DASYA
Data-Intensive Systems and Applications

RAD

INDEPENDENT RESEARCH FUND DENMARK

IT UNIVERSITY OF COPENHAGEN

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Data Management and Visualization for Benchmarking Deep Learning Training Systems

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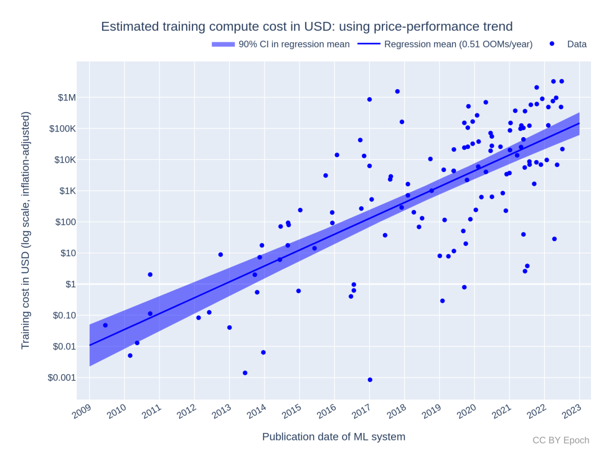
Need for systematic benchmarking with hardware metrics

- Energy and resource consumption is increasingly relevant
- Resource costs relevant on both academic and industrial scale



https://epochai.org/blog/trends-in-the-dollar-training-cost-of-machine-learning-systems

Requirements

- 1. Wide configuration support including collocation
- 2. Track hardware metrics in addition to software metrics
- 3. Handle continuous streams of data
- 4. Support multiple visualization use-cases
- 5. Filter large amounts of inconsequential data
- 6. Minimal code impact

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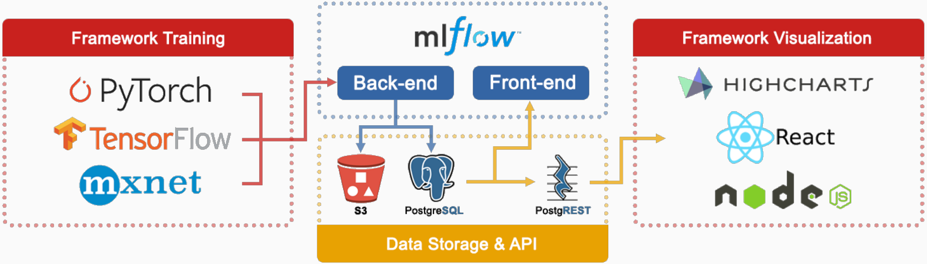
Resource-Aware Data systems Tracker (radT)



Framework Training

PyTorch

TensorFlow

mxnet

mlflow

Back-end

Front-end

S3

PostgreSQL

PostgREST

Data Storage & API

Framework Visualization

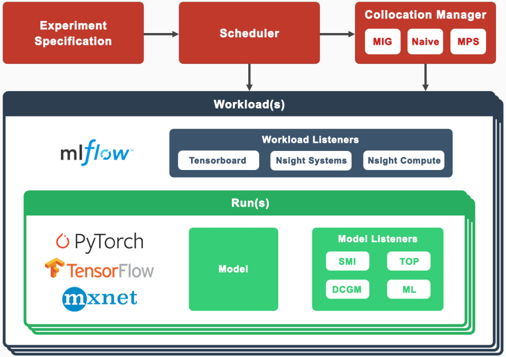
HIGHCHARTS

React

node js

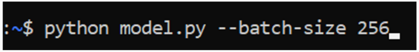
- Tracking and visualization of resources
- Extends MLFlow

1. Wide configuration support including collocation

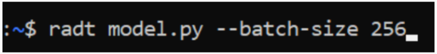


- Single model training (*run*) can be collocated together (*workload*)
- Workloads can be scheduled supporting large experiments

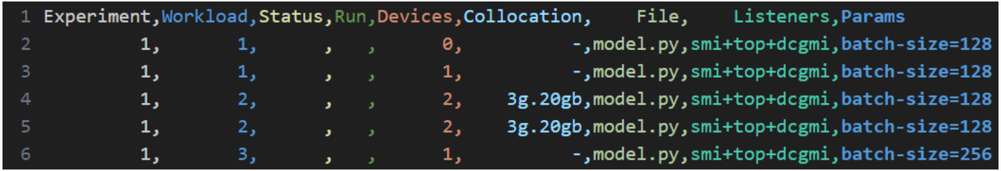
1. Wide configuration support including collocation



```
:~$ python model.py --batch-size 256
```

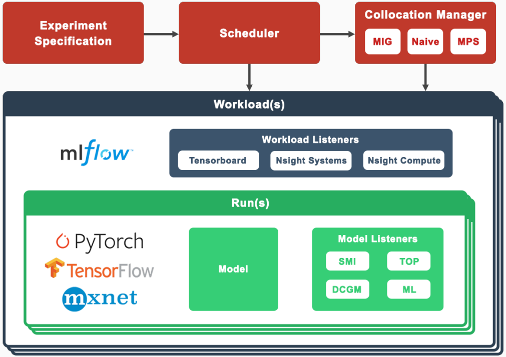


```
:~$ radt model.py --batch-size 256
```



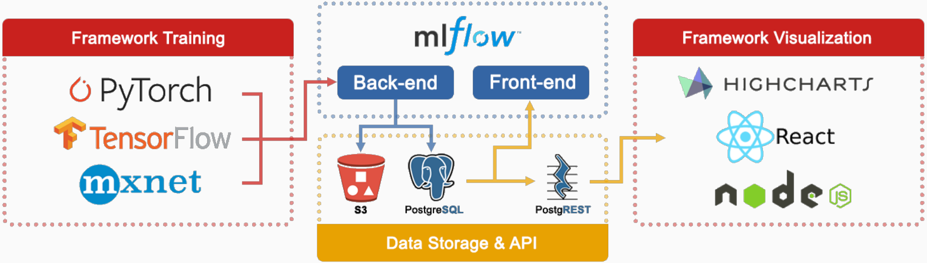
```
Experiment,Workload,Status,Run,Devices,Collocation,    File,    Listeners,Params
         1,       1,      ,   ,      0,          -,model.py,smi+top+dcgmi,batch-size=128
         1,       1,      ,   ,      1,          -,model.py,smi+top+dcgmi,batch-size=128
         1,       2,      ,   ,      2,    3g.20gb,model.py,smi+top+dcgmi,batch-size=128
         1,       2,      ,   ,      2,    3g.20gb,model.py,smi+top+dcgmi,batch-size=128
         1,       3,      ,   ,      1,          -,model.py,smi+top+dcgmi,batch-size=256
```

2. Track hardware and software metrics



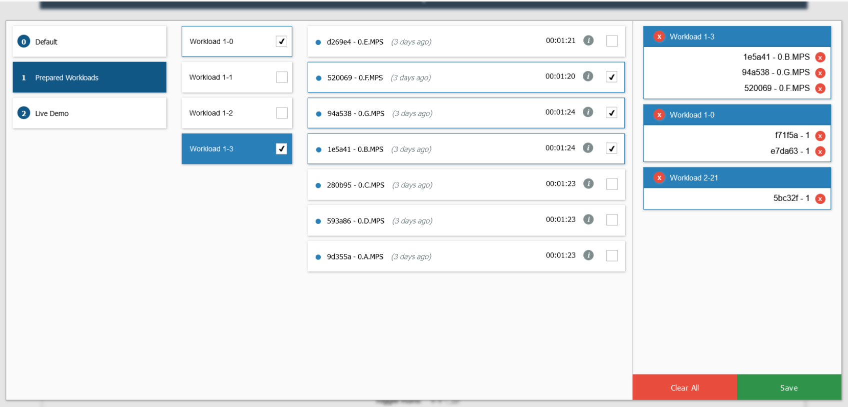
- Model Listeners: per run
- Workload Listeners: exclusive

3. Handle continuous streams of data



- Base configuration of MLFlow provides poor data scaling and interoperability
- MLFlow integration with dedicated PostgreSQL and S3 storage.

4. Support multiple visualization use-cases



0 Default

1 Prepared Workloads

2 Live Demo

☑ Workload 1-0

□ Workload 1-1

□ Workload 1-2

☑ Workload 1-3

● d269e4 - 0.E.MPS *(3 days ago)* 00:01:21 □

● 520069 - 0.F.MPS *(3 days ago)* 00:01:20 ☑

● 94a538 - 0.G.MPS *(3 days ago)* 00:01:24 ☑

● 1e5a41 - 0.B.MPS *(3 days ago)* 00:01:24 ☑

● 280b95 - 0.C.MPS *(3 days ago)* 00:01:23 □

● 593a86 - 0.D.MPS *(3 days ago)* 00:01:23 □

● 9d355a - 0.A.MPS *(3 days ago)* 00:01:23 □

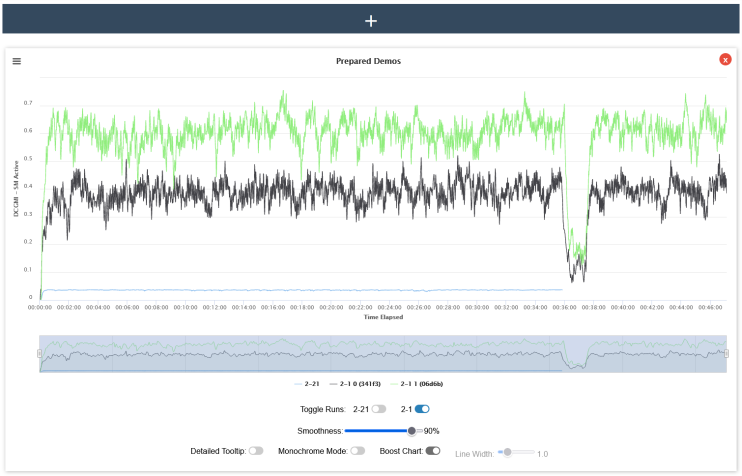
☒ Workload 1-3
- 1e5a41 - 0.B.MPS ☒
- 94a538 - 0.G.MPS ☒
- 520069 - 0.F.MPS ☒

☒ Workload 1-0
- f71f5a - 1 ☒
- e7da63 - 1 ☒

☒ Workload 2-21
- 5bc32f - 1 ☒

- Select data to compare in a hierarchical way

5. Filter large amounts of inconsequential data



Toggle Runs: 2-21 ○ 2-1 ●

Smoothness: 90%

Detailed Tooltip: ○ Monochrome Mode: ○ Boost Chart: ● Line Width: 1.0

- Create and share insights

6. Minimal code impact

PyTorch

TensorFlow

mxnet

⋮

```python
from radtrun import radT
...
with radT() as run:
  # Training loop
```

- No code required for hardware metric tracking
- Software tracking via MLFlow integration

- Minimal code for finer-grained control

Demo

Conclusion

- We need systematic benchmarking of both software and hardware resources

https://github.com/Resource-Aware-Data-systems-RAD/radt

- Track small and large experiments, including collocated ones
- Real-time, scalable data tracking and processing
- Efficient and effective data exploration

Thank you!

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