( $|L2| = 3$ )



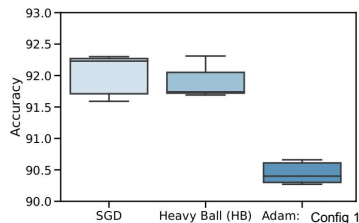
$F(L2) \rightarrow$  “Non-adaptive optimizers do not outperform adaptive ones”

# We therefore formalize the process of drawing conclusions from empirical studies using HPO

Epistemic Hyperparameter Optimization (EHPO) takes a set of HPO procedures and a function  $F$ , which maps a set of HPO procedure logs to conclusions about algorithm performance

Logically inconsistent

Log set **L1**  
( $|L1| = 3$ )



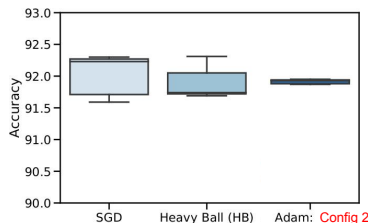
$F(L1) \rightarrow$

“Non-adaptive optimizers  
outperform adaptive ones”

=

$p$

Log set **L2**  
( $|L2| = 3$ )



$F(L2) \rightarrow$

“Non-adaptive optimizers do not  
outperform adaptive ones”

=

$\neg p$

# We frame drawing inconsistent conclusions from EHPO in terms of an adversary who can deceive us



Imagine an **evil demon** who  
is trying to deceive us about relative algorithm performance via EHPO  
maintains a set of log HPO logs which it can modify  
presents us with a final log set, from which we can draw conclusions



We want to be sure that we will not be deceived about algorithm performance by any logs the demon **could** produce by changing HPO configurations



# Modal logic is the standard way to formalize “could”

**Modal logic** extends propositional logic to allow us to reason about **possibility** introducing an additional operator

$\Diamond\phi$  reads, “It is **possible** that  $\phi$ .”

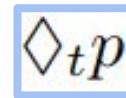
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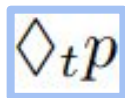
$\Diamond\phi$  reads, “It is **possible** that  $\phi$ .”

**We combine two modal operators** so that we can capture the idea that **it is not possible** to adopt inconsistent **beliefs** about the outcomes of EHPO

# Expressing the possible outcomes of EHPO with



Syntax



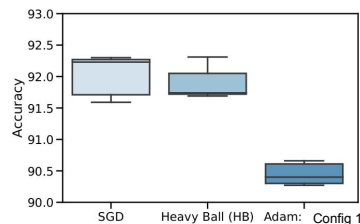
Intuition

The demon could adopt a strategy for running EHPO that is guaranteed to cause their desired outcome  $p$  in at most time  $t$  in expectation

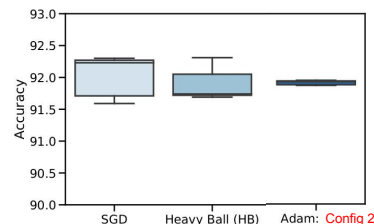
Semantics

A set of EHPO output logs **models** that it is possible  $p$  time  $t$

$\Diamond_t p$



$\Diamond_t \neg p$



# Expressing our belief with $Bp$

Syntax

$Bp$

Intuition

We believe/ conclude  $p$

Semantics

The set of EHPO output logs models our belief in  $p$

With both of these operators, we can formalize the problem of *hyperparameter deception*...

*t*-non-deceptive axiom

$$\neg (\Diamond_t \mathcal{B}p \wedge \Diamond_t \mathcal{B}\neg p)$$

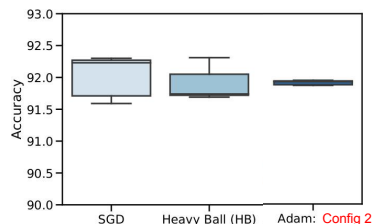
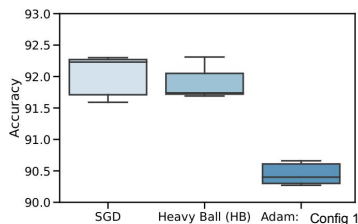
If it is possible for the demon can get us to believe  $p$  in time  $t$ , then it is not possible for the demon to get us to believe  $\neg p$  in time  $t$

# With both of these operators, we can formalize the problem of *hyperparameter deception*

*t*-non-deceptive axiom

$$\neg (\Diamond_t \mathcal{B}p \wedge \Diamond_t \mathcal{B}\neg p)$$

If it is **possible** for the **demon** can get us to **believe**  $p$  in time  $t$ , then it is **not possible** for the **demon** to get us to **believe**  $\neg p$  in time  $t$



Our motivating example is *t*-deceptive

# Using this formalization, we can prove $t$ -non-deceptive EHPO by showing they satisfy our axiom

Defense intuition:

Given some **naive reasoner**, we construct a **defended reasoner** that is always **more skeptical** than the naive reasoner

If the naive reasoner is  $t$ -non-deceptive, then any more skeptical reasoner is also  $t$ -non-deceptive

Defense takeaway:

It is always possible to construct a  $t$ -defended EHPO

# We suggest a concrete, $t$ -non-deceptive EHPO

We describe a variation of **random search** that produces a log with  $K * R$  random search trials

We divide the log into  $R$  logs each with  $K$  trials, and pass the divided log to an ensemble of  **$R$  naive reasoners**

The **defended reasoner** only concludes  $p$  if the  $R$  naive reasoners unanimously conclude  $p$

In **sublinear-in- $t$  time**, we can produce a log (of length  $K * R$ ) that will allow our  $t$ -non-deceptive reasoner to reach conclusions



# Takeaways

It is possible to construct t-defended EHPO, such as our t-defended random search

Any defense will depend on assumptions concerning how we configure underlying HPO, so researchers must be explicit about their configuration choices

Avoiding deception is just as important as ensuring reproducibility, as we want to ensure results are both replicable and correct