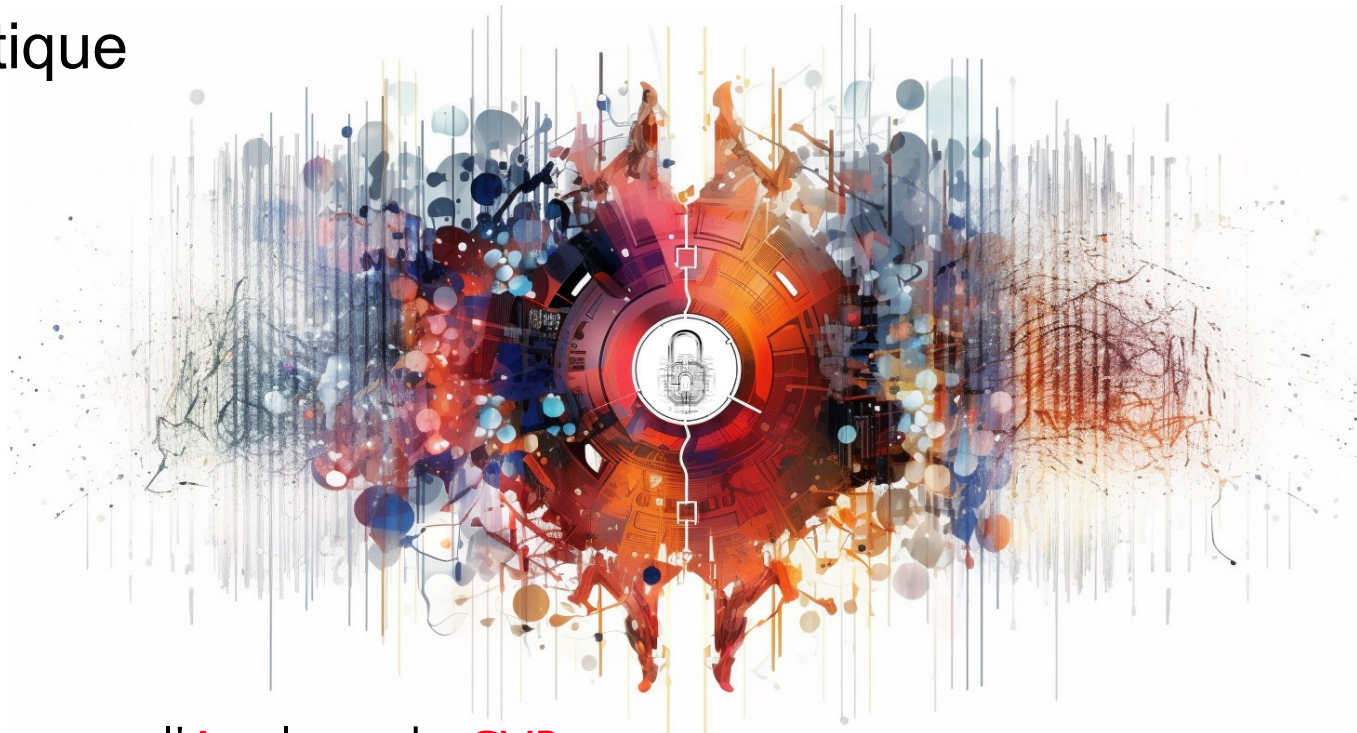


Projet Pack Quantique



AQACYB

Avantage **Q**uantique pour l'**A**nalyse de **CYB**ermenaces

Quantum Advantage for Cyber Threats Analysis

Proposé par



IQM



Avec l'accompagnement du



CYBERSECURITY

In today's VUCA world (Volatility, Uncertainty, Complexity, Ambiguity), cybersecurity is essential for states, citizens, and companies.



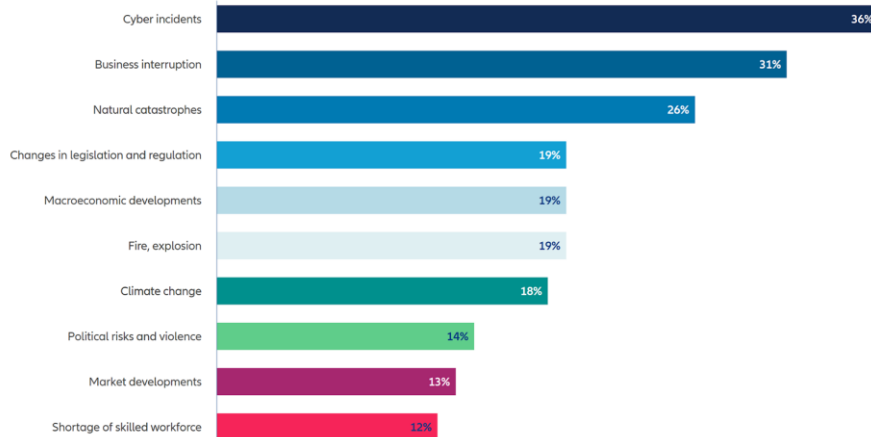
CYBERSECURITY - The Most Important Business risk



The most important business risks in 2024: global

Allianz Risk Barometer 2024

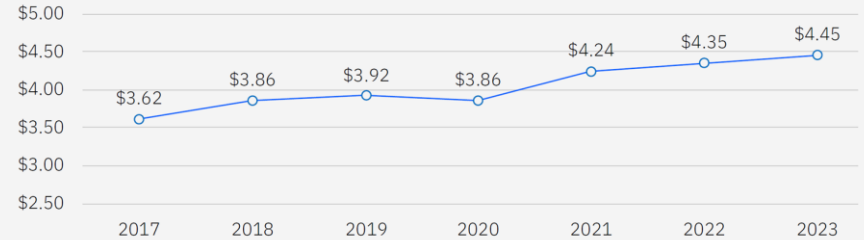
Figures represent how often a risk was selected as a percentage of all survey responses from 3,069 respondents. All respondents could select up to three risks per industry, which is why the figures do not add up to 100%.



Source : Allianz Risk Barometer 2024

Total cost of a data breach

million



Investing now can save millions

USD 4.45 million

The global average cost of a data breach in 2023 was USD 4.45 million, a 15% increase over 3 years.

51%
51% of organizations are planning to increase security investments as a result of a breach, including incident response (IR) planning and testing, employee training, and threat detection and response tools.

USD 1.76 million

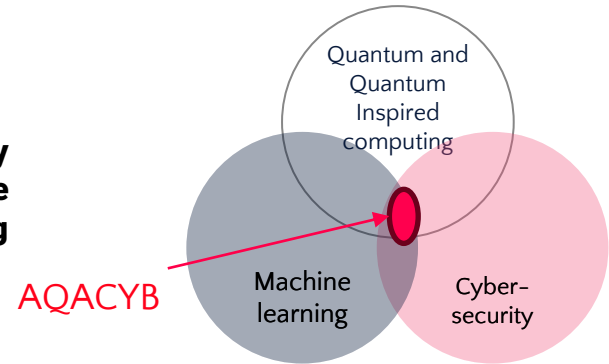
The average savings for organizations that use security AI and automation extensively is USD 1.76 million compared to organizations that don't.

Source : IBM Security Report 2023

PROJECT OBJECTIVE

Allianz, an insurance company, recognizes the importance of cybersecurity and is leveraging AI to prevent cyber threats. As part of this effort, they are exploring the potential benefits of quantum algorithms in improving cybersecurity threat detection.

Develop a product for threats detection in cybersecurity. Based on an AI model leveraging quantum and MULTIVERSE quantum-inspired algorithms applied in IQM QPU.



AQACYB 3 PARTNERS - 1 AIM



Allianz 

Global player and European leader in insurance



IQM *France*

Pan-European leader in the construction of quantum computers



MULTIVERSE

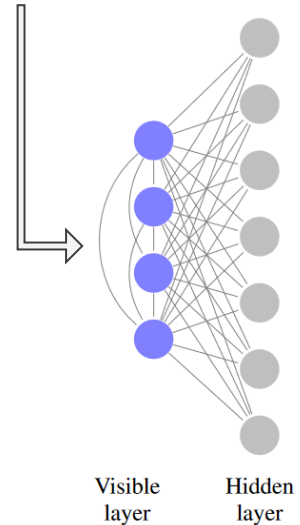
European leader in the development of quantum and quantum-inspired software

RELATED WORKS

Despite project time lag, AQACYB partners have been involved in other cyber projects e.g. Allianz and LMU explored unsupervised anomaly detection with *quantum Boltzmann machines*.

- EDR inspired synthetic dataset.
- Quantum Annealing based implementation.

Results: QBMs can outperform classical models (training steps and result quality).
Still not achieved with current QPUs.



Gate based implementation

1. Same QBM not feasible with limited number of qubits.
2. Different generative model to compare results on same dataset.

Exploring Unsupervised Anomaly Detection with Quantum Boltzmann Machines in Fraud Detection

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Keywords: Quantum Boltzmann Machines, Quantum Annealing, Anomaly Detection

Abstract: Anomaly detection in Fraud Detection and Response (EDR) is a critical task in cybersecurity programs of large companies. With rapidly growing amounts of data and the emergence of zero-day attacks, manual and rule-based detection techniques are no longer enough to protect. While classical machine learning approaches in this problem exist, they frequently show unsatisfactory performance in differentiating malicious from legitimate activities, a pressing approach to detect specific generalizations from currently employed machine learning techniques are quantum generative models. Allowing for the largest representation of data in available quantum hardware, we investigate Quantum Annealing based Quantum Boltzmann Machines (QBM) for the given problem. We compare the new fully unsupervised approach for the problem of anomaly detection using QBM, and compare its performance to an EDR inspired generative model. Our results indicate that QBM can outperform their classical analogs. In combination with the hidden layer, the QBM can generate data and training steps in special cases. When exploring Quantum Annealing from D-Wave Systems, we conclude that other more generic classical simulators or alternative more QPU time is needed to conduct the necessary hyperparameter optimization allowing to replicate our simulation results on quantum hardware.

1 INTRODUCTION

Anomaly detection is the identification of abnormal behavior in data, which manifests in individual data points that differ significantly from the majority of the data (Chandola, El, 2008). This task frequently appears in many domains including finance, healthcare and cybersecurity (Alcázar et al., 2012; Spitzer et al., 2018; Kitzler, 2020), particularly challenging application of Anomaly Detection can be found in Fraud Detection and Response (EDR), which aims at detecting and investigating suspicious activities on endpoints such as mobile phones or workstations in cybersecurity (Katz et al., 2020). In practice, the respective networks can be composed of billions of nodes, generating an immense amount of data, which the search for extremely rare, malicious anomalies can be very tedious.

This vast number of typically high-dimensional data points and additional impediments such as irregular attack rates demand for suitable anomaly detection techniques deviating from the still widely-used manual and rule-based approaches. While many

classical machine learning approaches to this mostly unsupervised learning problem exist, (e.g., clustering (Mansour et al., 2015), autoencoders (Falk et al., 2021) or Bayesian networks (Klein et al., 2015)), the distinction between malicious and benign activities frequently remains unclear due to manual observations on a track-of-hackers, detecting or simulating high number of false positives, too. Available data and failing to reliably detect all true positives (i.e., the detection accuracy).

In search for alternative approaches that can cope with the exponential real world data sizes, we investigate the application of Quantum Computing (QC) to this problem, as QC has shown promising performance in generative data modeling, which is a popular, as well as the search for unsupervised anomaly detection in that their core functionality of replicating a given data distribution yields a data model that closely represents the input dataset with the exclusion of all anomalies, as they are not seen as to be learned

RELATED WORKS

Despite project time lag, AQACYB partners have been involved in other cyber projects e.g. Multiverse has developed solution with quantum-inspired solutions (TN) and Qboost.

Tensor Networks for Explainable Machine Learning in Cybersecurity

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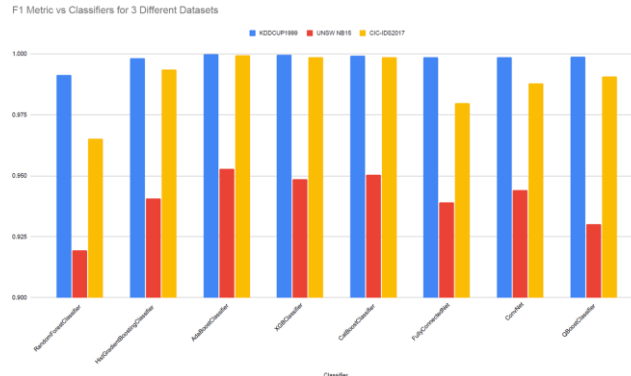
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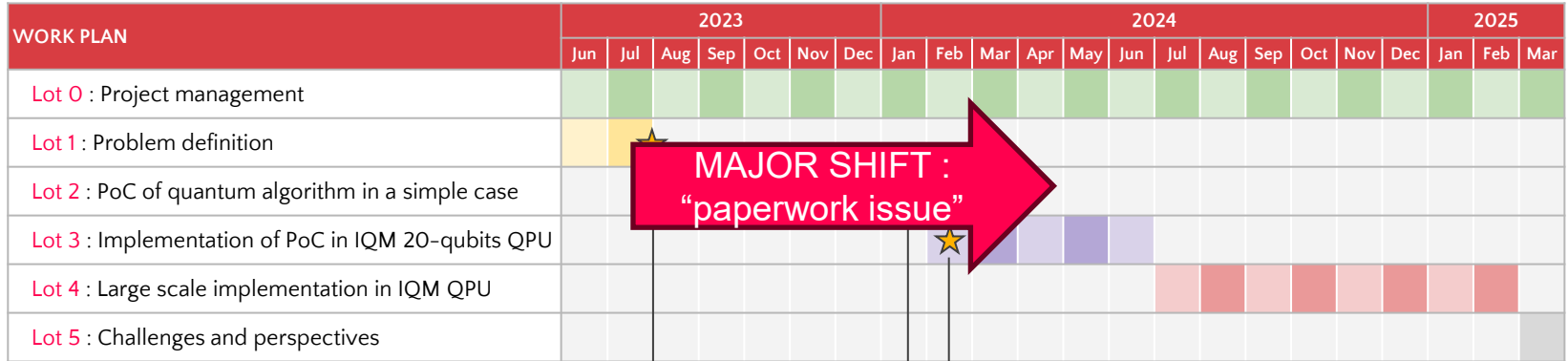
⁵Iker



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TIMELINE OVERVIEW



MAJOR SHIFT :
“paperwork issue”

Use-case selection

IQM 20 qubits available

Model working

Lot 0
Coordination
plification of the
project

All project long

Lot 1
Analysis, definition
and selection of use-
cases. Literature
review, data
preparation and
algorithm selection

2 months

Lot 2
Development of
selected algorithms.
Adaptation to IQM
hardware (co-
design). Use of IQM
simulator

6 months

Lot 3
Implementation in
IQM 20-qubits QPU.
Reduced dataset
comparison and full
scale analysis

5 months

Lot 4
Full scale
implementation in
IQM machine.
Benchmarks against
Allianz current
solution.

8 months

Lot 5
Bottlenecks
identification.
Deployment and
integration analysis.

1 month

NEXT STEP

Allianz red team is building a specific dataset

Accordingly envisaged approaches, quantum machine learning models, will highly depend on the problem type **unsupervised vs supervised**, the **data quality** and the different attributes of the dataset (**imbalance, size, etc.**):

	Classical (Benchmarking)	Quantum and Quantum-Inspired
Supervised	Random Forest & Boosting methods. Additionally, fully connected neural networks (FCNN) and convolutional neural networks (CNN)..	QBoost, quantum neural networks, VQA, etc
Unsupervised	DBSCAN, SVM, Variational Autoencoders, Isolation Forest, GAN.	TN-based GM

→ Approach will depend also on what we can do with the IQM QPU, the IQM simulator and the **superconducting quantum circuits** (e.g. adaptation of Allianz & LMU work on IQM QPU).

→ The exploration of highly innovative approaches could also potentially surpass the methods described above.



Thank you !