

1. Motivation

Hyperparameter optimization is a crucial step in the late development of machine learning models to improve their performance. Optimization campaigns require training the models multiple times, possibly **in parallel**, to explore the hyperparameter space, focusing on those regions where the model performs better.

Accessing *opportunistic resources* can drastically increase the number of trials in a campaign, especially when training involves the usage of GPUs. **Diversity** in the computing environment of the resource providers and **untrusted** storage solutions represent challenges to the existing services.

2. Hyperparameter optimization as a service

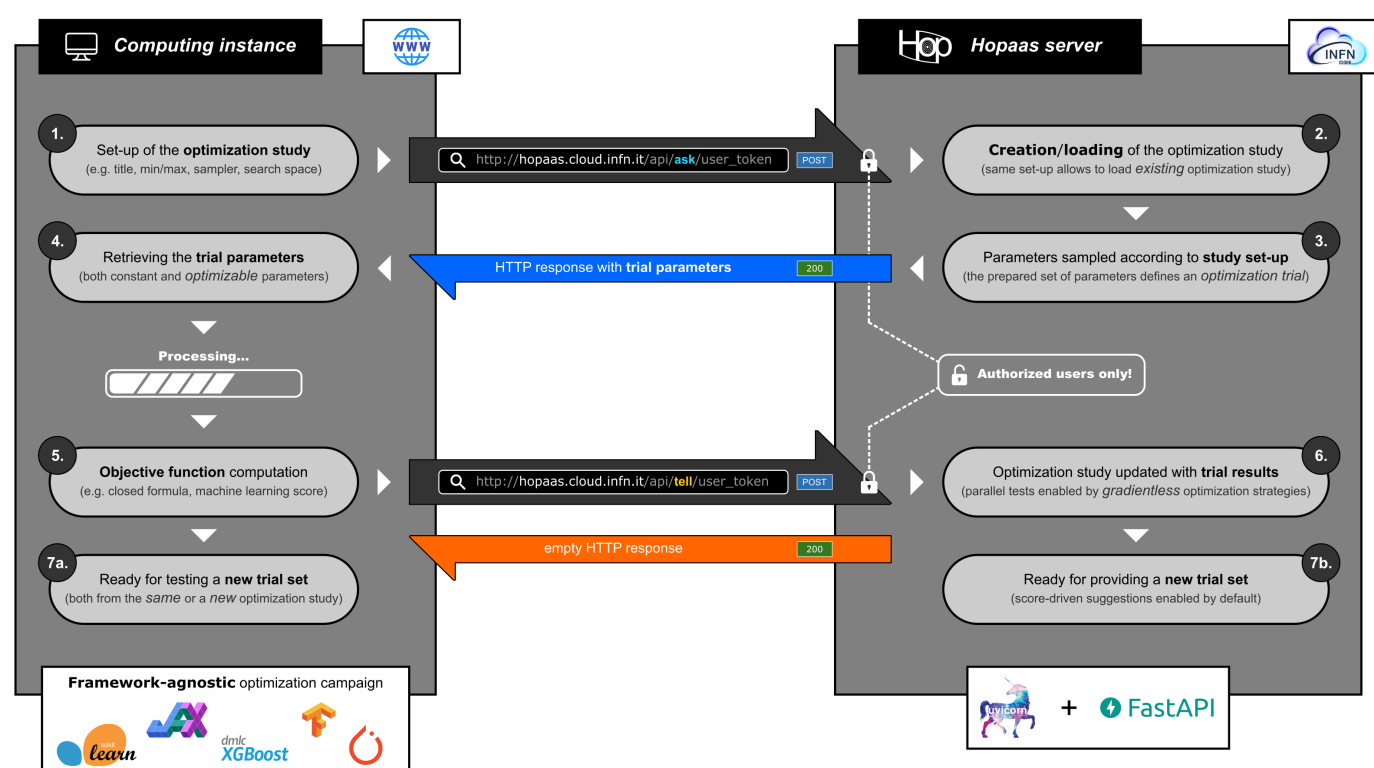
Hopaas (*Hyperparameter OPTimization As A Service*) is a service hosted by [INFN Cloud](https://hopaas.cloud.infn.it) that allows to orchestrate optimization studies across multiple computing instances via **HTTP requests**. Hopaas provides a set of REST APIs and a web interface to enable **user authentication** and to monitor the status of the user studies.

- **Back-end** based on [FastAPI](https://fastapi.tiangolo.com/);
- Underlying databases powered by [PostgreSQL](https://www.postgresql.org/);
- **Bayesian optimization** powered by [Optuna](https://optuna.org/);
- Service provided by [Uvicorn](https://docs.ingress-nginx.com/) and [NGINX](https://nginx.org/);
- Python **front-end** available ([hopaas_client](https://github.com/inf-nn/hopaas_client)).

3. Authorization via token

Accessing the Hopaas service is enabled through **API tokens** passed directly within the URL of the HTTP requests. Such tokens can be generated with user-selected validity interval (ranging from one day to one year), through a dedicated web-page at hopaas.cloud.infn.it after an **OAuth2 login** via the INFN official GitLab instance (baltig.infn.it).

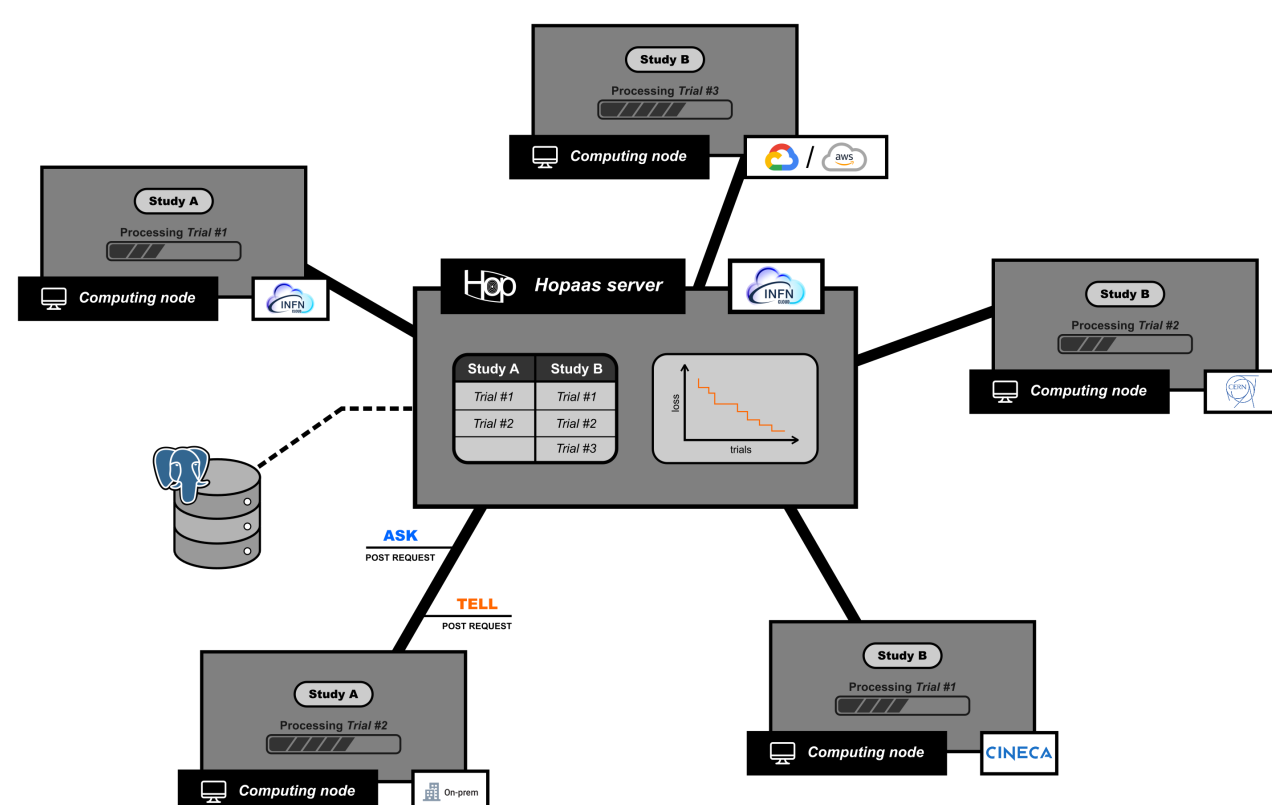
3. Client-server optimization system



Workflow of the client-server system defined by Hopaas to run optimization studies, and based on an *ask-and-tell* interface where the trial parameters and the objective score computed are retrieved from HTTP requests.

5. Multi-nodes optimization campaigns

Multiple **HPC centers** can concur to the same optimization study, requesting to the Hopaas server a new set of hyperparameters to be tested and then communicating the outcome of the training instance. Several trials of **one or more studies** can be tracked and monitored through the web interface provided by the Hopaas service.



Schematic representation of the Hopaas server as an orchestrator of two optimization studies ("Study A" and "Study B") distributed across five computing instances, and powered by a PostgreSQL database.

6. Example use-cases

```
import hopaas_client as hpc

## Create the client
client = hpc.Client(servers="https://hopaas.cloud.infn.it",
                   token="user-api-token")

## Create (or retrieve) the study
study = hpc.Study(name="ExampleStudy",
                  properties=dict(
                      int_param = hpc.suggestions.Int(0, 10),
                      float_param = hpc.suggestions.Float(-1, 1)
                  ),
                  direction="minimize", # or "maximize"
                  client=client)

## Start polling trials
while True:
    with study.trial() as trial:
        ## Retrieve hopaas-suggested parameters
        int_param = trial.int_param
        float_param = trial.float_param

        ## Define the training loop (if any)

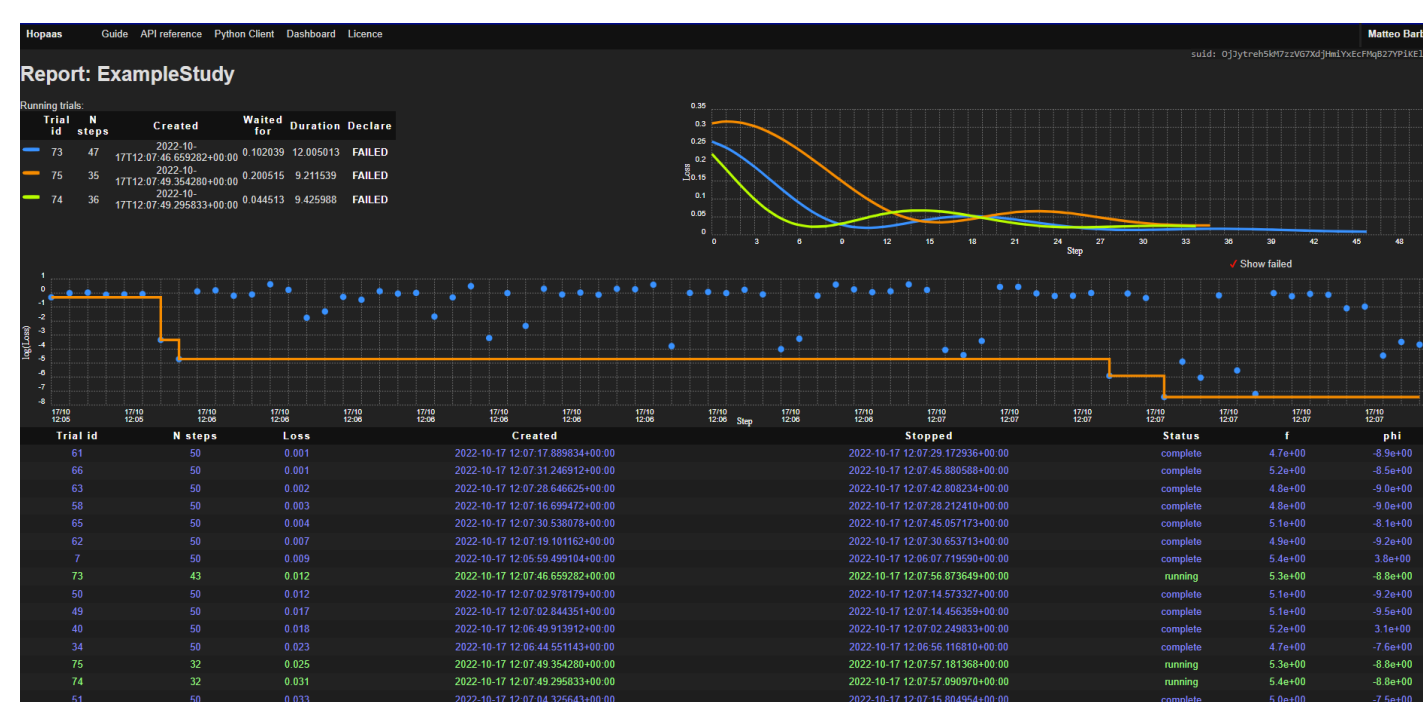
        for iStep in range(50):
            my_loss = # compute the loss at this epoch/step
            trial.loss = my_loss

            ## Discards poorly-started trials
            ## to save computing time
            if trial.should_prune:
                break
```

Fully runnable example at [L.infn.it/hopaascolab](https://l.infn.it/hopaascolab).

7. Web-powered monitoring

A simple **web interface** based on [Chartist](https://github.com/inf-nn/chartist) enables live monitoring of the ongoing optimization trials, while organizing the history of the past studies.



Web dashboard produced by Hopaas for [L.infn.it/hopaascolab](https://l.infn.it/hopaascolab). The top right plot shows three ongoing trial trainings, while the center plot reports the global status of the optimization study. Finally, the bottom table traces general information from all the trials.

8. Conclusions

Several optimization campaigns has been successfully distributed and coordinated by the Hopaas server using **diverse computing instances**, from scientific HPC resources (like [INFN Cloud](https://www.infn.it/) and [CINECA MARCONI100](https://www.cineca.it/)), and from public Cloud Provider (like GCP or AWS).

Hopaas is currently in **alpha testing** and is made available to a limited amomunt of INFN researchers. The source code will be *open-sourced* once a more advanced state of development will be reached.

References

1. R. Liaw *et al.*, *Tune: A Research Platform for Distributed Model Selection and Training*, [arXiv:1807.05118](https://arxiv.org/abs/1807.05118)
2. T. Akiba *et al.*, *Optuna: A Next-generation Hyperparameter Optimization Framework*, [arXiv:1907.10902](https://arxiv.org/abs/1907.10902)
3. D. Spiga *et al.*, *Dynamic integration of distributed, Cloud-based HPC and HTC resources using JSON Web Tokens and the INDIGO IAM Service*, [EPL Web Conf **245** \(2020\) 07020](https://www.epj-conferences.org/doi/pdf/10.1051/epjconf/202024507020)
4. M. Mariotti, D. Spiga and T. Boccali, *A possible solution for HEP processing on network secluded Computing Nodes*, [PoS **ISGC2021** \(2021\) 002](https://arxiv.org/abs/2101.002)
5. E. Wulff, M. Girone and J. Pata, *Hyperparameter optimization of data-driven AI models on HPC systems*, [arXiv:2203.01112](https://arxiv.org/abs/2203.01112)

