Bringing the power of Quantum Computing to Earth Observation

Bertrand Le Saux

ESA ESRIN Φ-lab

15/11/2022

Apollo 17, 1972


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sentinel-6
European Space Agency

High-Performance Computing / Quantum Computing

QC4EO: AI-enhanced Quantum Computing for EO

Today’s talk

1. Roadmap definition (QC4EO study)

2. QML and QC Exploratory activities

3. QC4EO Network

1. Roadmap definition (QC4EO Study)

The ESA Φ-lab@ESRIN

Accelerate the future of Earth Observation
via **transformational innovation***
strengthening Europe's world-leading **competitiveness**

*transformational innovation: with the ability to completely transform or create entire industries via new technologies

Why Quantum Computing for Earth observation?

- Strategic vision, with long term application
    - Seize the potential of QC as a transformative tech
    - Benefit from and contribute to the huge, global effort around HPC and QC

- Identify potential use-cases among EO applications

  From signal / image / data processing to weather forecast, climate change monitoring, sustainable development goals, green energy, distributed computing…
- Prepare workforce and develop the agency architecture to exploit HPC / QC
- Experiment with EO data and modular HPC to inspire creativity and unlock innovation
- Develop a network of experts and talents aware of specificities of both fields

Defining a QC4EO Roadmap

- Are there any problems that quantum computing could solve more efficiently?
- What kind of advantage can be expected:

  speed-up, optimal solutions, better modelling, energy efficiency ?

1. How could Quantum Computing (QC) bring a “quantum advantage” to Earth Observation (EO) Science & Applications?
2. What are the "relevant" EO problems that could be solved by QC “faster” or “better” than any known classical algorithm on the best classical computer?
3. What kind of “hybrid” computing paradigm would be needed to deliver such quantum advantage?
4. By when would it become possible?

QC4EO Study ITT and contract

- Invitation to tender run in 2022 → https://doing-business.sso.esa.int/
- Selected consortium to be announced soon!
- Study will contribute to define ESA EOP roadmap on QC/HPC

Objectives:

- ***Identify use cases relevant to the Earth Observation domain****, for which QC is expected to dramatically enhance computational performances with respect to traditional methods in the short and longer term.*
- ***Provide options for QC or hybrid machine architectures*** *required to solve the identified QC4EO use cases, with the relevant sizing, e.g. in term of Qubits.*
- *Perform a* ***maturity and forecast assessment of the QC machine industry roadmaps****; and*
- ***Derive a credible QC4EO timeline of use cases*** *that could take advantage of a QC approach*

2. Exploratory activities in QML and Quantum Computing

Exploratory activities in QML and Quantum Computing

Investigating QML with EO data (~ multispectral images, time-series) = **general purpose QML**

- ➢ Many challenges!

- Challenge 1: All data is big wrt. NISQ devices → How to compress/reduce it for quantum processing?
- Challenge 2: How to transfer classical data to quantum?
- Challenge 3: How to define efficient hybrid architectures / circuits ?
- Challenge 4: How to make the most of the various hardware architectures ?

Through currently 2 main axis of research:

- ✓ **Quantum Kernels (Projected Quantum Features, SVMs…)**
- ✓ **Hybrid Classical Quantum Networks (Quantum Convnets, Recurrent nets)**

Exploratory activities in QML and Quantum Computing

Past/ongoing projects:

- 2021: QML (Quantum Neural Networks) for Classification of EO data, with Uni Sannio (IT)

- 2022-2023: QML for Classification of EO data (spectral info, change detection), with CAMK (PL)
- 2021-2024: Generative Modelling of EO data for classification and synthesis, with CERN (CH)
- 2022-2025: Hybrid Supercomputing-Quantum processing of EO data, with FZ Julich (DE)

Starting projects:

- 2022-2024: QML (Quantum Kernels) for Classification of EO data, with Jiagellonian Univ. (PL)
- 2022-2025: QML (Reservoir computing) for Time Series Processing, with CERN (CH)
- 2022-2025: Quantum Computing for Ground Motion Measurements, with Uni Bari (IT)

Exploratory activities on quantum kernels

Quantum Neural Networks for Spectral Information Processing

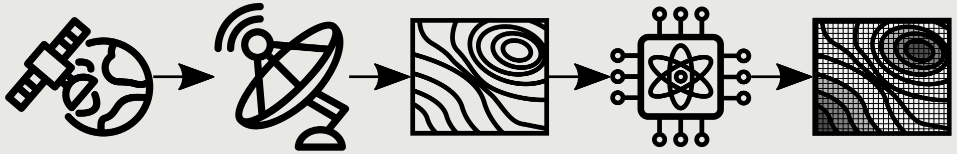
CAMK: Manish Gupta, Piotr Gawron

ASTROCENT

European Funds Smart Growth
Republic of Poland
FNP Foundation for Polish Science
European Union European Regional Development Fund

NICOLAUS COPERNICUS ASTRONOMICAL CENTER OF THE POLISH ACADEMY OF SCIENCES

Spectral Information Processing with Quantum Neural Networks (QNNs)



Problem Statement:

- ❑ EO data are geo-spatial information not a priori governed by quantum mechanics = classical data
- ❑ Known challenges: big data, representation learning for understanding

Research Question:

- ❑ What kind of classical and quantum resources (under what conditions) are needed to successfully apply QNN for spectral information classification and change detection?
- ❑ Is there a practical reason to use QNNs rather than classical classification techniques for spectral classification task?

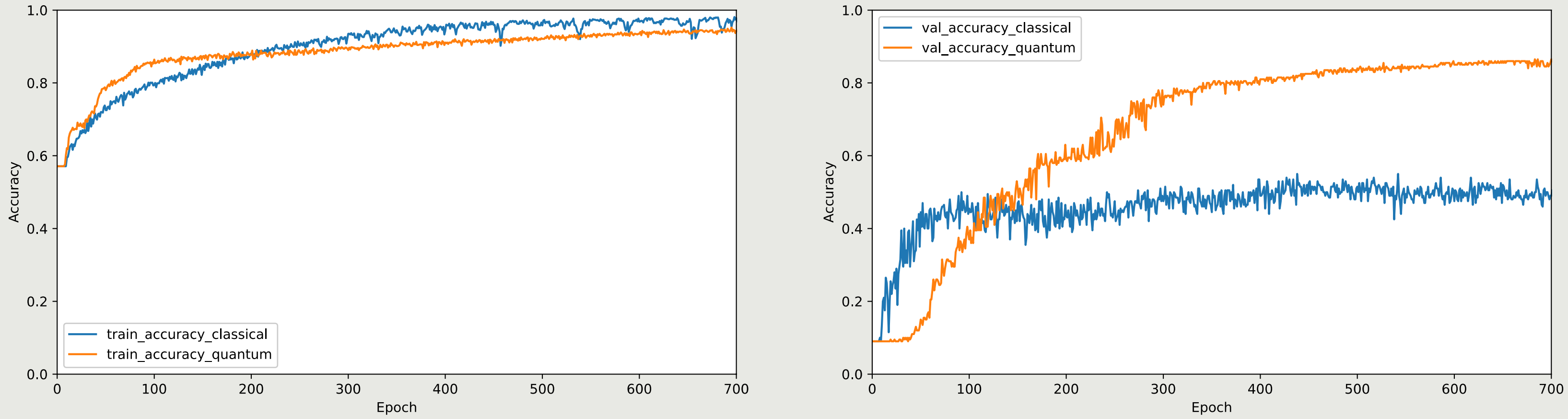
➢ Quantum features [1] obtained from quantum embedding may provide a significant prediction advantage in learning tasks!

[1] Huang et al, "Power of data in quantum machine learning", Nature Com 2021

Spectral Information Processing with Quantum Neural Networks (QNNs)

HOW QUANTUM COMPUTING-FRIENDLY MULTISPECTRAL DATA CAN BE ?

Gupta, Beseda & Gawron, "How QC-friendly multispectral data can be?", IGARSS 2022



Training and validation accuracy of feedforward neural network with and without access to quantum features for classes "Broadleaf tree cover" and "Herbaceous vegetation".

Result:

- ✓ Empirical study shows existence of artificial EO dataset that is easy for the quantum model and hard for the classical model to learn – that is, with good generalisation properties, regardless of network model architecture or training algorithms used.
- ✓ This study shows the potential for quantum machine learning methods to Earth Observation data and provides key evidence for further investigation.

Support Vector Machines With Quantum Kernels

Inst. Theor. Physics, Jagellonian Univ. in Crakow: Artur Miiroszewski, Jakub Mielczarek KP Labs &
Silesian University of Technology in Gliwice: Jakub Nalepa

JAGIELLONIAN UNIVERSITY IN KRAKÓW

KP LABS Mission Complete

Silesian University of Technology

SVMs with Quantum Kernels for EO data

Problem Statement:

- ❑ If quantum circuits can be seen as quantum kernels, but how to leverage them for EO data processing?

Research Question:

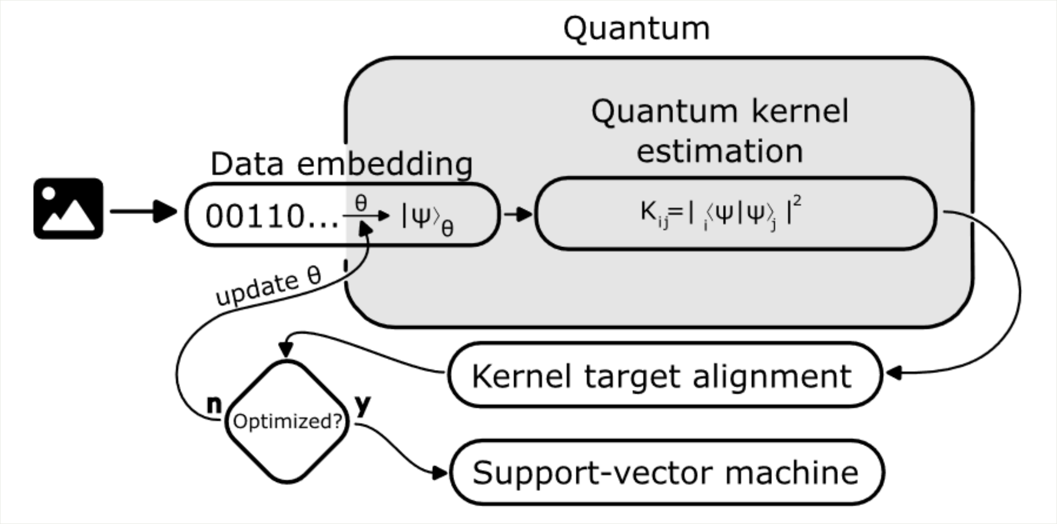
- ❑ How to parametrize a quantum circuit for suitable EO embedding?
- ❑ How to design a suitable (hybrid) architecture for learning with quantum kernels (e.g., SVM)?
- ❑ What advantage bring current NISQ devices e.g., gate-based quantum computers?

- ➢ Classical SVM optimisation framework + quantum circuit as kernel
- ➢ Quantum Kernel Alignment [2] as a kernel metric for optimizing circuit parameters

[2] Christiannini et al., "On Kernel-Target Alignment", NeurIPS 2001

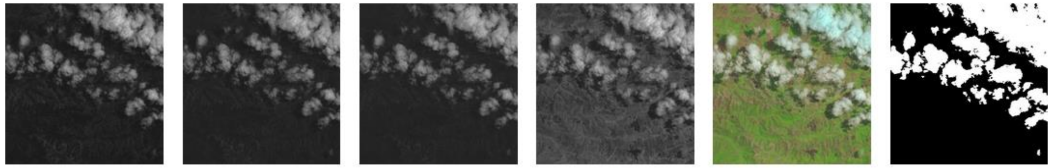
SVMs with Quantum Kernels for EO data

- ➢ Classical SVM optimisation framework + quantum circuit as kernel
- ➢ Quantum Kernel Alignment as a kernel metric for optimizing circuit parameters



Current take-home message:

- ➢ SVMs with the quantum kernel classification accuracy on par with classic SVMs with RBF kernel



Red Green Blue NIR False color Ground truth

	$\mathcal{T}_i$	$\mathcal{T}_f$	hSVM	SVM
Average	0.049	0.081	0.778	0.788
Standard deviation	0.018	0.024	0.038	0.029

Ongoing works:

- ❑ EO data encoding and embedding
- ❑ Moving to simulation to real NISQ devices

Miroszewski et al., “Multispectral Satellite Data Analysis Using Support Vector Machines With Quantum Kernels”, to appear.

Hybrid Quantum-Classical Processing Workflows in Modular Supercomputing Architectures

FZ Julich / Univ. of Iceland: Amer Delilbasic
Forschungszentrum Jülich: Gabriele Cavallaro, Kristel Michielsen

Hybrid Supercomputing-Quantum processing of EO data

Problem Statement

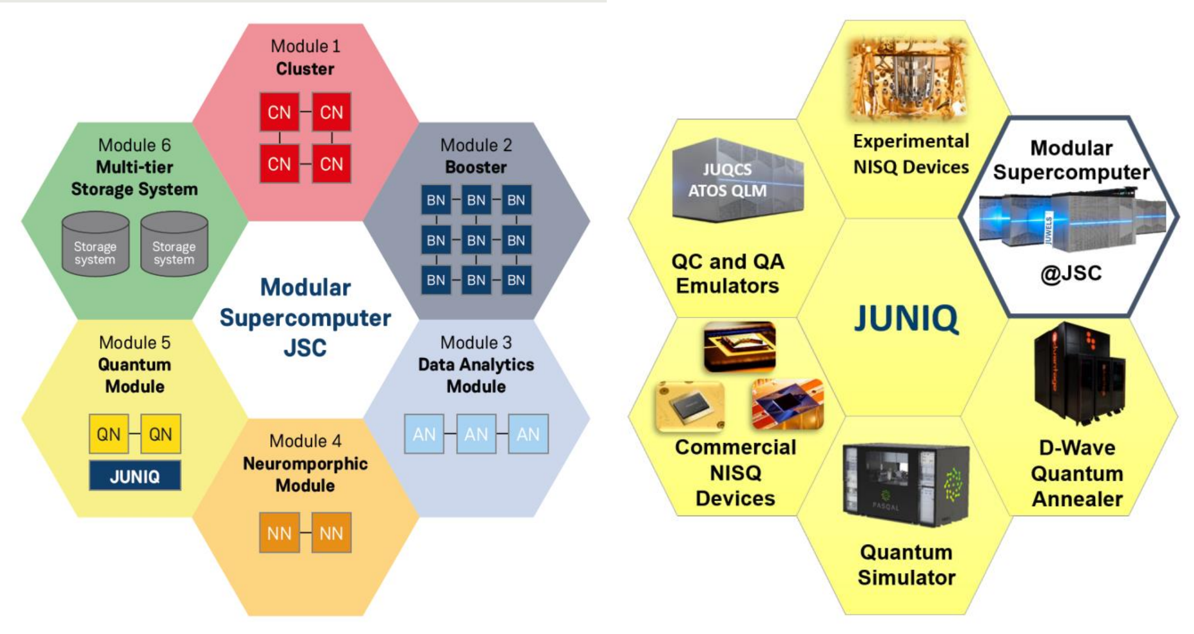
Big EO Data framework:
- Growing rate of collected data
- Need to extract timely and interpretable information
- Focus on enhancement of computing capabilities

→ Availability of advanced computing infrastructures at FZJ !

Modular Supercomputing Architecture (MSA)
- Union of specialized computing modules
- Optimized hybrid task decomposition

Jülich UNified Infrastructure for Quantum computing (JUNIQ)
- Access to multiple quantum computing systems

JÜLICH Forschungszentrum | JÜLICH SUPERCOMPUTING CENTRE



Research Question

"How effective is the combination of **supercomputing** and **quantum computing** for the development of parallel and scalable learning algorithms that can efficiently transform large amounts of remote sensing data into interpretable information?"

G. Cavallaro, M. Riedel, T. Lippert, and K. Michielsen, "Hybrid Quantum-classical Workflows In Modular Supercomputing Architectures With The Julich Unified Infrastructure For Quantum Computing," in Proceedings of the IEEE IGARSS, 2022 (accepted) https://www.fz-juelich.de/ias/jsc/EN/Expertise/JUNIQ/_node.html

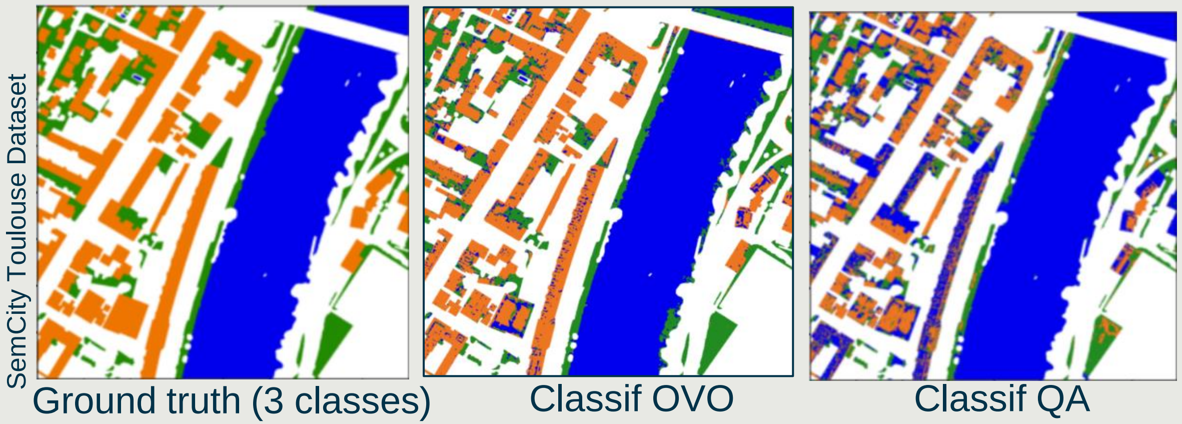
Hybrid Supercomputing-Quantum processing of EO data

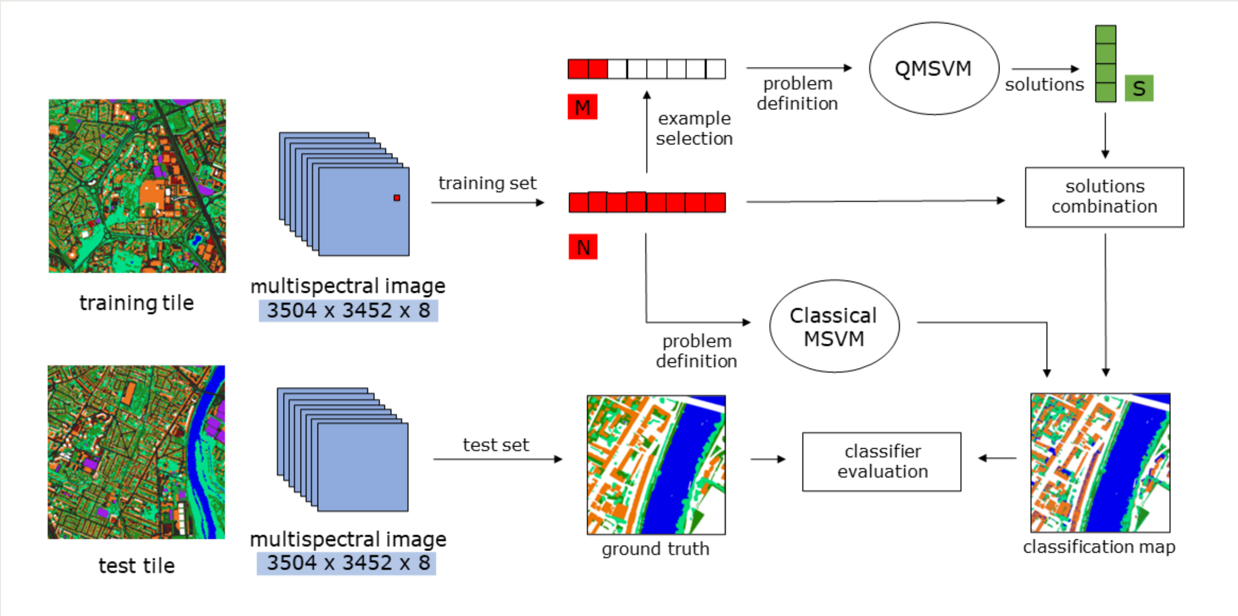
Classification of multispectral EO data on Julich SC Quantum Annealer

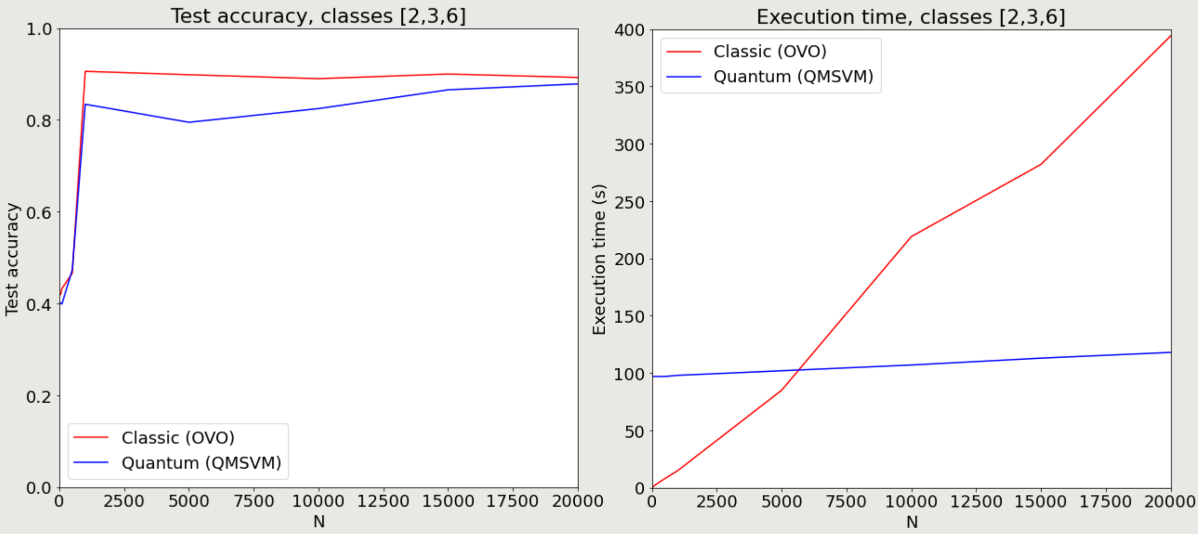
- Provides efficient optimization for specific problems (QUBO)
- Easy and flexible configuration using the Ocean library

Quantum Multiclass Support Vector Machine (QMSVM)

- Limited number of samples for Quantum optimization
- But execution times increase linearly!







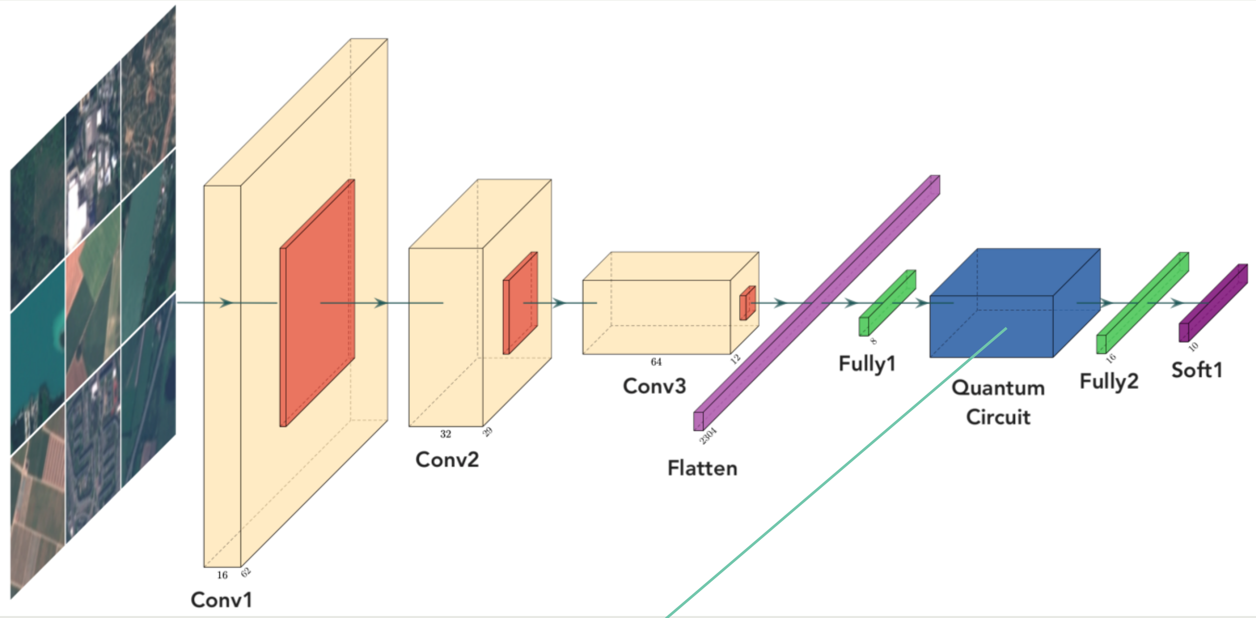
Delilbasic, Cavallaro, Le Saux, Riedel & Michielsen, “Multiclass SVM with Quantum Annealing”, ECML-PKDD QML ws 2022

Exploratory activities on hybrid quantum-classical neural networks

Satellite Remote Sensing through Machine Learning and Quantum Computing techniques

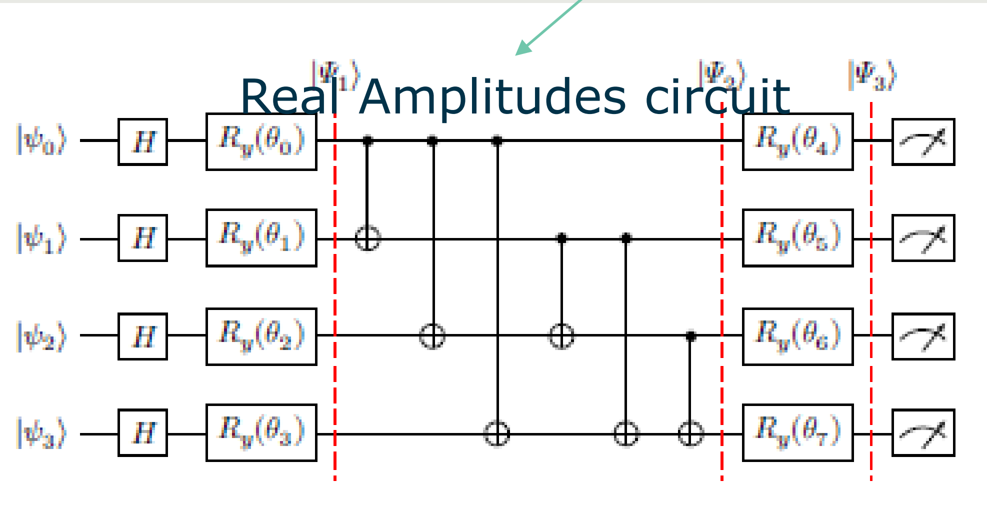
ESA Φ-lab / Uni Sannio: Alessandro Sebastianelli
MIT: Daniela Zaidenberg
ESA Φ-lab: Dario Spiller, Bertrand Le Saux
Univ. of Sannio: Silvia Liberata Ullo

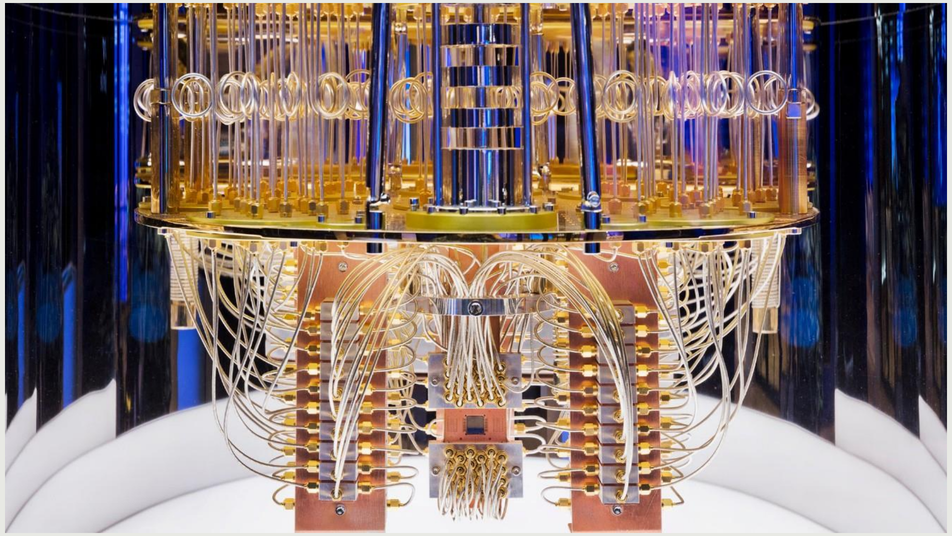
On Circuit-based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification (1)



In this work we presented a multi-class **hybrid quantum neural network** classifier for LULC task, by also exploring 3 different quantum circuits.

Real Amplitudes circuit

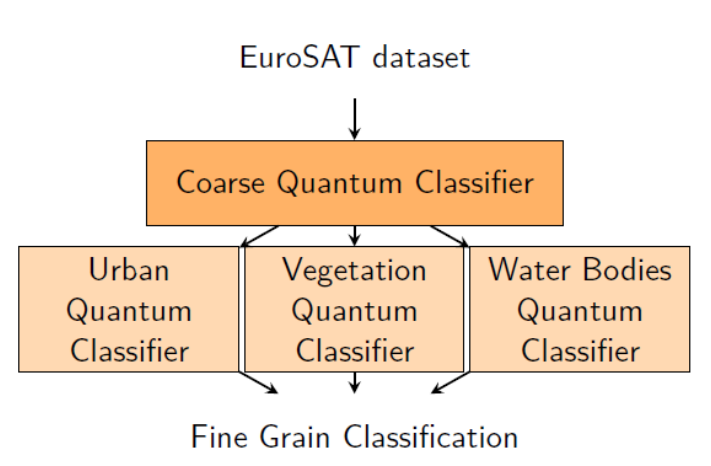




IBM Qiskit Elements for building a quantum future PyTorch

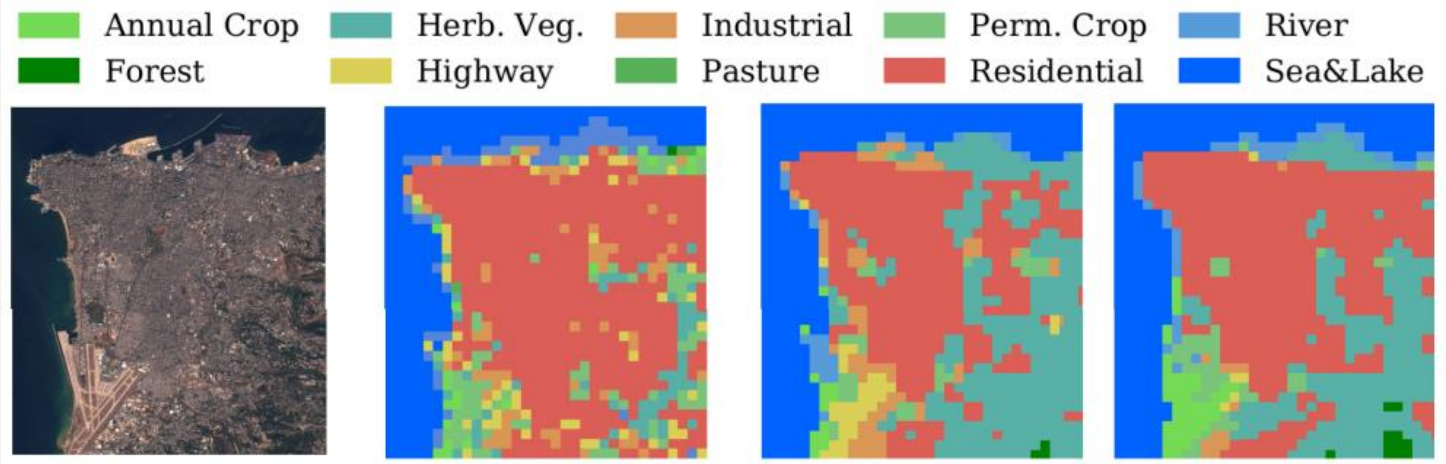
On Circuit-based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification (2)

→ Results demonstrated that the QCNN is able to overpass the classical counterpart. The best quantum solution is the coarse-fine grain classifier, shown in Figure, and it is able to reach the same performances of Helber et Al. solutions.



COMPARISONS WITH STATE-OF-THE-ART AND CLASSICAL METHODS

Model	Overall Accuracy	N. layers	N. parameters
Helber et Al. [35] ResNet-50	0.98	50	25.6M
Helber et Al. [35] GoogleNet	0.98	27	7M
Li et Al. [77] ResNet-18	0.98	18	11M
Sumbul et Al. [36] S-CNN-RGB	0.70	3	23.584
Classical V1	0.82	6	42.338
Classical V2	0.83	7	329.290
No entanglement circuit	0.79	6	42.338 + 4q
Bellman circuit	0.84	6	42.338 + 4q
Real Amplitude circuit	0.92	6	42.338 + 8q
Fine land-cover classifier	0.97	6	42.338 + 8q



A. Sentinel-2 input
B. Coarse-to-fine quantum classifier
C. Wide-ResNet [19]
D. JEM [19]

Sebastianelli et al. "On Circuit-based Hybrid Quantum Neural Networks for Remote Sensing Imagery Classification", IEEE JSTARS (15) 2021

Quantum Artificial Intelligence for Earth Observation (QuAI4EO): Quantum Generative Modelling for better EO interpretation and land-use classification

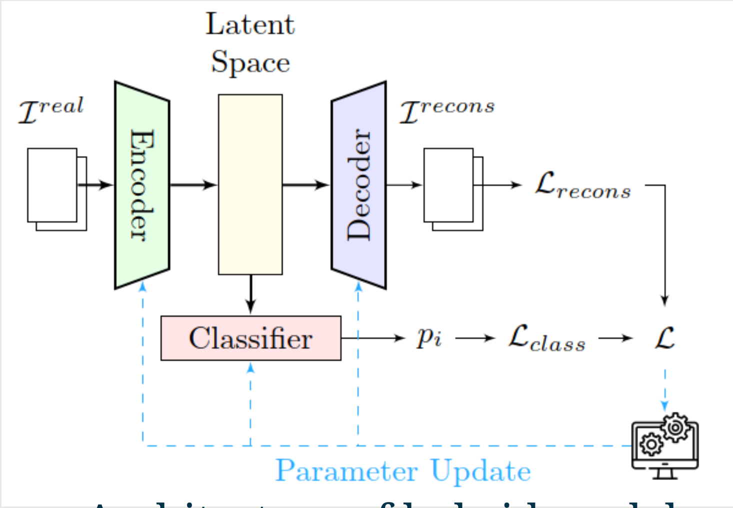
CERN / EPFL: Su-yeon Chang
CERN: Sofia Vallecorsa, Michele Grossi, Alberto di Meglio

Quantum Generative Modelling for EO

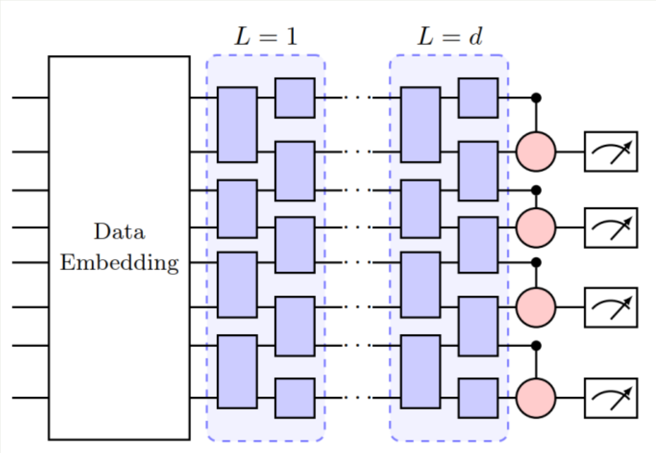
- Objective: Construct Quantum Generative Adversarial Networks (Quantum GANs) for **EO image modelling** *(e.g., for applications such as image generation, out-of-distribution or anomaly detection, etc.)*
- Initial step : Start with classification of EO images to understand different quantum circuit architecture

Standard approach, simple quantum classifier : Feature extractor first, and then train the classifier

Our approach, Hybrid model : Train Classical Autoencoder + Quantum Classifier all at once



Architecture of hybrid model

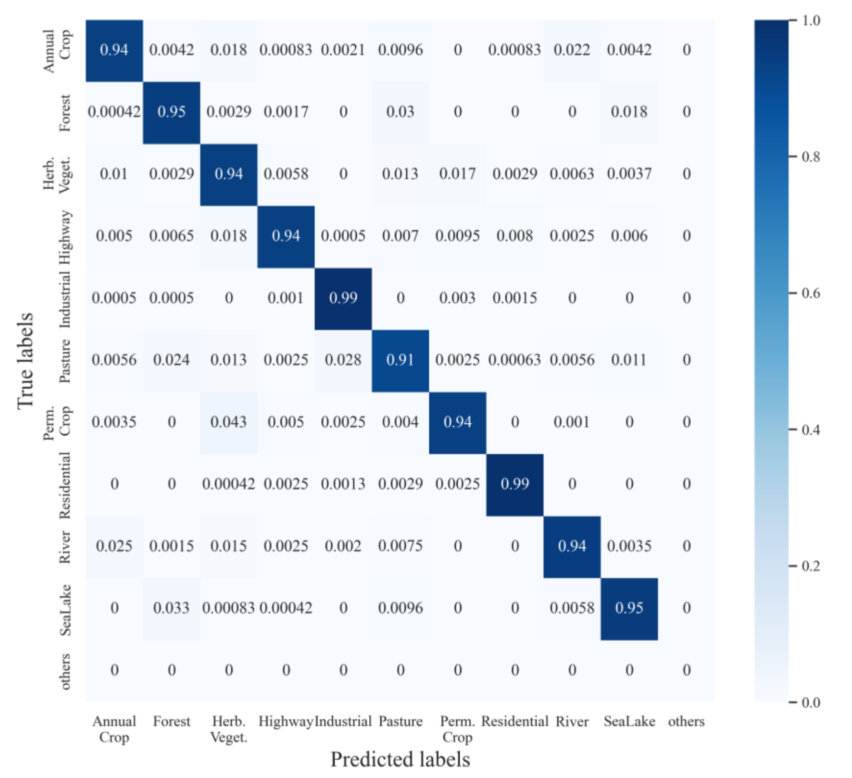


Quantum Convolutional Neural Networks

Multi-task hybrid model for image classification

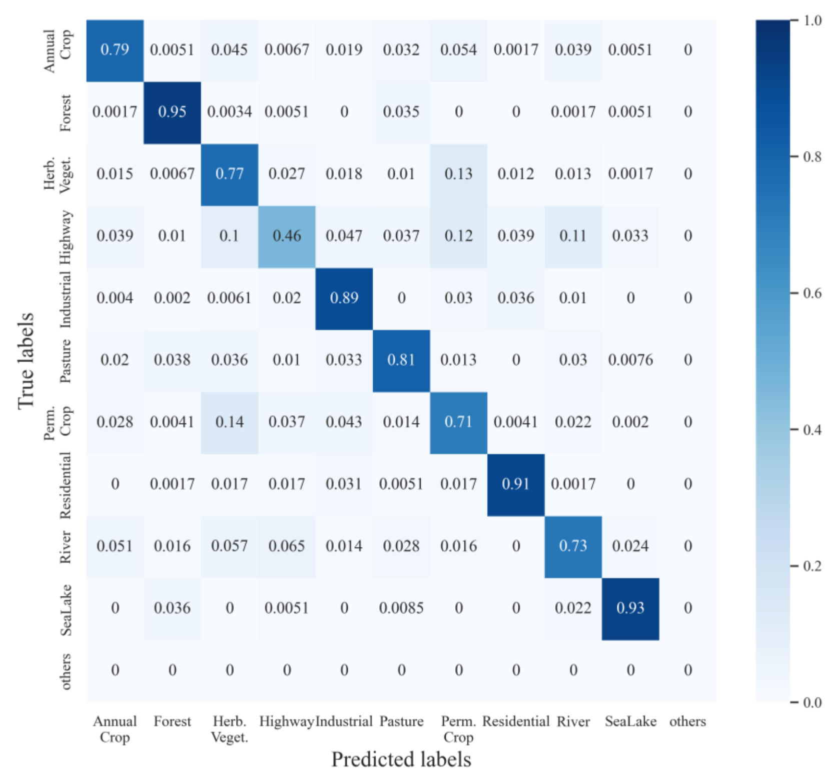
- Successful classification for EuroSAT dataset (10 classes)
- Challenge : Cannot observe quantum advantage with current model

→ Investigate latent feature arrangement to understand the limitation



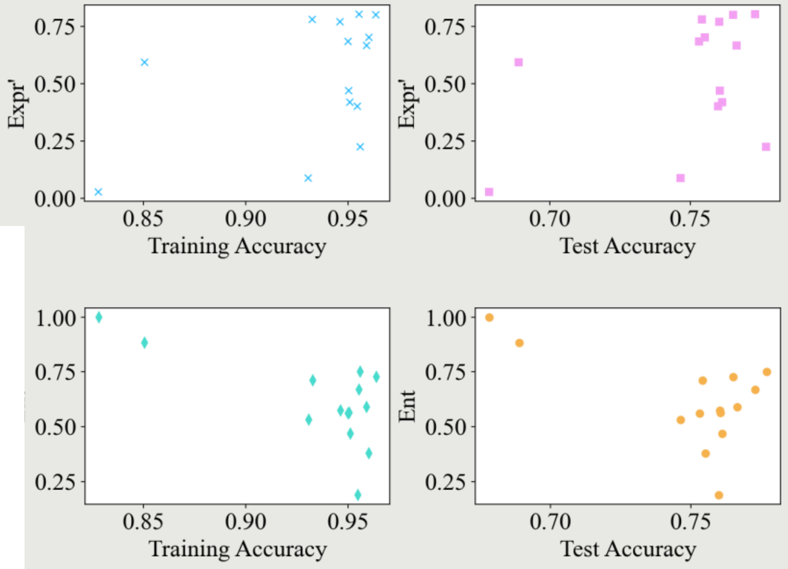
True labels \ Predicted labels	Annual Crop	Forest	Herb. Veget.	Highway	Industrial	Pasture	Perm. Crop	Residential	River	SeaLake	others
Annual Crop	0.94	0.0042	0.018	0.00083	0.0021	0.0096	0	0.00083	0.022	0.0042	0
Forest	0.00042	0.95	0.0029	0.0017	0	0.03	0	0	0	0.018	0
Herb. Veget.	0.01	0.0029	0.94	0.0058	0	0.013	0.017	0.0029	0.0063	0.0037	0
Highway	0.005	0.0065	0.018	0.94	0.0005	0.007	0.0095	0.008	0.0025	0.006	0
Industrial	0.0005	0.0005	0	0.001	0.99	0	0.003	0.0015	0	0	0
Pasture	0.0056	0.024	0.013	0.0025	0.028	0.91	0.0025	0.00063	0.0056	0.011	0
Perm. Crop	0.0035	0	0.043	0.005	0.0025	0.004	0.94	0	0.001	0	0
Residential	0	0	0.00042	0.0025	0.0013	0.0029	0.0025	0.99	0	0	0
River	0.025	0.0015	0.015	0.0025	0.002	0.0075	0	0	0.94	0.0035	0
SeaLake	0	0.033	0.00083	0.00042	0	0.0096	0	0	0.0058	0.95	0
others	0	0	0	0	0	0	0	0	0	0	0

Train set



True labels \ Predicted labels	Annual Crop	Forest	Herb. Veget.	Highway	Industrial	Pasture	Perm. Crop	Residential	River	SeaLake	others
Annual Crop	0.79	0.0051	0.045	0.0067	0.019	0.032	0.054	0.0017	0.039	0.0051	0
Forest	0.0017	0.95	0.0034	0.0051	0	0.035	0	0	0.0017	0.0051	0
Herb. Veget.	0.015	0.0067	0.77	0.027	0.018	0.01	0.13	0.012	0.013	0.0017	0
Highway	0.039	0.01	0.1	0.46	0.047	0.037	0.12	0.039	0.11	0.033	0
Industrial	0.004	0.002	0.0061	0.02	0.89	0	0.03	0.036	0.01	0	0
Pasture	0.02	0.038	0.036	0.01	0.033	0.81	0.013	0	0.03	0.0076	0
Perm. Crop	0.028	0.0041	0.14	0.037	0.043	0.014	0.71	0.0041	0.022	0.002	0
Residential	0	0.0017	0.017	0.017	0.031	0.0051	0.017	0.91	0.0017	0	0
River	0.051	0.016	0.057	0.065	0.014	0.028	0.016	0	0.73	0.024	0
SeaLake	0	0.036	0	0.0051	0	0.0085	0	0	0.022	0.93	0
others	0	0	0	0	0	0	0	0	0	0	0

Test set



Study correlation between PQC architecture & classification accuracy

- **Pearson Correlation Coefficient** calculated for Expressibility /Entanglement capability v.s. Accuracy
- Higher Expr' → Higher Accuracy
- Higher Ent → Lower Accuracy

Chang et al., "Quantum Conv Circuits for EO image classif.", IGARSS 2022

Trained on openlab qti nodes

Quantum Generative Modelling for EO

- Quantum Generative Adversarial Networks : **Quantum Generator + Classical Discriminator**
- Features extracted from images via a **pretrained autoencoder** used as GAN training set
- Generated features passed back to the autoencoder to reconstruct images
- **Successful GAN training with MNIST dataset** → Plan to apply on EO images
- **Future work** : Implement fully quantum GAN with quantum generator and quantum discriminator

→ Can quantum GAN perform better than the hybrid one?

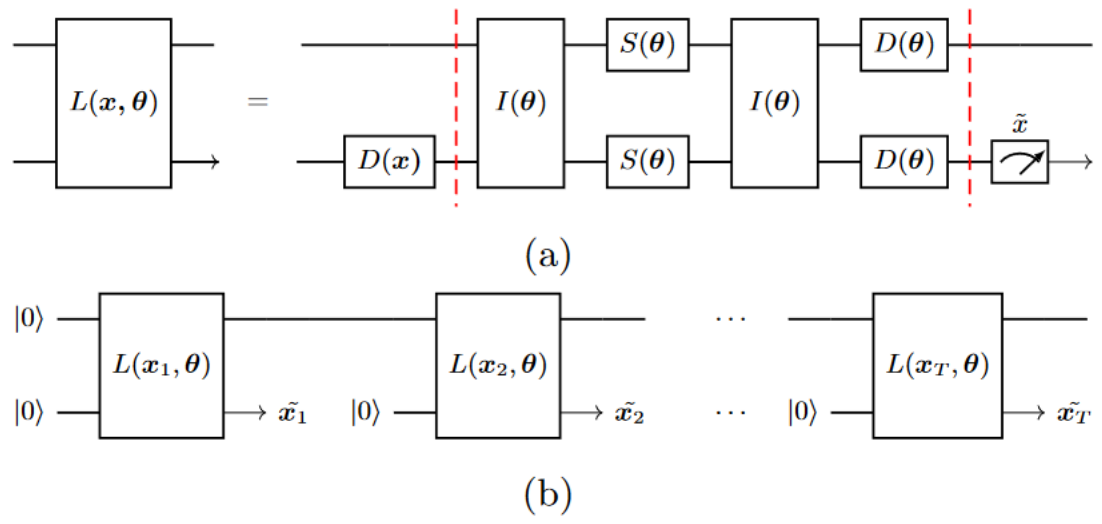
Real and generated MNIST images, classified with pretrained ResNet50

Rapid Training of Recurrent Neural Networks

Univ. of Warsaw: Michal Siemaszko, Magdalena Stobinska

Rapid Training of Recurrent Neural Networks

- Recurrent Neural Networks for time-series
- Continuous-Variable Quantum Computing:
  - “analog” QC vs. “digital” qubit-based QC
  - Implemented on quantum optics or ion-trap quantum systems



Recurrent Neural Networks for time-series on Continuous-Variable QC:

- 2-variable ansatz with cyclic and new incoming information

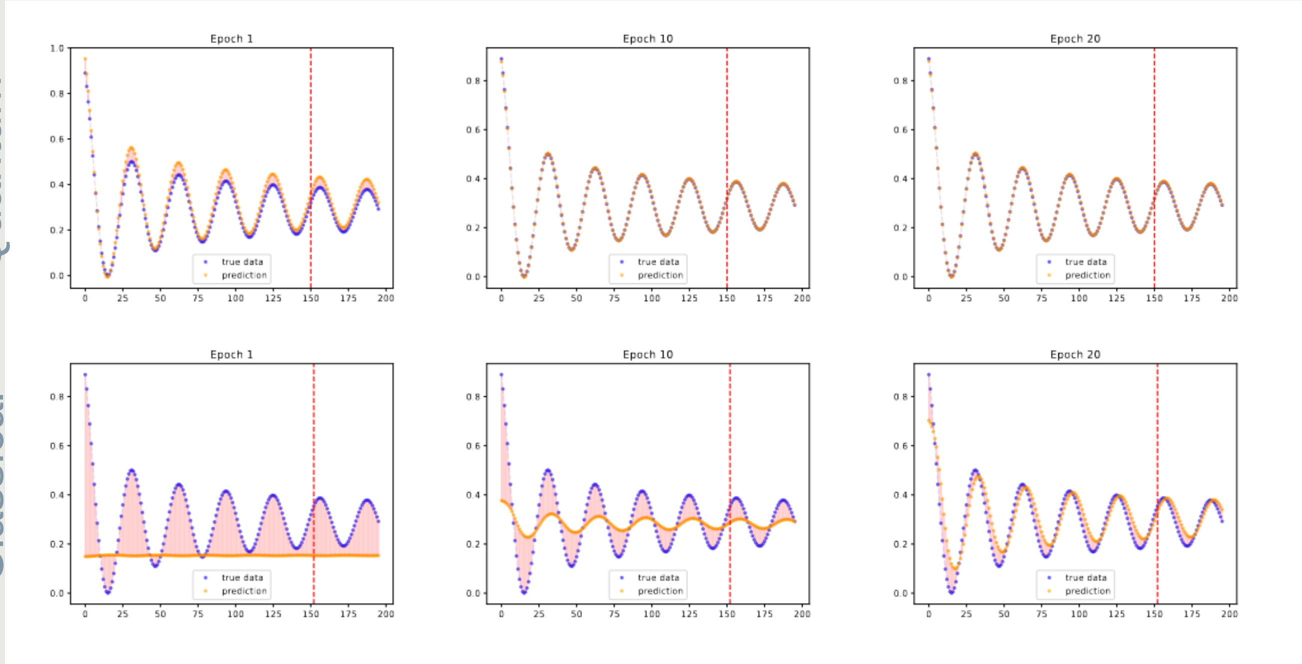
Rapid Training of Recurrent Neural Networks

➢ Promises of faster training convergence ?!

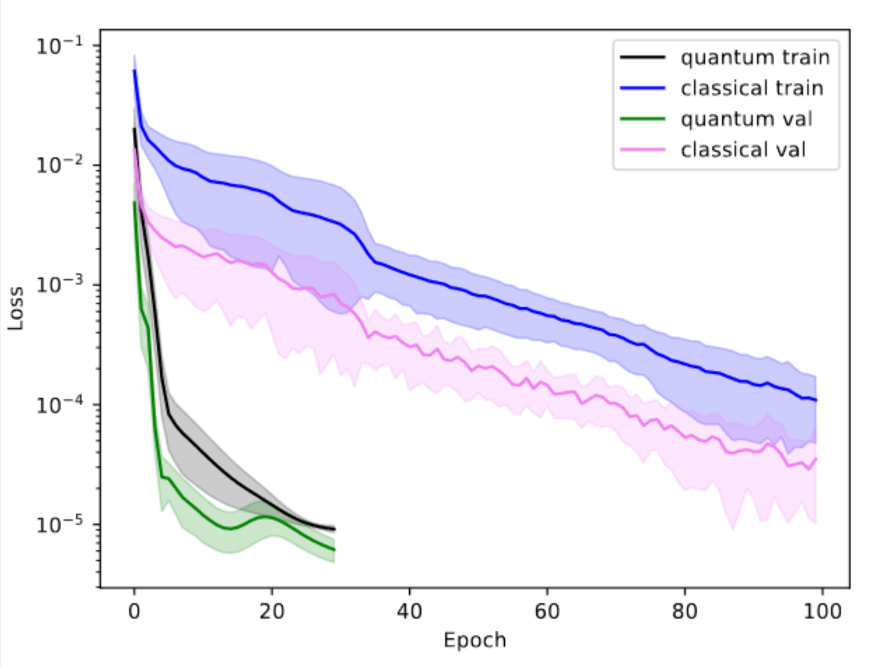
Evolution of model prediction wrt. training time (different checkpoints: epoch 1, 10, 20)

Quantum

Classical



Loss evolution over epochs during training of CV-QRNN, for train and validation sets



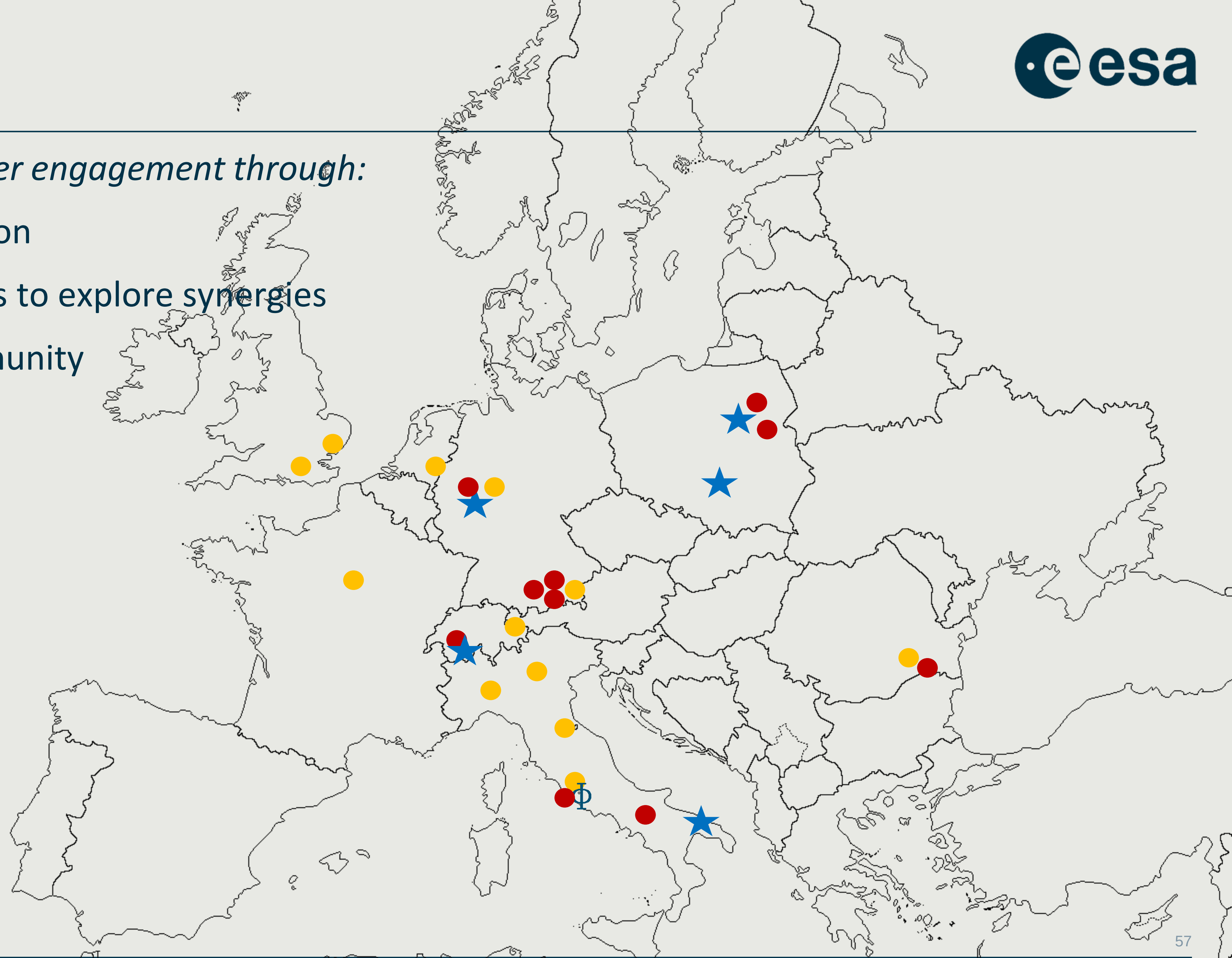
Siemaszko, McDermott, Buracsewski, Le Saux & Stobinska “Rapid training or recurrent quantum neural networks”, QTML 2022

3. QC4EO Network

QC4EO Network

Community building and stakeholder engagement through:

- Workshop and event organisation
- Consult QC and EO communities to explore synergies
- Support emerging QCxEO community



★ Co-funded research

● Partners / visitors

● Community / events

QC4EO Network: workshops and events

- 2019 Workshop on Quantum Processing: from Quantum Computing to Earth Observation in Rome,
  https://philab.phi.esa.int/workshop-quantum-for-earth-observation/
- 2021 ESA-Ellis Workshop on Quantum Algorithms and Machine Learning for EO applications,
  https://ellisqphml.github.io/ellisphilab2021
- 2021 Φ-week QC4EO session in Frascati,
  https://phiweek.esa.int
- 2021 ESA 5th Quantum Conference Quantum Computing session,
  https://atpi.eventsair.com/5th-quantum-technology-conference/
- 2022 Living Planet Symposium, Agora Session on "Future of Computing for FutureEO"

QC4EO Network: organisations

Stakeholder engagement

- AI-enhanced Quantum Computing for EO: Joint initiative between CERN and ESA-EOP
- QC4EO JP: Consultation with CERN, DLR, TU Munich, LRZ, Ellis, etc…

Community events and thematic initiatives

- IEEE GRSS High-performance and Disruptive Computing (HDCRS) Summer School

  https://www.hdc-rs.com → Once again in May-June 2023!
- Quantum Open Software Foundation mentoring https://qosf.org/
- Quantum Climate initiative https://q4climate.github.io/

Publications

- IEEE JSTARS Special Issue on “Quantum resources for Earth Observation” → Open until Dec.2022!

  Ed. M. Datcu (DLR), J. Le Moigne (NASA), B. Le Saux (ESA) → *https://ieeexplore.ieee.org*

QC4EO Network: visiting researchers

Senior visiting researchers:

- 2021: Mihai Datcu (DLR / Politehnica University of Bucharest)
- 2022: Gabriele Cavallaro (Forschungszentrum Jülich)
- 2022: Piotr Gawron (Nicolaus Copernicus Astronomical Center of the Polish Academy of Sciences)

Early-career researchers:

- 2022: Michal Siemaszko (PhD Student Univ. Warsaw – Magdalena Stobinska group)
- 2022: Alice Barthe (PhD Student CERN / Leiden University – Vedran Djunko group)

> - **We are welcoming visiting researchers from academia and industry!**
> - **Spend short stays or residencies at the Φ-lab to mingle with EO, AI, and QC experts!**
> - **Let’s get in touch!**

Conclusion

ESA Φ-lab's Initiative on Quantum Computing for Earth Observation (QC4EO)

General perspectives:

- *Increase the mutual awareness of the needs and capabilities of the Quantum Computing and Earth Observation communities*
- *Create new synergies, building on shared experience in AI, data mining and optimisation*
- *Prepare the ground for the opportunities that will be presented when the quantum community will be able to produce hardware and software for applied problems*

ESA Φ-lab's Initiative on Quantum Computing for Earth Observation (QC4EO)

Practical perspectives:

- *Look for **practical applications and use-cases**, as quantum volume is likely to increase*
- *Understand the **advantages** (faster, better, etc.?) brought by QC with **exploratory activities***
- ***Design hybrid computing** frameworks including traditional CPU, GPU, HPC and new paradigms such as quantum and neuromorphic computing for optimal problem solving*

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