



MerLin: A PyTorch-Integrated Framework for Scalable QM

FROM UTILITY TODAY TO QUANTUM
ADVANTAGE TOMORROW

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About Quandela - We are focused in delivering cutting-edge solutions

→ We build full-stack Quantum Computers



2017

year of incorporation.
1st quantum computing
startup in France

35 years

history of state-of-
the art research

2018

first commercialized
quantum device



140+

people

50+

people with PhD

55

research scientists

>40

patents & scientific
articles

>30,000

citations for the lead scientists



2

Production facilities

4

main locations worldwide





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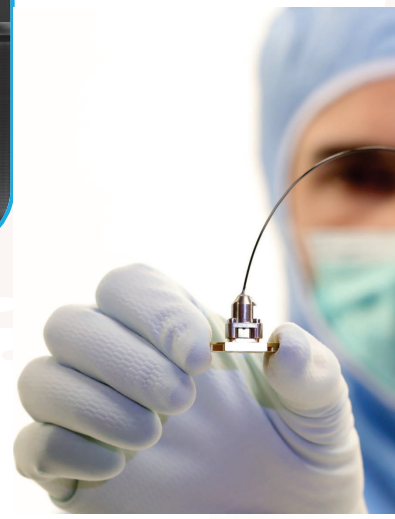
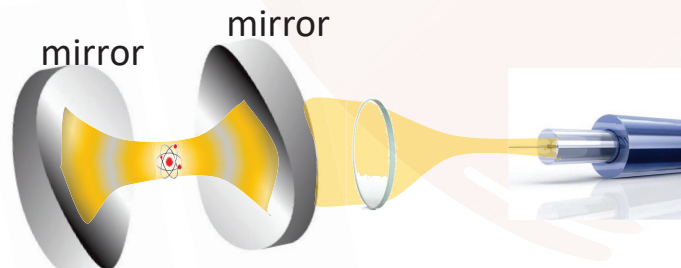
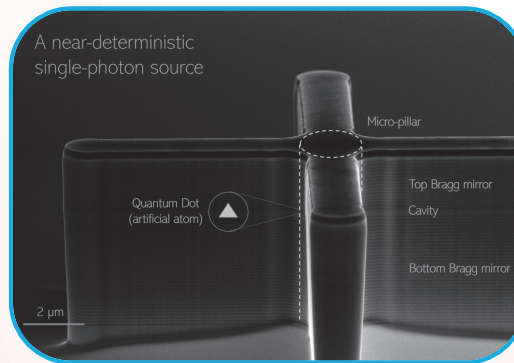
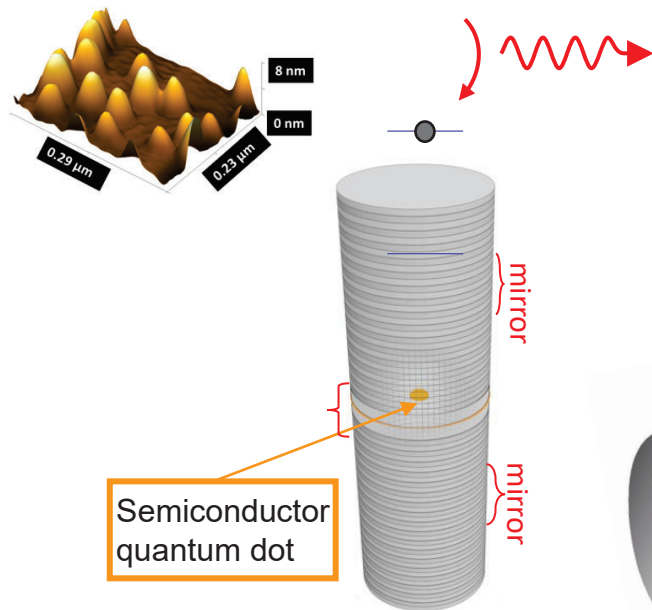


Anatomy of a photonic quantum computer

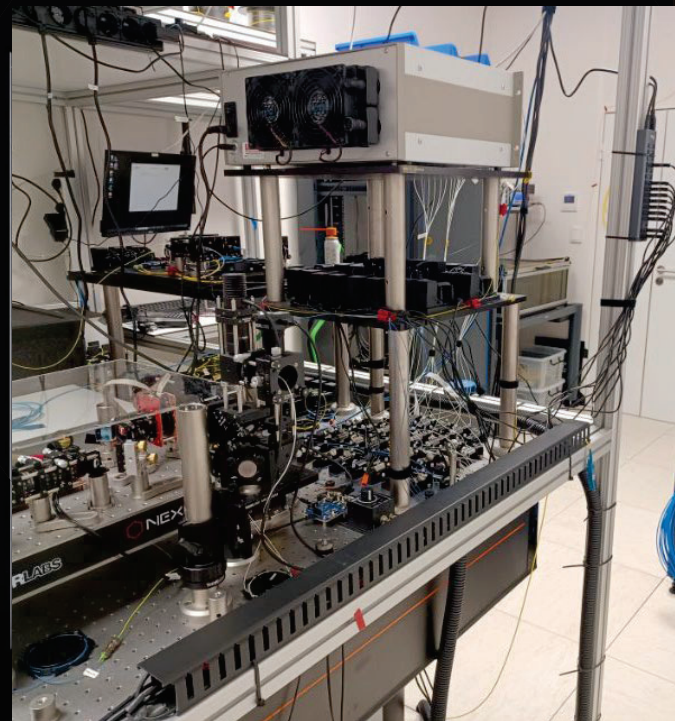
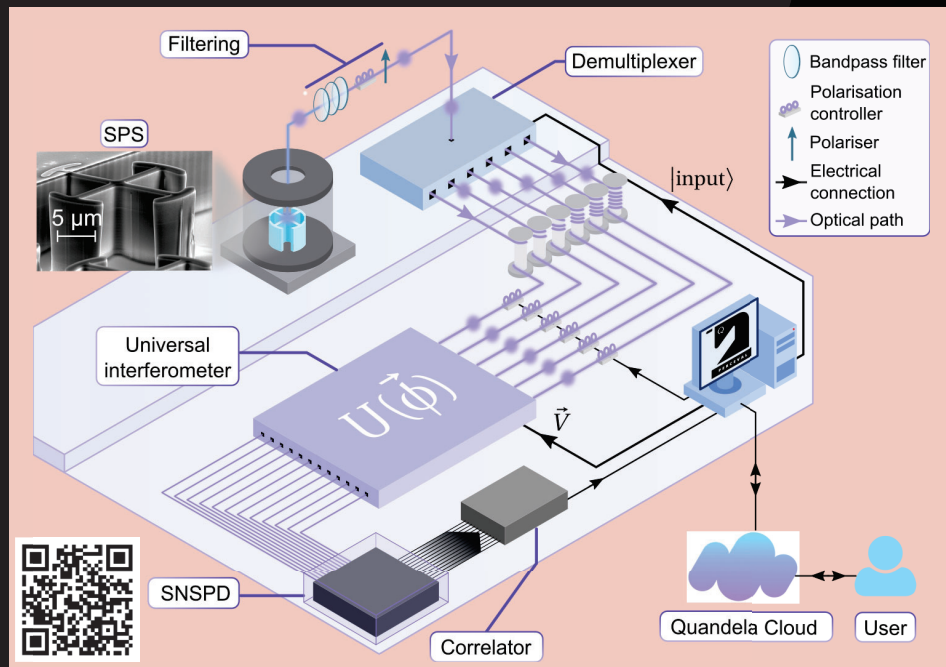
Turning Light into Qubits

Quandela Quantum Dots

- Single photons are the building blocks of our quantum computer
- Now being fabricated in our semiconductor pilot line



Ascella - the first photonic quantum processor available in the Quandela cloud

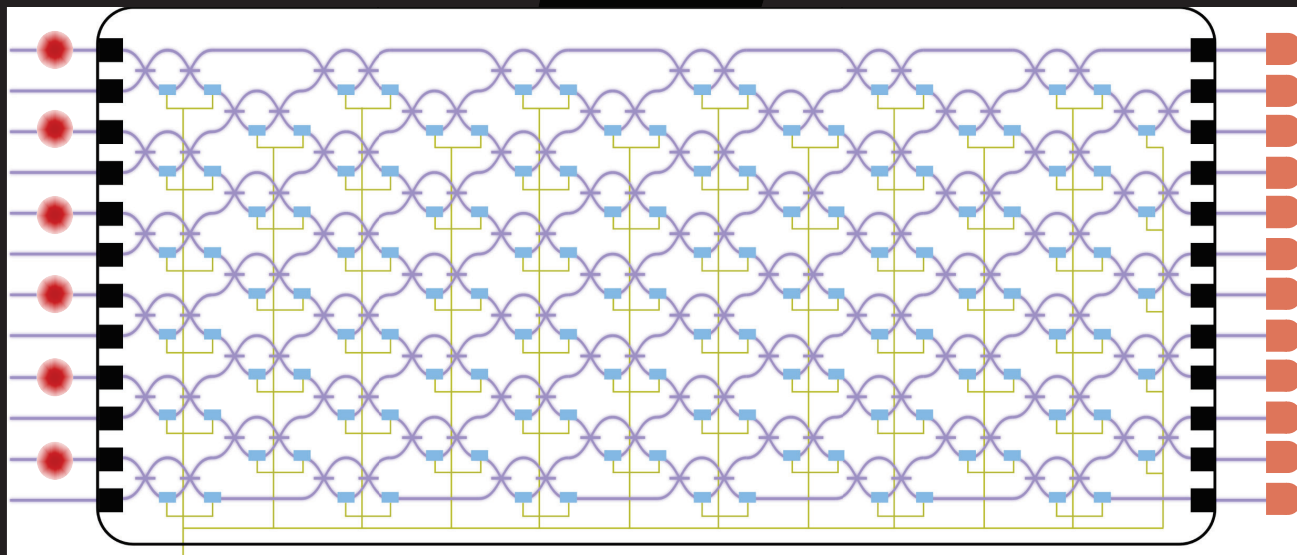


<https://www.nature.com/articles/s41566-024-01403-4>

Quantum Computing with photons

Starting with Boson Sampler

Generic interferometer representing a unitary transformation $U(x_i)$



Output photon distribution

x_i

Quantum Computing with photons

Starting with Boson Sampler

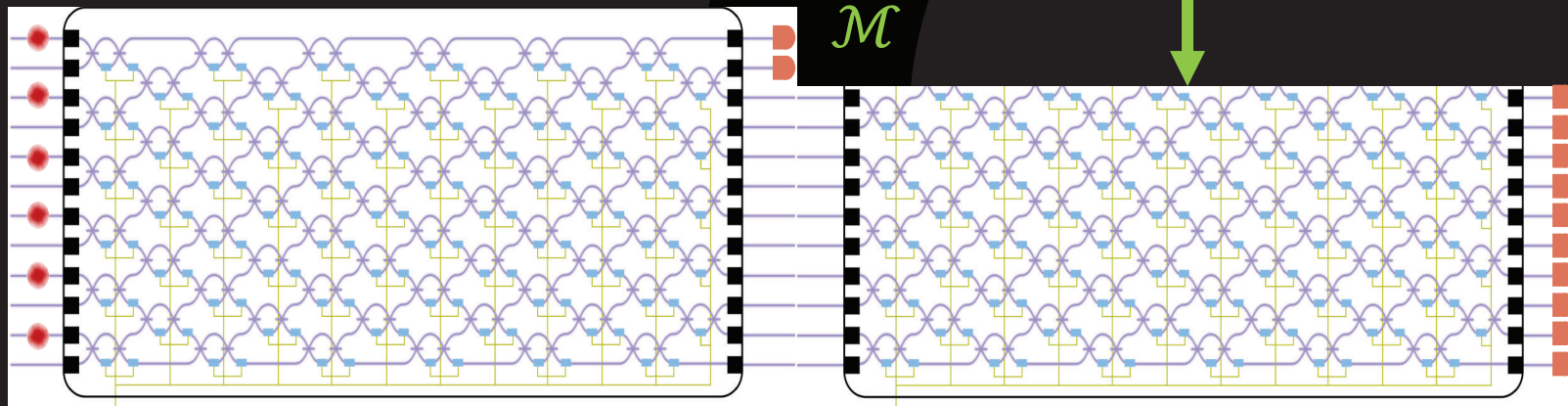
Time necessary to perform/simulate 1000 samples on n photons:

n	Number of operations per sample	High Performance Laptop	Jean Zay HPC #274 worldwide	1GHz QPU with 80% transmission	1GHz QPU with 90% transmission
4	64	milliseconds	milliseconds	milliseconds	milliseconds
10	10240	milliseconds	milliseconds	milliseconds	milliseconds
20	21M	seconds	milliseconds	milliseconds	milliseconds
30	32B	hour	1s	milliseconds	milliseconds
48	$3 \cdot 10^{15}$	4 days	100s	milliseconds	milliseconds
80	10^{26}	-	95 years	1 hour	1 second

But competitive approximative algorithms !

Quantum Computing with photons

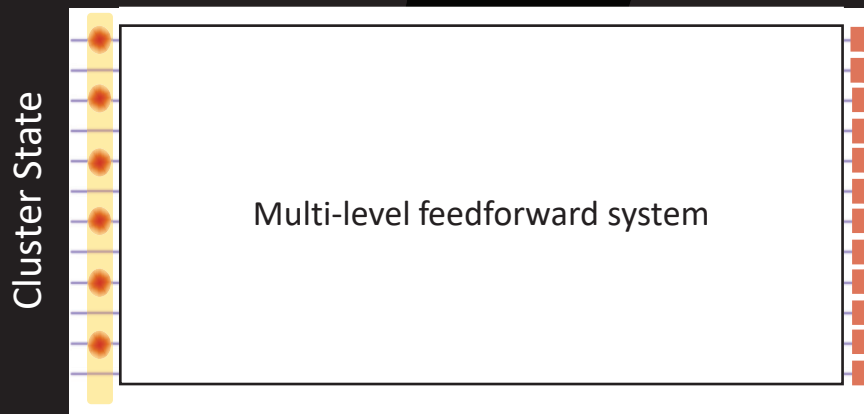
Boson sampling with Feedforward



Provably harder to simulate

Quantum Computing with photons

Generalized Entangled Boson Sampler

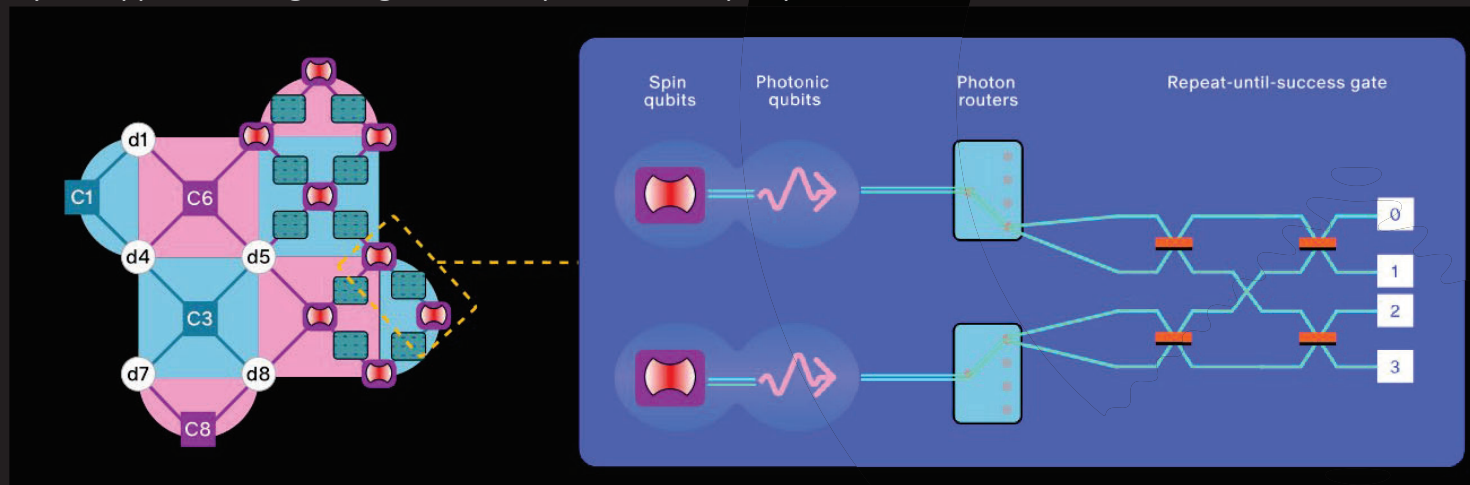


Provably even harder to simulate

Quantum Computing with photons

Spin Optical Quantum Computing

→ Hybrid approach using strengths of both photons and spin qubits



Universal Quantum Computing Scheme

From NISQ to Quantum Advantage

Today's Quantum Opportunity

- "If it's simulable, it has no utility."
- "Noise kills any chance of advantage."
- "Quantum is too slow to compete with GPUs."

NISQ

Small number of physical qubits
Noisy system
Short-time decoherence

UTILITY

Identifying useful applications
outperforming brute force

FAULT TOLERANT

Large number of logical qubits
Error correction scheme

PROOF OF CONCEPT

USEFUL APPLICATIONS
ENERGETIC ADVANTAGE

QUANTUM ADVANTAGE

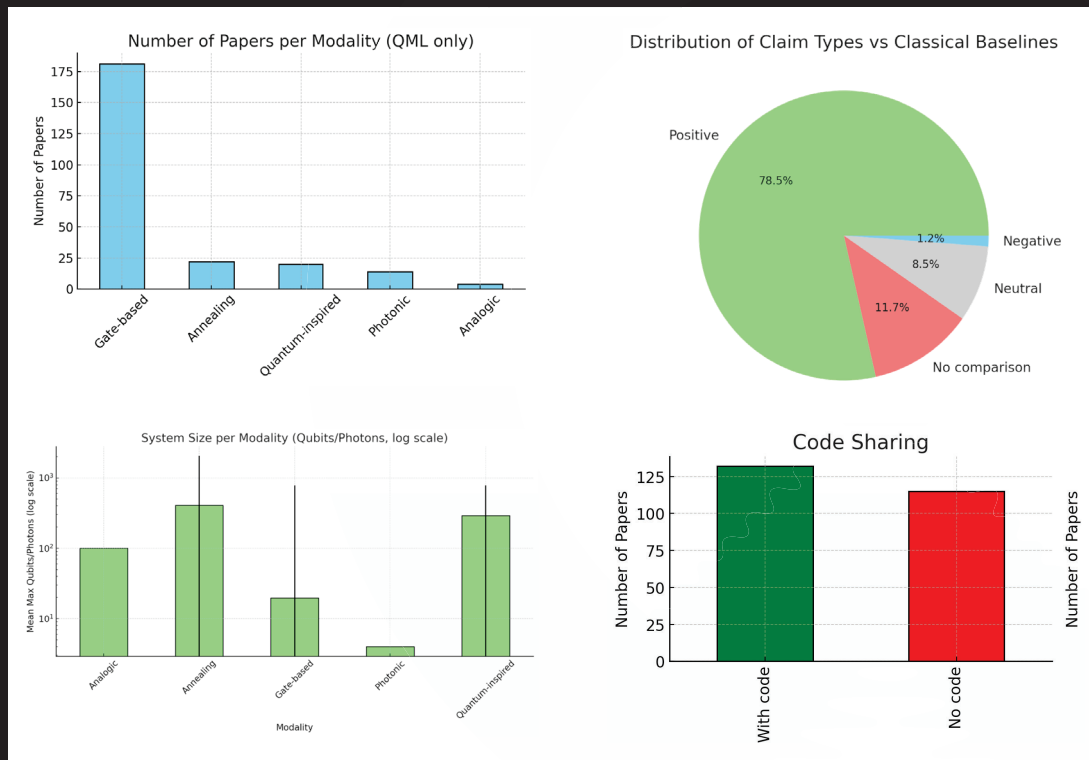
First Generation of Quandela online computers

Intermediate computers

SPOQC Architecture



QML Landscape – over 10000 published papers



Positive Claims

- « **Better performance** »
- **Comparable performance** *with better data/parameters budget.*
- **Qualitative Improvement:** *faster convergence, or qualitative benefits (e.g., interpretability).*
- **Robustness / stability:** Claims of more stable training, smoother learning curves, or improved resilience to noise.

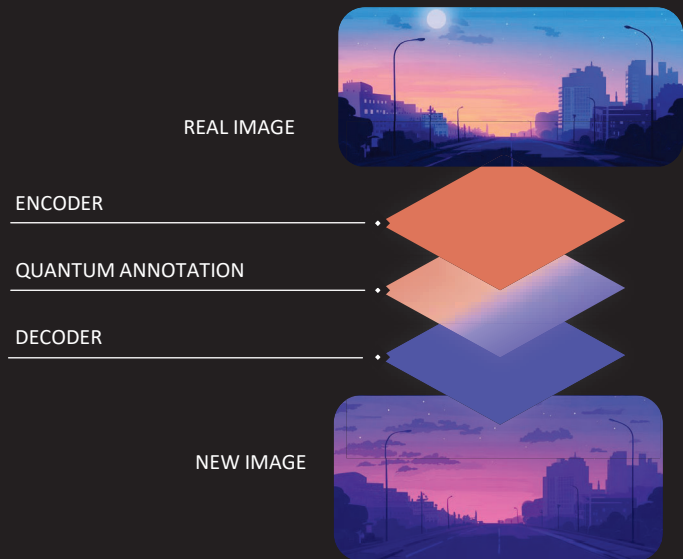
**Many claims,
little reproducibility,
hard to compare.**

Thorough analysis on 250 papers (QML+MNIST)



Proving the Value of Quantum ML – Airbus & BMW

2024 Challenge



01 → Quantum transformation: no need for model training.
It only requires source image annotation

02 → Integration of Boson Sampling primitive improved translation and reduced hallucinations.



MERLIN, ROADMAP AND CONCLUSION

MerLin — our first step toward ML frameworks for hybrid AI+Quantum.

Photonic focus, open design

<https://merlinquantum.ai>

1. Start Anywhere – Simulator First

- Develop and test quantum-enhanced ML models without hardware dependency
- Run everything locally or in the cloud
- **Focus on cross-modality paper reproduction**

2. Train at Scale – GPU Acceleration on HPC

- Train **hybrid quantum–classical models** efficiently on GPUs
- Use familiar PyTorch APIs

3. Deploy on Hardware – QPU Ready

- Fine-tune and execute on Quandela's photonic QPUs
- Framework evolves with new features (feedforward, entangled sources, SPOQC)

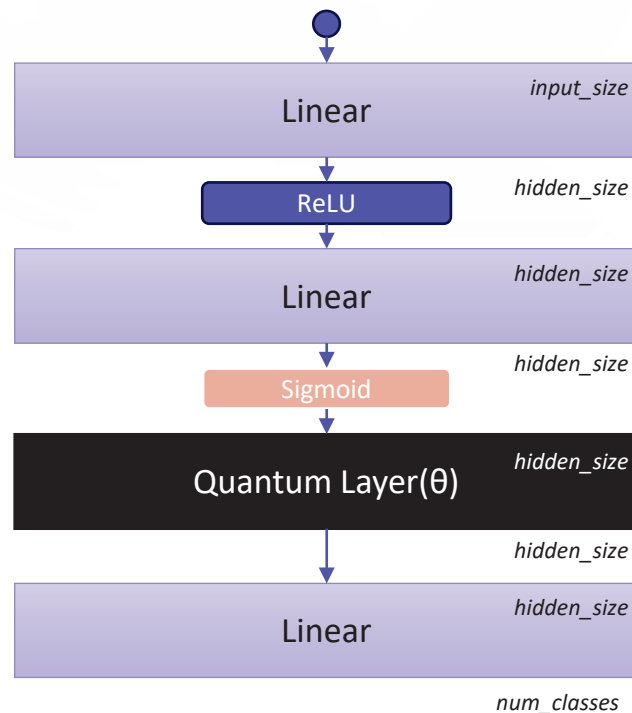


Example Hybrid Models

A hybrid classifier

```
def create_quantum_classifier(input_size=10, hidden_size=16, num_classes=2):
    # Create a quantum circuit
    n_modes = 4
    circuit = pcvl.Circuit(n_modes)
    wl = pcvl.GenericInterferometer(n_modes, lambda i: pcvl.BS() // pcvl.PS(pcvl.P(f"theta{i}")))
    circuit.add(0, wl, merge=True)

    # Create the model with a quantum layer in the middle
    model = nn.Sequential(
        nn.Linear(input_size, hidden_size),
        nn.ReLU(),
        nn.Linear(hidden_size, 2), # Compress to 2 features for quantum input
        nn.Sigmoid(), # Scale to [0, 1] range
        QuantumLayer(
            input_size=2,
            output_size=hidden_size,
            circuit=circuit,
            trainable_parameters=["theta"],
            input_parameters=["x"],
            input_state=[1, 0, 1, 0], # 2 photons in 4 modes,
            output_mapping_strategy=OutputMappingStrategy.LINEAR
        ),
        nn.Linear(hidden_size, num_classes)
    )
    return model
```



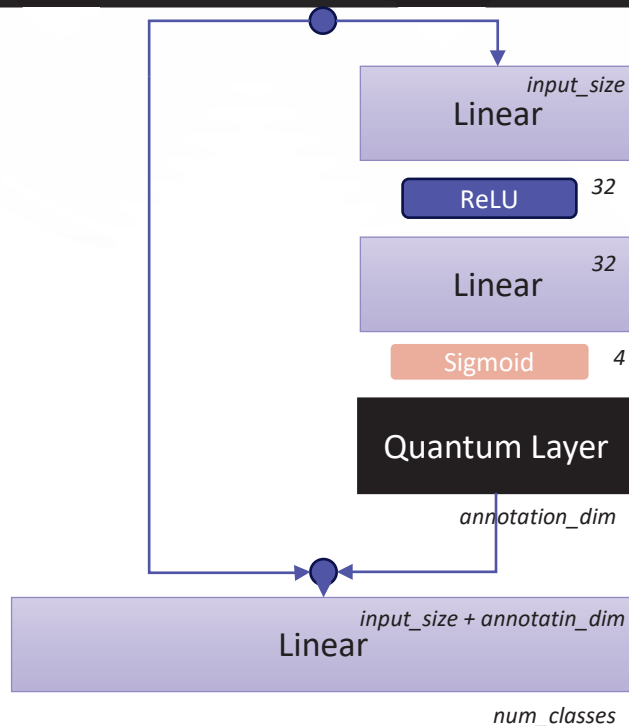
Example Hybrid Models

Quantum Annotation in a classical classifier

```
# Initial feature compression
self.feature_compressor = nn.Sequential(
    nn.Linear(input_dim, 32),
    nn.ReLU(),
    nn.Linear(32, 4),
    nn.Sigmoid() # Scale to [0, 1] for quantum input
)

# Quantum annotation layer
self.quantum_annotator = QuantumLayer(
    input_size=4,
    output_size=annotation_dim,
    circuit=circuit,
    input_parameters=["x"],
    input_state=input_state,
    output_mapping_strategy=OutputMappingStrategy.LINEAR
)

# Original path - processes raw input
self.original_path = nn.Sequential(
    nn.Linear(input_dim + annotation_dim, 64),
    nn.ReLU(),
    nn.Linear(64, num_classes)
)
```

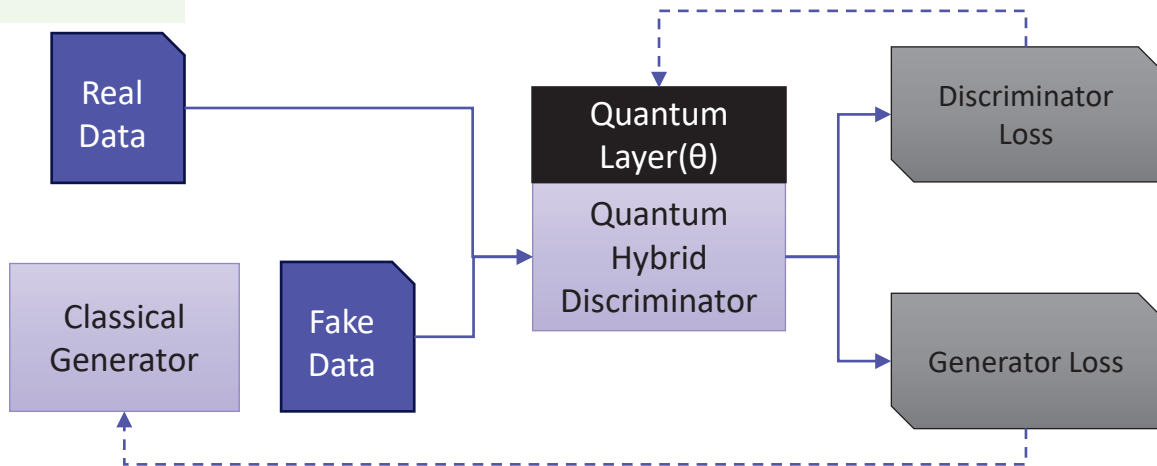


Example Hybrid Models

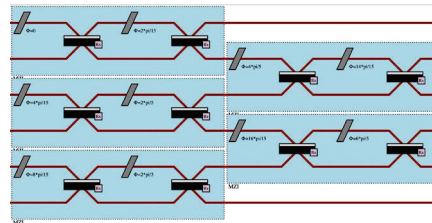
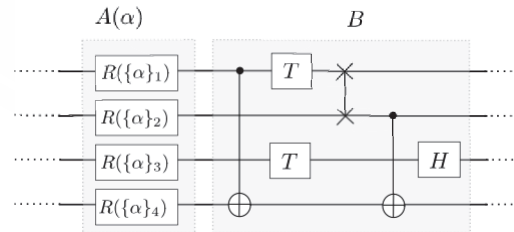
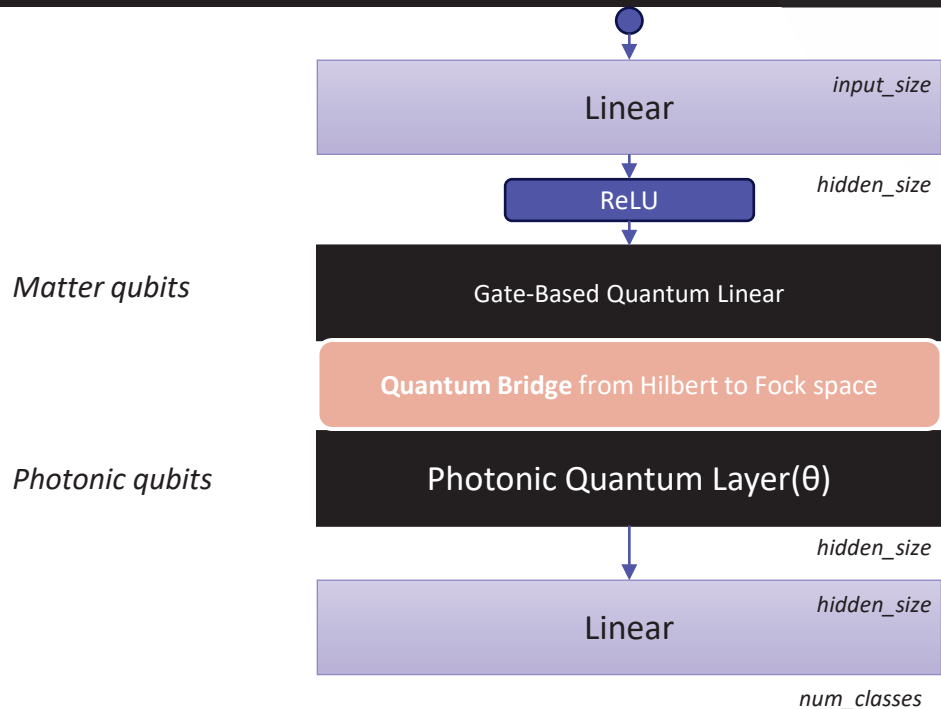
GAN with a Quantum Discriminator

```
class QuantumGAN:
    def __init__(self, latent_dim=100, img_dim=28*28):
        self.latent_dim = latent_dim
        self.generator = ClassicalGenerator(latent_dim, img_dim)
        self.discriminator = QuantumDiscriminator(img_dim)

    # Setup optimizers
    self.g_optimizer = torch.optim.Adam(self.generator.parameters(), lr=0.0002)
    self.d_optimizer = torch.optim.Adam(self.discriminator.parameters(), lr=0.0002)
    self.criterion = nn.BCELoss()
```



Example Hybrid Models. With Cross-Platform Quantum Layers



Example of Reproduced Papers

Quantum Self-Supervised Learning

B. Jaderberg,^{1,*} L. W. Anderson,^{1,*} W. Xie,² S. Albanie,³ M. Kiffner,^{1,4} and D. Jaksch^{1,4,5}

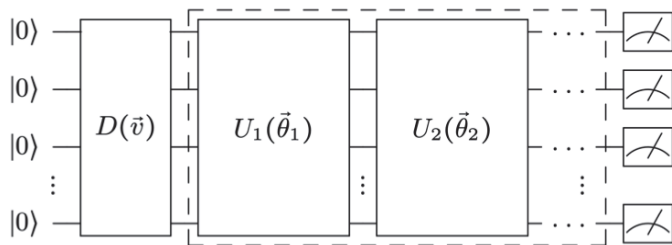
¹Clarendon Laboratory, University of Oxford, Parks Road, Oxford OX1 3PU, United Kingdom

²Visual Geometry Group, Department of Engineering Science, University of Oxford

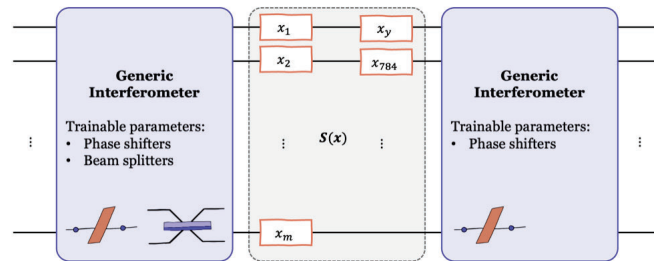
³Department of Engineering, University of Cambridge

⁴Centre for Quantum Technologies, National University of Singapore, 3 Science Drive 2, Singapore 117543

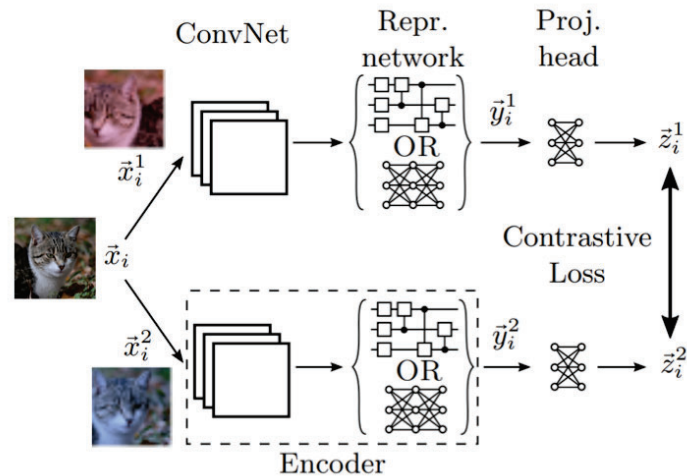
⁵Institut für Laserphysik, Universität Hamburg, 22761 Hamburg, Germany



Gate-based Ansatz

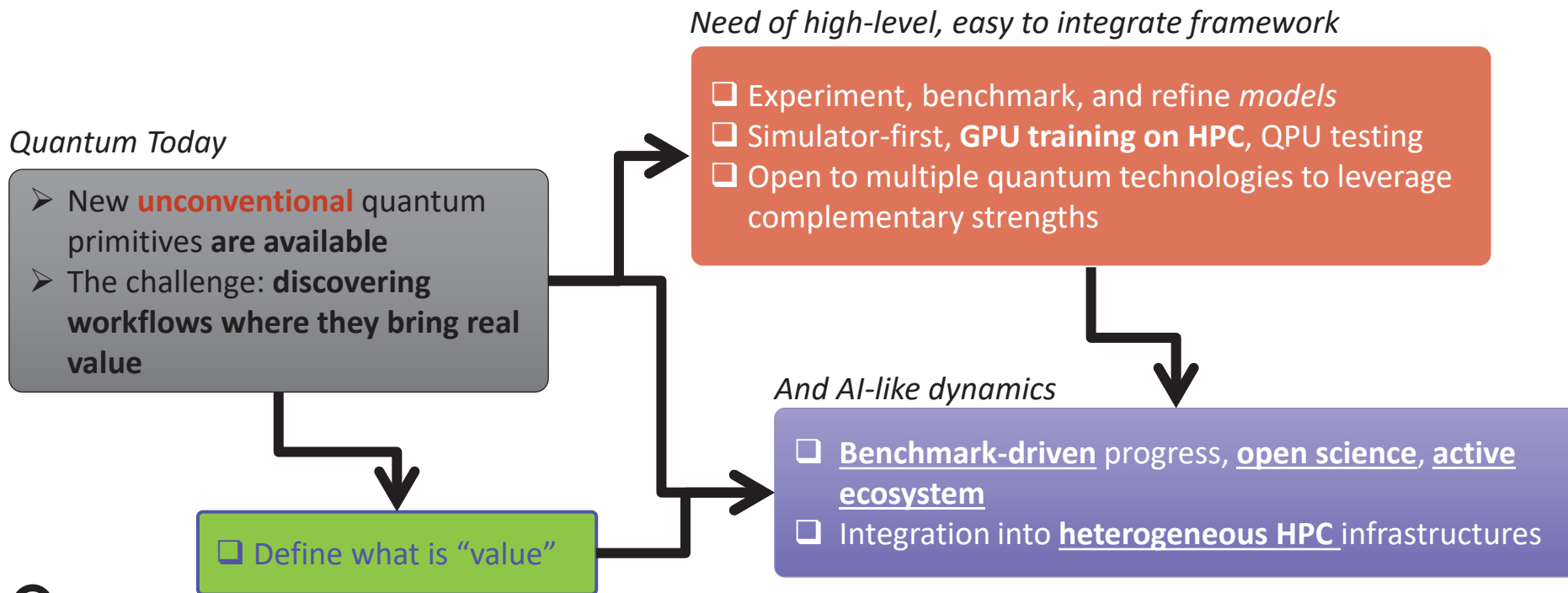


Photonic Ansatz



https://github.com/merlinquantum/reproduced_papers/tree/main/qSSL

Quantum + AI + HPC: Unlocking the Next Steps





→ <https://cloud.quandela.com>

→ <https://merlinquantum.ai>

Thank you!