


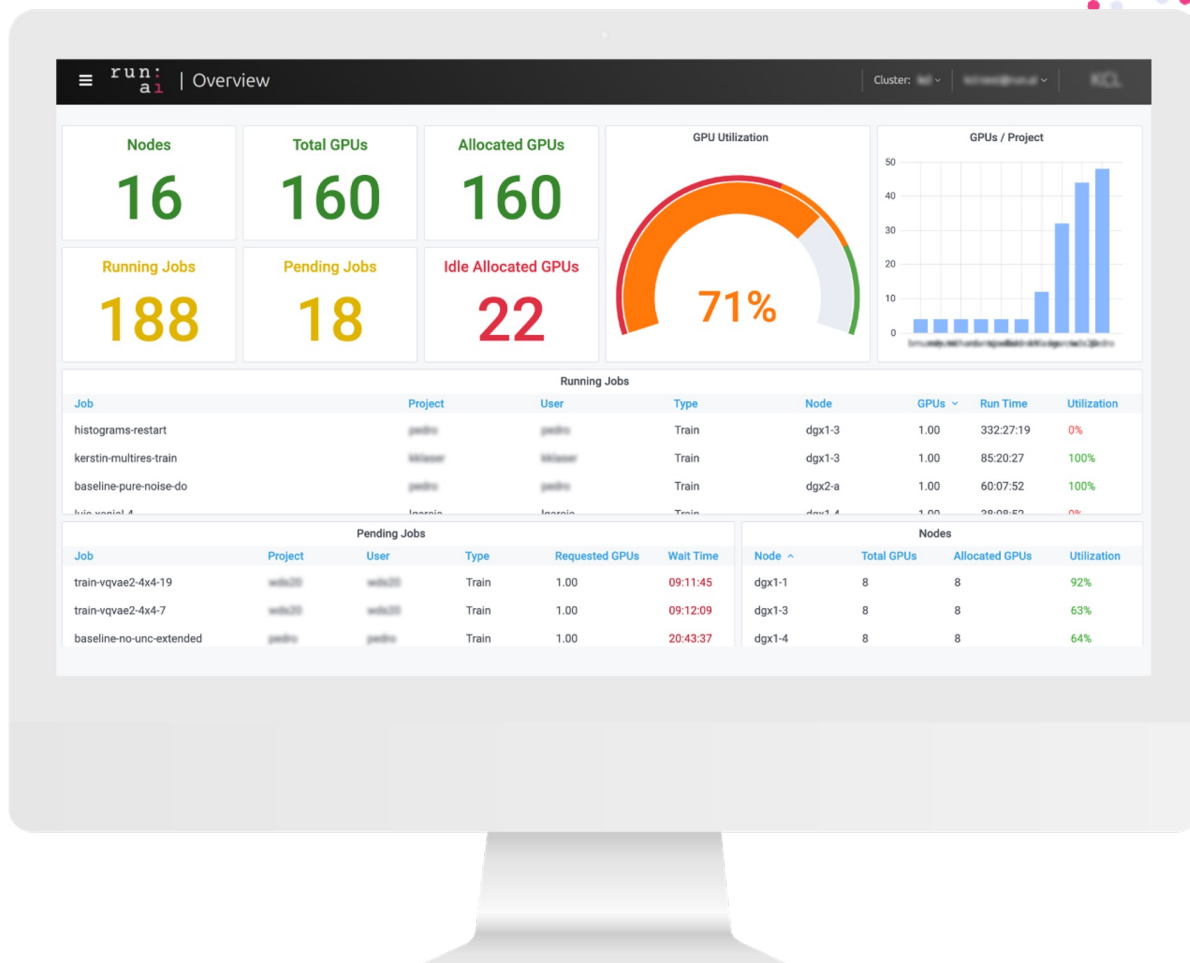
run: Researcher  
a1 Training



An abstract graphic on the left side of the slide, featuring a tunnel-like structure composed of many small, colored dots (red, blue, and white) that recede into the distance, creating a sense of depth and perspective.

# Gain visibility and control over AI workloads to increase GPU utilization

Run:AI brings HPC capabilities to Kubernetes with batch scheduling and GPU virtualization, enabling seamless distributed training and full utilization of GPU resources.



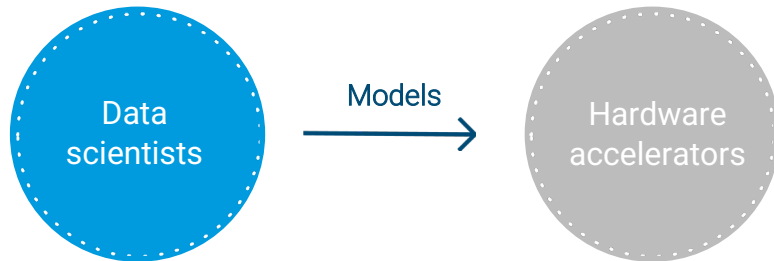
# Concepts

# Basics & Assumptions

## Locality → Global considerations

- At the heart of Run:AI is the premise that “optimization” requires finding the “right resources for your Job”. With this assumption in mind, the researcher is no longer **permanently** assigned a **local** machine.
- Instead, upon request, Run:AI will allocate resources on different machines according to your needs taking into account global considerations

The Run:AI Vision  
Full Hardware Abstraction



# Basics & Assumptions

## Containers & Images

- To be able to abstract the resource location, Run:AI uses docker images to instantiate containers on the right machine
- It is assumed that you are already familiar with docker images and are using them today.



# Basics & Assumptions

## Shared Storage

- As a researcher, you use data: training data, scripts, interim checkpoints, docker image, etc.
- To be able to abstract the resource location, your data must be stored in a location which is *shared by all machines in a uniform way*. You can no longer rely on data being stored on the local machine
- If not already there, as part of the Run:AI implementation, your IT department will make such a shared location available



# Basic Run:AI Concepts

## Projects

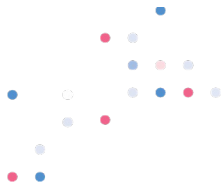
- As a researcher, each request for cluster resources should be accompanied by a reference project. Without a project, resources cannot be allocated
- Depending on your organization's preference, projects can be modeled as **individuals**, as **teams** of people (e.g. team-ny) or as actual **business** activities (e.g. ct-scan-2020)



# Basic Run:AI Concepts

## Guaranteed Quotas

- Projects are assigned with a *guaranteed quota* of GPUs
- Projects can go over quota and consume more GPUs than assigned to them
- The Run:AI scheduler preempts and queues over-quota workloads when there are not enough resources to run under-quota workloads, taking into account fairness and priorities
- For more information on the Run:AI scheduler, including over-quota fairness, preemption, priorities, bin packing, elasticity and more, see [here](#).



# Basic Run:AI concepts:

Run:AI can schedule interactive “build” workloads, unattended “train” workloads and “inference” workloads

## Build



- **Development & debugging**
- **Interactive** sessions
- **Short** cycles
- Performance is **less** important
- **Low** GPU utilization

## Training



- **Model Training**
- **Remote, unattended** execution
- **Long** workloads
- **Throughput** is highly important
- **High** GPU utilization

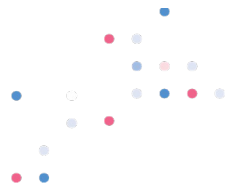
## Inference

- **Run Model in Production**
- **Services multiple users**
- **Typically low GPU memory requirements**
- **Performance is key**

# Basic Run:AI Concepts

## Build (Interactive)

- Build workloads are meant for interactive work.
- It is the responsibility of the researcher to stop a build workload.
- The Run:AI scheduler will usually not preempt a build workload with two notable exceptions:
  - The administrator has set a duration limit on interactive jobs for your project
  - The researcher has used the flag `-preemptible`
- Build workloads cannot extend beyond *guaranteed* quota (as they cannot be stopped automatically).
- See [Quickstart](#) of how to run a build job.



# Basic Run:AI Concepts

## Training

- Run:AI allows non-interactive training workloads to extend beyond *guaranteed* quotas and into *over-quota* as long as computing resources are available.
- To achieve this flexibility, the system needs to be able to safely stop a training workload and restart it again later. This means that:
  - The docker image should have an entrypoint instruction that initiates the training automatically upon restart.
  - Highly recommended: save 'checkpoints' frequently and allow the training to restart from the latest checkpoint
- See [Quickstart](#) on how to run a training job



# Basic Run:AI Concepts

## Inference

- Run:AI allows submitting inference workloads.
  - Inference workloads are considered production workloads and thus take precedence over training workloads.
  - It is the responsibility of the researcher to stop an inference workload.
  - The Run:AI scheduler will usually not preempt a inference workloads.
  - Inference workloads cannot extend beyond *guaranteed* quota (as they cannot be stopped automatically).
- 
- See [Quickstart](#) on how to run a inference workload



# Components

# The Run:AI Components

## The Command Line interface

Designed to be used by the researcher in order to do things like:

- Run and delete workloads
- View list of workloads and their status
- View list of available and allocated GPUs
- Access workloads via bash and view online logs
- Similar to Docker API

### Docker Syntax

```
docker run --shm-size 16G -it --rm -e  
HOSTNAME=`hostname` -v  
/raid/public/my_datasets:/root/dataset  
nvcr.io/nvidia/pytorch
```

### Run:AI Syntax

```
runai submit myjob --large-shdm -e  
HOSTNAME=`hostname` -v  
/raid/public/my_datasets:/root/dataset -i  
nvcr.io/nvidia/pytorch
```

See Run:AI [CLI reference](#)

# The Run:AI Components

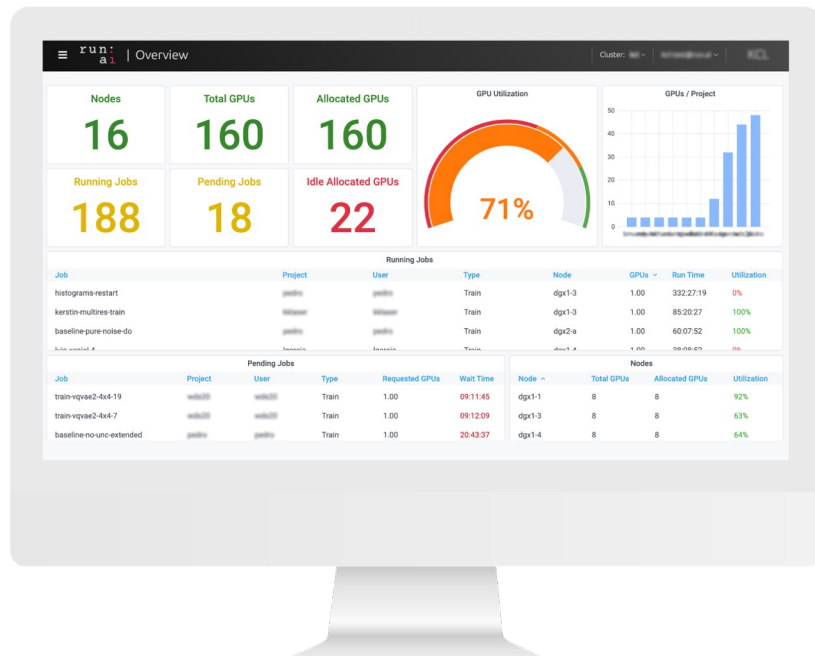
## The Run:AI Administrative User Interface

Designed to be used by IT and occasionally by researchers.

Goals are:

- Show holistic view of system resources (nodes, jobs etc). Both current status and long term status
- Allocate resources to researchers via projects
- Resolve conflicts

See: [app.run.ai](https://app.run.ai)





# The Command Line Interface

# Let's Try

## Interactive Build

```
runai submit --help
```

```
runai config project team-a
```

### **Interactive Build job:**

```
runai submit build1 -i ubuntu -g 1 --interactive --command -- sleep infinity
```

### **Get execution data on job:**

```
runai describe job build1
```

### **Get shell:**

```
runai bash build1
```

```
nvidia-smi
```

### **List all jobs:**

```
runai list jobs
```

### **List delete job:**

```
runai delete build1
```

# Let's Try

## Interactive Build- More Examples

### **Attach directly to job**

```
runai submit build2 -i ubuntu -g 1 --interactive --attach
```

### **Forgo the name:**

```
runai submit -i ubuntu -g 1 --interactive --attach
```

### **Interactive Build job with attached volume:**

```
runai submit build3 -i ubuntu -g 1 -v /mnt/nfs_share/files:/nfs --attach --interactive
```

### **Add a load balancing point (for details on Jupyter notebook see next slide):**

```
runai submit jupyter2 -i my-image -g 1 --interactive --service-type=ingress --port 8888:8888
```

### **Many other options:**

```
runai submit --help
```

# Tooling

It is possible to invoke interactive containers with Run:AI and attach to them via the development tool of your choice.

Some tools support remote development:

- Visual Studio Code: <https://docs.run.ai/Researcher/tools/dev-vscode/>
- PyCharm: <https://docs.run.ai/Researcher/tools/dev-pycharm/>

The recommendation in these cases is to use 'portforwarding' to expose ports

Some tools, use container based web-development. Most notably jupyter notebooks.

- Jupyter: <https://docs.run.ai/Researcher/tools/dev-jupyter/>
- TensorBoard: <https://docs.run.ai/Researcher/tools/dev-tensorboard/>
- Others: <https://docs.run.ai/Researcher/Walkthroughs/walkthrough-build-ports/>

# Let's Try

## Remote PyCharm / VSCode

**Start a remote container with port-forwarding**

```
runai submit build-remote -i gcr.io/run-ai-demo/pycharm-demo --interactive --service-type=portforward -  
-port 2222:22 -v /mnt/nfs_share/remote:/workspace/mydir
```

**Add a new PyCharm interpreter connecting to 127.0.0.1 (root/root)**

**Run and debug your code remotely**

# Let's Try

## Training: Preparation

Under network file storage: (e.g. `/nfs/testuser`)

- Create a **requirements.txt** file with python dependencies
- Put your python code (e.g. **main.py**)
- Create a startup script (**startup.sh**) that runs both:

```
#!/bin/bash
```

```
pip install -r requirements.txt
```

```
python main.py
```

startup.sh

# Let's Try Training

## Unattended job:

```
runai submit train1 -i tensorflow/tensorflow:1.14.0-gpu-py3 -g 1 -v  
/mnt/nfs_share/john:/workspace/mydir --working-dir /workspace/mydir/ --command -- ./startup.sh
```

## Show logs:

```
runai logs train1 --follow
```

## Unattended job with parameters

```
runai submit train2 -i tensorflow/tensorflow:1.14.0-gpu-py3 -g 1 -v  
/mnt/nfs_share/john:/workspace/mydir --working-dir /workspace/mydir/ --command -- ./startup.sh  
-e 'EPOCHS=30' -e 'LEARNING_RATE=0.02'
```

## Minimal version:

```
runai submit -i gcr.io/run-ai-demo/quickstart -g 1
```

# Let's Try

## Working with Projects

### List of projects

```
runai list projects
```

### Set a default project

```
runai config project team-b
```

### Running on another project

```
Runai submit train-b -i gcr.io/run-ai-demo/quickstart -g 1 -p team-b
```

### Listing all projects

```
Runai list jobs -A
```



# GPU Fractions

- You can opt to allocate fractions of GPUs
- Run:AI provides memory isolation between multiple workloads using the same GPU
- Fractions can be interactive or none. If none, then all preemptions and consolidation rules apply.

# Let's Try Fractions

## **Allocate 1/2th of a GPU:**

```
runai submit frac05 -i ubuntu --project team-a -g 0.5 --attach --interactive
```

```
nvidia-smi
```

## **Allocate more fractions to fill node:**

```
runai submit frac03 -i ubuntu --project team-a -g 0.3 --attach --interactive
```

```
runai submit frac02 -i ubuntu --project team-a -g 0.2 --attach --interactive
```

## **Allocate fractions by memory size**

```
runai submit fixed-gpu-mem -i ubuntu --project team-a --gpu-memory 3G --attach --interactive
```

# Overquota & Bin-packing

See quickstart for overquota behavior and bin-packing

<https://docs.run.ai/Researcher/Walkthroughs/walkthrough-overquota/>

See quickstart for queue fairness:

<https://docs.run.ai/Researcher/Walkthroughs/walkthrough-queue-fairness/>

# Hyperparameter Optimization

- Hyperparameter optimization (HPO) is the process of choosing a set of optimal hyperparameters for a learning algorithm (e.g. learning rate, batch size)
- To search for good hyperparameters, Researchers start a series of small runs with different hyperparameter values, let them run for a while, and then examine results to decide what works best.
- Run:AI automates the management and scheduling of HPO
- The Run:AI python Researcher library automates the experiment management and result gathering of HPO.
- See [Quickstart](#) for a step by step introduction

# Let's Try

## Hyperparameter Optimization

**HPO run, 12 combinations, only 3 at a time:**

```
runai submit hpo1 -i gcr.io/run-ai-demo/quickstart-hpo -g 1 --parallelism 3 --completions 12 -v  
/mnt/nfs_share/files:/nfs
```

**Watch**

```
runai list jobs  
runai describe job hpo1
```

**Relate to a specific pod**

```
runai logs hpo1 --pod <pod-name>  
runai bash hpo1 --pod <pod-name>
```

# Sample code for usage with Run:AI library

```
# import Run:AI HPO library
import runai.hpo

# select Random search or grid search
strategy = runai.hpo.Strategy.GridSearch

# initialize the Run:AI HPO library. Send the NFS directory used for sync
runai.hpo.init("/hpo")

# pick a configuration for this HPO experiment
# we pass the options of all hyperparameters we want to test
# `config` will hold a single value for each parameter
config = runai.hpo.pick(
    grid=dict(
        batch_size=[32, 64, 128],
        lr=[1, 0.1, 0.01, 0.001]),
    strategy=strategy)

....

# Use the selected configuration within your code
optimizer = keras.optimizers.SGD(lr=config['lr'])
```

# Distributed Training

- The ability to split the training of a model among multiple processors (workers)
- Workers work in parallel, in different containers and perhaps in different nodes, to speed up model training
- Should not be confused with allocating multiple GPUs to a single container
- Distributed Training requires the user program to sync data and timing between different workers and there are a number of Deep Learning frameworks that support this. [Horovod](#) is a good example.
- Run:AI automates the management and scheduling of the workers and the communication links between them, providing the ability to easily run, manage and view Distributed Training.
- Run:AI employs [gang-scheduling](#), in the sense that all worker-nodes are scheduled together and if one preempts, all others close down.
- See [Quickstart](#) for a step by step introduction

# Let's Try

## Distributed Training (MPI)

### Unattended Distributed Training (2 workers):

```
runai submit-mpi dist1 --processes=3 -g 1 -i gcr.io/run-ai-demo/quickstart-distributed
```

### Watch

```
runai list jobs
```

```
runai describe dist1
```

```
runai logs dist1
```

### Interactive Distributed Training (for testing)

```
runai submit-mpi dist-int --processes=2 -g 1 -i gcr.io/run-ai-demo/quickstart-distributed \
--interactive --command -- sh -c sleep infinity
```

### Bash and run

```
runai bash dist-int
```

```
horovodrun -np 2 python scripts/tf_cnn_benchmarks/tf_cnn_benchmarks.py --model=resnet20 --
num_batches=1000000 --data_name cifar10 --data_dir /cifar10 --batch_size=64 --
variable_update=horovod
```



# Allocation of CPU & Memory

- GPUs are typically the most critical resource. But memory and cpu resources are no less important
- The *runai submit* command allows allocation of CPU & memory
- CPU *--cpu* command guarantees a quota. Over-allocation of CPU happens automatically if not requested by others
- Memory *--memory* command guarantees a quota. Over-allocation of Memory is possible, but you will receive an OOM exception if requested by others
- Without these flags, the system has defaults based on ratios to the number of requested GPUs

For information on how the Run:AI Scheduler allocates CPU & memory see [here](#).

# Let's Try

## Allocation of CPU & Memory

### **CPU & Memory guarantee**

```
runai submit job1 -i ubuntu --gpu 2 --cpu 12 --memory 1G
```

### **CPU & Memory limits**

```
runai submit job1 -i ubuntu --gpu 2 --cpu 12 --cpu-limit 24 --memory 1G --memory-limit 4G
```

(you will never receive more than 24 CPUs, you will get an OOM if you request more than 4GB)

# Let's Try

## Other Useful Commands

### Information about nodes

```
runai top node
```

### Information about jobs

```
runai top job
```

### Update CLI to latest version

```
sudo runai update
```

# Inference

# Inference Overview

- Machine learning (ML) inference is the process of running live data points into a machine-learning algorithm to calculate an output.
- Inference lends itself nicely to the usage of Run:AI Fractions. You can, for example, run 4 instances of an Inference server on a single GPU, each employing a fourth of the memory.
- Inference workloads can be submitted via Run:AI Command-line interface as well as Kubernetes API/YAML. Internally, spawning an Inference workload also creates a Kubernetes Service. The service is an endpoint to which clients can connect.

# Let's Try

## Basic Inference Commands

### Submit an inference workload

```
runai submit --name inferencel --service-type nodeport --port 8888 --inference \  
-i gcr.io/run-ai-demo/quickstart-inference-marian -g 1
```

### Retrieve Host and Port information

```
runai list jobs
```

### Connect to inference service

```
runai submit inference-client -i gcr.io/run-ai-demo/quickstart-inference-marian-client \  
-- --hostname <HOSTNAME> --port <PORT> --processes 1
```

# Let's Try

## Inference with Fractions

**Submit an inference workload. 4 Replicas on a single GPU**

```
runai submit inference2 --service-type nodeport --port 8888 --inference \  
-i gcr.io/run-ai-demo/quickstart-inference-marian --replicas 4 -g 0.25
```

**Retrieve Host and Port information**

```
runai list jobs
```

**Connect to inference service**

```
runai submit inference-client -i gcr.io/run-ai-demo/quickstart-inference-marian-client \  
-- --hostname <HOSTNAME> --port <PORT> --processes 1
```

# Let's Try

## Create an Inference Workload using YAML

### **Submit an inference workload. 1 Replica**

```
kubect1 apply -f https://raw.githubusercontent.com/run-ai/docs/master/examples/inference-single-replica.yaml
```

### **Submit an inference workload. 2 Replicas on a single GPU**

```
kubect1 apply -f https://raw.githubusercontent.com/run-ai/docs/master/examples/inference-two-replicas.yaml
```

### **Submit an inference (triton) workload. 1 Replicas on a single GPU**

```
kubect1 apply -f https://raw.githubusercontent.com/run-ai/docs/master/examples/inference-triton-one-replicas.yaml
```



# Advanced

# CLI Templates

The CLI has a templating mechanism that is useful for shortening the command line. There are two kinds of templates:

- Named templates (e.g. *runai submit... --template batch\_ops*)
- Default template. Command line parameters used when the `--template` flag is not used.

Templates are set by the IT administrator. For further information see: [setting up templates](#)

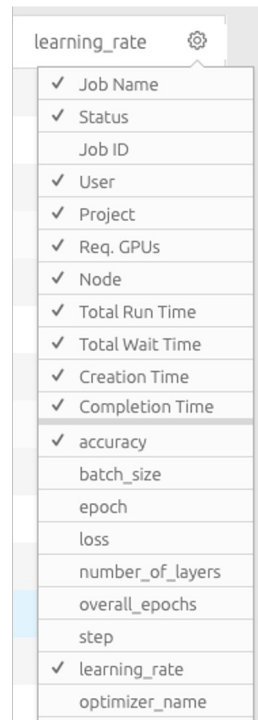
# The Run:AI Components

## Training Library (Optional)

Run:AI provides a python library which can optionally be installed within your docker image and activated during the deep learning session.

If installed, the library provides:

- Additional progress [reporting](#) and metrics (accuracy, loss, batch size, etc.) externalized from the training run and shown on the Run:AI UI as metrics and graphs
- Ability to [dynamically](#) stretch and compress jobs according to GPU availability.
- Hyperparameter optimization support



learning_rate
✓ Job Name
✓ Status
Job ID
✓ User
✓ Project
✓ Req. GPUs
✓ Node
✓ Total Run Time
✓ Total Wait Time
✓ Creation Time
✓ Completion Time
✓ accuracy
batch_size
epoch
loss
number_of_layers
overall_epochs
step
✓ learning_rate
optimizer_name

# Additional Material

Researcher documentation exists [here](#) under the “Researcher” tab. Noteworthy documents:

- CLI [reference](#).
- Run:AI Scheduler [internals](#)
- Various [Quickstart guides](#).
- Researcher [Library](#).
- This presentation is [here](#)

# How to Get Help

Write to [support@run.ai](mailto:support@run.ai)

or

Use the “help” button at [app.run.ai](https://app.run.ai) and [docs.run.ai](https://docs.run.ai)



# Next Steps

- See [document](#) on how to ramp up new researchers. Including installation and configuration.
- Submit your first workload with Run:AI.
  - Start by submitting an ‘interactive’ build workload.
  - After which ssh to the container and run your code.



# Thank you

Contact: [support@run.ai](mailto:support@run.ai)