

Maximizing run:ai gains:

An intro for Data Scientists

Maximizing run:ai gains

Who is this for?

Data Scientist/Researchers who are now using run:ai





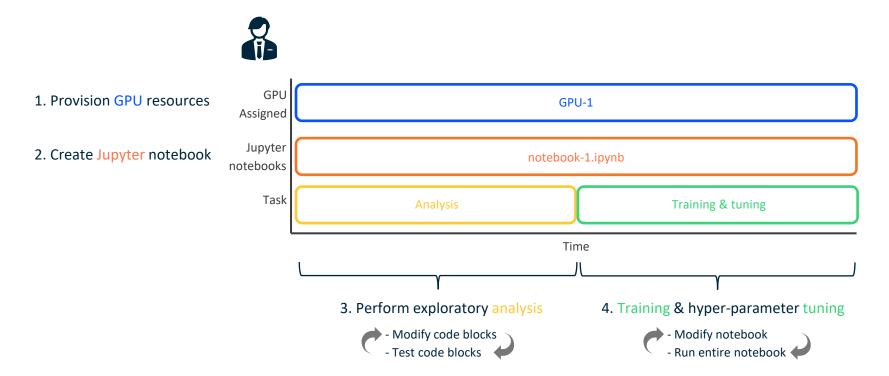
What is it for?

Inform on **best practices** with run:ai



What is often done

Common workflow for data scientist



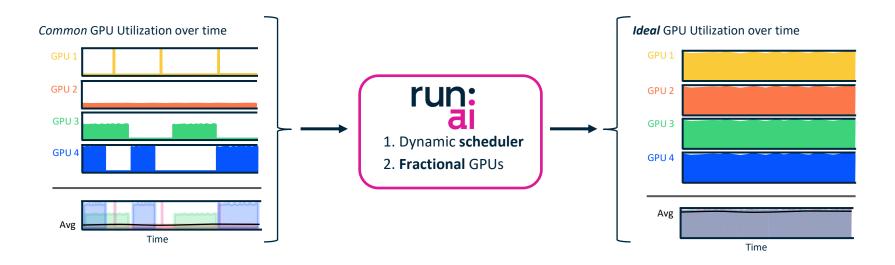
Common workflow for data scientist

GPU 1. Provision GPU resources GPU-1 Assigned Jupyter 2. Create Jupyter notebook notebook-1.ipynb notebooks Task Training & tuning Time 3. Perform exploratory analy 4. Training & hyper-parameter tuning - Modify code blocks - Modify notebook - Test code blocks - Run entire notebook

Why not to do it

Understanding goal of run:ai

The run:ai software seeks to maximize GPU utilization



Some run:ai terminology

Two types of 'jobs'

INTERACTIVE TRAINING

For both, resources are allocated as long as the job exists

'Interactive' jobs

- Jobs that run indefinitely
- Only stops if user deletes the job

Resources can be tied up forever

'training' jobs

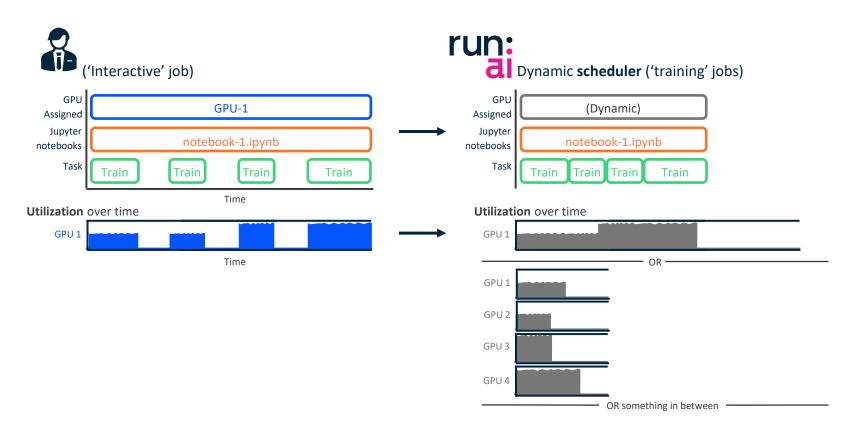
- Jobs that run until script finishes
- Will automatically stop once done

Resources are only tied up while job is running

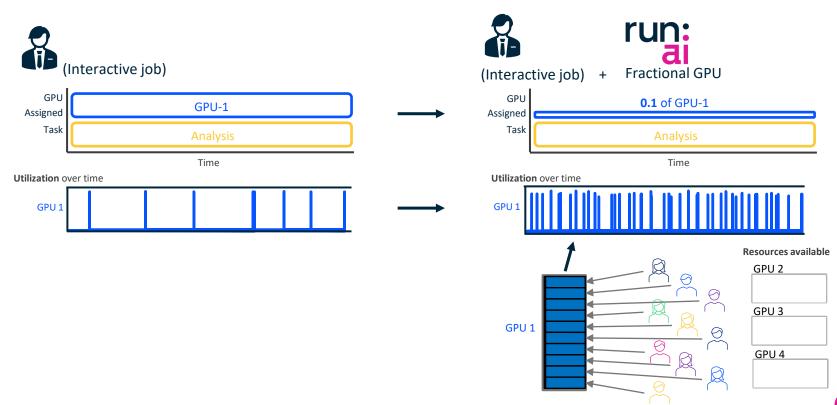
How common workflow can inhibit run:ai

Working like this... GPU GPU-1 Assigned Jupyter notebook-1.ipynb notebooks Task Analysis Train Train Train Train Time ...can lead to this utilization **Utilization** over time GPU 1 Time Sporadic and infrequent usage Steady but low usage Long periods of **idle** usage How to do it right (with run:ai)

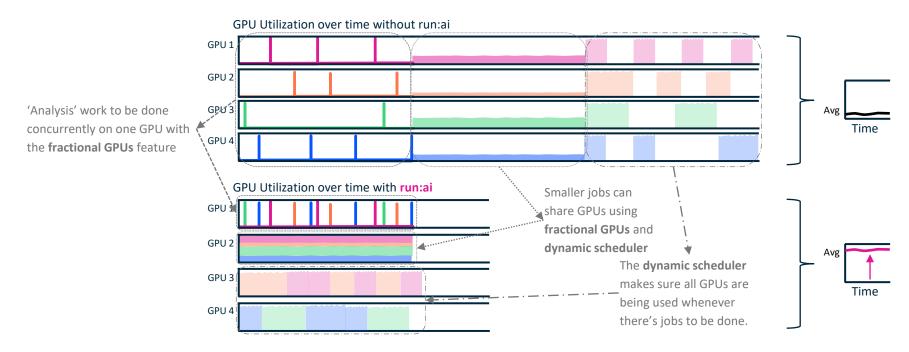
Use the run:ai scheduler for training & tuning



Use the run:ai fractional GPU for analysis



Gains in GPU Utilization with run:ai



Net result of optimization with run:ai

- Resources become free much sooner
- More work gets done in less time

Summary

Summary of run:ai best practices

Fractional GPUs

('interactive' jobs)

Analysis

- When GPUs usage is sporadic/intermittent
- For example, when you are writing scrips/notebooks or
- when you are testing segments/blocks of code

Dynamic scheduler

('training' jobs)

Training/tuning/ETL

- When GPUs usage is consistent or steady
- When you are running entire scripts or notebooks until they finish

Fractional + Scheduler

('training' jobs)

Training/tuning/ETL

- When GPUs usage is consistent or steady, but low
- For example, when training small models that do not fully saturate
 a GPU

Full GPU

('interactive' jobs)

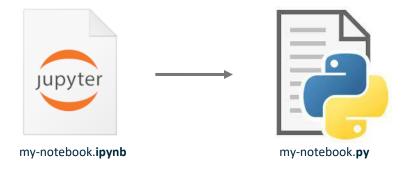
- This should be done rarely
- For example, this can be done if you are trying to figure out max batch size to saturate a GPU
- 'Interactive' job should be stopped after max batch size is determined; 'training' job should be submitted afterwards



Tips

1. You can turn a jupyter notebook into a python script with the *jupyter nbconver* command

jupyter **nbconvert --to script** my-notebook.ipynb



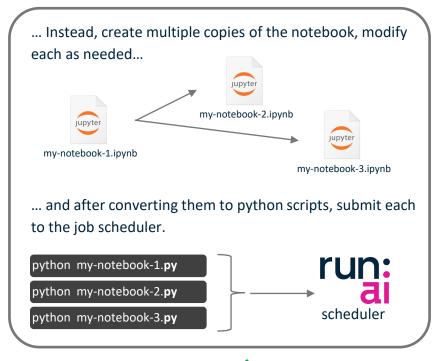
2. Then run the python script (note that any blocks with 'cell magic' will not convert properly; comment out or remove 'cell magic' lines before converting the notebook)

python my-notebook.py



Tips

If in your workflow, you modify and run your notebook multiple times.... Training & hyper-parameter tuning Modify notebook - Run entire notebook my-notebook-1.ipynb







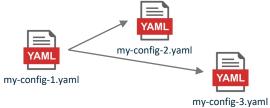
Tips

1 If you pass in configuration files (e.g. a yaml file) to your python scripts...



python my-script.py --config my-config-1.yaml

2 ...you can create multiple configuration files...



3 ... and submit each configuration to the job scheduler.



Thank you!

