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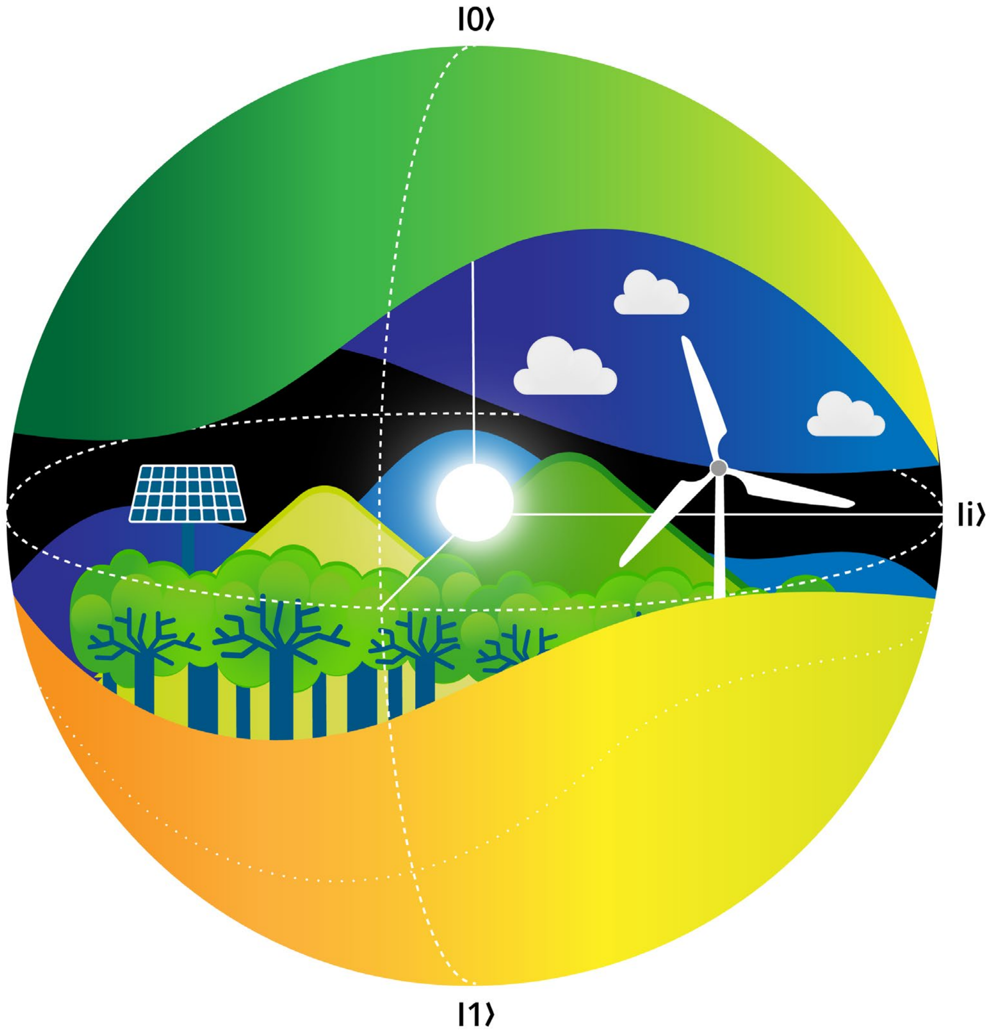

Deloitte's Quantum Climate Challenge 2024

Flood Prediction

Goal of the challenge

Deloitte's Quantum Climate Challenge 2024 aims to explore the potential of quantum computers in enhancing flood forecasting to improve climate resilience. Climate change has amplified the urgency of disaster prediction in recent years. Rising temperatures and shifting weather patterns have led to more intense floods, wildfires, and other extreme events. As our climate becomes increasingly volatile, accurate forecasting of extreme events can be the difference between life and death.

To advance disaster prediction methods, the challenge seeks to explore the application of Quantum Machine Learning (QML) for forecasting floods along the Wupper River in Germany. The challenge aims to develop a new approach in predicting river floods, leveraging nascent quantum computing technologies. By doing so, it endeavors to assess the prerequisites for quantum hardware to significantly enhance disaster prediction on a larger scale and to gauge the potential timeframe for its implementation.

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Due to the limitations of currently accessible quantum hardware, the goal of the challenge is two-fold:

1. Develop and train quantum models for next-day flood predictions
The primary focus lies on developing and improving a model that uses quantum computers. Due to limitations of current quantum hardware, we do not expect models to outperform classical models at this stage.

2. Devise a path for handling more complex problems
Here, the focus lies on developing a concept for quantum or hybrid methods that may assist the improvement of flood prediction models on further advanced quantum computers. The central objective is to extend lead times for advanced warnings and to enhance the efficacy of disaster preparedness measures.

This document provides background information on natural disaster occurrence because of climate change, the relevancy of flood prediction, and a brief introduction to QML in addition to the description of the challenge's tasks.

Higher frequency and intensity of natural disasters because of climate change
The surge in global temperature has transitioned from a mere prediction to an unsettling reality. In 2023, we witnessed a noteworthy elevation in global surface temperature of +1.18°C compared to pre-industrial times.[1] This unfolding climate crisis is unequivocally a consequence of human activities, notably the emission of greenhouse gases and the disruptive modifications inflicted upon earth's natural climate system, such as rampant deforestation. The repercussions of escalating global temperatures are profound, causing disruptions in atmospheric and oceanic systems, resulting in rapidly shifting weather patterns.

One of the most pressing outcomes of these environmental transformations is the heightened frequency and intensity of various natural disasters. A stark illustration of this escalating trend emerges from the data reported by the United Nations, which documents a staggering 7,348 natural disasters between 2000 and 2019. This stands in severe contrast to the preceding two decades, where a comparatively modest 4,212 disasters were recorded – representing an almost two-fold increase in the occurrence of such calamities.[2] The numbers underscore the urgency with which we must address and rectify environmental imbalances that contribute to escalating frequencies and severity of natural disasters.

We need to develop a new resiliency facing the increase in natural disasters caused by the climate crisis.

[1] "climate.gov Global Temperature" 2024. [Online]. Available: https://www.climate.gov/news-features/understanding-climate/climate-change-global-temperature. [Accessed January 2024].
[2] "UNDRR: Disaster cost" 2020. [Online]. Available: https://www.undrr.org/publication/human-cost-disasters-overview-last-20-years-2000-2019. [Accessed January 2024].

Extreme weather

One of the most apparent manifestations of climate change is the intensification of extreme weather events. As the atmosphere temperature rises, air can hold more moisture, leading to heavier rainfall during storm events. Conversely, in other regions, the warmer atmosphere can exacerbate evaporation rates of water to the atmosphere, contributing to drier conditions and increased incidences of droughts. In 1990, the likelihood of a severe rainfall storm in Texas annually stood at 1%, climbing to 6% by 2017 and is now projected to surge to 18% by 2100.[3]

The occurrence rate of more extreme weather events is further influenced by sea surface temperature rise. The ten warmest recorded years have all occurred since 1997.[4] This is a notable factor in the intensification of tropical storms and hurricanes since warmer waters provide more energy to these systems, potentially increasing their frequency and severity. Moreover, changes in atmospheric circulation patterns have the potential to redirect storms along unconventional paths, occasionally bringing them to regions ill-equipped for such occurrences.

Climate change is also influencing the distribution and behavior of high and low-pressure systems, which in turn affect the prevailing wind patterns. These changes can disrupt established weather patterns, leading to unseasonal weather events such as unexpected cold snaps or heatwaves.

Forecasting storms is of paramount importance to enable regions to make necessary preparations. Residents can take measures to secure outdoor belongings, reinforce windows and doors, and stock up on essential supplies - medicine, batteries, food, and first aid materials. In the most severe circumstances, evacuation may become necessary.

Droughts

The impact of droughts is profound, affecting both human and natural systems. Agricultural sectors are especially vulnerable, with droughts leading to reduced yields, crop failures, and, subsequently, financial losses. Additionally, aridities can exacerbate water scarcity issues, impacting communities and ecosystems alike. While droughts had an impact on human history for millennia, there are climate change-related factors leading to vastly increased occurrence and severity of droughts. Changes in weather patterns can result in diminished rainfall and accelerated evaporation of surface water in any given area. This leads to a reduction in soil moisture over time, as more water exits the soil, and less rain replenishes it. Decreased snowpack and earlier snowmelt in mountainous regions may also heavily affect the timing and availability of water resources, particularly in regions dependent on snowmelt for their water supply.

It is likely that within this century, Southwestern South America, Mediterranean Europe, and Northern Africa will face unprecedented aridity lasting several years.[5] As droughts and extreme rainfall become more frequent, predicting their occurrence becomes increasingly vital for enhancing resilience to impacts to humans, flora, and fauna. Timely prediction can enable the conservation of water reserves in advance and enable transport to depleted regions, diminishing the impact during dry periods.

Wildfires

The increasingly arid landscapes are significantly more susceptible to wildfires. Reduced levels of forest and soil moisture, coupled with climate-induced pest outbreaks that weaken forests, create favorable conditions for wildfires to ignite. Their incidence has surged in recent decades. From 1984 to 2000, the average annual loss was only 1.69 million acres, but in the subsequent following 17 years, this average nearly doubled to 3.35 million acres.[6]

The repercussions of escalating wildfires are multifold. Ecosystems face severe disruptions, while human communities grapple with loss of life, property, and a veil of hazardous air quality shrouding regions in smoke. Prediction of wildfires can give emergency response teams a swift start to initiate containment efforts, minimizing disastrous impacts to local communities.

[3] "Assessing the present and future probability of Hurricane Harvey's rainfall," Kerry Emanuel, [Online]. Available: https://www.pnas.org/doi/full/10.1073/pnas.1716222114. [Accessed January 2024].

[4] "An Overview of Ocean Climate Change Indicators: Sea Surface Temperature, Ocean Heat Content, Ocean pH, Dissolved Oxygen Concentration, Arctic Sea Ice Extent, Thickness and Volume, Sea Level and Strength of the AMOC (Atlantic Meridional Overturning Circulation)" frontiers. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fmars.2021.642372/full. [Accessed January 2024].

[5] "The timing of unprecedented hydrological drought under climate change" nature, Yusuke Satoh et al. 2022 [Online]. Available: https://www.nature.com/articles/s41467-022-30729-2. [Accessed January 2024].

[6] "Increasingly frequent wildfires linked to human-caused climate change" University of California, 2021 [Online]. Available: https://www.sciencedaily.com/releases/2021/11/211105114305.htm. [Accessed January 2024].

River flooding
Background

This challenge focuses on floods, more specifically, river floods. They are natural events that occur when water levels in rivers rise and overflow their banks. These events can be triggered by various factors such as intense rainfall, rapid snowmelt, ice jams, and the failure of man-made structures like dams and levees. The dynamics of river floods involve not just meteorological factors but also hydrological processes and human activities.

Climate change is intensifying the frequency and severity of river floods through several mechanisms. As global temperatures rise, the atmosphere retains more moisture, resulting in heightened instances of heavy precipitation. This has been observed in numerous regions where intense rainstorms have become more common, resulting in rivers receiving large amounts of water in short periods. This again leads to an increase in river floods.[7] Additionally, warmer temperatures contribute to more rapid snowmelt, particularly in mountainous regions, which can lead to sudden increases in river flow during spring. Furthermore, climate change alters weather patterns, influencing jet streams and fostering extreme weather events, which can induce prolonged rainfall or drought conditions. The latter harden the soil, reducing its ability to absorb water, resulting in increased runoff into rivers and a greater likelihood of flooding. Sea-level rise, another consequence of climate change, also exacerbates river flooding, particularly in coastal and delta regions, by elevating base levels in rivers, reducing their capacity to accommodate overflow and heightening the risk of flooding.

Out of 52 floods studied, which took place between 1951 and 2010, 20 flood events were influenced by human-induced climate change. While earlier floods were occasionally mitigated by climate change, floods that occurred between 2001 and 2010 were consistently intensified.[7]

Human activities exacerbate these natural processes. Urbanization and land conversion for agricultural use have increased runoff by reducing the amount of land covered by vegetation that can absorb rainfall. Poor land management, deforestation, and the destruction of wetlands, which serve as natural sponges, also contribute to heightened flood risk.

The impacts of river floods are widespread, affecting ecosystems, human health, infrastructure, and economies. Floodwaters can contaminate drinking water supplies, destroy crops, and cause property damage and lead to loss of life. They can also displace populations, leading to long-term social and economic hardships. Mitigation strategies to reduce the impact of river floods in the context of climate change are vital. These include investing in flood defenses, restoring natural landscapes such as wetlands and forests, and improving water management systems. Adaptation endeavors, particularly the development of early warning systems, as emphasized in this challenge, are crucial. Besides these long-term strategies, short-term responses are also essential. With a longer warning period, the loss of life and economical damage can be drastically reduced. In some cases, prolonged warning periods may avert floods altogether by utilizing dams and reservoirs to modify water distribution.

[7] "Enhancement of river flooding due to global warming" University of California, 2021 [Online]. Available: https://www.nature.com/articles/s41598-022-25182-6#:~:text=Human,streamflow%20process%2C%20the%20historical%20impact. [Accessed January 2024].

Warning systems

Predicting river floods is a complex task that involves the analysis of various hydrological, meteorological, and geographical factors. Advances in technology and data analysis have significantly improved the ability to forecast such events, potentially saving lives and minimizing economic damage.

The prediction process begins with monitoring rainfall patterns through radar technology and satellite imagery. Hydrologists use this data to estimate the amount of rainfall that will contribute to a river's flow. They also assess the ground's saturation levels, which affect how much rainfall will run off into the river rather than being absorbed by the soil. River gauge data is another critical component. Gauges measure the water level and flow rate, providing real-time data that can be compared against historical trends. This information, combined with rainfall data, helps to create a picture of current conditions versus expected norms. Geographical information systems play a crucial role by mapping the terrain surrounding rivers. These systems can identify changes in the landscape, such as new construction or deforestation, which might affect runoff patterns and the river's ability to absorb water.

Predictive models, which are mathematical representations of the river systems, integrate cast datasets to simulate various scenarios. These models can be quite sophisticated, incorporating the effects of dams, levees, and natural riverbanks. As they run, they predict how different factors will interact and what levels of flooding might occur. Meteorological forecasting is a crucial part of this prediction model. Weather predictions help determine the likelihood of future rainfall and its potential impact on river levels. Forecasters use these models to issue flood warnings and alerts, affording communities to prepare or evacuate if necessary.

Challenges

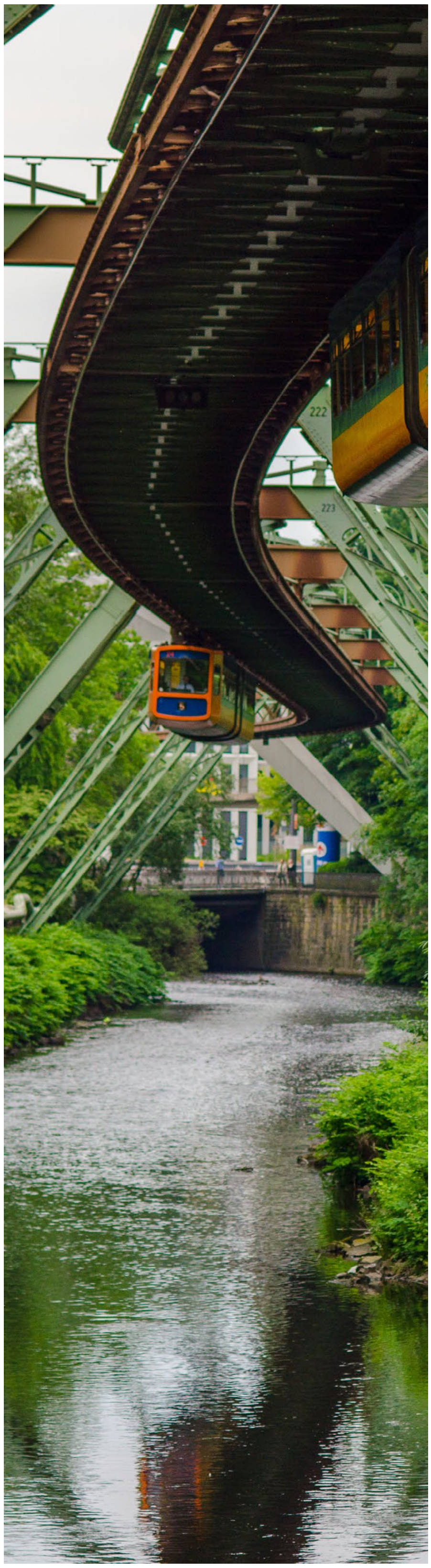
The task of predicting river floods is becoming increasingly challenging due to climate change. More frequent and severe weather patterns mean that historical data may no longer offer a reliable basis for prediction models. As a result, scientists are continually refining models to incorporate new data and emerging patterns. Furthermore, human activity, such as urban development and changes in land use, can alter water flow and absorption, necessitating continuous monitoring and model adjustment.

Predictive accuracy also depends on the timeliness and quality of data. In remote areas, data collection may be more challenging, resulting in less accurate predictions. Investing in data collection infrastructure, such as additional river gauges and enhanced satellite coverage, can improve prediction capabilities.

The Wupper River in Germany

This challenge will focus on developing a flood prediction model using the Wupper River in Germany as a case study. The Wupper River, a mid-size 116 km-long river in the western part of Germany, serves as the right tributary of the Rhine, encompassing a catchment basin totaling 813 km². Originating near Marienheide, it flows into the Rhine near Leverkusen, south of Düsseldorf. Notably, the region includes the city of Solingen, renowned worldwide for its knife grinding manufacturing. In 2021, the Wupper flooded Solingen, causing significant damage to many historical grinding manufactories. With its history of flooding, the Wupper presents an interesting case study whose results could be used to examine similar sized rivers.

To simplify the challenge, the occurrence of floods at solely the Kluser Brücke measurement station will be predicted. Kluser Brücke, located in the middle of Wuppertal, has been used to operate a dam and reservoir since its construction in 1989. There are 30 years of water level data for Kluser Brücke.



Predictive machine learning models

Machine Learning (ML) is a subfield of Artificial Intelligence (AI) that uses algorithms trained on datasets to create models. Unlike traditional programming, where a programmer defines explicit rules, ML models can perform tasks (semi-)autonomously that would otherwise only be possible for humans. Additionally, algorithms enable the system to learn and develop from given data to make decisions or predictions without being explicitly programed to do so. Possible tasks could include categorizing images, predicting pricing fluctuations, and many more.

ML is widely used in various fields, from medical diagnosis and financial modeling to speech recognition and autonomous vehicles. Its ability to extract insights from large volumes of complex data and improvement of performance over time makes it a powerful tool in the modern technological landscape. However, it also faces challenges such as data privacy, ethical considerations, and the need for large amounts of data to train sophisticated models.

At the core of ML are algorithms, which are sets of rules or instructions that the computer follows to process data and learn from it. These algorithms can be categorized broadly into three types: supervised learning, unsupervised learning, and reinforcement learning.

Supervised learning

This is currently the most prevalent form of ML. Here, the algorithm is trained on a labeled dataset. This means that the data is already tagged with the correct answer or outcome. The algorithm analyzes the training data to learn how to make predictions or decisions. An example of supervised learning could be an algorithm that is trained to recognize cats in photographs by being shown thousands of labeled images of cats and non-cats.

Unsupervised learning

Here, the algorithm is trained using data that is not labeled. The algorithm tries to find patterns and relationships in the data on its own. A common application of unsupervised learning is clustering, where the algorithm groups data based on similarities. For example, the algorithm might group customers into different clusters based on their shopping habits.

Reinforcement learning

This is about making sequences of decisions. The algorithm learns to achieve a goal in an uncertain, potentially complex environment. In reinforcement learning, an agent makes decisions, observes the outcomes, and receives rewards or penalties. This process helps the agent learn the best strategies over time. A classic example is a computer program learning to play chess or a video game by continuously playing matches.

There are additional concepts integral to ML, including:

Neural networks

These are inspired by the human brain and, as such, consist of layers of interconnected nodes. Each node represents a mathematical function. Data is processed through the layers of nodes, enabling the network to learn complex patterns. Deep learning, a subset of ML, involves neural networks with many layers, which makes deep learning adept at processing large amounts of complex data, such as images and speech.

Overfitting and underfitting

Overfitting occurs when an algorithm learns the training data too well, including the noise and outliers, making it perform poorly on new, unseen data. Underfitting is a result of an oversimplified model that fails to capture the underlying trend in the data.

Time series predictions

Time series prediction using ML involves analyzing sequential data to forecast future events. This data is typically organized in chronological order. Flood forecasting can be classified as a type of time series prediction.

A key characteristic of time series data is its temporal dependence, meaning the data at a given time is often dependent on previous data and reoccurring patterns, if existing, in the previous data. ML models for time series prediction are designed to capture these dependencies.

Feature engineering is crucial in time series prediction. It involves creating new, temporal inspired input features, such as lagged values, rolling averages, and aspects of time itself (day of the week, month, etc.).

Time series prediction in ML faces unique challenges, such as dealing with seasonality trends and making predictions in the face of concept drift or changing data patterns. The end goal of time series prediction is to create a model that generalizes well and can make accurate predictions on future, unseen data.

Quantum machine learning

Quantum Machine Learning (QML) combines quantum computing with machine learning. This fusion aims to leverage the computational prowess of quantum computers to solve complex machine learning problems more efficiently than classical computers. While there have been explorations of pure quantum machine learning algorithms, QML today typically describes the approach of enhancing classical machine learning techniques with quantum computing. Of the current QML approaches, Quantum Support Vector Machines (QSVMs) and Quantum Neural Networks (QNNs) are the two key areas where quantum computing is thought to significantly improve classical algorithms.

Quantum support vector machines

Classical Support Vector Machines (SVMs) are a machine learning technique for classification tasks, where they identify the optimal hyperplane that segregates different classes in a dataset. When a hyperplane can't separate datasets correctly, a kernel is used to cast the feature space in a higher dimensional manifold. Then, a hyperplane is created, and the points are evaluated. QSVMs instead utilize quantum algorithms, such as the quantum version of kernels, to easily cast data in a higher manifold.

In a QSVM, quantum states represent the data points and quantum operations are employed to compute the inner products necessary for the SVM algorithm. This can significantly reduce computational complexity and potentially offer exponential speedups in certain applications.[8] When dealing with high-dimensional data, classical SVMs encounter a computational bottleneck due to not being able to reach the needed dimension to create a hyperplane that separates the data points. This bottlenecking of classical SVMs highlights the importance of QSVMs due to their computational complexity reduction and exponential speedup capability.

Quantum neural networks

Quantum Neural Networks (QNNs) represent another opportunity for machine learning advances through quantum computing. Inspired by classical neural networks, QNNs aim to harness the principles of quantum mechanics for learning tasks. QNNs process and store information in a more intricate manner than classical NNs using quantum bits (qubits) instead of classical bits.

The intricacy of QNNs is due to their ability to exploit quantum superposition and entanglement, leveraging the non-locality characteristic of qubits, while processing a vast amount of data with a low overhead. This property is not available to classical neural networks. Additionally, quantum gates, analogous to the linear layering of classical networks, manipulate these qubits and enable complex transformations during the learning process.

Overall, QNNs have the potential to revolutionize deep learning by offering solutions to problems that are currently difficult for classical neural networks. Problems suited for QNNs could include handling datasets with intrinsic quantum properties, solving complex optimization problems quickly, and many more.

Quantum machine learning frameworks

Guides and tutorials on the most used, freely available frameworks for using and creating QML models can be found here:

Tab. 1 – Overview of Quantum Machine Learning Frameworks

Framework	Publisher	Basis
Qiskit-Machine-Learning	IBM	Qiskit
TensorFlow Quantum	Google	Cirq
Q#Machine Learning	Microsoft	Q# Quantum Developer Kit
Pennylane	Xanadu	Pennylane (useable with Amazon Braket)

[8] "Quantum algorithms for supervised and unsupervised machine learning" Seth Lloyd, Masoud Mohseni, Patrick Rebentrost, 2013. [Online]. Available: https://arxiv.org/pdf/1307.0411.pdf. [Accessed January 2024].

Challenge tasks

Quantum machine learning models can be created using hybrid classical-quantum computation in a myriad of ways. To reduce the complexity of the challenge to a level that is manageable in the given time frame, we have simplified the problem.
It is highly encouraged to analyze the problem as a whole and deviate from these simplifications to further improve performance of the calculations and the fit of the calculated solution. It is sufficient to solve the challenge using the simplifications. However, producing a solution to a higher complexity problem will raise the likelihood of achieving a good ranking.

Details on how to access the simulators and quantum computers (on IBM Quantum, Nvidia and Amazon Braket) as well as the data provided by the Wupperverband can be found on the Resources tab of the challenge webpage. The details and data are only visible for registered participants of the challenge.

Once registered for the challenge, to successfully complete this challenge, you need to perform the following tasks:

Task 1A Create a quantum algorithm, a (hybrid) quantum machine learning model, that predicts if a flood is happening on each day of 2023. To reduce the complexity, you can assume that a water level above 90 cm is a flood. Run your algorithm on a quantum computer or simulator and provide information on the resource requirements of your solution (e.g., total number of shots, compute time, etc.)

Task 1B Evaluate your solution, describing the advantages and disadvantages of your approach(es). Evaluate the performance differences between your solution and classical approaches. Use at least the following evaluation criteria:

- **Training time**

- **Accuracy of all predictions for the year 2023, including:**
  - In relation to a classification:
    - False-Positive
    - True-Positive
    - False-Negative
    - True-Negative

  - **In relation to a water level forecast:**
    - Mean-Absolute-Error
    - Mean-Squared-Error

- **Learning curve (for models using epoch training)**

Task 2A Conceptualize a quantum or hybrid solution that will scale the calculation to achieve a more general/advanced model.

Task 2B Discuss the requirements for your solution to 2A to be implemented in real quantum computers. Give an estimate for the time horizon at which implementation may become feasible. Examples of requirements include: the number of logical qubits needed, coherence times, etc.

Task 3 Compile a report (as a single *.pdf file) that includes a short problem statement, your solution, and a detailed explanation for how you solved it. Give an overview of your research and the resources used during the challenge, provide *.csv or *.xls files for all data resulting from the calculations in your report and supply your comprehensively commented code (in either a repository or file.)

Ideas to increase problem complexity:

- Collect additional publicly available data that might be useful for the model and integrate them.

- Increase the time span between when a flood forecast is made and the time of the flood. You could, for example, predict the next three/seven/ten days at any point in time.

- Predict water levels or water level intervals instead of a binary outcome.

- Add additional evaluation criteria that might be useful.

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