Comparing Modern Scalable Hyperparameter Tuning Methods

A comparison of Random search, Bayesian search using HyperOpt, Bayesian search combined with Asynchronous Hyperband and Population-Based Training

Ayush Chaurasia Sep 28 · 6 min read ★

Source — https://pixabay.com/photos/excavators-bucket-wheel-excavators-1050501/

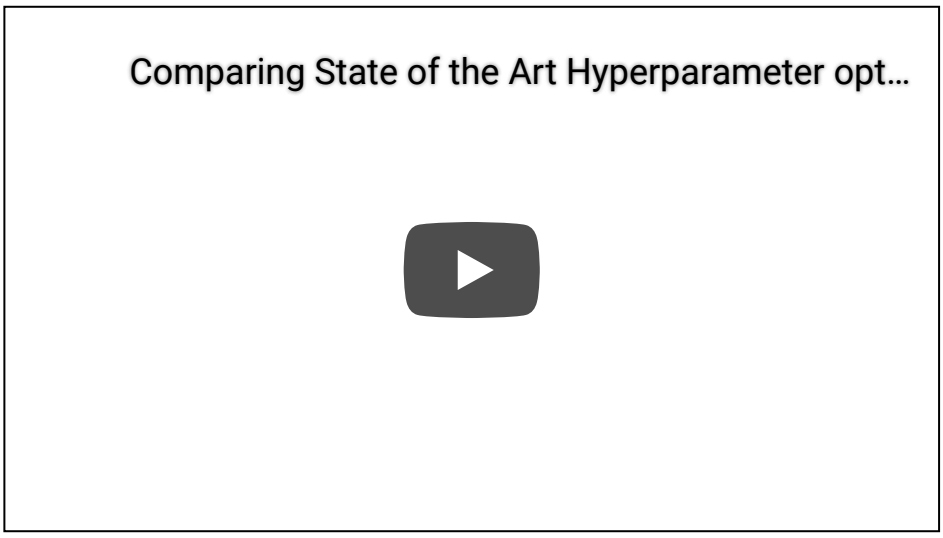
In this post, we'll compare the following hyper-parameter optimization methods.

- Random Search
- Bayesian Search using HyperOpt
- Bayesian Search combined with Asynchronous Hyperband
- Population-Based Training

maximizing the inception score.

We'll use Ray Tune to perform these experiments and track the results on the W&B dashboard.

I also did a video on my channel that goes in-depth in explaining this experiment -



Link to the Live Dashboard

The Search Space

We'll use the same search space for all the experiments in order to make the comparison fair.

```
config = {
        "netG_lr": lambda: np.random.uniform(1e-2, 1e-5),
        "netD_lr": lambda: np.random.uniform(1e-2, 1e-5),
        "beta1": [0.3,0.5,0.8]
}
```

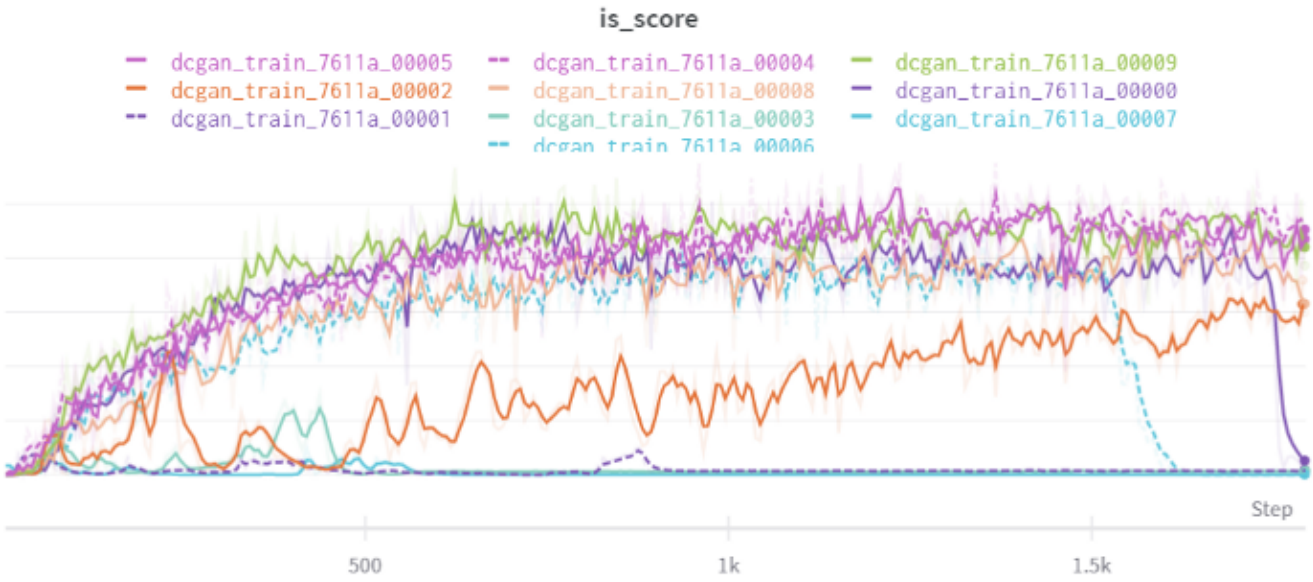
space.py hosted with ♡ by GitHub view raw

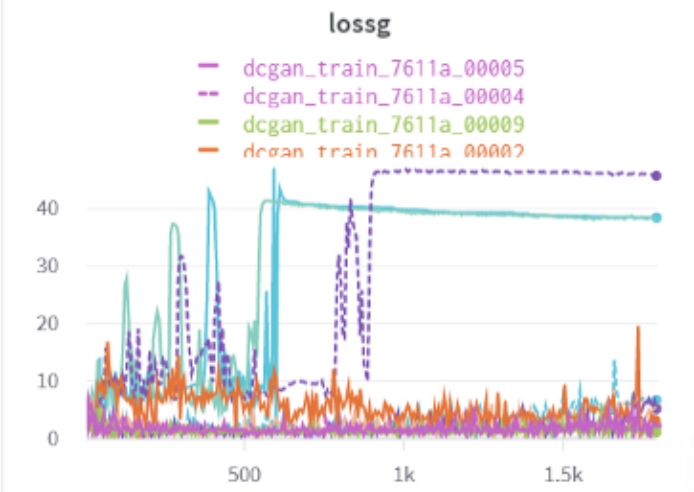
This will also act as the baseline metric for our comparison. Our experimental setup has 2 GPUs and 4 CPUs. We'll parallelize the operation across multiple GPUs. Ray Tune does this automatically for you if you specify the `resources_per_trail` .

```
analysis = tune.run(
    dcgan_train,
    resources_per_trial={'gpu': 1,'cpu':2}, # Tune will use this information to parallelize the
    num_samples=10,
    config=config
)
```

randoms.py hosted with ♡ by GitHub view raw

Let's see the results





As expected, we get varied results.

- **Some of the models did optimize** as the tuner got lucky and chose the right set of hyper-parameters
- but some models' **inception score graph remained flat** as they did not optimize due to bad hyper-parameter values.
- Thus, when using a random search, you might end up reaching the optimal value but **you definitely end up wasting a lot of resources** on the runs that don't add any value.

Bayesian Search With HyperOpt

The basic idea behind Bayesian Hyperparameter tuning is to **not be completely random in your choice for hyper-parameters** but instead use the **information from the prior runs** to choose the hyperparameters for the next run. Tune supports HyperOpt which implements Bayesian search algorithms. Here's how you do it.

```
# Step 1: Specify the search space
hyperopt_space= {
     "netG_lr": hp.uniform( "netG_lr", 1e-5, 1e-2),
    "netD_lr": hp.uniform( "netD_lr", 1e-5, 1e-2),
    "beta1":hp.choice("beta1",[0.3,0.5,0.8])  }

#step 2: initialize the search_alg object and (optionally) set the number of concurrent runs
hyperopt_alg = HyperOptSearch(space = hyperopt_space,metric="is_score",mode="max")
hyperopt_alg = ConcurrencyLimiter(hyperopt_alg, max_concurrent=2)

#Step 3: Start the tuner
analysis = tune.run(
    dcgan_train,
    search_alg = hyperopt_alg, # Specify the search algorithm
    resources_per_trial={'gpu': 1,'cpu':2},
    num_samples=10,
    config=config
    })
```

hyperopt.py hosted with ♡ by GitHub view raw

Here's what results look like

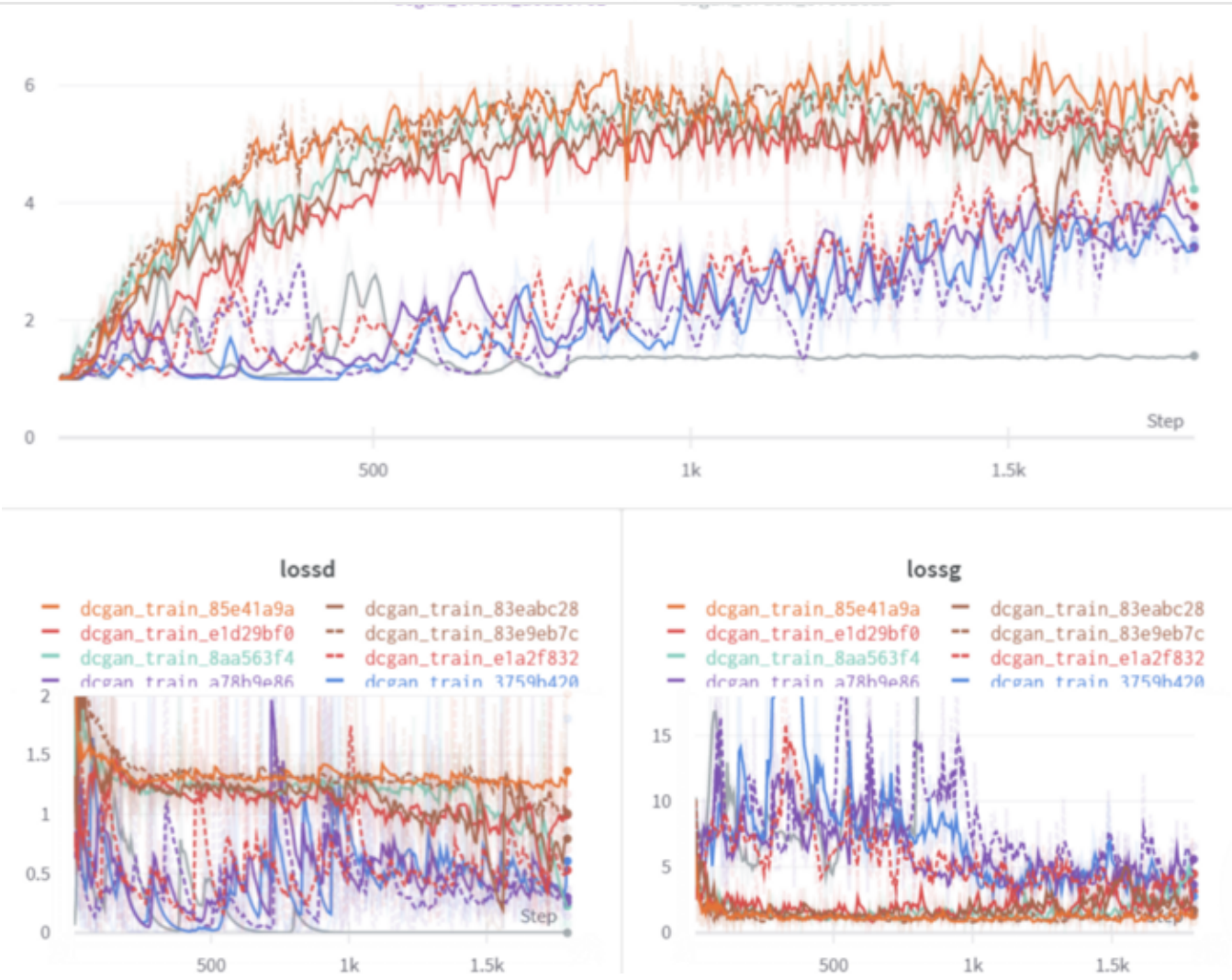


Image by author

Inference

- There are significant improvements compared to the previous run as there is only 1 flat curve.
- This implies that the search algorithm chose the hyper-parameter values based on the results of previous runs.
- On average, the runs performed better than random search
- Resource wastage can be avoided by terminating the bad runs earlier.

Bayesian Search with Asynchronous HyperBand

The idea Asynchronous Hyperband is to **eliminate or terminate the runs that don't perform well**. It makes sense to combine this method with the Bayesian search to see

```python
from ray.tune.schedulers import AsyncHyperBandScheduler
sha_schedular = AsyncHyperBandScheduler(metric="is_score",
                            mode="max",max_t=300)

analysis = tune.run(
    dcgan_train,
    search_alg = hyperopt_alg, # Specify the search algorithm
    scheduler = sha_schedular, # Specify the scheduler
    ...
    })
```

hyperband.py hosted with ♡ by GitHub view raw

Let us now see how this performs

Image by author

terminated earlier.

- The highest accuracy achieved was still slightly higher than the runs without the Hyperband scheduler.
- Thus, by terminating bad runs early on in the training process, we have not only speeded up the tuning job but also saved compute resources.

Population-Based training

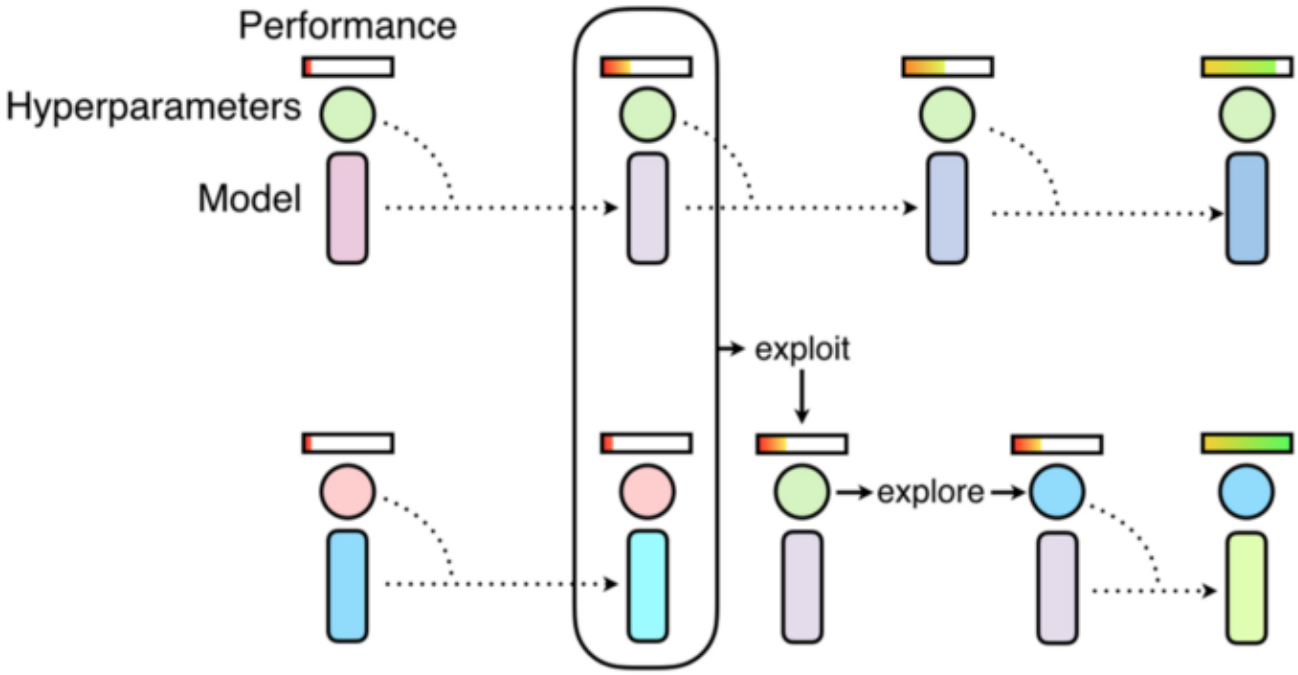


Image source — https://wandb.ai/wandb/DistHyperOpt/reports/Modern-Scalable-Hyperparameter-Tuning-Methods--VmlldzoyMTQxODM

The last tuning algorithm that we'll cover is population-based training (PBT) introduced by Deepmind research. The basic idea behind the algorithm in layman terms:

- Run the optimization process for some samples for a given time step(or iterations) T.
- After every T iterations, compare the runs and copy the weights of good performing runs to the bad performing runs and change their hyper-parameter

seems simple, there is a lot of complex optimization math that goes into building this from scratch. **Tune provides a scalable and easy-to-use implementation of the SOTA PBT algorithm**

```
# Step 1: Initialize the PBT schedular
pbt_scheduler = PopulationBasedTraining(
    time_attr="training_iteration", # Set the time attribute as training iterations
    metric="is_score",
    mode="max",
    perturbation_interval=5, #The time interval T after which you perform the PBT operation
    hyperparam_mutations={
        # distribution for resampling
        "netG_lr": lambda: np.random.uniform(1e-2, 1e-5),
        "netD_lr": lambda: np.random.uniform(1e-2, 1e-5),
        "beta1": [0.3,0.5,0.8]
    })

# step 2: run the tuner
analysis = tune.run(
    dcgan_train,
    scheduler=pbt_scheduler, #For using PBT
    resources_per_trial={'gpu': 1,'cpu':2},
    num_samples=5,
    config=config
  )
```

pbt.py hosted with ♡ by GitHub view raw

Let us now look at the results.

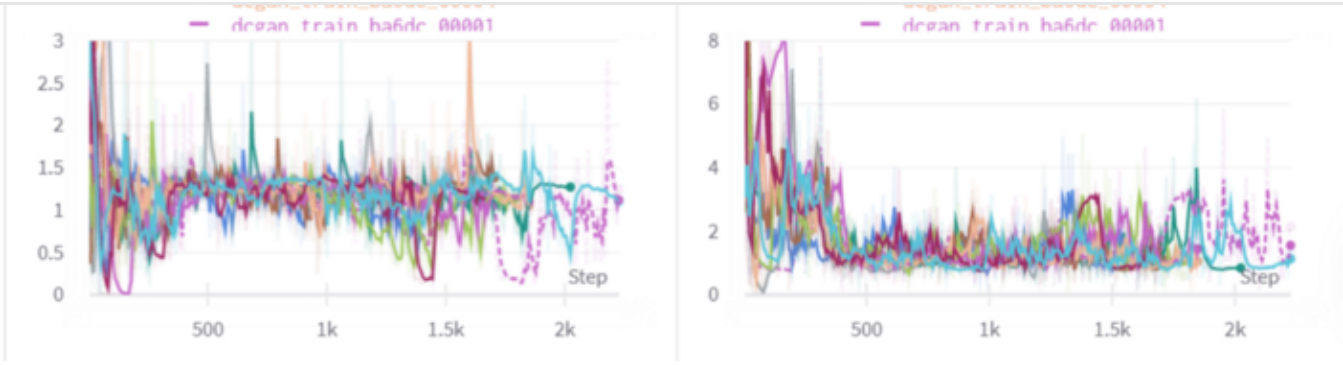


Image by author

Inference

The results look quite surprising. There are multiple factors that are unique about these results.

- Almost all the runs have reached the optimal point
- The highest score(of 6.29) was achieved by one of the runs
- The runs that started off as bad performers or outliers have also converged as the experiment proceeded.
- There are no runs that have a flat inception score graph
- Some bad performing runs were stopped in the middle of the process
- Thus, **no resource has been wasted** on bad runs

how did PBT optimize the runs that started off with bad Hyper-parameter Values?

The answer is the **hyper-parameter mutation** done by the PBT scheduler. After every `T` time steps, the algorithm also mutates the values of hyper-parameters to maximize the desired metric. Here's how the parameters were mutated by the PBT scheduler for this experiment.

Hyper-parameter Mutations

Let us now see how the hyper-parameters were adjusted by the PBT algorithm to maximize the inception score

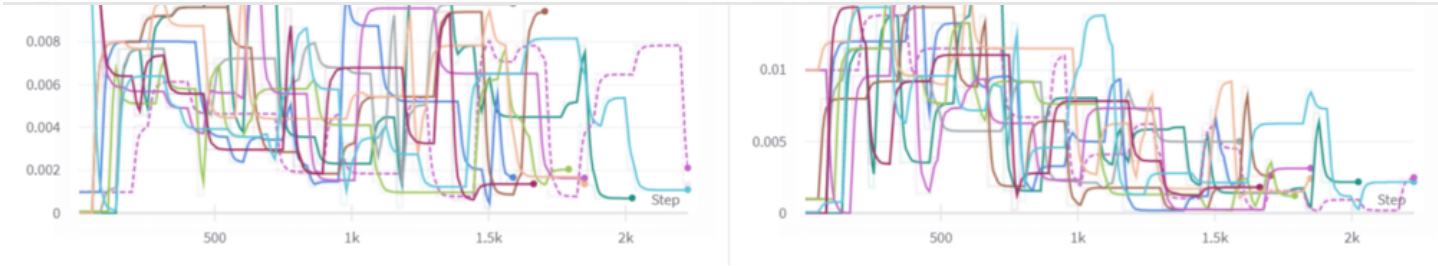


Image by author

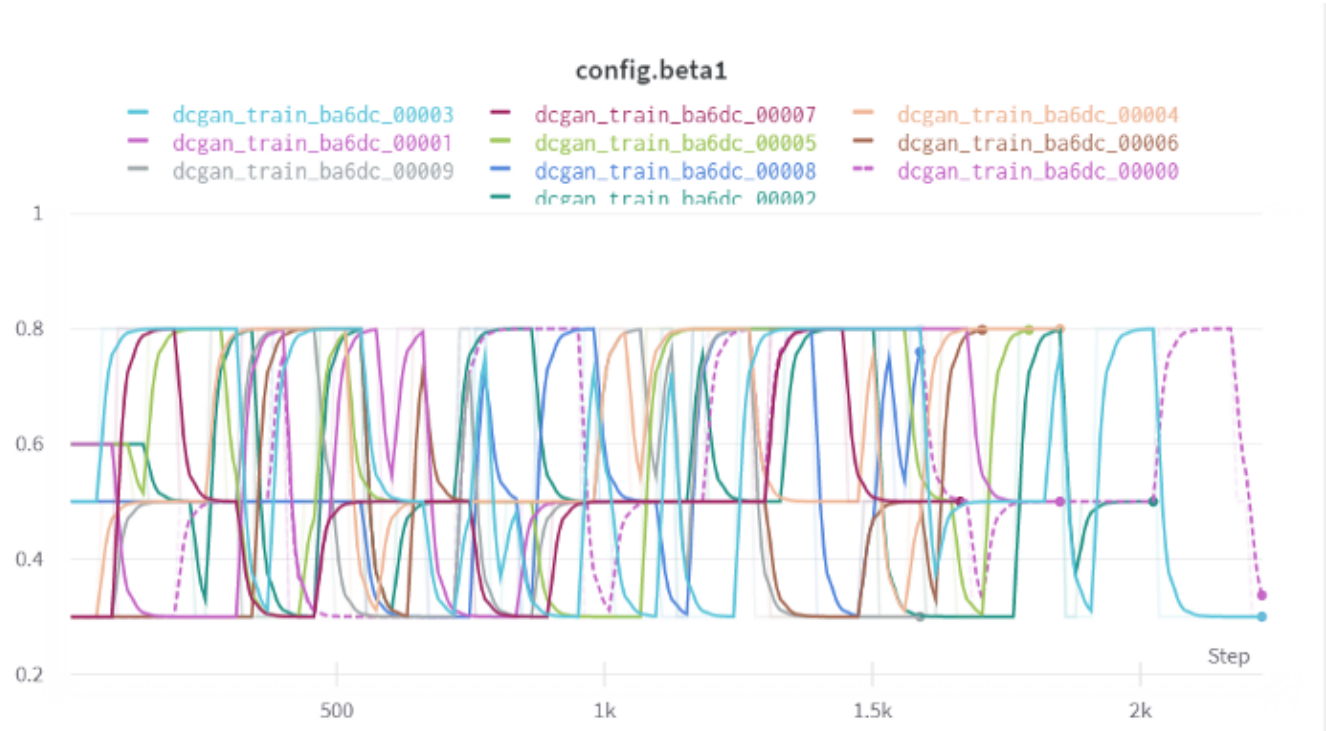


Image by author

Inference

- The hyper-parameter values are constantly adjusted throughout the experiment.
- The runs that start off with a bad hyper-parameter value are soon updated.
- PBT operates on **explore and exploit** methodology exploring the space for good parameter values and exploits by updating the bad runs.

Reducing the Number of Runs

We'll now **reduce the number of runs to 5** in order to make things difficult for PBT. Let's see how it performs under this restricted circumstance.

Image by author

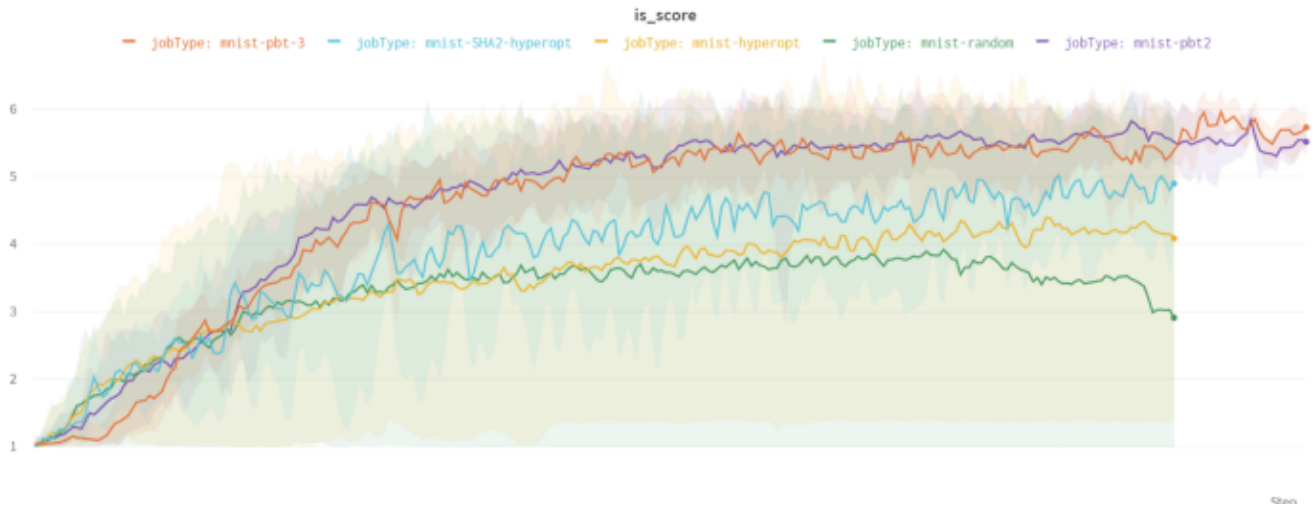
Inference

- Even after reducing the number of runs to 5, PBT optimizer still outperforms random search and bayesian optimization.
- As expected, the bad performing runs were terminated early on in the training process

Comparing average inception scores across runs

Here's how the final comparison of the average inception scores looks like. We've averaged across 5 run sets:

- Random Search — 10 Runs (Job Type — mnist-random)
- Bayesian Search — 10 Runs (Job Type — mnist-hyperopt)
- Bayesian Search with Hyperband — 20 Runs (Job Type- mnist-SHA2-hyperopt)
- PBT scheduler — 10 Runs (Job Type — mnist-pbt2)
- PBT scheduler — 5 Runs (Job Type — mnist-pbt3)



Ending Note

If you enjoyed reading this, you can follow me on twitter to get more updates. I also make deep learning videos on my youtube channel.