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Th-PM1-5-4

Quantum Feature Extraction for THz Multi-Layer Imaging

Toshiaki Koike-Akino, Perry Wang
Mitsubishi Electric Research Laboratories (MERL), Cambridge, MA 02139, USA.
Genki Yamashita, Wataru Tsujita
Mitsubishi Electric Corporation Advanced Technology R&D Center, Hyogo 661-8661, Japan.
Makoto Nakajima
Institute of Laser Engineering, Osaka University, Osaka 565−0871, Japan.

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Cambridge, Massachusetts, USA
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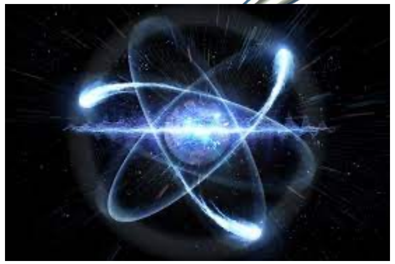
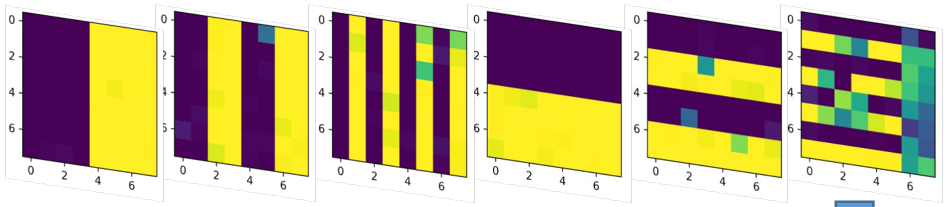
Outline

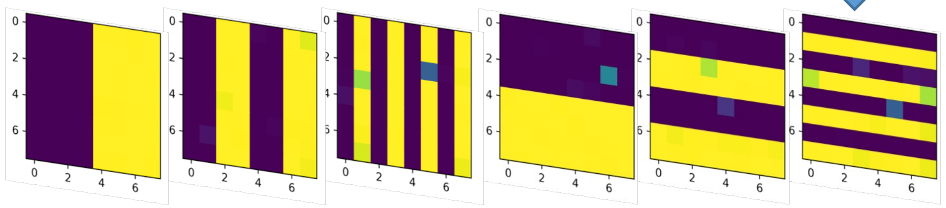
- Trends of Artificial Intelligence (AI)
  - Deep Learning: Deep Neural Networks (DNN)
  - Post Deep Learning: Quantum Machine Learning (QML)
- THz Sensing for Non-Destructive Inspection
  - Inspection/Positioning
  - Challenges
  - DNN solutions
  - Hybrid QNN+DNN solutions
  - Experimental validation
- Summary

Quantum AI

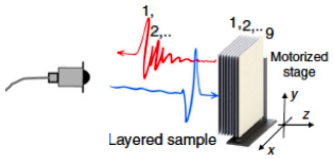


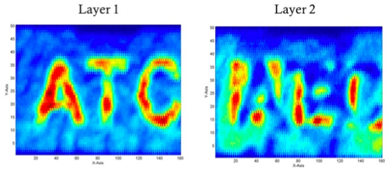


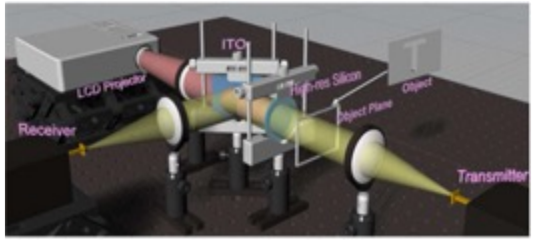
DNN (97.6% Accuracy)

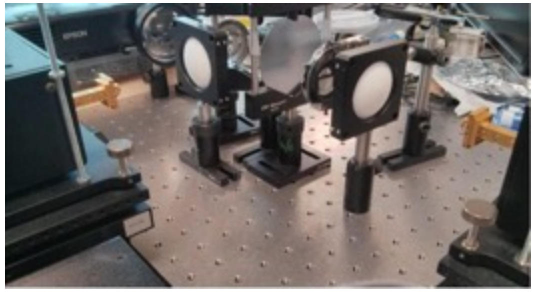


QNN + DNN (99.6% Accuracy)



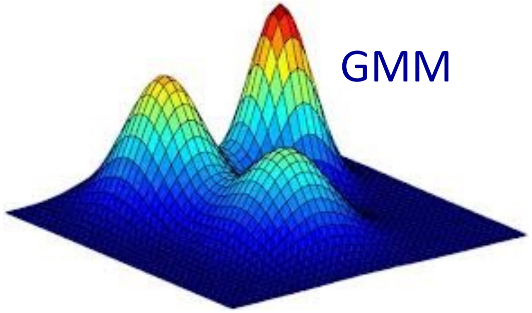


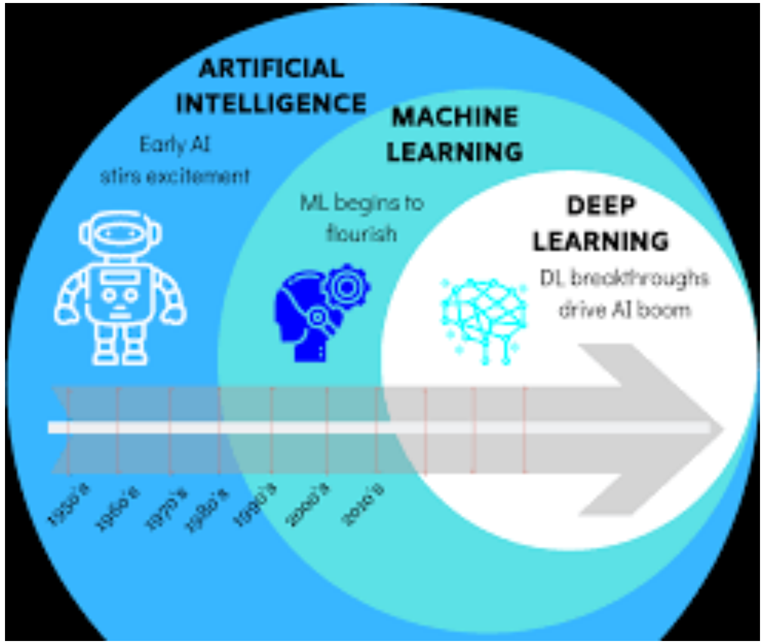




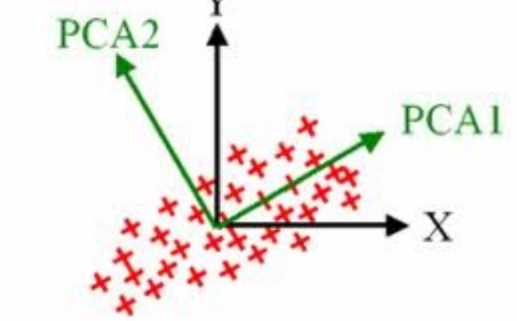
Artificial Intelligence (AI)

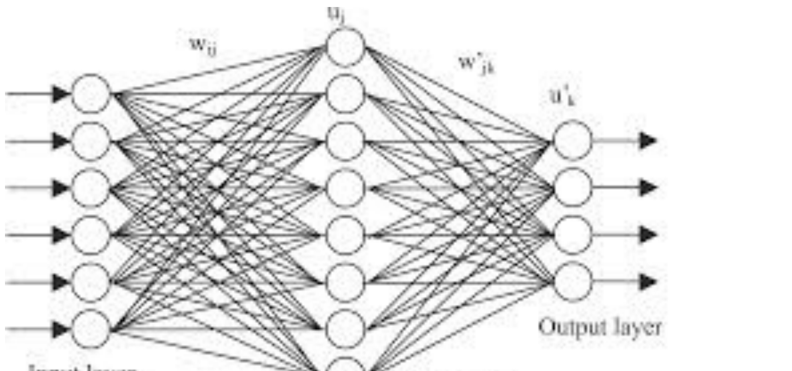
- K-means
- Gaussian mixture model (GMM)
- Principal component analysis (PCA)
- Independent component analysis (ICA)
- Logistic regression (LR)
- **Support vector machine (SVM)**
- Self-organizing map (SOM)
- Hidden Markov model (HMM)
- Artificial neural networks (ANN)
- **Deep learning (DL)**
- **QML …**


GMM



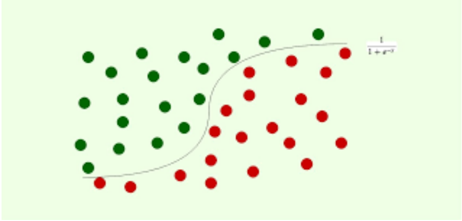
PCA

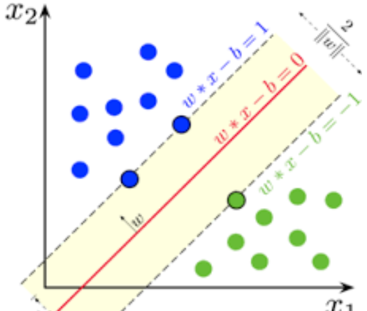


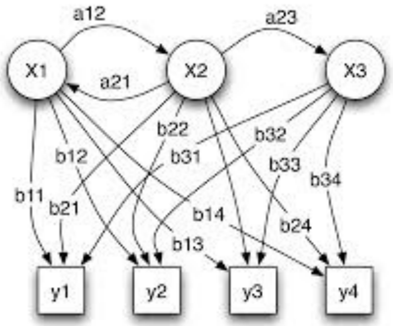


ANN

LR



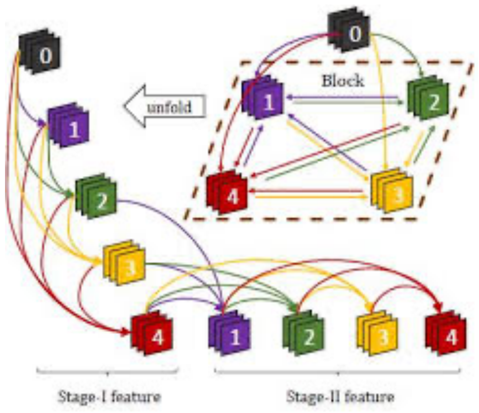

SVM



HMM

DNN Architectures

- Residual Multi-Layer Perceptron (ResMLP)
- Residual Convolutional Neural Network (ResCNN)
- Bidirectional Long Short-Term Memory (BiLSTM)
- Transformer, U-net
- Implicit ODE, DEQ, CVX, …



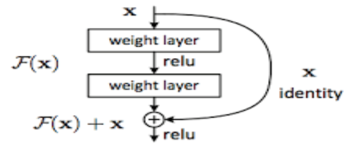
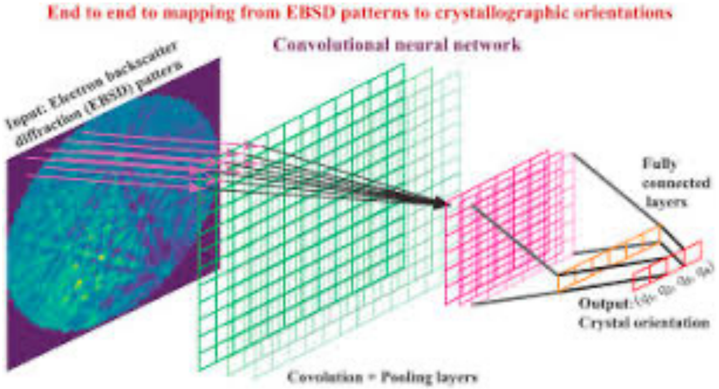
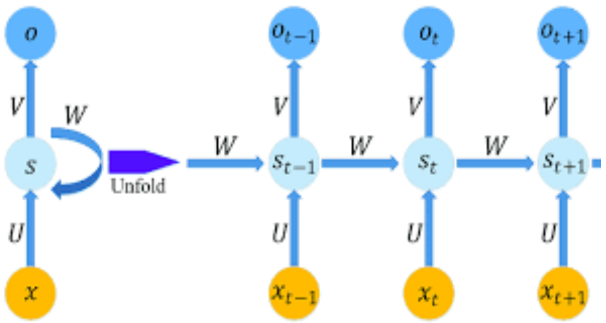
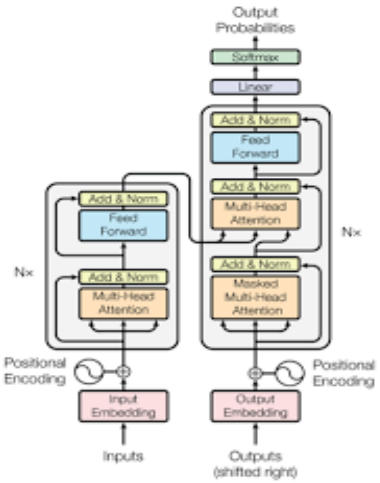
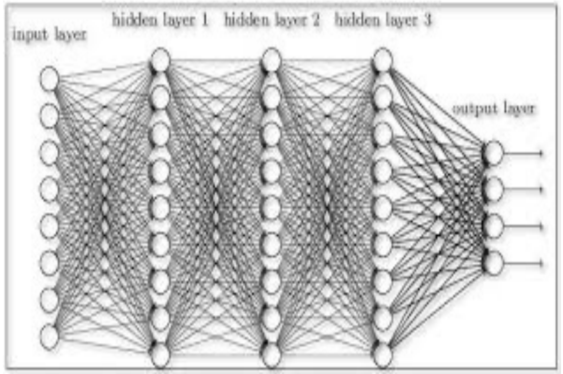


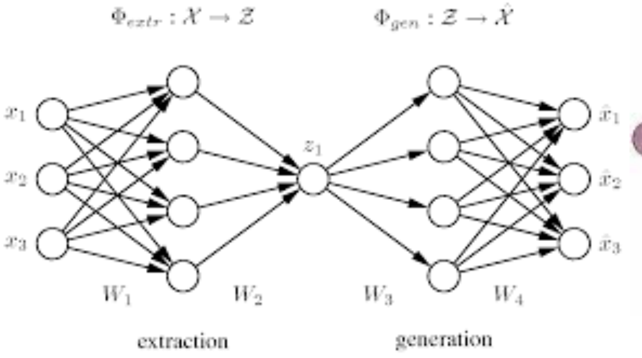
Figure 2. Residual learning: a building block.

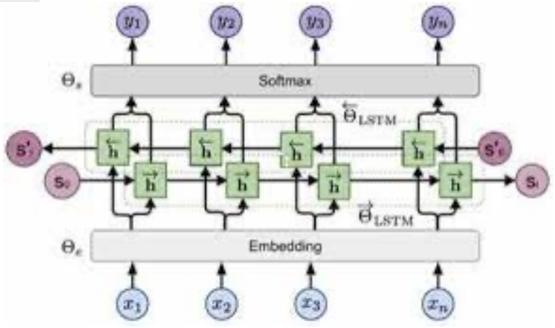


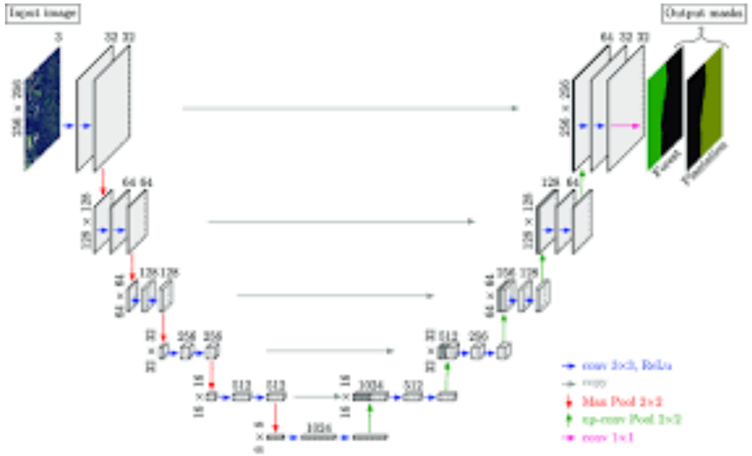


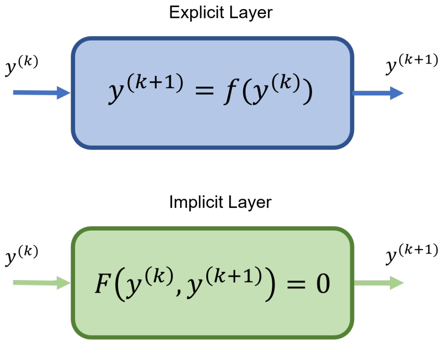






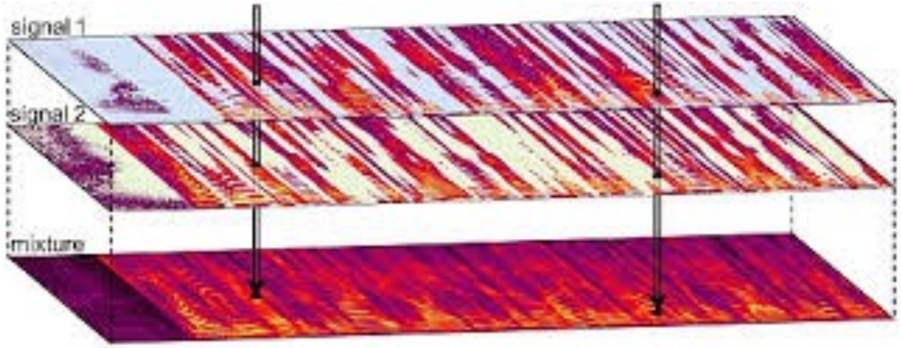


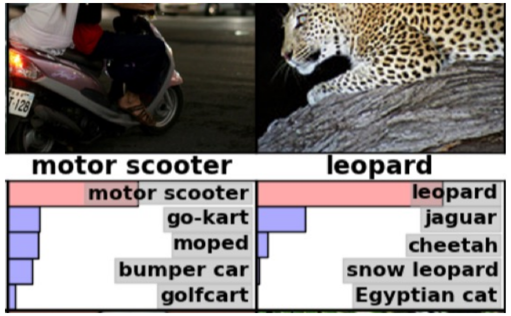


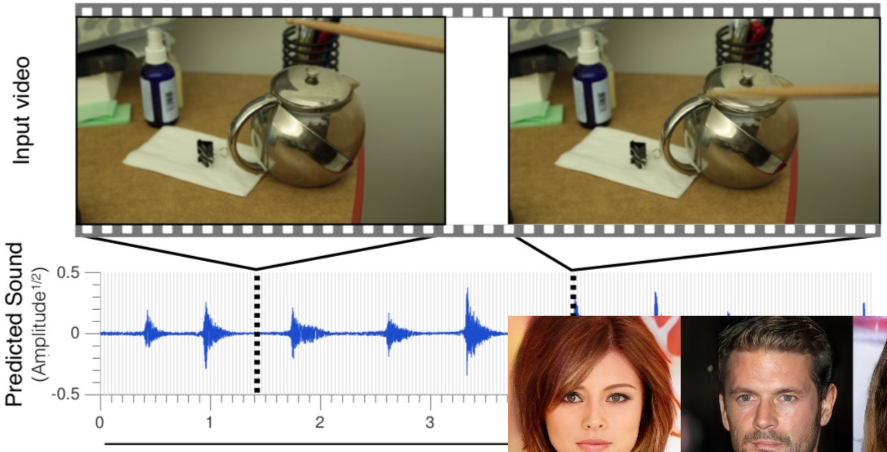


AI Success in Media (Audio & Visual) Signal Processing

- Denoising, segmentation, classification, translation, dialog, recognition, decomposition, generation, super-resolution, …



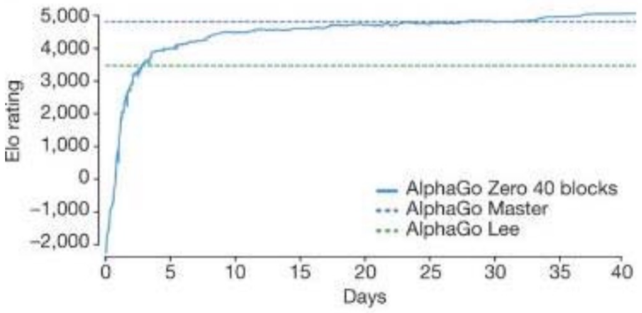


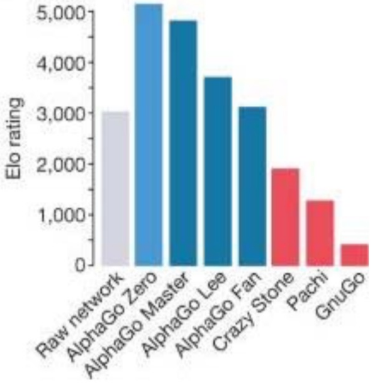


"man in black shirt is playing guitar."

AI Surpassed Human-Level Performance

- For some applications like gaming





Deep Learning Crisis for Sustainable Growth

- Escalating power consumption of DNN training
  - [Strubell et al. Energy and policy considerations for deep learning in NLP. 2019]
  - 1-big DNN training with network architecture search (NAS) on GPUs requires **5-fold** higher carbon emission of single car lifetime!
- New computing modality alternative to CPU/GPU/TPU is desired
  - **Natural computing:** **Quantum computing**, DNA computing, etc.

Consumption	CO_2e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

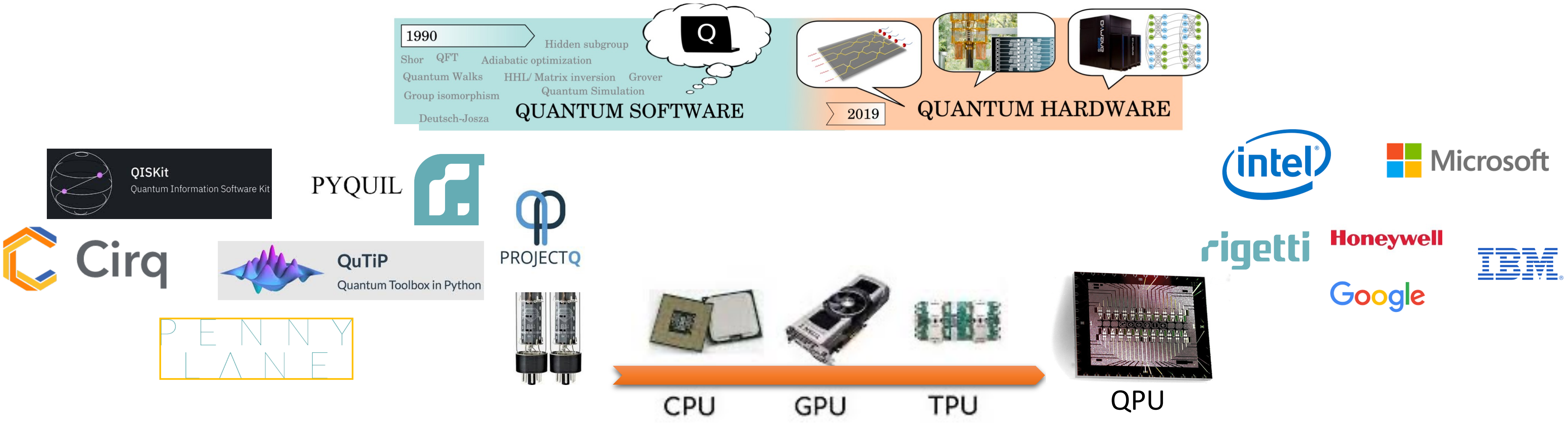
Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

Model	Hardware	Power (W)	Hours	kWh·PUE	CO_2e	Cloud compute cost
$\text{Transformer}_{base}$	P100x8	1415.78	12	27	26	\$41–\$140
Transformer_{big}	P100x8	1515.43	84	201	192	\$289–\$981
ELMo	P100x3	517.66	336	275	262	\$433–\$1472
BERT_{base}	V100x64	12,041.51	79	1507	1438	\$3751–\$12,571
BERT_{base}	TPUv2x16	—	96	—	—	\$2074–\$6912
NAS	P100x8	1515.43	274,120	656,347	626,155	\$942,973–\$3,201,722
NAS	TPUv2x1	—	32,623	—	—	\$44,055–\$146,848
GPT-2	TPUv3x32	—	168	—	—	\$12,902–\$43,008

Table 3: Estimated cost of training a model in terms of CO_2 emissions (lbs) and cloud compute cost (USD).[7] Power and carbon footprint are omitted for TPUs due to lack of public information on power draw for this hardware.

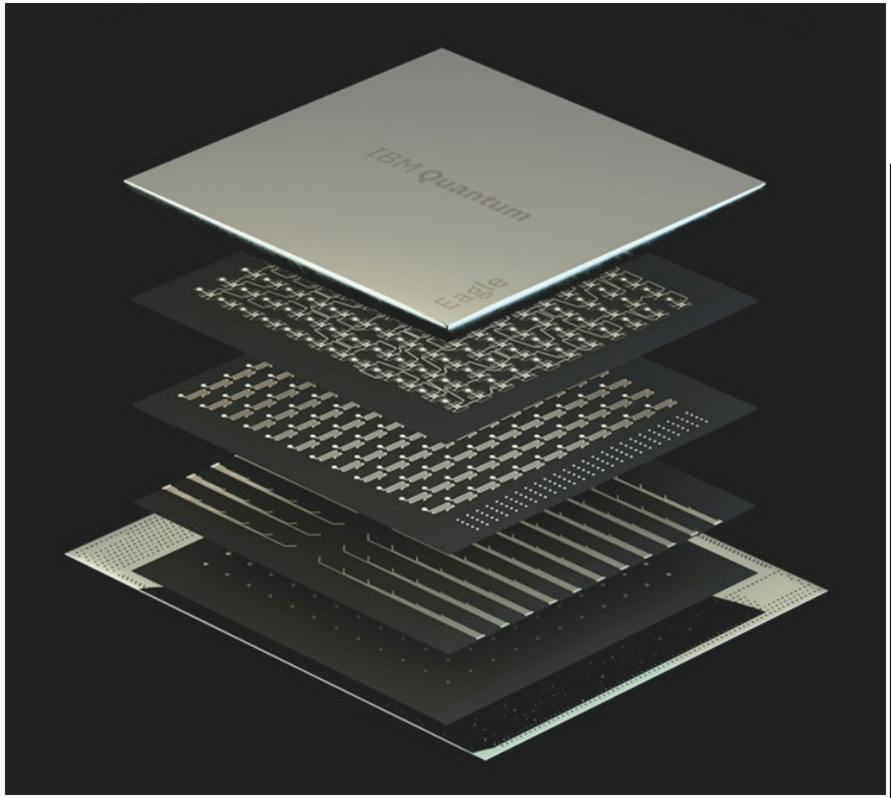
Quantum Computing

- Morgan Stanley: Quantum tech. can drive **4th industrial revolution**
- Quantum processing units (QPU) venders: **IBM**, **Google**, **Microsoft**, **Honeywell**, Intel, Nokia, AirBus, IONQ, rigetti, …
- Quantum cloud services: IBMQ, Amazon Bracket, Microsoft Azure, …
- Free libraries to evaluate quantum computing on realistic simulators or real devices

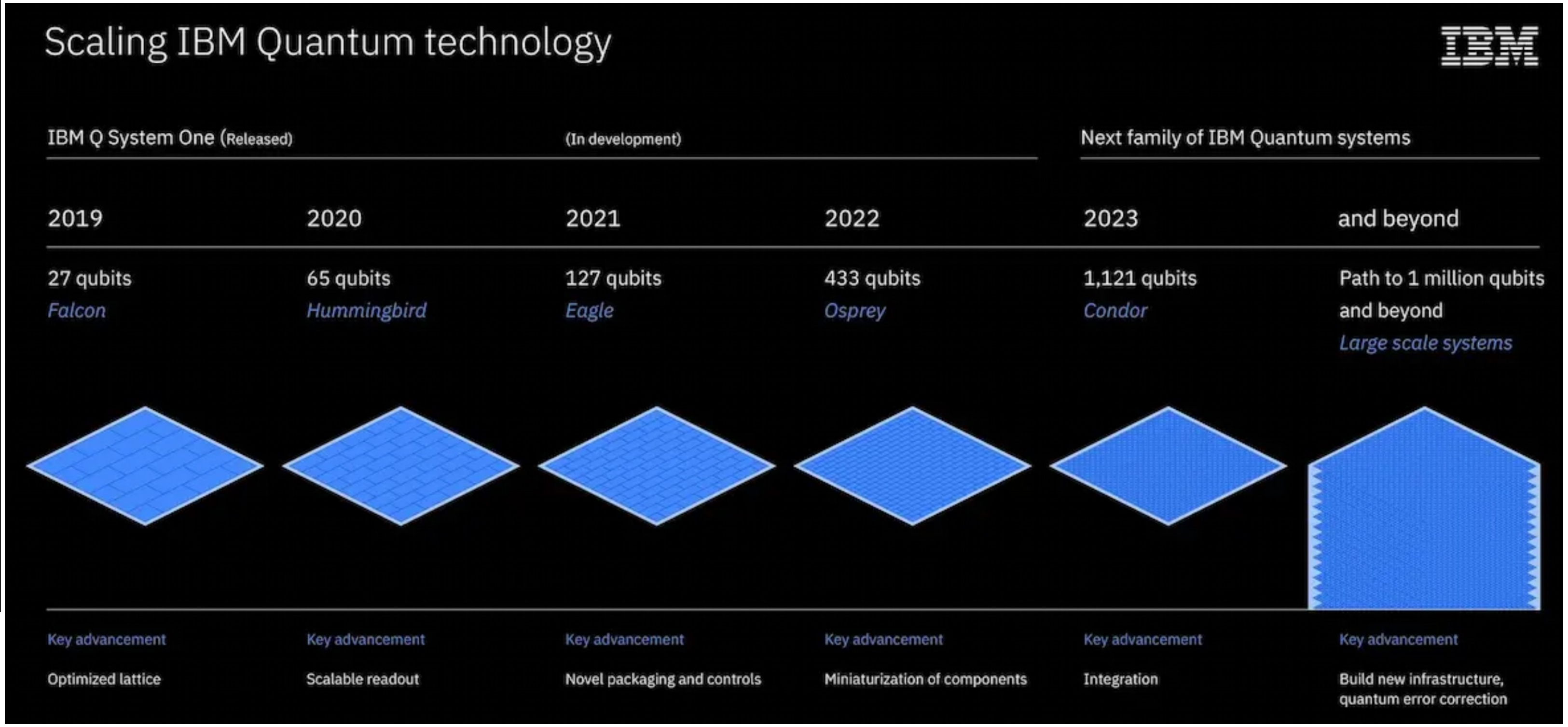


Evolution of Quantum Processing Unit (QPU)

- QPU development has been advancing rapidly to allow many qubits
  - IBM released **127-qubit** QPUs in Nov. 2021
  - IBM plans to release **1121-qubit** QPUs by 2023



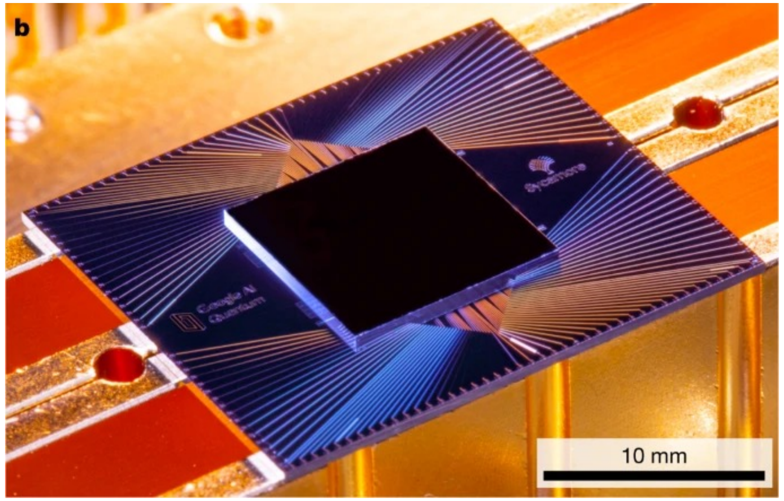
IBM 127-qubit QPU (Nov. 2021)

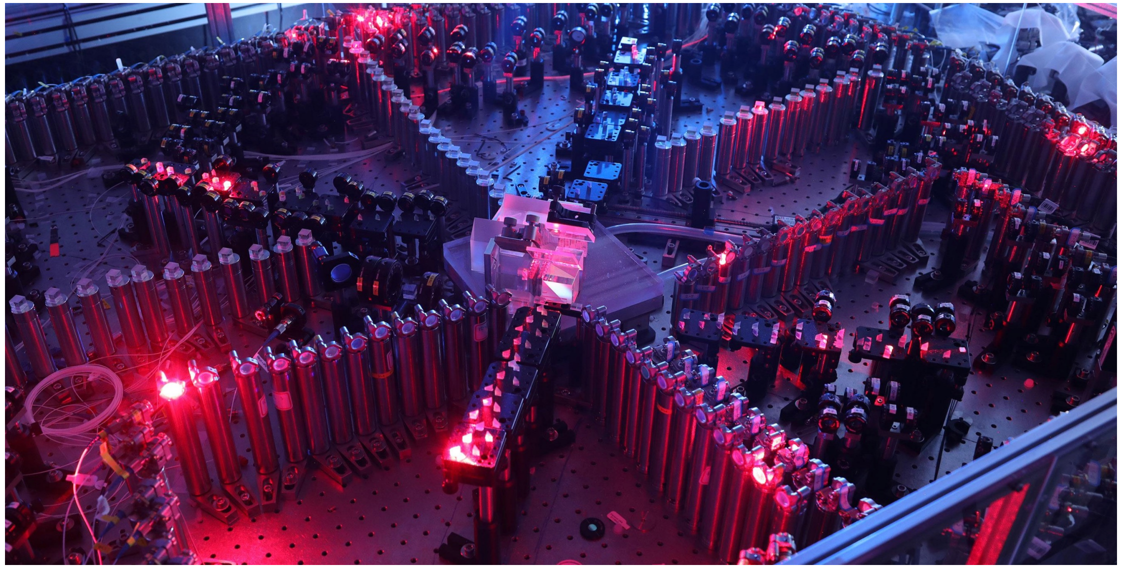


IBM QPU development roadmap (as of 2020)

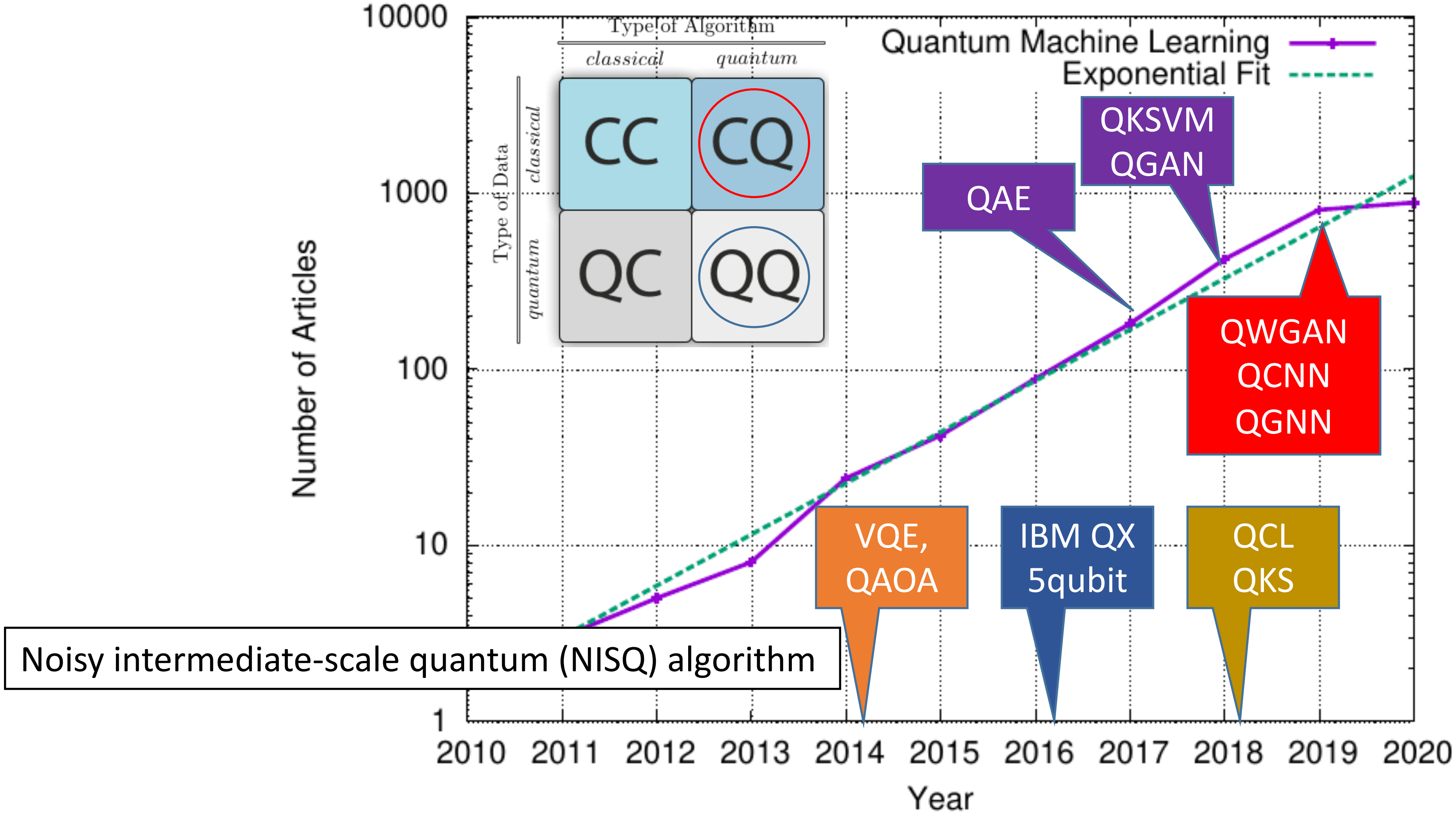
Quantum Supremacy

- Some reports claiming to have achieved ***quantum supremacy***:
  - Arute, F., Arya, K., Babbush, R. *et al.* Quantum supremacy using a programmable superconducting processor. *Nature* **574,** 505–510 (2019). https://doi.org/10.1038/s41586-019-1666-5
    - 53-qubit QPU: 200 sec. for 10,000-year job required for classical computer
  - Zhong HS, Wang H, Deng YH, Chen MC, Peng LC, Luo YH, Qin J, Wu D, Ding X, Hu Y, Hu P. Quantum computational advantage using photons. Science. 2020 Dec 18;370(6523):1460-3.
    - Boson sampling: 10^{14} faster than classic computer
- Quantum advantage is still argued for general applications





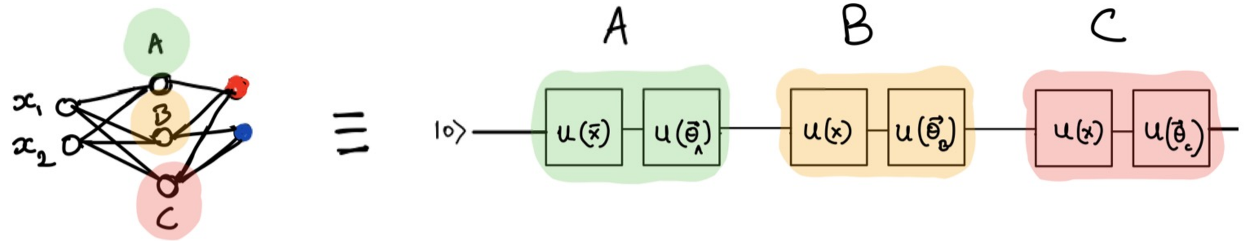
Quantum Machine Learning (QML)



VQE: Variational Quantum Eigensolver, QAOA: Quantum Approximate Optimization Algorithm
QAE: Quantum AutoEncoder, QKSVM: Quantum Kernel Support Vector Machine, Q(W)GAN: Quantum (Wasserstein) Generative Adversarial Network,
QCNN: Quantum Convolutional Neural Network, QGNN: Quantum Graph Neural Net, QX: Quantum Experience, QCL: Quantum Circuit Learning, QKS: Quantum Kitchen Sink

Universal Approximation Theorem/Property (UAT/UAP)

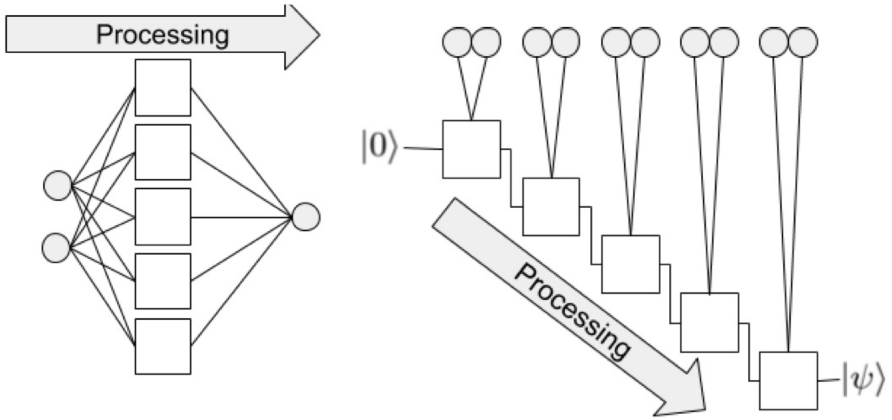
- UAP for classical neural networks:
  - Single hidden neural networks can approximate arbitrary bounded continuous functions [Cybenko 1989]
  - Deep hidden neural networks can asymptoticly approximate arbitrary functions [Zhou 2017]
- UAP still holds for quantum computing [Perez 2019]
  - *Data re-uploading* trick



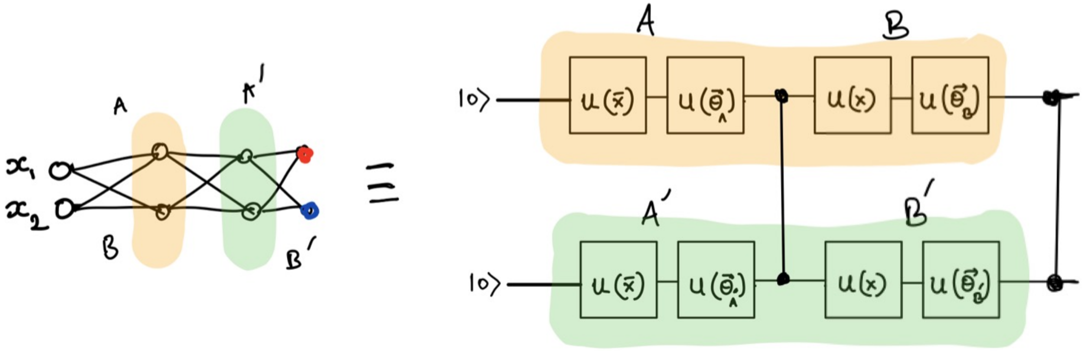
Wider/deeper neurons can reduce approximation error

$$h(\vec{x}) = \sum_{i=1}^{N} \alpha_i \; \varphi\left(\vec{w}_i \cdot \vec{x} + b_i\right)$$

$$\mathcal{U}(\vec{x}) = U_N(\vec{x}) U_{N-1}(\vec{x}) \cdots U_1(\vec{x}) = \prod_{i=1}^{N} e^{i\vec{\omega}(\vec{\phi}_i(\vec{x}))\cdot\vec{\sigma}}$$



(a) Neural network (b) Quantum classifier

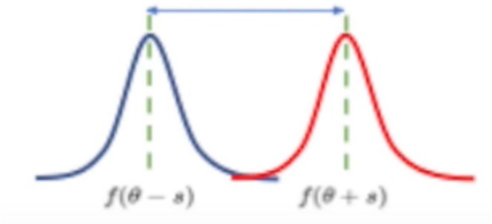


Wider neuron → More quantum layers
Deeper layer → More qubits

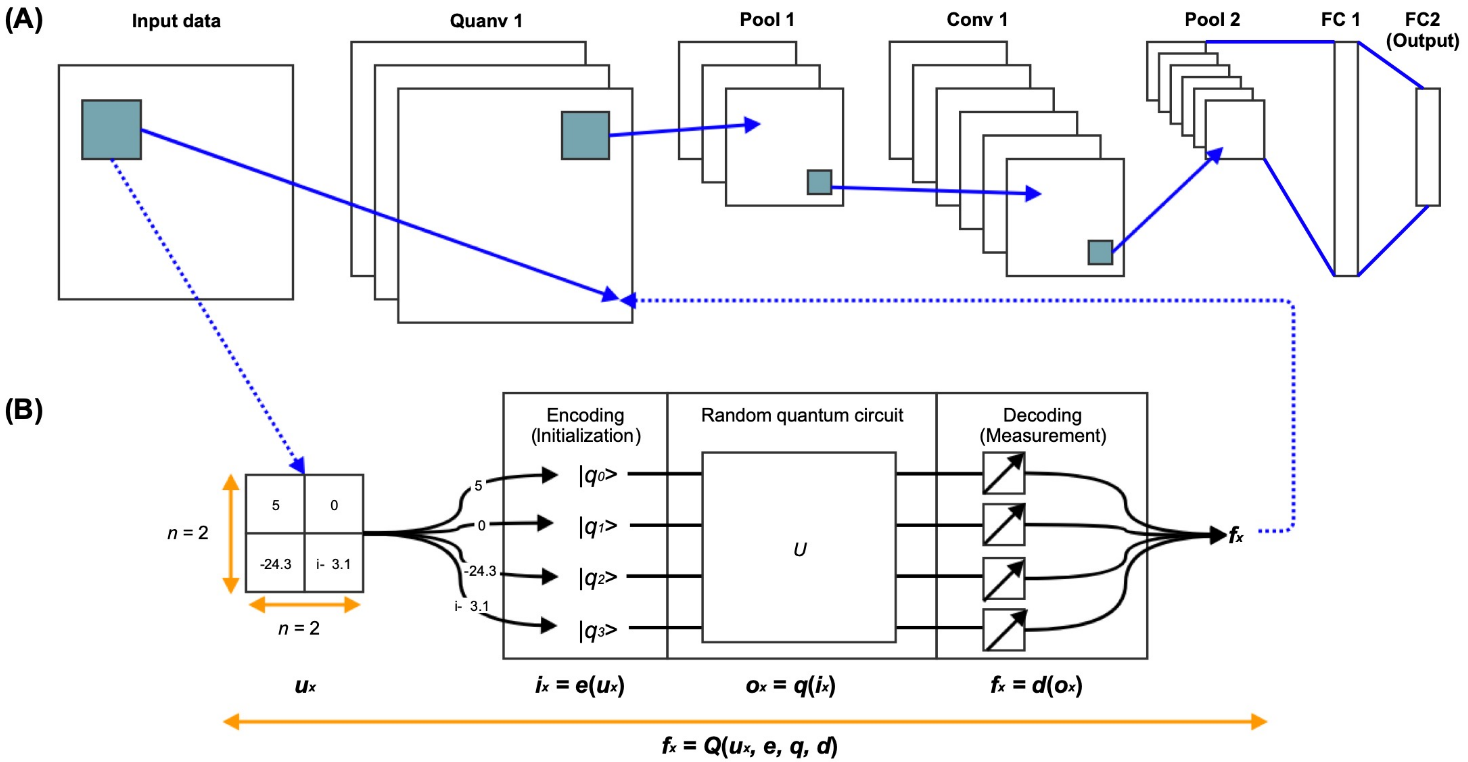
Differential Programming

$$\partial_\mu f(\mu) = c\big(f(\mu+s) - f(\mu-s)\big)$$

- Quantum operation is differentiable:
  - *Parameter shift rule* [Mitarai/Schuld 2018] (exact gradient)

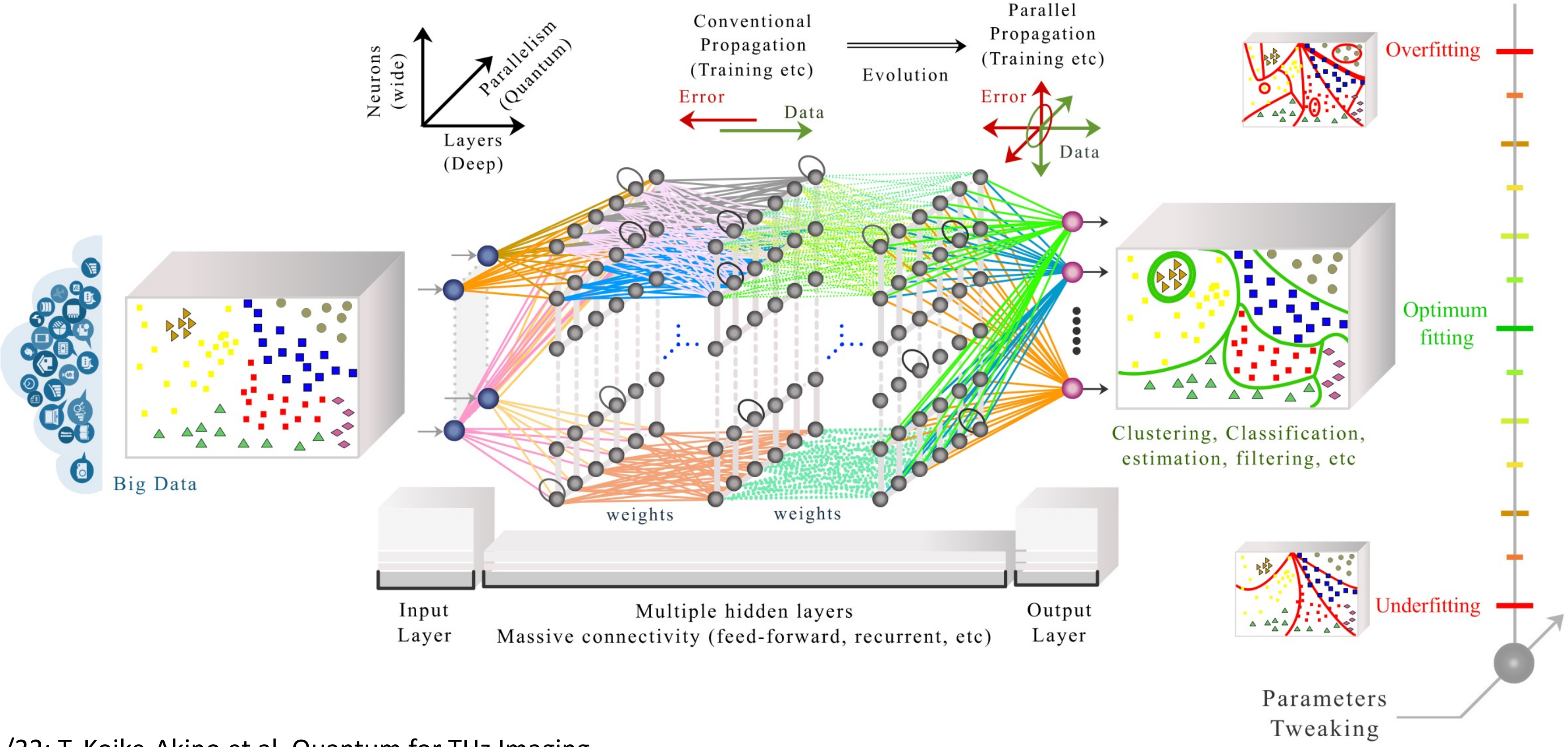


- Backpropagation through hybrid classical/quantum chips
  - Able to integrate *(implicit) quantum layers* into DNN models
  - e.g., Quanvolutional Neural Network [Henderson2019]



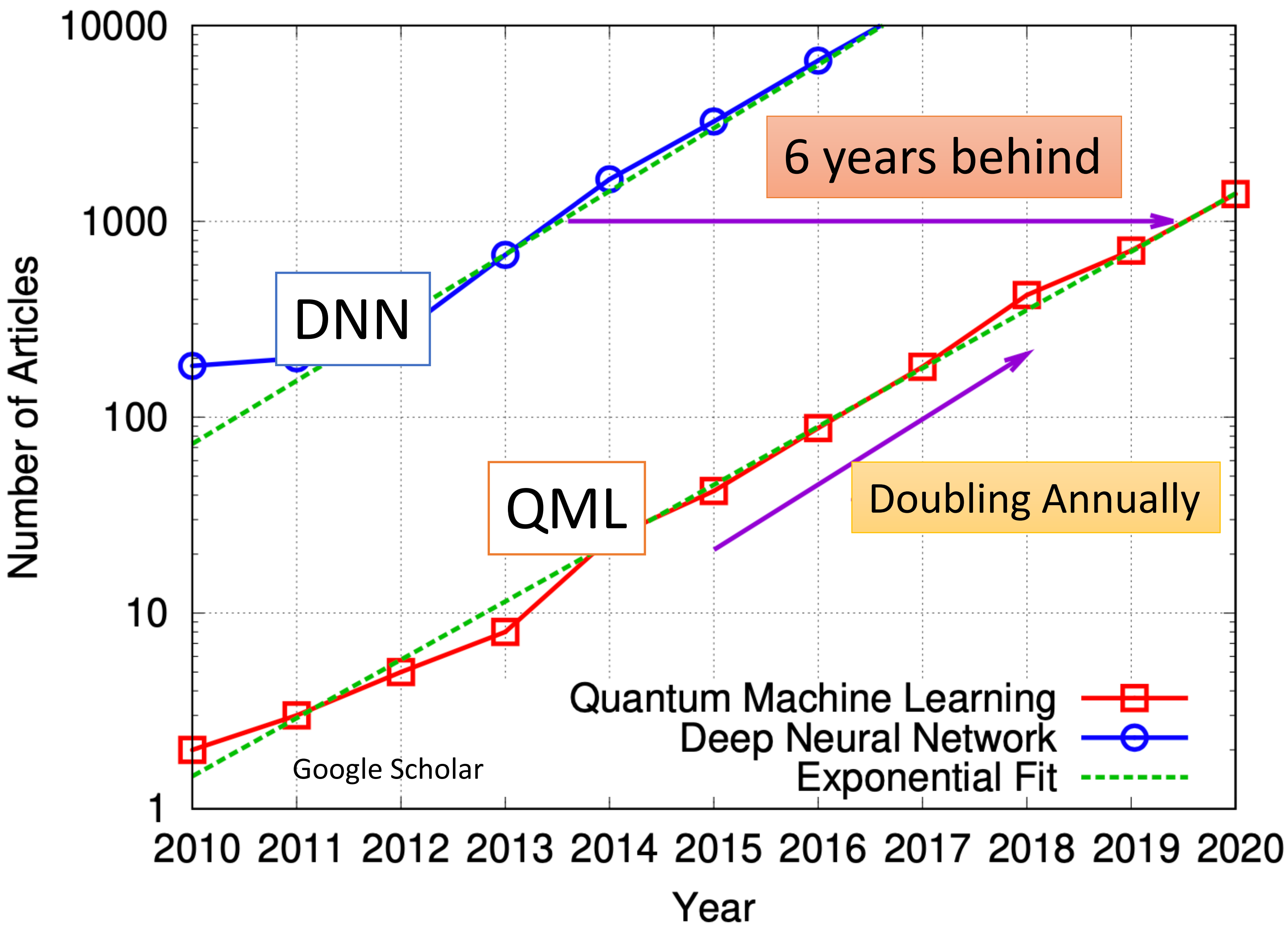
Quantum Neural Network (QNN)

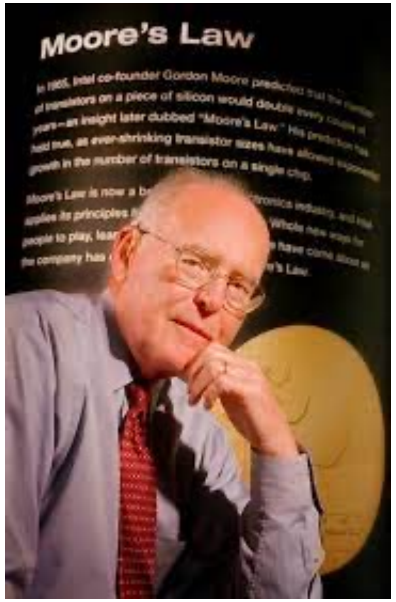
- QML is a key major driver for **6G applications** [Nawaz et al. Access 2019]
- (Hyped) expectation of QNN advantage:
  - Fewer trainable parameters to support exponentially large quantum states in parallel
  - Parallel ensemble to prevent overfitting and underfitting
  - Low-power processing



Quantum Machine Learning (QML): Moore's Law

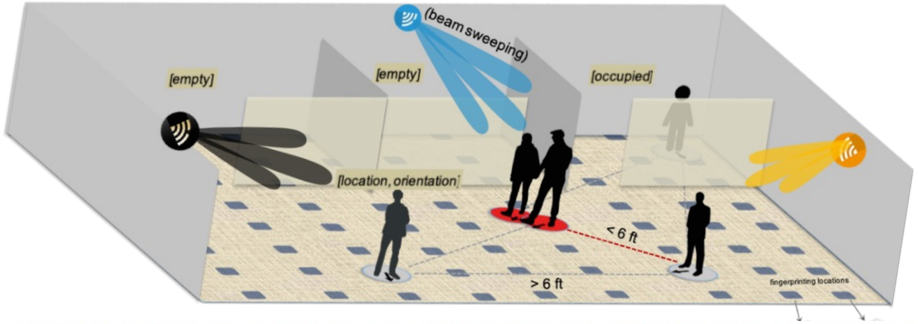
- Number of articles on QML is doubling annually, just **6 years** behind of DNN



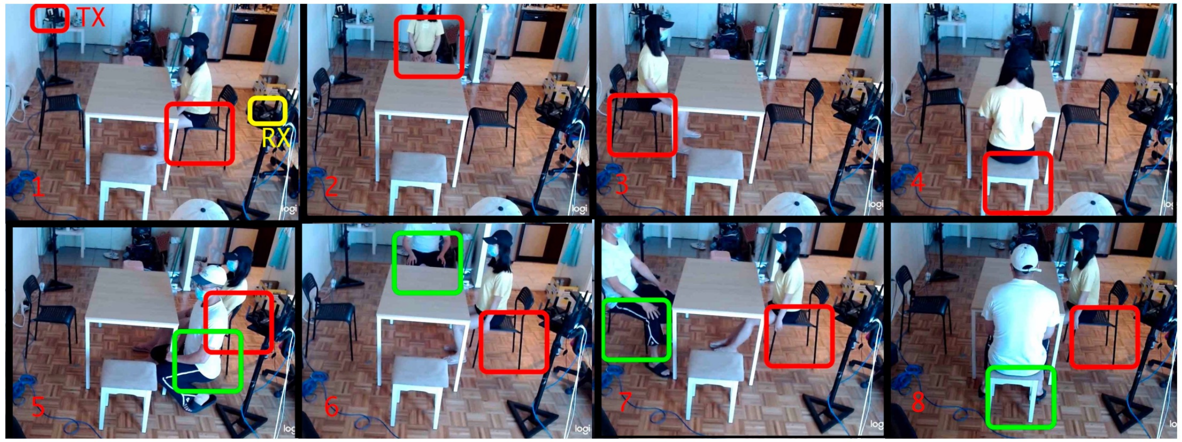


QML Meets *WiFi* Sensing → *THz* Sensing

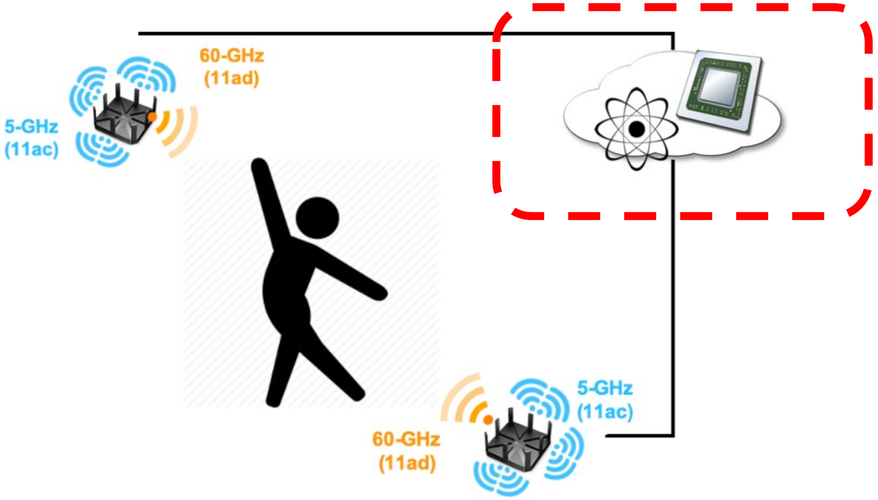
- Indoor Monitoring: [Koike-Akino, et al., "Quantum Transfer Learning for Wi-Fi Sensing", ICC 2022]
  - Indoor Localization: [Koike-Akino, et al., "Fingerprinting-Based Indoor Localization with Commercial MMWave WiFi: A Deep Learning Approach", Access 2020]
  - Human Monitoring: [Yu, et al., "Human Pose and Seat Occupancy Classification with Commercial MMWave WiFi", GLOBECOM 2020]



Indoor localization



Occupancy Sensing



(a) Wi-Fi pose recognition empowered by QML

(b) Pose snapshots

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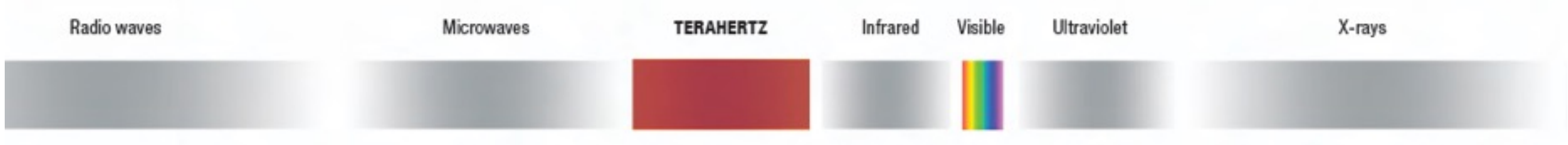
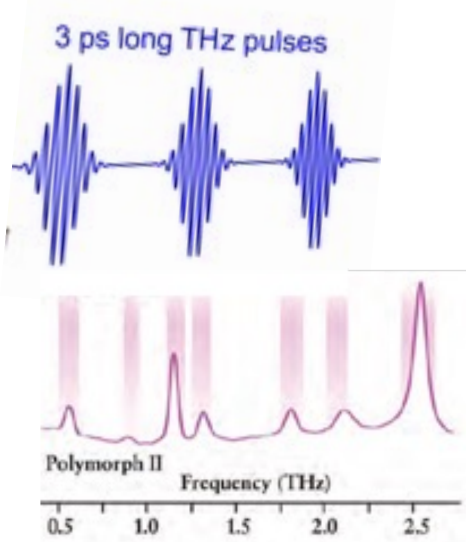
Changes for the Better

THz Sensing: Non-Destructive Inspection

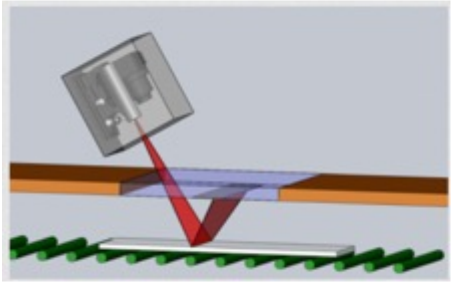
- THz spectrum is located in between infrared (IR) and microwaves (MW)
- Fine Resolution: ultra-wideband spectrum for a wavelength of 300 μm at 1 THz
- THz wave penetrates many materials (advantages compared to IR) and exhibits better spatial resolution (compared to MW)
- Substances show characteristic fingerprints at THz spectrum due to collective molecular excitations
- THz wave is non-ionizing





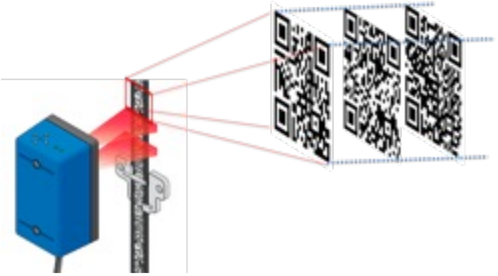
Substance Inspection

Internal Defect Detection



Factory Automation

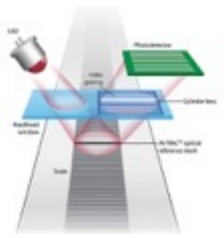
THz Multi-Layer Barcode Positioning



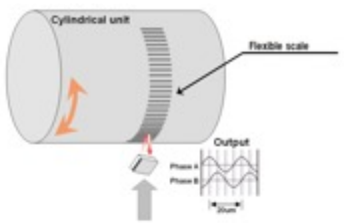
THz Positioning: 1D Barcode

Optical Encoders

Linear



Cylindrical



Magnetic Encoders

Linear

Cylindrical

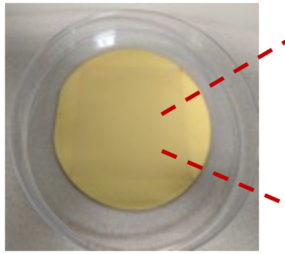
Rotary

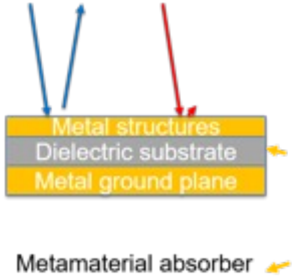
- Why THz encoder
  - High-capacity 2D/3D positioning
  - Robustness against dust, smoke & fire
  - Resilient to light conditions
  - Contactless (robust to vibration)

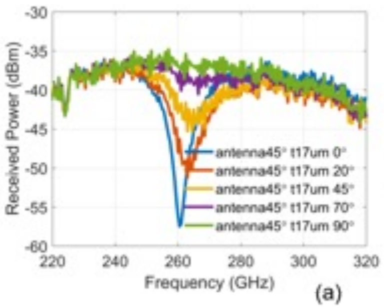
THz Polarizer + Metamaterial Absorber

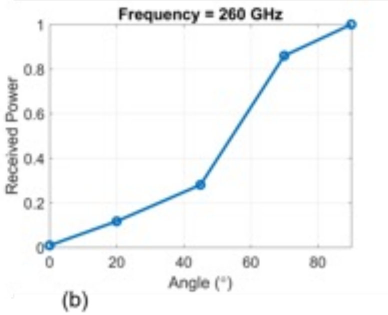
(MERL, SPIE Phtonitcs'18, IRMMW-THz'18, '19' 20)

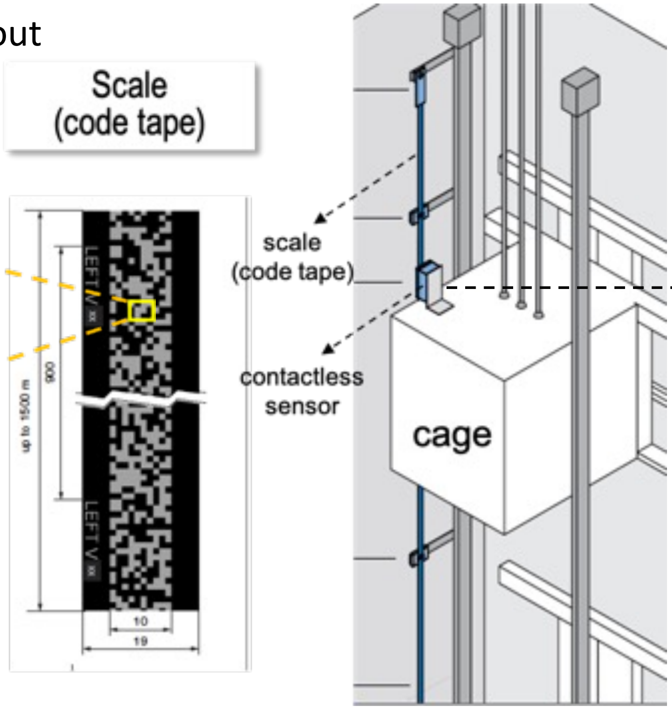
Embedding Codes Into Polarization Angles Without Additional Reflections from Substrate





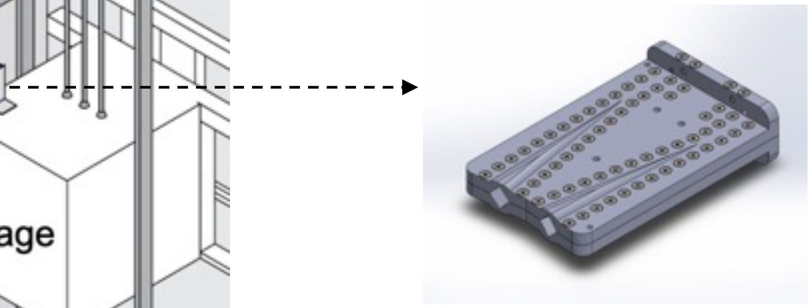






THz 1-D Barcode

- Polarization-based binary bit embedding



THz transceiver at 220-320 GHz

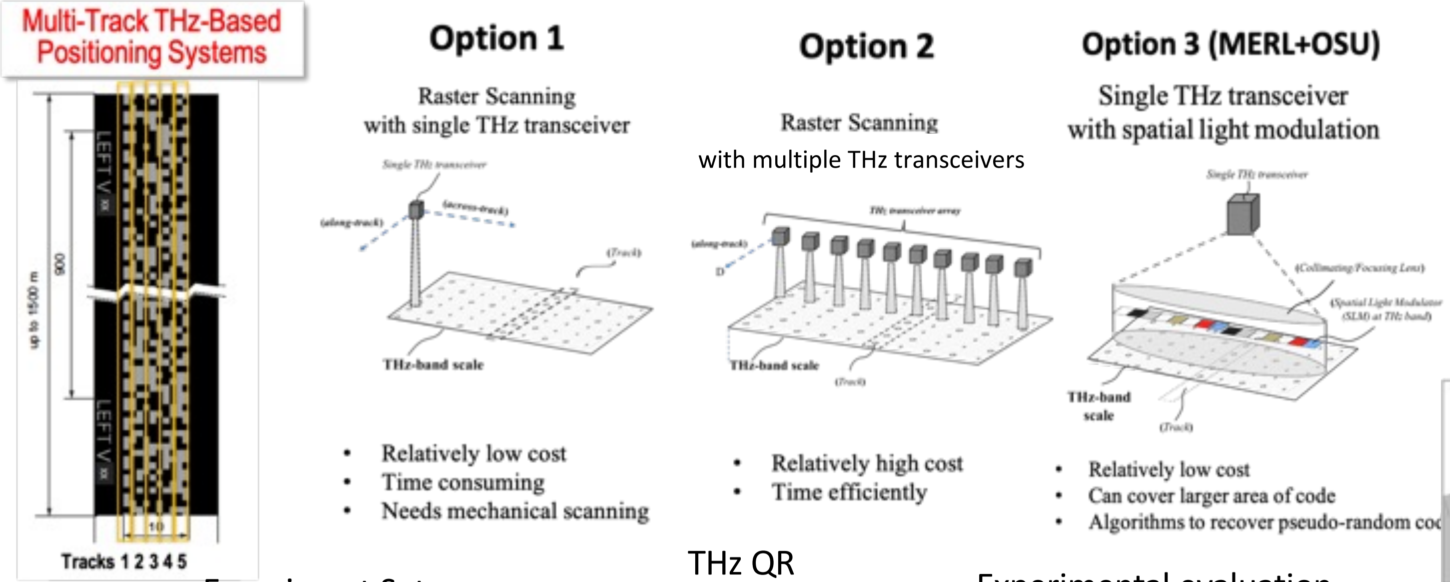
(collaboration with Prof. Ruonan Han (MIT))

THz Positioning: 2D QR-code

From THz barcode (Single Track) to THz QR code (Multiple Tracks)

1. THz-band spatial light modulator (SLM): OSU
2. Recovery algorithm of pseudo-random patterns: MERL

(IRMMW-THz’18, ’20, ICASSP’18)



$$y_n = \mathbf{a}_n^T \mathbf{x} + v_n$$

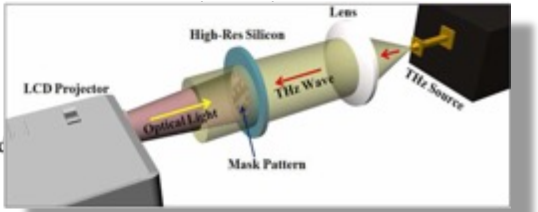
noise at time n

single measurement at time n

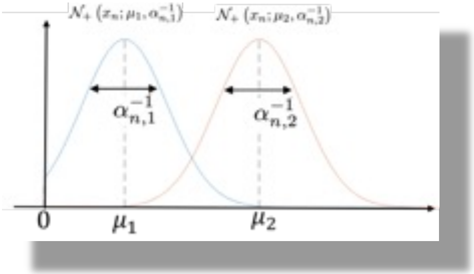
random mask

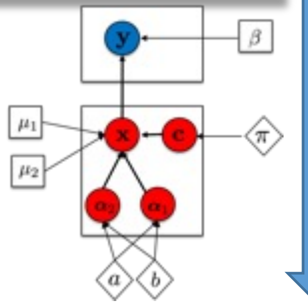
pseudo-random binary sequences with unknown alphabet

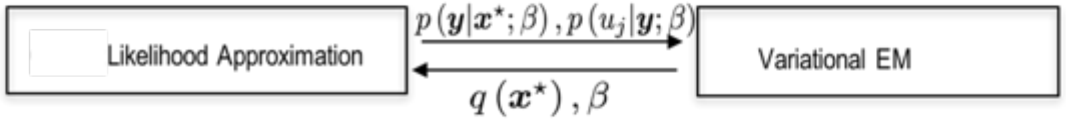
THz-band SLM
by photoexcitation of silicon



Incorporate prior truncated Gaussian mixture model (binary)

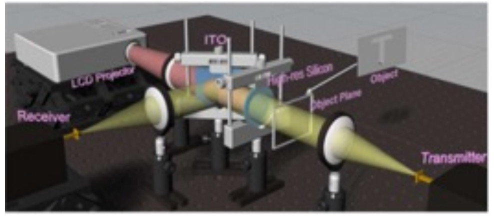


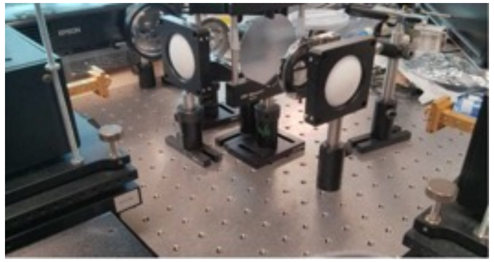




Iterative variational Bayesian inference (VBI) to recover x from y

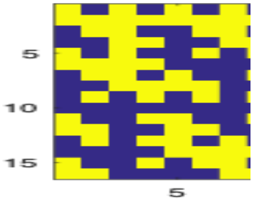
Experiment Setup



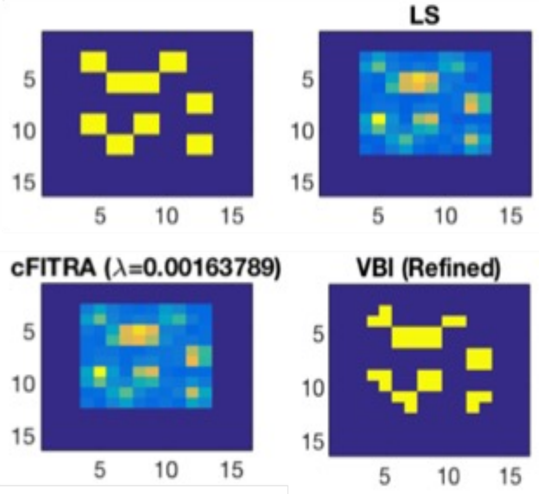


THz QR sample

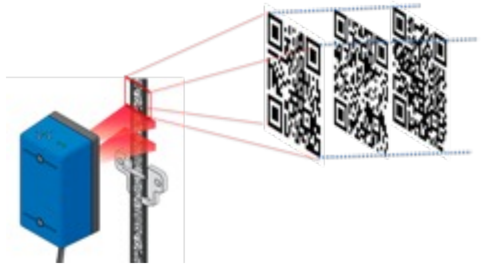
One mask (a_n)



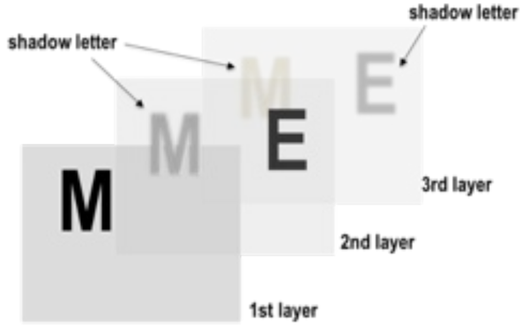
Experimental evaluation



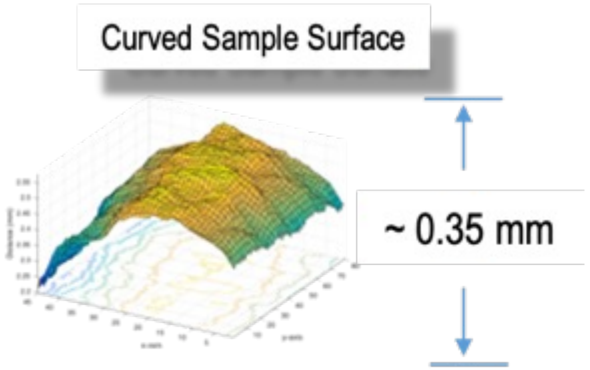
THz Positioning: 3D QR-code



From THz barcode (Single Track), via THz QR code (Multiple Tracks), to Multi-layer QR code

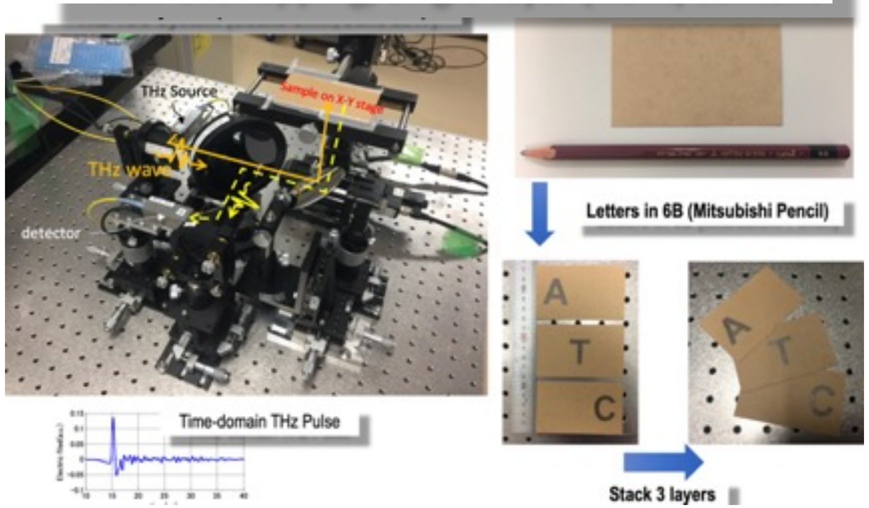


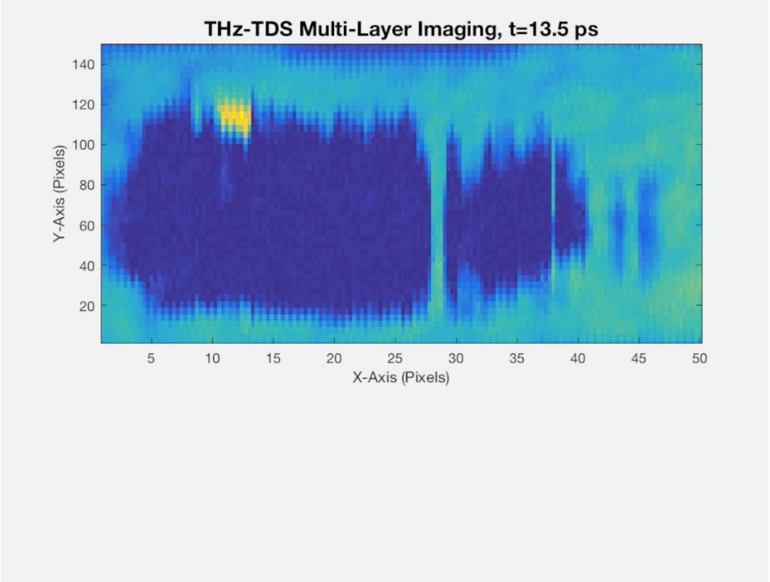
Shadowing effect



Sweep distortion
(due to sample curvature and motor stage vibration)

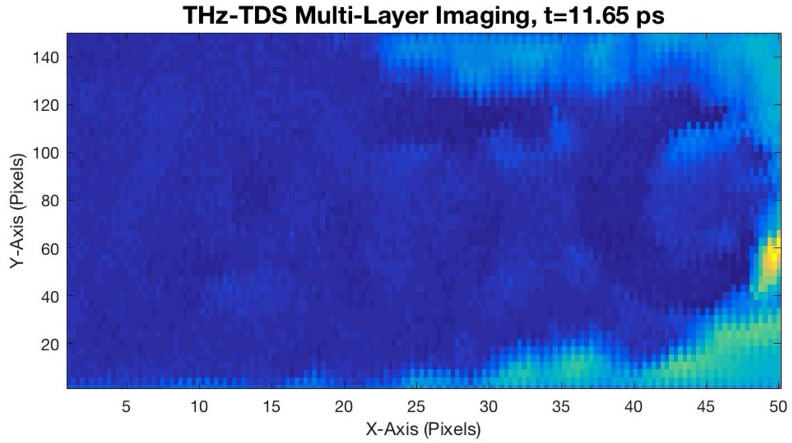
Non-overlapping, single-layer (front) content





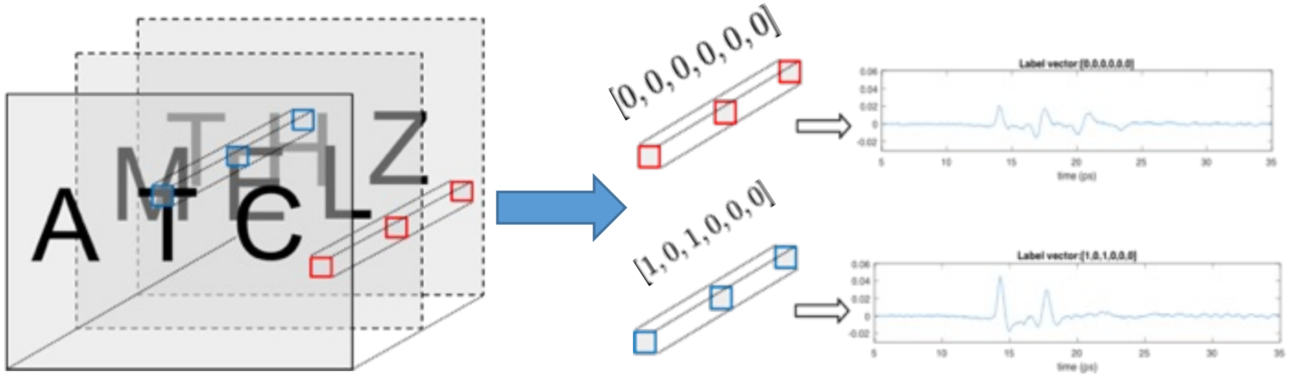
Overlapping, single-layer (front) content

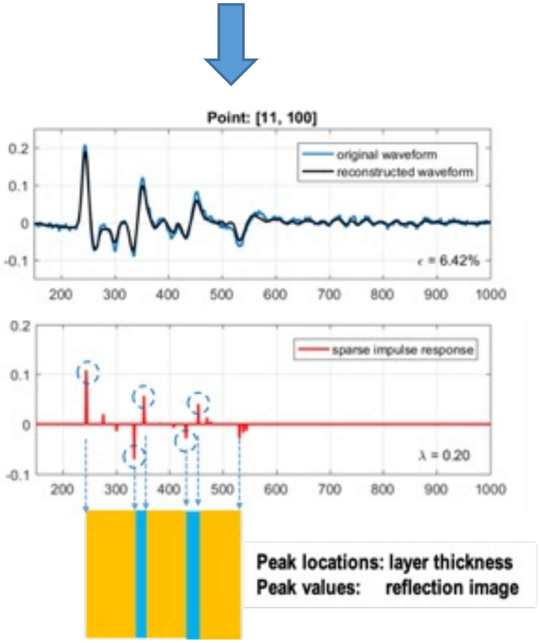
1st layer 2nd layer 3rd layer



Deep Learning for THz Sensing

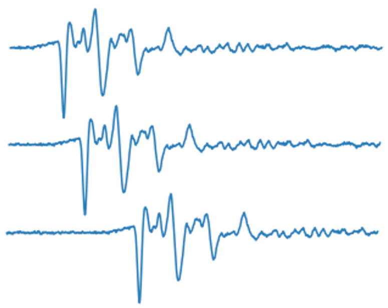
- IRMMW-THz'17/21





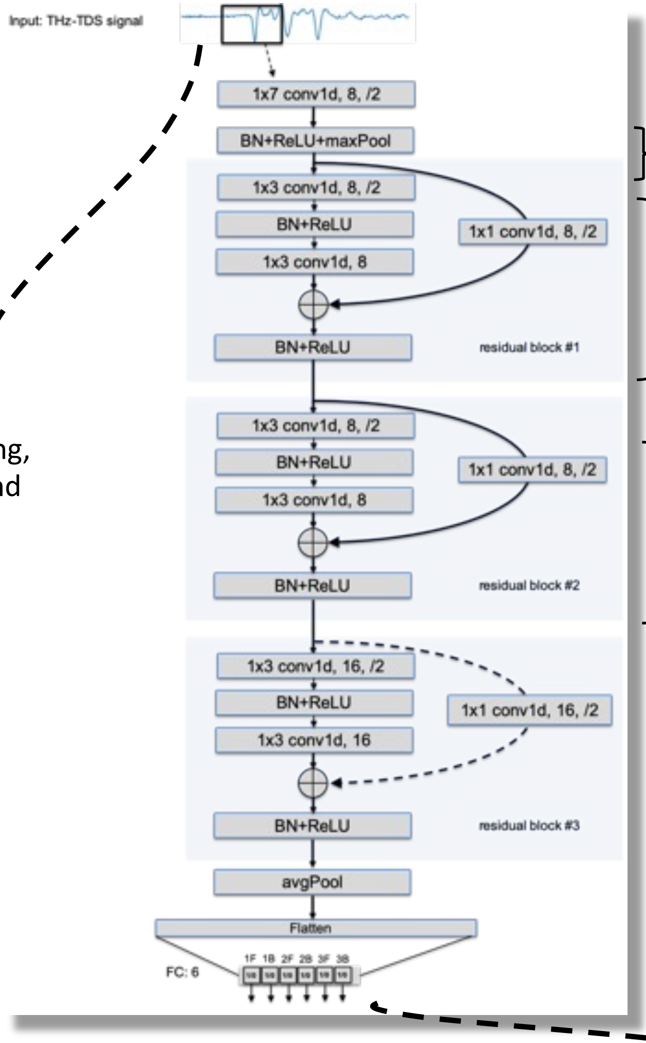
Layer identification
(sparse deconvolution – LASSO/FISTA)

- **Data augmentation (invariant to sweep distortion):** augment training data by shifting, attenuating waveforms (a scaling factor), and adding noise



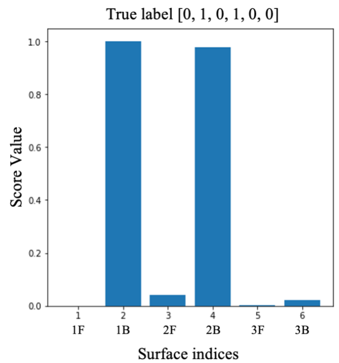
Learning-based multi-layer THz imaging

Neural Network Architecture
(1-D ResNet)



$$\mathbf{y}_0 = \mathrm{maxPool}\{f_0(\mathbf{x}, \boldsymbol{\theta}_0)\}$$

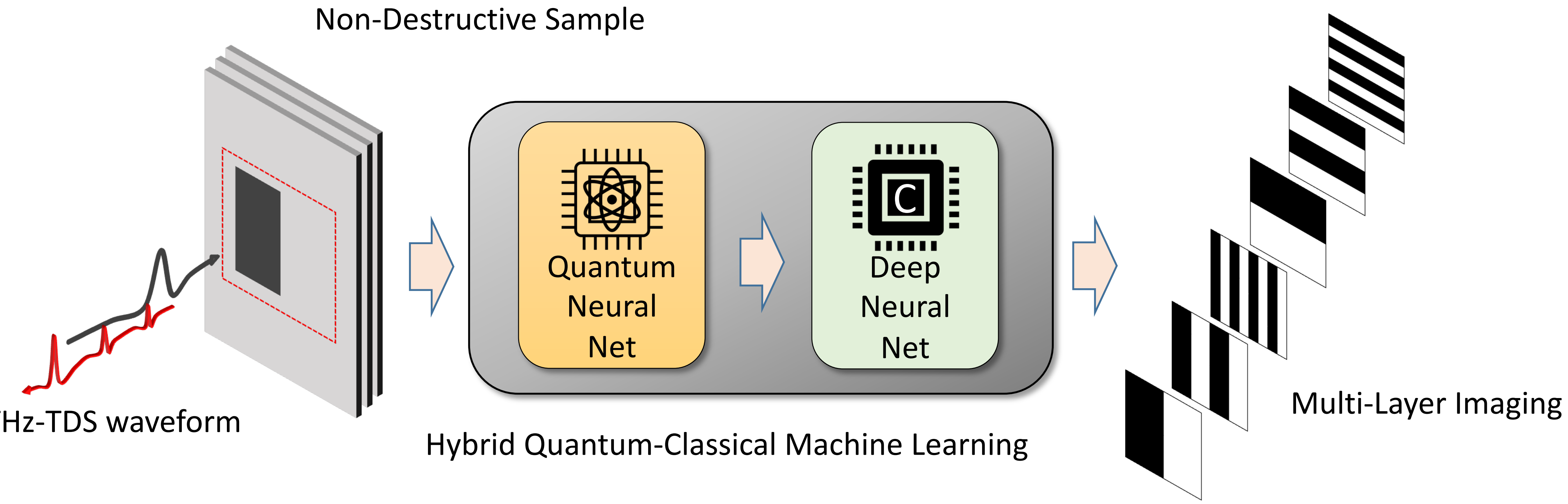
$$\mathbf{y}_\ell = f_\ell(\mathbf{y}_{\ell-1}, \boldsymbol{\theta}_\ell) + \mathbf{W}_{\ell-1}\mathbf{y}_{\ell-1}$$



Multi-layer/multi-label classification
(shadowing effect)

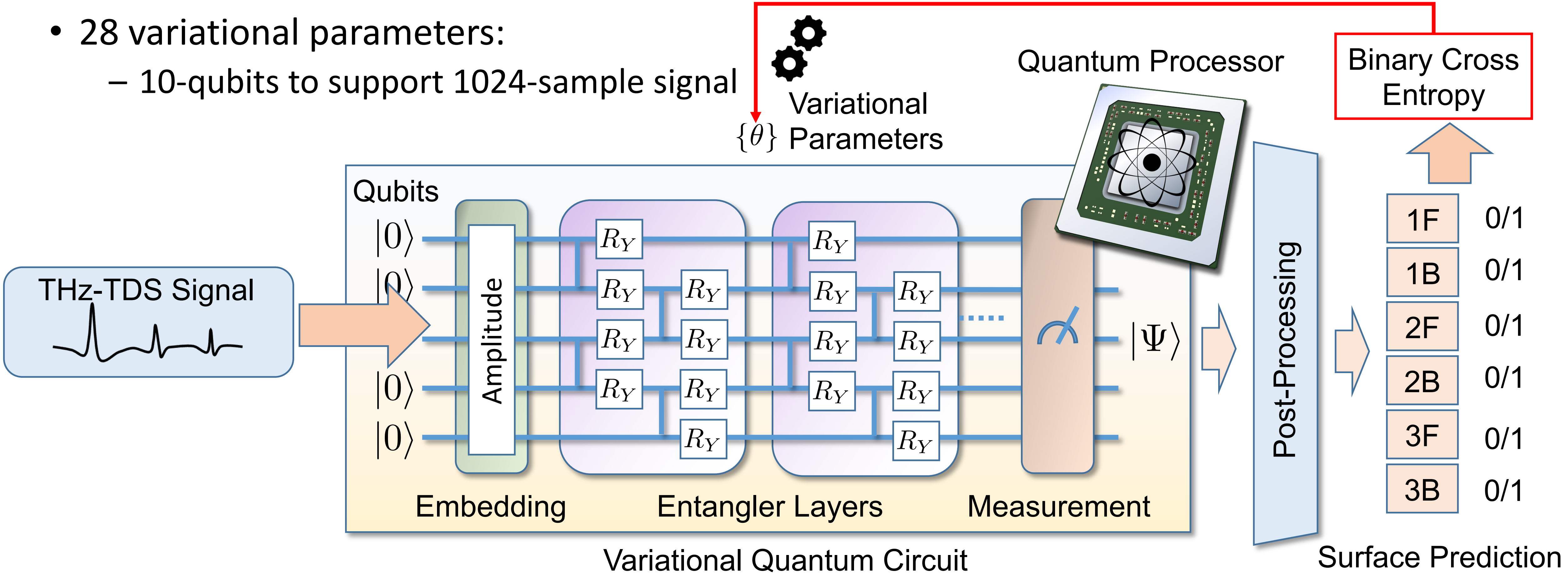
Hybrid Quantum-Classical Neural Network

- Quantum neural network (QNN) is used to support DNN model

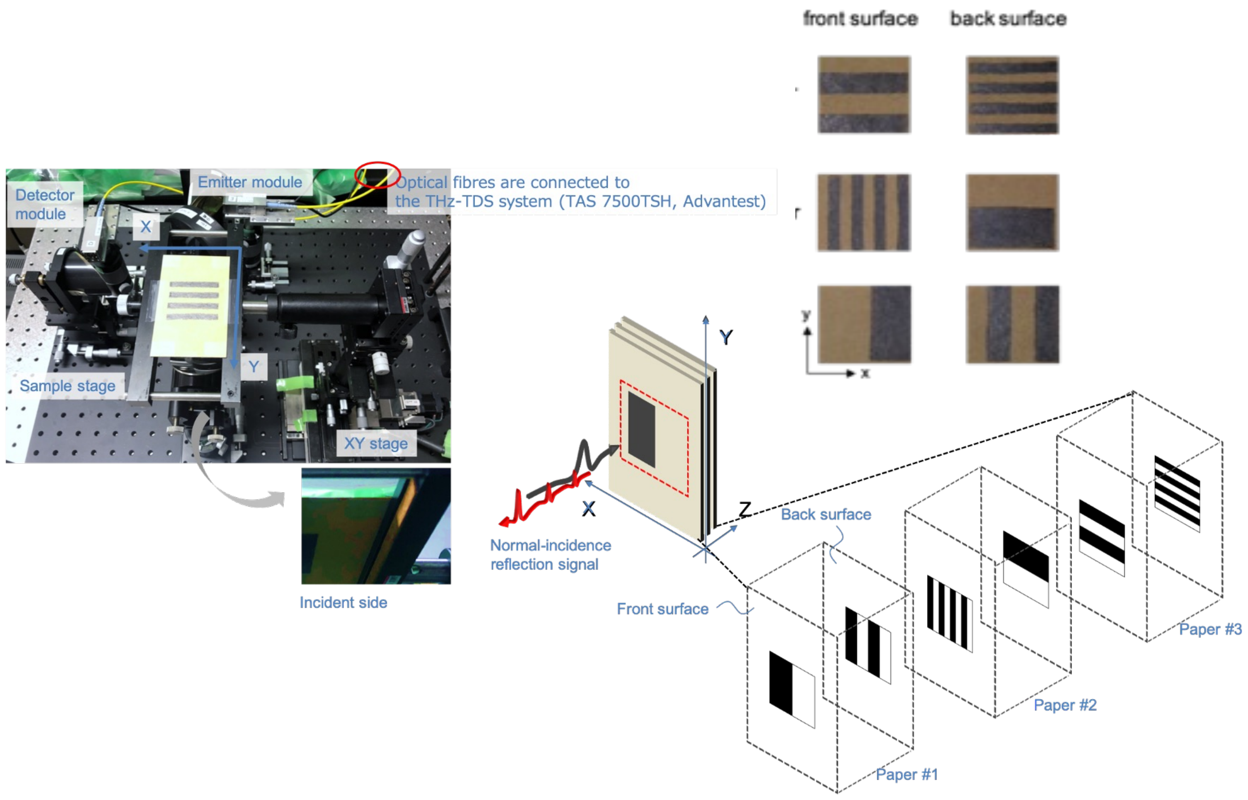


Quantum Neural Network (QNN) for Feature Extraction

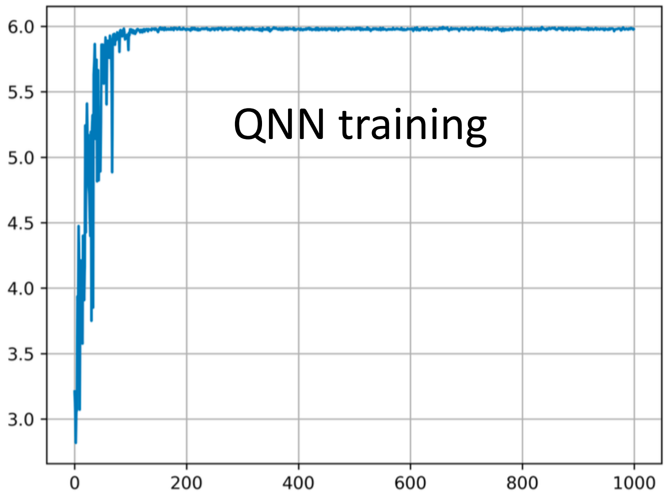
- Simplified two-design (S2D) ansatz:
  - Staggered Pauli-Y rotations with controlled Z gates
  - Holding statistical properties identical to ensemble random unitaries with respect to the Haar measure up to the first 2 moments: SO(2^N) -> $2N$
- 28 variational parameters:
  - 10-qubits to support 1024-sample signal



THz Experiments (Osaka Univ.)

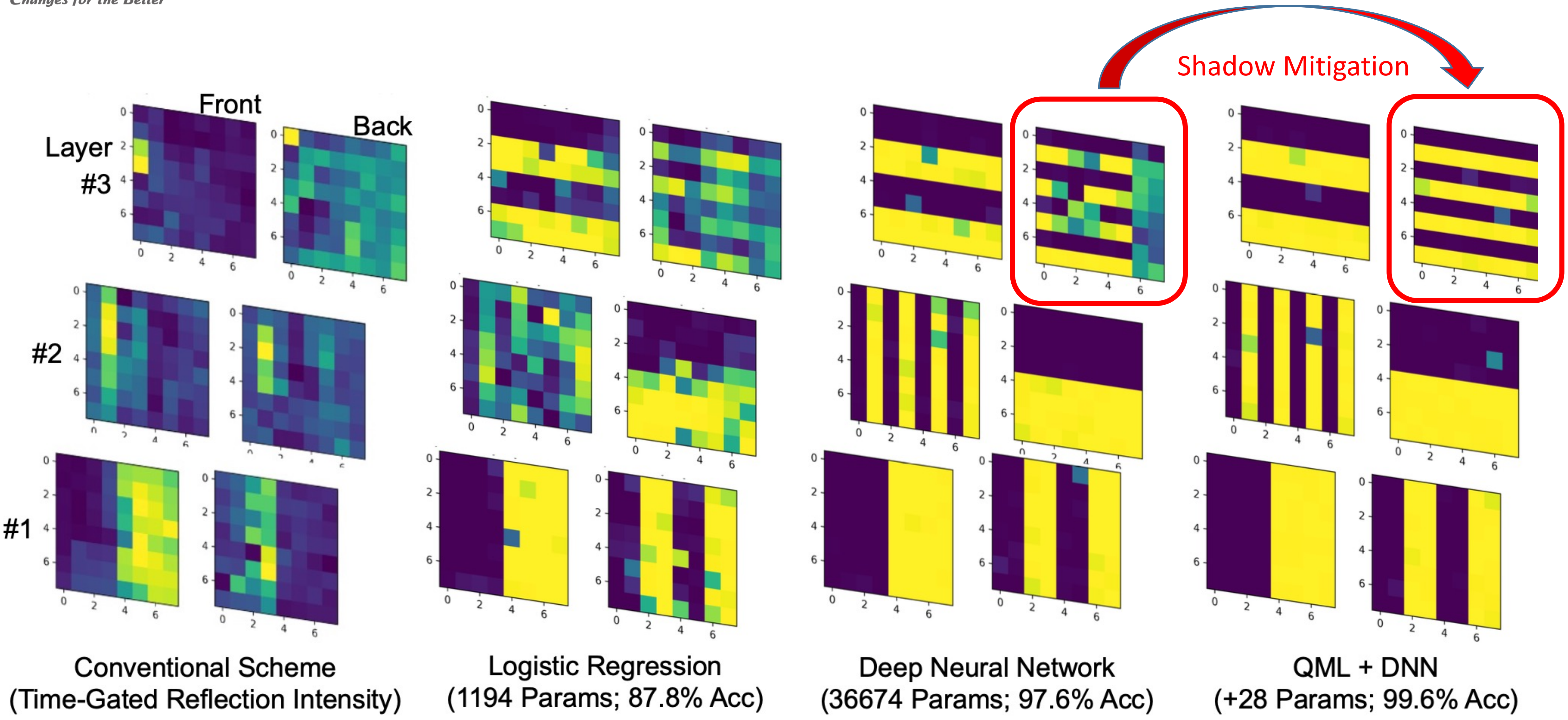


Variable	Size	Note
datasetArray	4096 × 101 × 101	3-D data cube with sample waveforms - Dimension 1: time axis - Dimension 2: X axis - Dimension 3: Y axis
nSamp	1	Number of time-domain data points (= 4096)
nX	1	Number of x-axis data points (= 101)
nY	1	Number of y-axis data points (= 101)
pos	1x101	X- and Y-axis [mm] (= -25 : 0.5 : 25)
ref	4096x1	Reference waveform (Aluminum mirror)
time	4096x1	Time axis [ps]



- Each class (2^6=64 in total) covers 10 x 10 = 100 pixels (0.5x0.5 mm^2) with 4096 time-domain samples for each pixel.
- We randomly split the experimental data for each pixel into training (0.6), validation (0.1), and test (0.3) samples.
- We applied data augmentation to the training dataset including downsampling, shifting, scaling, adding noise, etc.

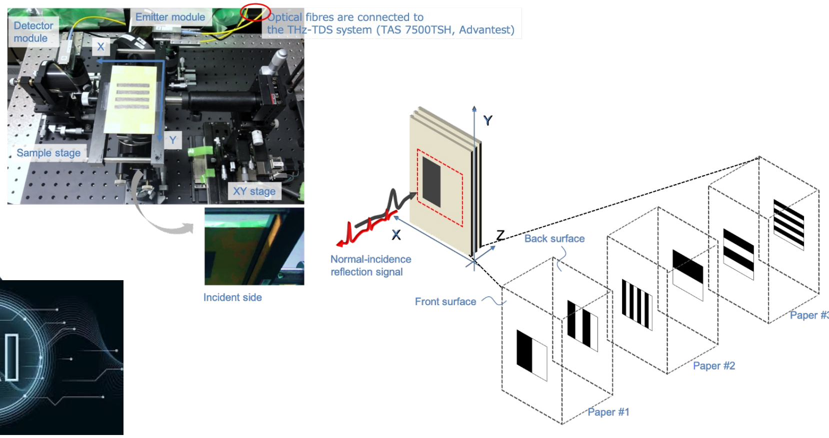
THz Imaging Results



Conclusions

- We showed recent **AI** trends overview: ML for everything in community
- We overviewed recent advancement on **QML**
- We introduced the use of emerging QML for **THz imaging**
  - Demonstrated the first proof-of-concept study for future quantum-era
  - Experimented the feasibility of QML-assisted THz imaging systems
  - Achieved state-of-the-art performance with few-parameter QML
  - Validated nearly 100% accuracy for 3-layer double-sided imaging
  - Showed gain via hybrid QNN + DNN
- There are many fascinating topics and high potentials for future work
- Questions?
  - Please contact me: koike@merl.com

Quantum AI



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