Solution Overview

NetApp Solutions

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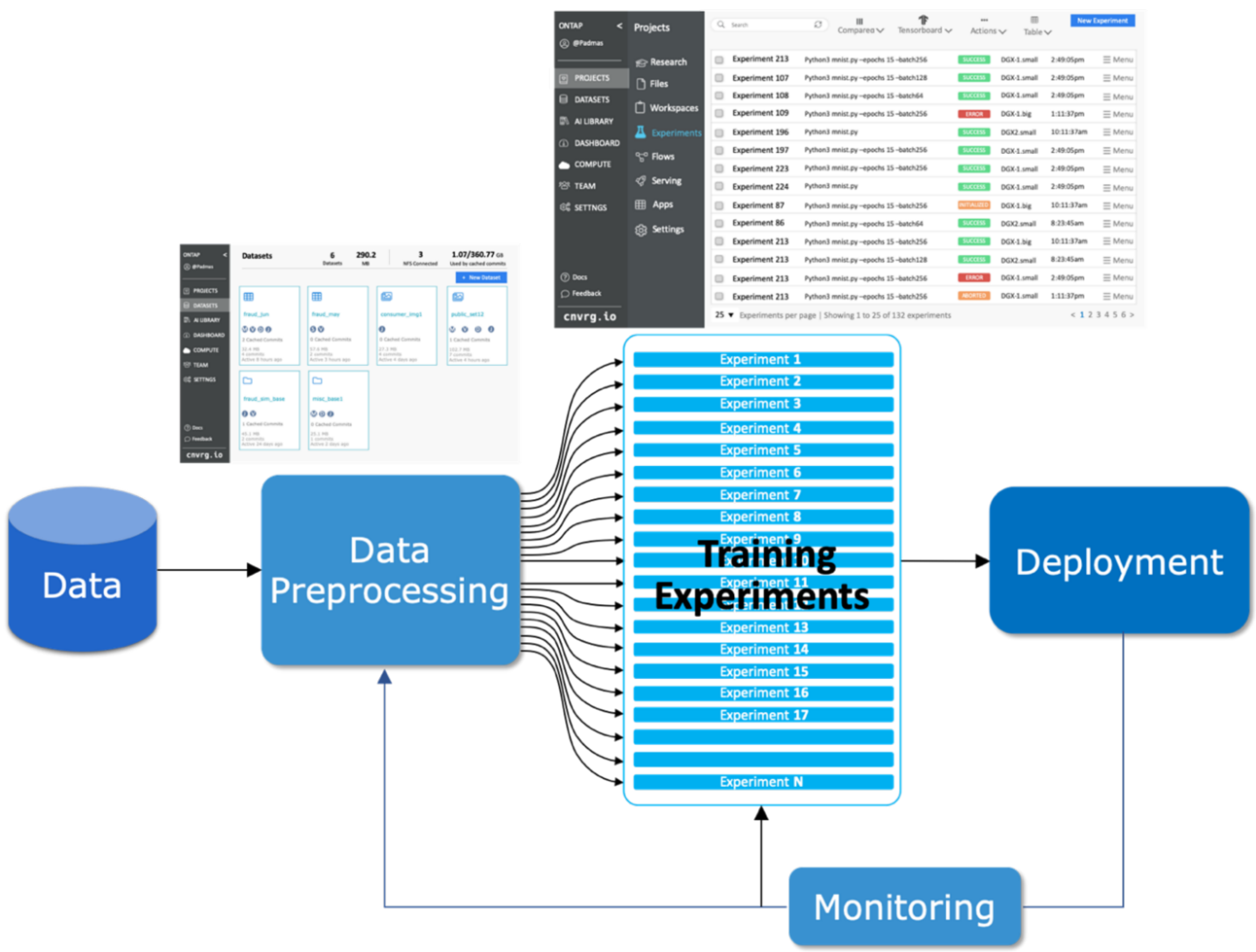
Solution Overview

This section reviews a conventional data science pipeline and its drawbacks. It also presents the architecture of the proposed dataset caching solution.

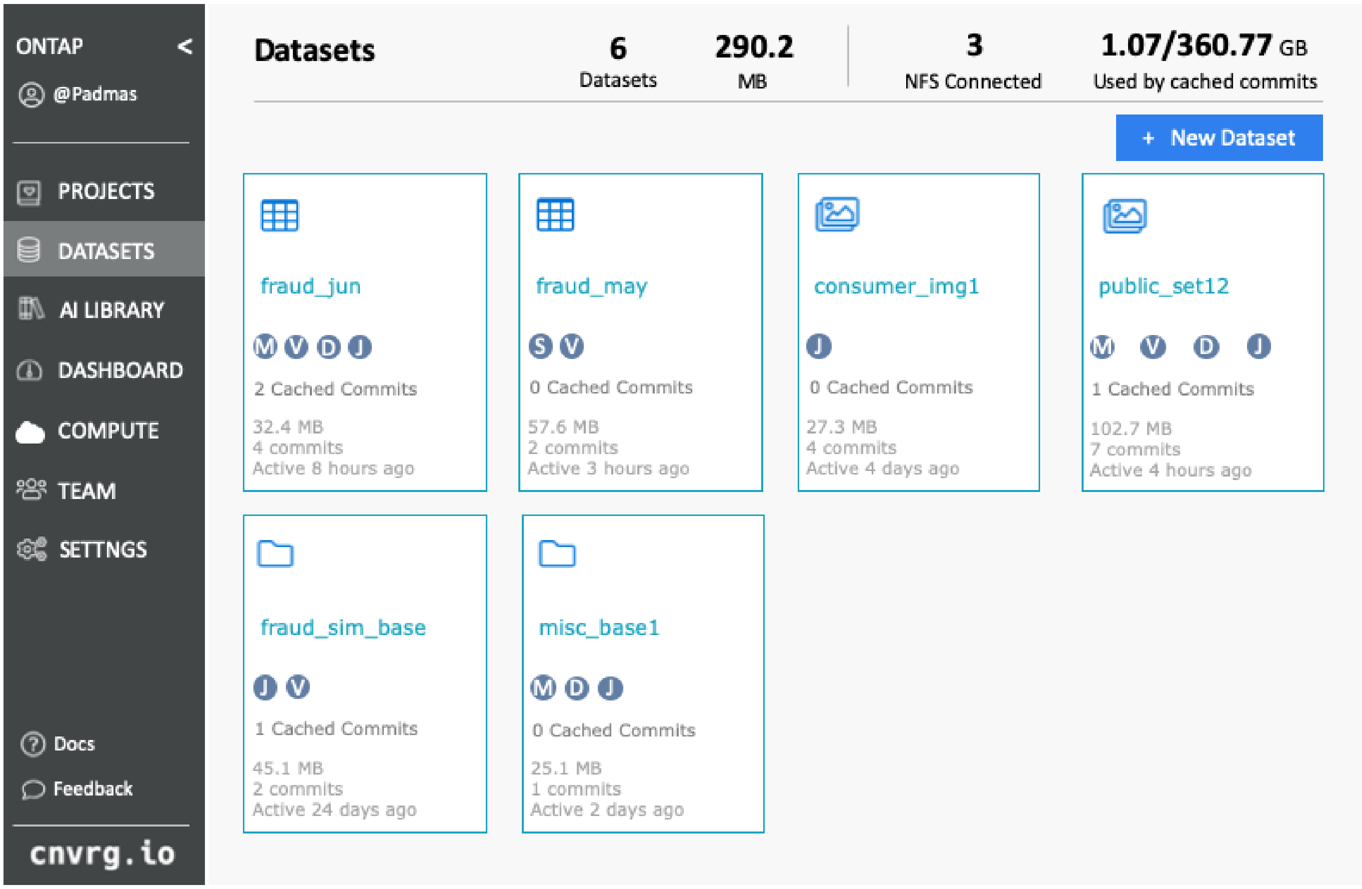
Conventional Data Science Pipeline and Drawbacks

A typical sequence of ML model development and deployment involves iterative steps that include the following:

- Ingesting data
- Data preprocessing (creating multiple versions of the datasets)
- Running multiple experiments involving hyperparameter optimization, different models, and so on
- Deployment
- Monitoringcnvrg.io has developed a comprehensive platform to automate all tasks from research to deployment. A small sample of dashboard screenshots pertaining to the pipeline is shown in the following figure.



It is very common to have multiple datasets in play from public repositories and private data. In addition, each dataset is likely to have multiple versions resulting from dataset cleanup or feature engineering. A dashboard that provides a dataset hub and a version hub is needed to make sure collaboration and consistency tools are available to the team, as can be seen in the following figure.



The next step in the pipeline is training, which requires multiple parallel instances of training models, each associated with a dataset and a certain compute instance. The binding of a dataset to a certain experiment with a certain compute instance is a challenge because it is possible that some experiments are performed by GPU instances from Amazon Web Services (AWS), while other experiments are performed by DGX-1 or DGX-2 instances on- premises. Other experiments might be executed in CPU servers in GCP, while the dataset location is not in reasonable proximity to the compute resources performing the training. A reasonable proximity would have full 10GbE or more low-latency connectivity from the dataset storage to the compute instance.

It is a common practice for data scientists to download the dataset to the compute instance performing the training and execute the experiment. However, there are several potential problems with this approach:

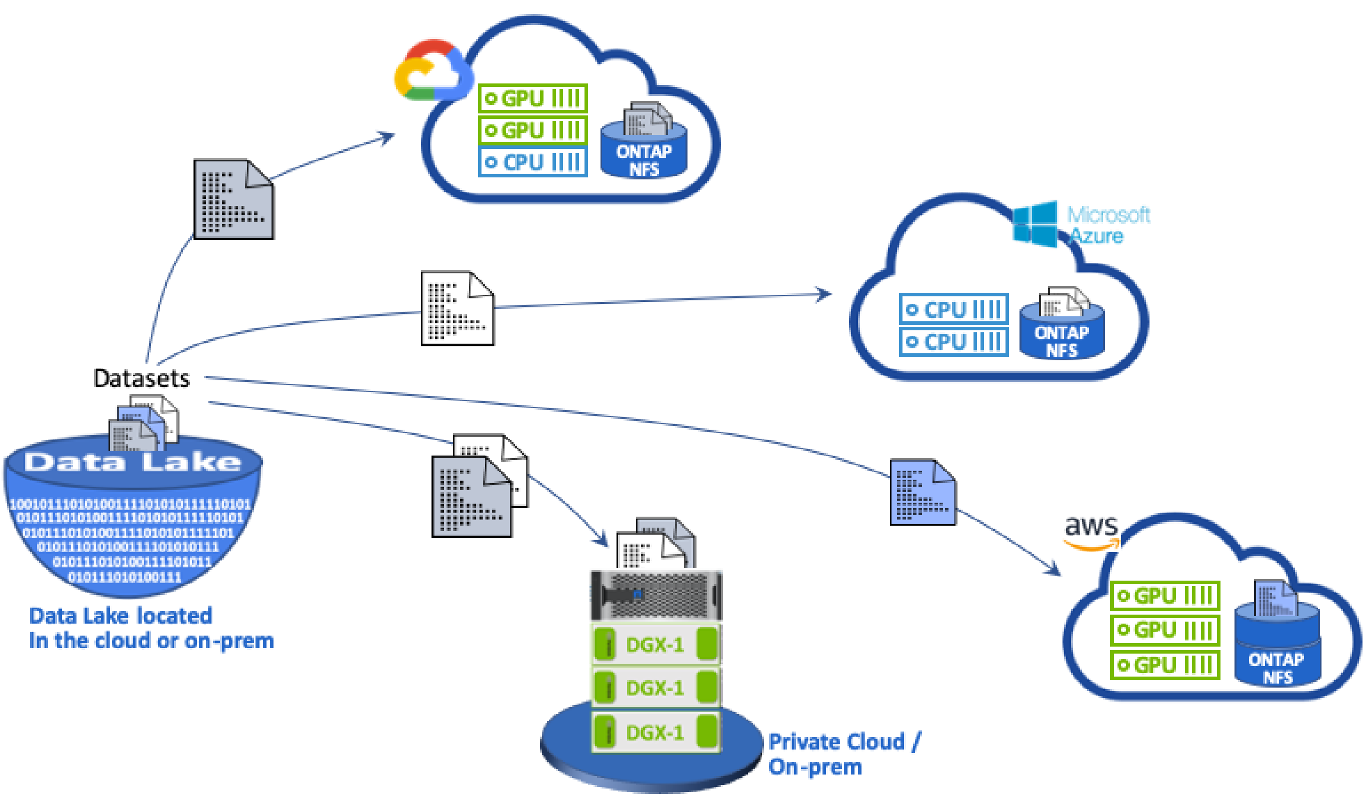
- When the data scientist downloads the dataset to a compute instance, there are no guarantees that the integrated compute storage is high performance (an example of a high-performance system would be the ONTAP AFF A800 NVMe solution).
- When the downloaded dataset resides in one compute node, storage can become a bottleneck when distributed models are executed over multiple nodes (unlike with NetApp ONTAP high-performance distributed storage).
- The next iteration of the training experiment might be performed in a different compute instance due to queue conflicts or priorities, again creating significant network distance from the dataset to the compute location.
- Other team members executing training experiments on the same compute cluster cannot share this dataset; each performs the (expensive) download of the dataset from an arbitrary location.

- If other datasets or versions of the same dataset are needed for the subsequent training jobs, the data scientists must again perform the (expensive) download of the dataset to the compute instance performing the training.NetApp and cnvrg.io have created a new dataset caching solution that eliminates these hurdles. The solution creates accelerated execution of the ML pipeline by caching hot datasets on the ONTAP high- performance storage system. With ONTAP NFS, the datasets are cached once (and only once) in a data fabric powered by NetApp (such as AFF A800), which is collocated with the compute. As the NetApp ONTAP NFS high-speed storage can serve multiple ML compute nodes, the performance of the training models is optimized, bringing cost savings, productivity, and operational efficiency to the organization.

Solution Architecture

This solution from NetApp and cnvrg.io provides dataset caching, as shown in the following figure. Dataset caching allows data scientists to pick a desired dataset or dataset version and move it to the ONTAP NFS cache, which lies in proximity to the ML compute cluster. The data scientist can now run multiple experiments without incurring delays or downloads. In addition, all collaborating engineers can use the same dataset with the attached compute cluster (with the freedom to pick any node) without additional downloads from the data lake. The data scientists are offered a dashboard that tracks and monitors all datasets and versions and provides a view of which datasets were cached.

The cnvrg.io platform auto-detects aged datasets that have not been used for a certain time and evicts them from the cache, which maintains free NFS cache space for more frequently used datasets. It is important to note that dataset caching with ONTAP works in the cloud and on-premises, thus providing maximum flexibility.



Next: Concepts and Components