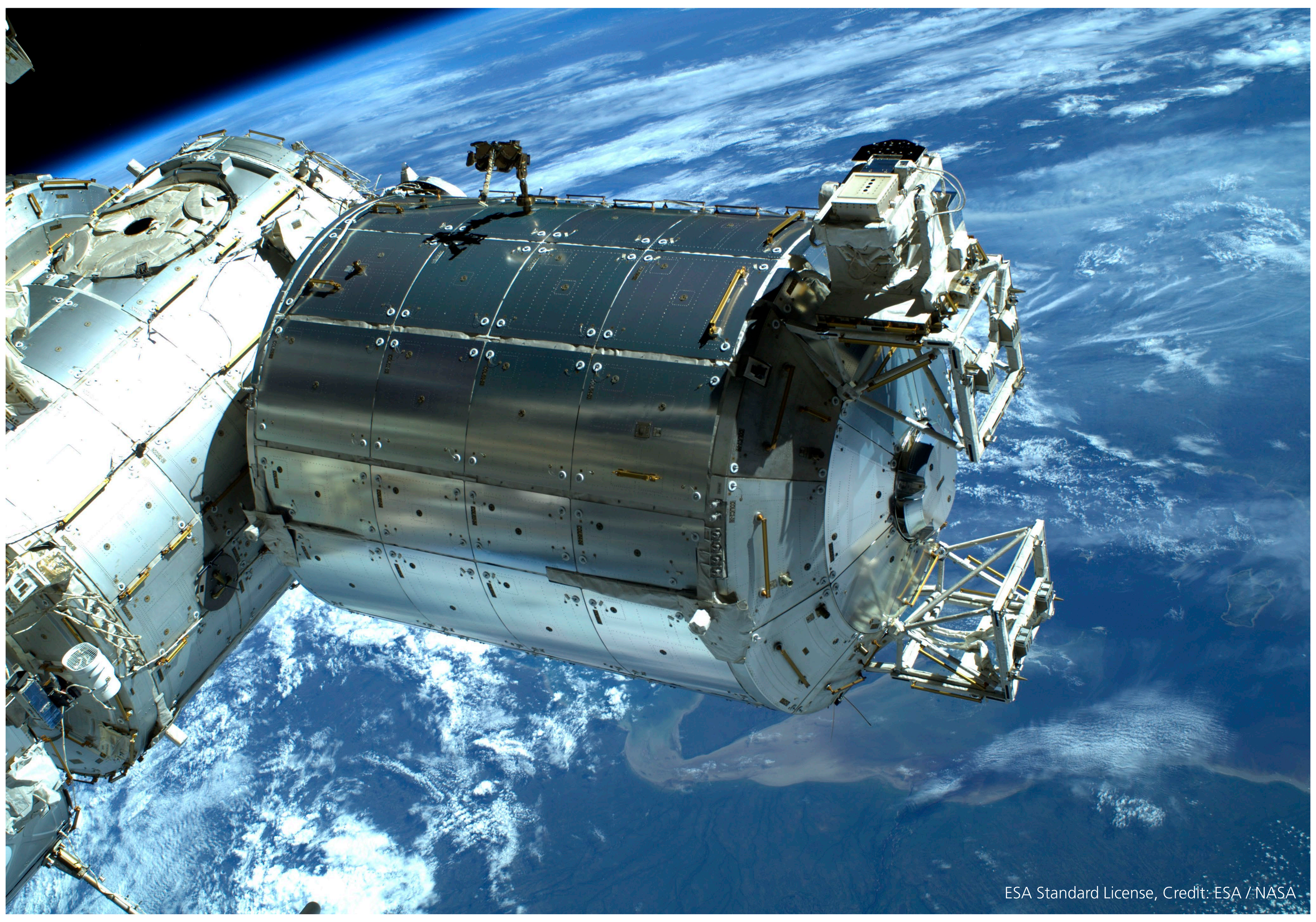
QCoKaIn
Hybrid Quantum High-Performance Computing using Causal Inference

We develop and evaluate a hybrid Quantum High-Performance Computing (Q-HPC) algorithm for anomaly detection in telemetry data in combination with causal inference techniques. The hybrid algorithm will be trained on data from the ISS Columbus module using a state-of-the-art MLOps platform.

- Applications
- Quantum High-Performance-Computing
- Quantum Machine Learning



Motivation

Quantum computing is an innovative technology that holds the potential for huge economic impact in a diverse field of applications. Today's quantum computers are still limited in terms of error rates and qubit numbers, which limits their usability. Therefore, so-called hybrid Quantum High-Performance Computing (Q-HPC), which combines quantum computing with classical high-performance computing, offers a promising way to expand the field of applications.

In this project, we develop a hybrid quantum anomaly detection pipeline that is accelerated by diverse techniques from high-performance computing. Furthermore, we include techniques from causal inference (Fig. 1), which is a modern research field within statistics and machine learning. It deals with the data-driven analyses of cause-effect relations and enables an understanding of complex processes beyond mere correlation.

The Columbus Module

As the European contribution to the International Space Station, the Columbus module is Europe's first permanent outpost in orbit. It was built by Airbus Defence and Space in Bremen and was launched in 2008 on the Space Shuttle Atlantis. As a state-of-the-art research facility with its own life support system, it provides an environment for up to three astronauts to conduct experiments at the same time.

The highly complex system generates a large amount of sensor data. Several thousand telemetry parameters are recorded with an average sampling rate of 1 Hz, resulting in approx. 10 GB per year, including sensor measurements as well as sensor states.

The Environmental Control and Life Support Subsystem (ECLSS) is one of several Columbus subsystems and was selected as one use case for anomaly detection using telemetry data in the scope of this project. The process leading to an anomaly report (AR) is highlighted in Fig. 2.

HPC Pipeline (MLOps Platform)

The MLOps platform is built around Kubeflow as the Kubernetes-based MLOps environment. It leverages GitOps principles through ArgoCD for continuous deployment. The platform implements a multi-tenant architecture where data scientists can develop, train, and deploy ML models in isolated namespaces with centralized monitoring through Prometheus and Grafana. Security is enforced through Istio service mesh, providing fine-grained access control in combination with Keycloak.

ML-Pipelines are defined as code using Kubeflow Pipelines SDK, automating the whole ML lifecycle from data ingestion to model serving.

The platform provides integration with different quantum state-vector simulators that support distributed GPU computations. In combination with frameworks like PennyLane, it enables hybrid classical-quantum ML experiments.

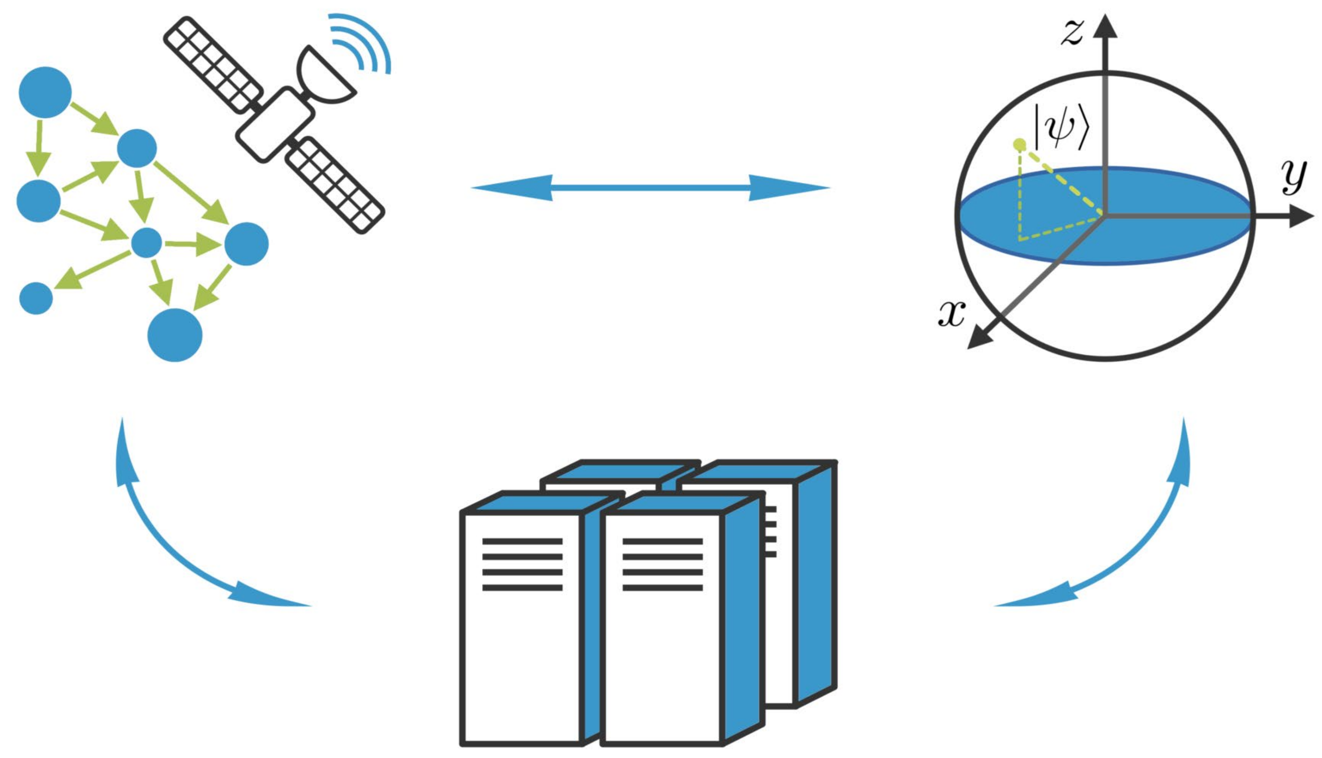


Fig. 1: The essential constituents of the project: Causal inference within the context of telemetry data (left), high-performance computing (middle), and quantum computing (right)

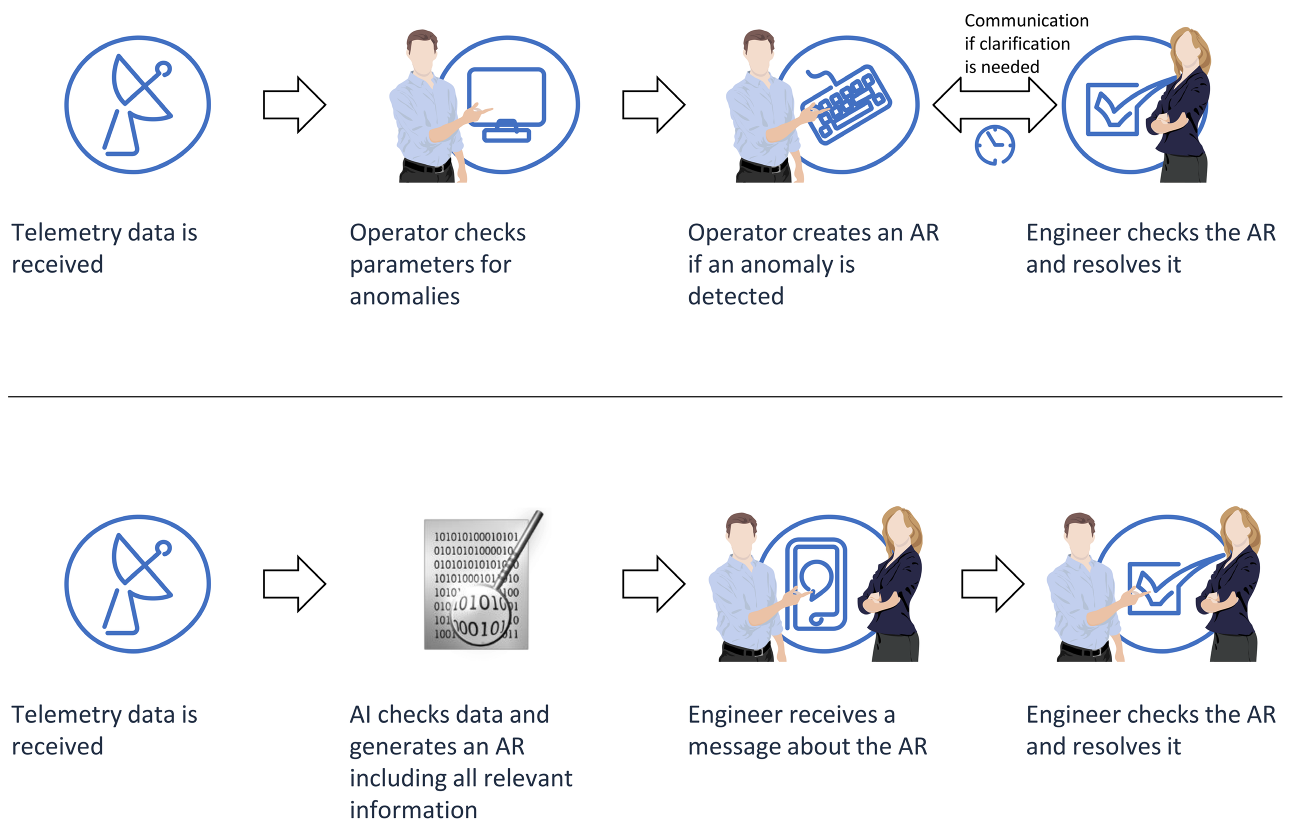


Fig. 2: Process leading to an anomaly report (AR) in the context of operations without using anomaly detection system (top) and with using an anomaly detection system (bottom) Credits: Airbus

Hybrid Quantum High-Performance Computing

Hybrid quantum computing holds the opportunity to significantly increase the performance of classical algorithms. This increase relies on the inclusion of so called quantum circuits into classical algorithms. Within the project, we utilize this hybrid approach to implement techniques from quantum machine learning into a classical anomaly detection pipeline. The classical pipeline as well as the use case are delivered by our contractor, Airbus Defence & Space.

First small-scale investigations show a performance increase of a hybrid quantum autoencoder (AE) over a comparable classical variational AE. The associated metrics, accuracy-, precision-, and recall error, are shown in Fig. 3. The origin of this performance increase can be interpreted in terms of the reconstruction error (Fig. 4). Here, the hybrid AE (Fig. 4 lhs, inset) shows a substantially lower misclassification rate compared to the classical variational AE (Fig. 4 rhs, inset). A normal (anomalous) sample is misclassified if its reconstruction error is above (below) the threshold (Fig. 4, dashed black line). This lower misclassification rate eventually increases the algorithms overall performance.

Fig. 3

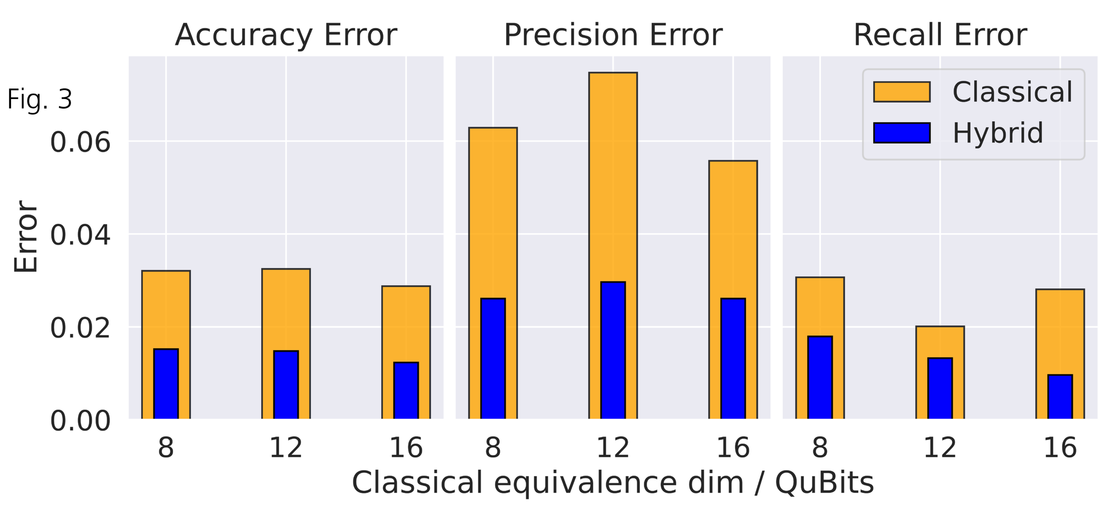
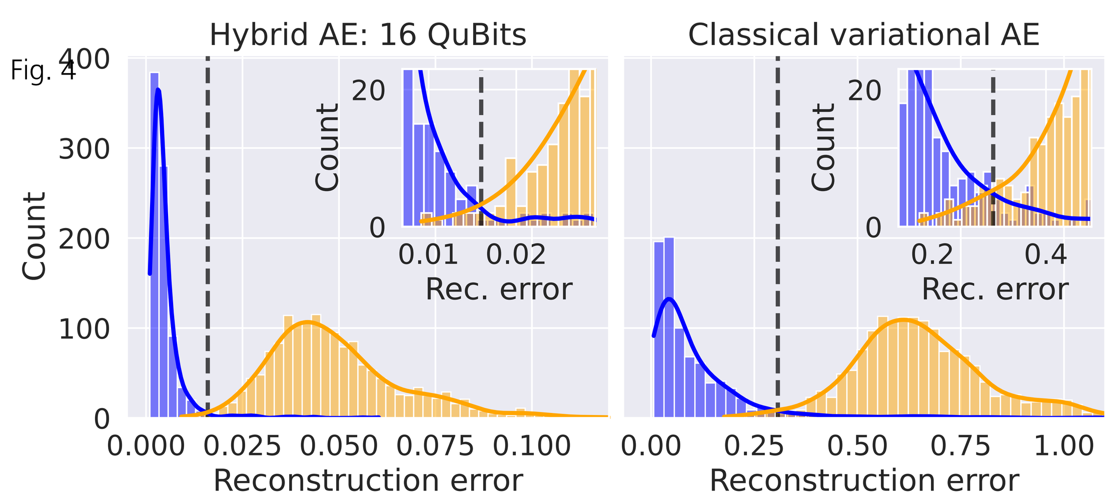


Fig. 4



Discussion and Future Perspective

We have compared the performance of a classical variational autoencoder (AE) and a hybrid AE within the context of time series anomaly detection. The hybrid AE shows a substantial increase in performance by approximately halving the respective error rates compared to the classical variational AE. Due to this increase in performance, we are optimistic about further investigations.

Next, we will examine the performance of hybrid algorithms for data from the Columbus Module and similar systems. Two of the upcoming challenges could be the data complexity and, eventually, access to quantum resources.

More information about the Project can be found on our website.

A project of

DLR Institute of Data Science

Contractor

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