IEEE BHI-BSN 2022

IEEE-EMBS INTERNATIONAL CONFERENCE ON BIOMEDICAL AND HEALTH INFORMATICS (BHI'22)
JOINTLY ORGANISED WITH THE IEEE-EMBS INTERNATIONAL CONFERENCE ON WEARABLE AND IMPLANTABLE BODY SENSOR NETWORKS (BSN'22)

Ioannina, Greece | September 27-30, 2022

Big Data and AI (I)

quEEGNet: Quantum AI for Biosignal Processing

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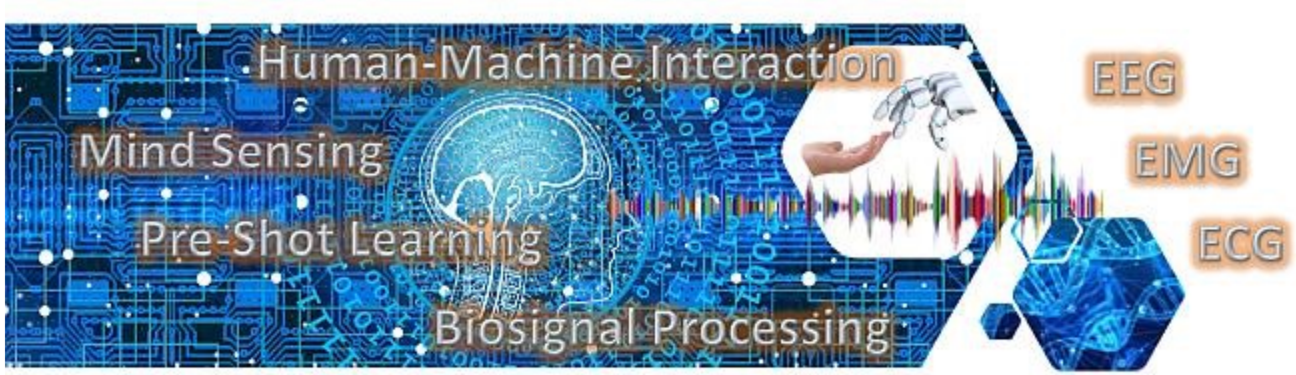
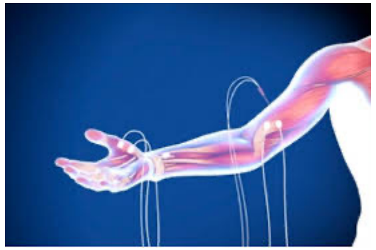
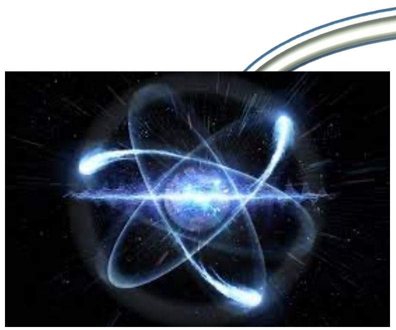
Outline

- Human-Machine Interaction (HMI)
  - Biosignal processing
  - Brain computer interface (BCI)
- Artificial Intelligence (AI)
  - Deep Learning: Deep Neural Networks (DNN)
  - Post Deep Learning: Quantum Machine Learning (QML)
- Proposal and Validation
  - quEEGNet: Hybrid QNN+DNN solutions
  - Physiological data
  - Experimental validation
- Summary





Quantum AI



Brain Machine/Computer Interfaces (BMI/BCI)

- BMI/BCI for reading human's mind, intention and feelings
- Active researches all over the world
  - Biosignal sensors (ECG, EMG, EEG, ECoG)
  - Robotics, acuators
  - 6G communications
  - Deep learning, Artificial Intelligence (AI)


Neuro-Prosthetics

Comfort/Emotion Detection

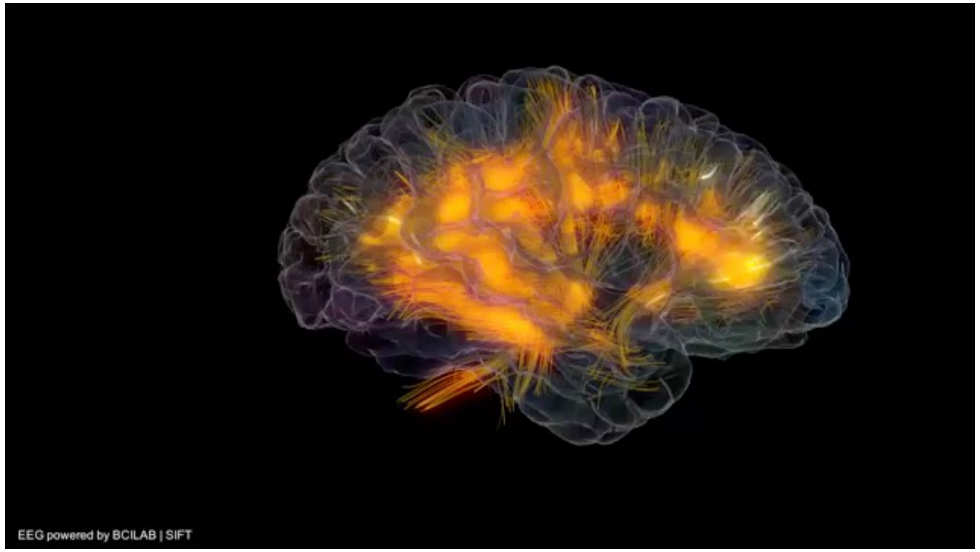

Mobility Assistance





Neuro-Stimulation

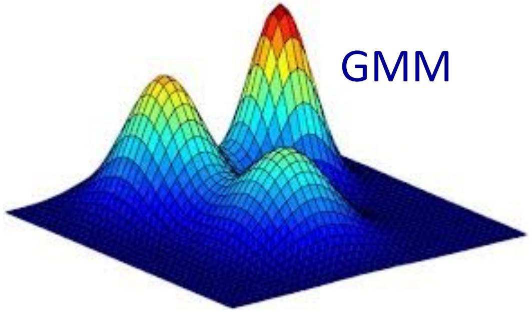

Driver Assistance

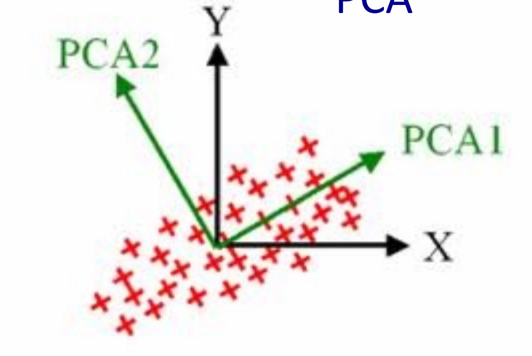


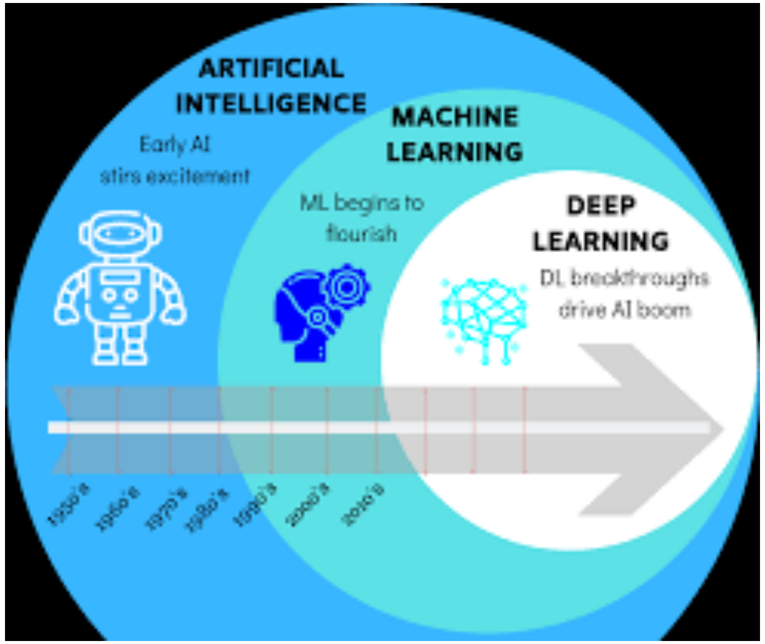

Neuro-Visualization

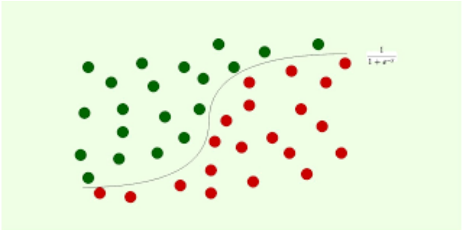
Artificial Intelligence (AI)

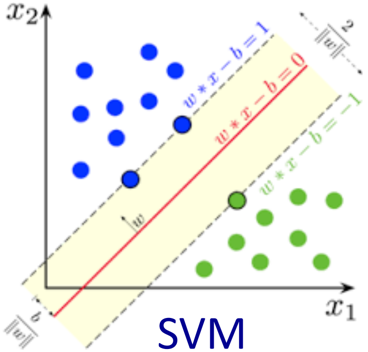
- K-means
- Gaussian mixture model (GMM)
- Principal component analysis (PCA)
- Independent component analysis (ICA)
- Logistic regression (LR)
- **Support vector machine (SVM)**
- Self-organizing map (SOM)
- Hidden Markov model (HMM)
- Artificial neural networks (ANN)
- **Deep learning (DL)**


GMM

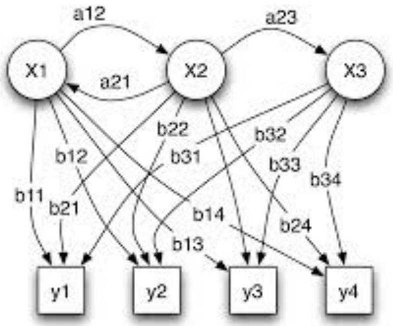
PCA




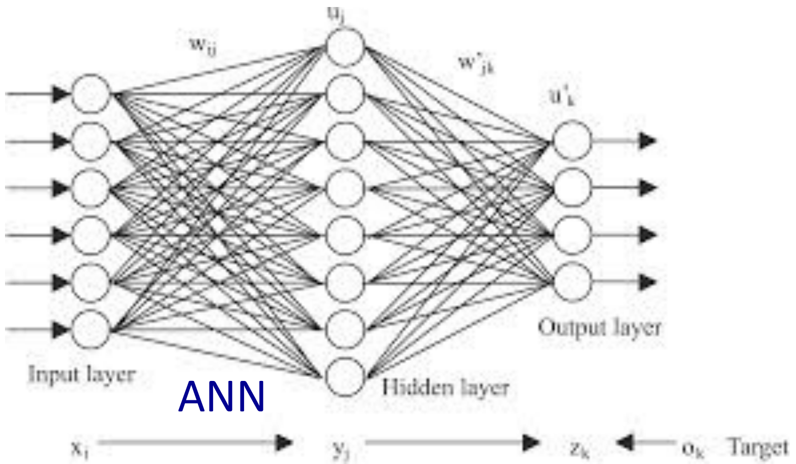
LR




SVM



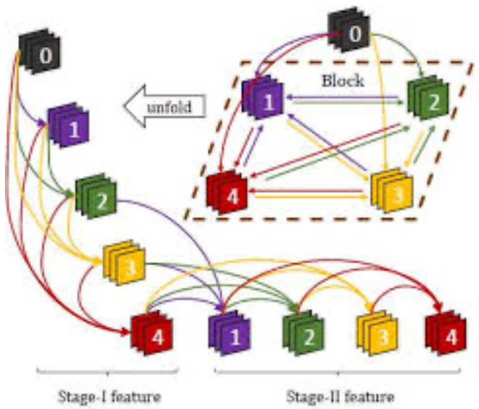
HMM



ANN

DNN Architectures

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



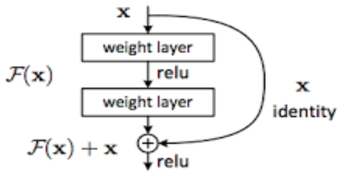
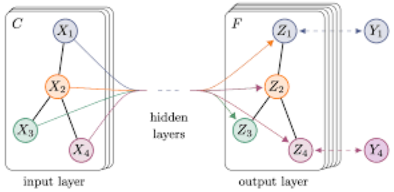
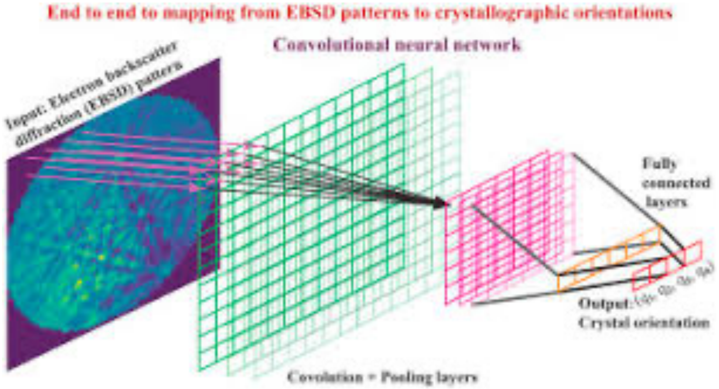
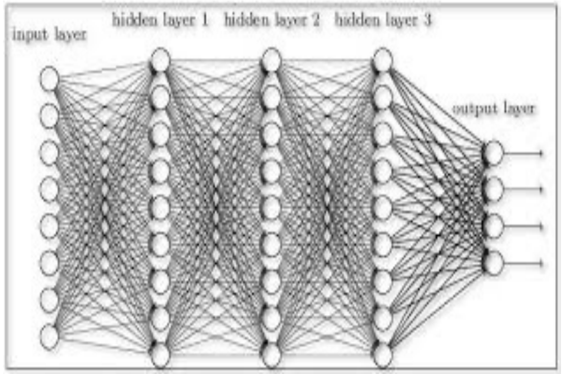
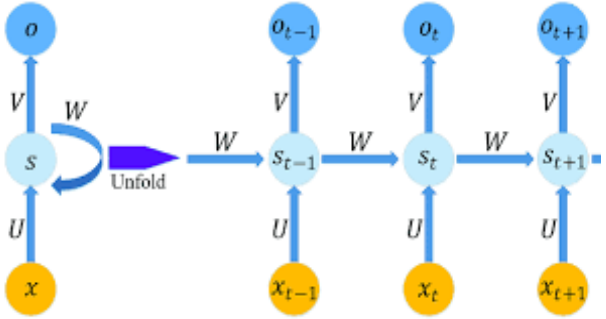


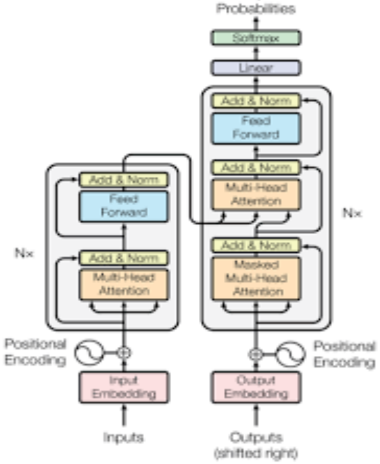
Figure 2. Residual learning: a building block.

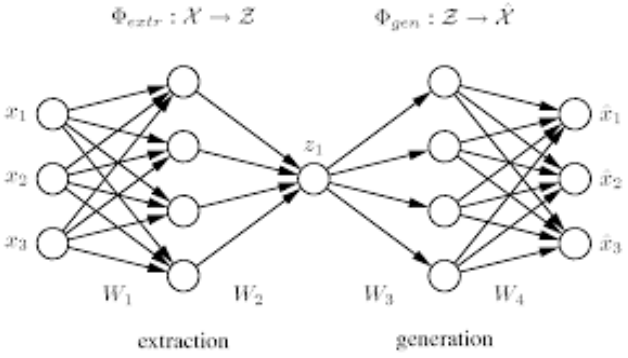


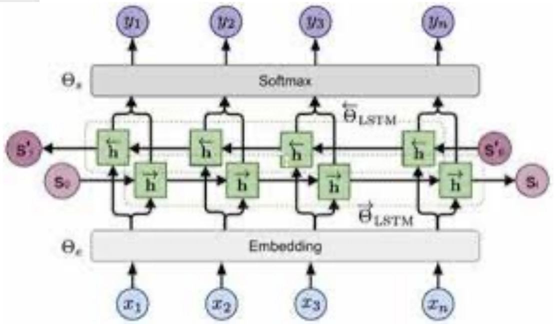


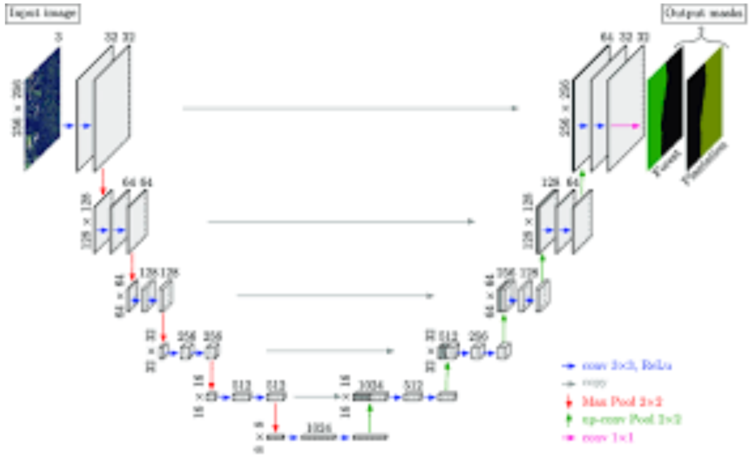


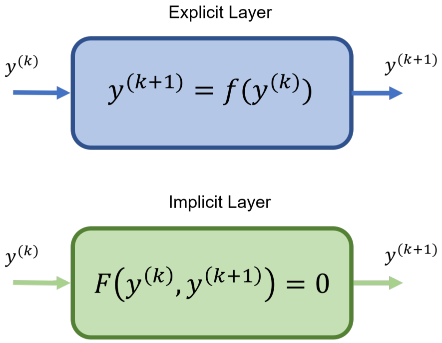






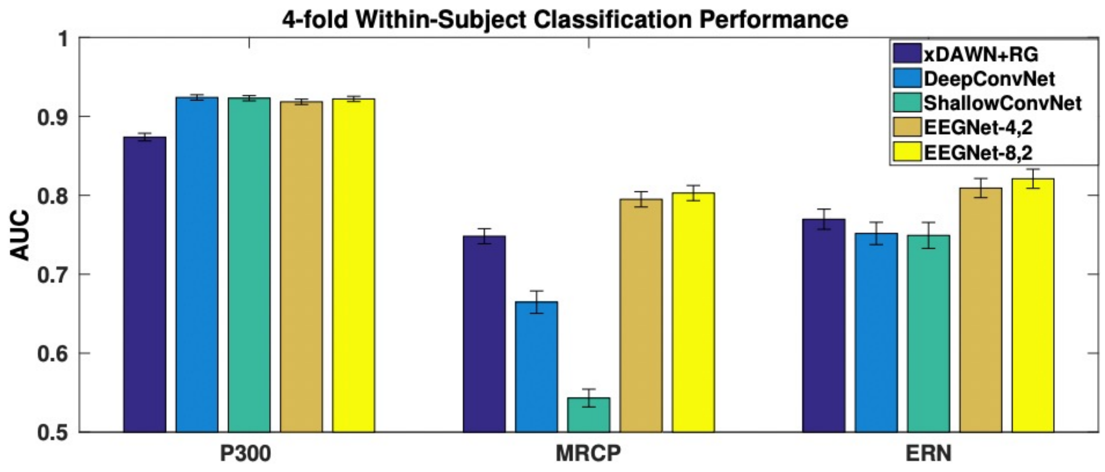


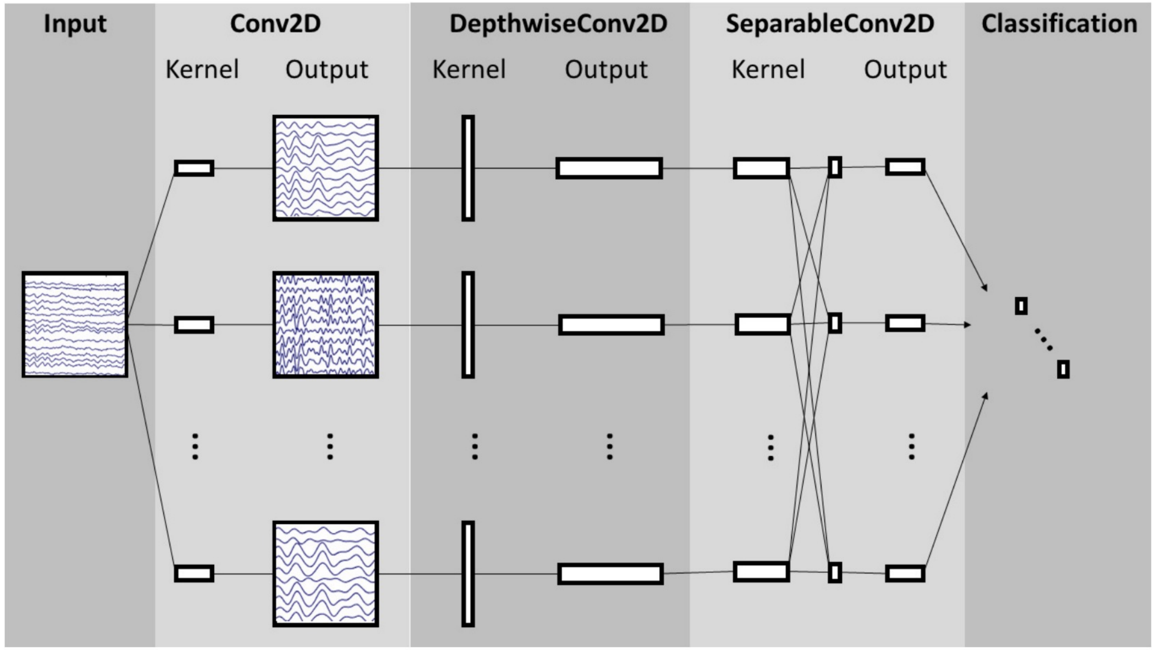




EEGNet

- Lawhern, Vernon J., Amelia J. Solon, Nicholas R. Waytowich, Stephen M. Gordon, Chou P. Hung, and Brent J. Lance. "EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces." *Journal of neural engineering* 15, no. 5 (2018): 056013.
- Compact CNN yet performing well



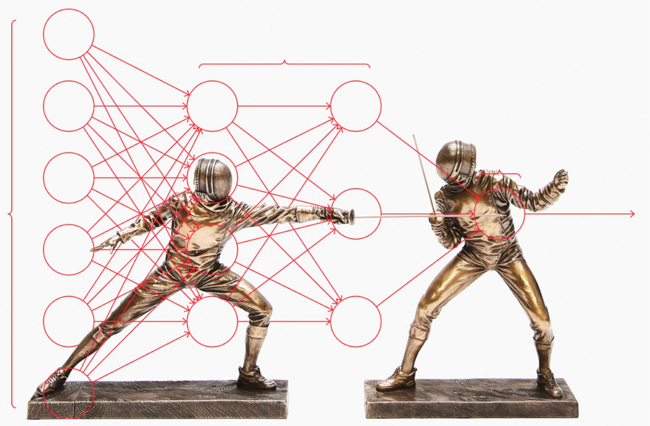


	Trial Length (sec)	DeepConvNet	ShallowConvNet	EEGNet-4,2	EEGNet-8,2
P300	1	174,127	104,002	**1,066**	2,258
ERN	1.25	169,927	91,602	**1,082**	2,290
MRCP	1.5	175,727	104,722	**1,098**	2,322
SMR*	2	152,219	40,644	**796**	1,716

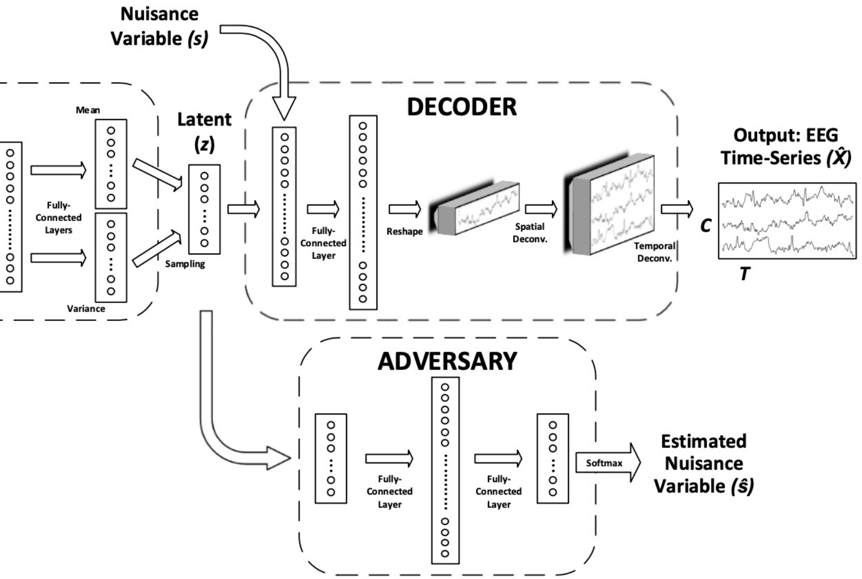
Our Publications: Deep Learning for Biosiginal Processing

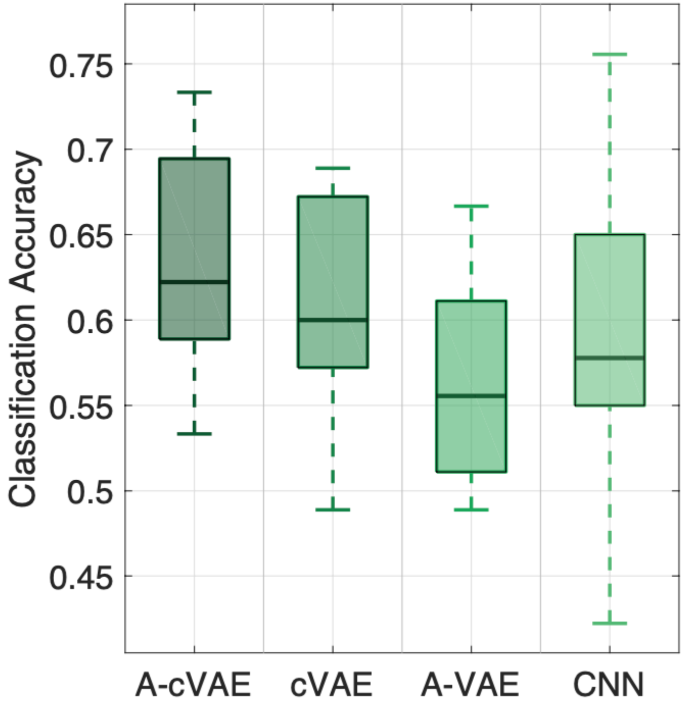
1. Koike-Akino, T., Mahajan, R., Marks, T.K., Tuzel, C.O., Wang, Y., Watanabe, S., Orlik, P.V., **"High-Accuracy User Identification Using EEG Biometrics"**, IEEE EMBC, Aug. 2016
2. Wang, Y., Koike-Akino, T., Erdogmus, D. “**Invariant Representations from Adversarially Censored Autoencoders**”, arxiv:1805.08097, May 2018.
3. Quivira, F., Koike-Akino, T., Wang, Y., Erdogmus, D., **"Translating sEMG Signals to Continuous Hand Poses using Recurrent Neural Networks"**, IEEE BHI, January 2018.
4. Wei, C.-S., Koike-Akino, T., Wang, Y., **"Spatial Component-wise Convolutional Network (SCCNet) for Motor-Imagery EEG Classification"**, IEEE NER, March 2019.
5. Ozdenizci, O., Wang, Y., Koike-Akino, T., Erdogmus, D., **"Transfer Learning in Brain-Computer Interfaces with Adversarial Variational Autoencoders”**, IEEE NER, March 2019. (arxiv:1812.06857, Dec. 2018)
6. Ozdenizci, O., Wang, Y., Koike-Akino, T., Erdogmus, D., **"Adversarial Deep Learning in EEG Biometrics"**, IEEE SPL, March 2019. (arxiv:1903.11673, May 2019)
7. Ozdenizci, O., Wang, Y., Koike-Akino, T., Erdogmus, D., **"Learning Invariant Representations from EEG via Adversarial Inference"**, IEEE Access , April 2020.
8. Koike-Akino, T., Wang, Y., **"Stochastic Bottleneck: Rateless Auto-Encoder for Flexible Dimensionality Reduction"**, IEEE ISIT, June 2020. (arxiv:2005.02870, May 2020)
9. Han, M., Ozdenizci, O., Wang, Y., Koike-Akino, T., Erdogmus, D., **"Disentangled Adversarial Transfer Learning for Physiological Biosignals"**, IEEE EMBC, July 2020. (arxiv:2004.08289, Apr. 2020)
10. Han, M., Ozdenizci, O., Wang, Y., Koike-Akino, T., Erdogmus, D., **"Disentangled Adversarial Autoencoder for Subject-Invariant Physiological Feature Extraction"**, *IEEE Signal Processing Letters*, DOI: 10.1109/LSP.2020.3020215, Vol. 27, pp. 1565-1569, September 2020.
11. Demir, A., Koike-Akino, T., Wang, Y., Erdogmus, D., **"AutoBayes: Automated Bayesian Graph Exploration for Nuisance-Robust Inference"**, *IEEE Access*, DOI: 10.1109/ACCESS.2021.3064530, Vol. 9, pp. 39955-39972, March 2021.
12. Haruna, M., Ogino, M., Koike-Akino, T., “**Proposal and Evaluation of Visual Haptics for Manipulation of Remote Machine System**,” Frontiers, Aug. 2020.
13. Haruna, M., Ogino, M., Koike-Akino, T., **"Comparison of Three Feedback Modalities for Haptics Sensation in Remote Machine Manipulation"**, *IEEE Robotics and Automation Letters*, DOI: 10.1109/LRA.2021.3070301, Vol. 6, No. 3, pp. 5040-5047, March 2021.
14. Han, M., Ozdenizci, O., Koike-Akino, T., Wang, Y., Erdogmus, D., **"Universal Physiological Representation Learning with Soft-Disentangled Rateless Autoencoders"**, *IEEE Journal of Biomedical and Health Informatics*, DOI: 10.1109/JBHI.2021.3062335, Vol. 25, No. 8, pp. 2928-2937, April 2021.
15. Demir, A., Koike-Akino, T., Wang, Y., Erdogmus, D., Haruna, M., **"EEG-GNN: Graph Neural Networks for Classification of Electroencephalogram (EEG) Signals"**, *International IEEE EMBS Conference on Neural Engineering*, DOI: 10.1109/EMBC46164.2021.9630194, October 2021.
16. Demir, A., Koike-Akino, T., Wang, Y., Erdogmus, D., **"EEG-GAT: Graph Attention Networks for Classification of Electroencephalogram (EEG) Signals"**, *International Conference of the IEEE Engineering in Medicine & Biology Society (EMBS)*, DOI: 10.1109/EMBC48229.2022.9871984, July 2022.
17. Smedemark-Margulies, N., Wang, Y., Koike-Akino, T., Erdogmus, D., **"AutoTransfer: Subject Transfer Learning with Censored Representations on Biosignals Data"**, *International Conference of the IEEE Engineering in Medicine & Biology Society (EMBS)*, DOI: 10.1109/EMBC48229.2022.9871649, July 2022.

Subject Transfer Learning: Pre-Shot Adversarial Censoring



- Adversarial autoencoder for BCI [Ozdenizci et al, NER'19]
- Complementary adversary [Han et al, SPL'20]
- Rateless autoencoder for soft disentangling [Han et al, JBHI'21]
- Automated Bayesian inference: AutoBayes [Demir et al, Access'21]
- Automated disentanglement: AutoTransfer [Smedemark-Margulies et al, EMBC'22]
  - **Rank 1** in subject transfer task of NeurIPS'21 challenge

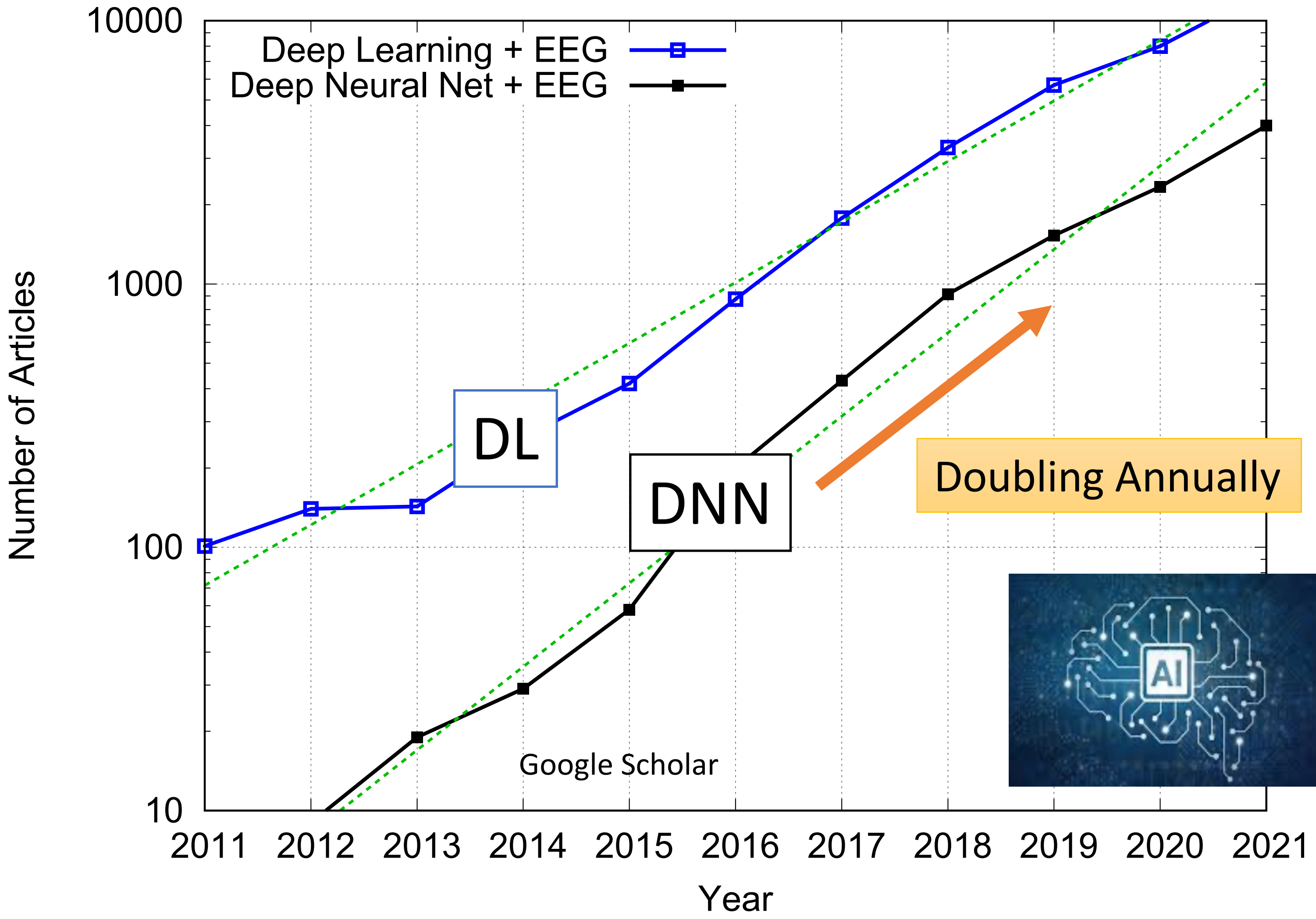


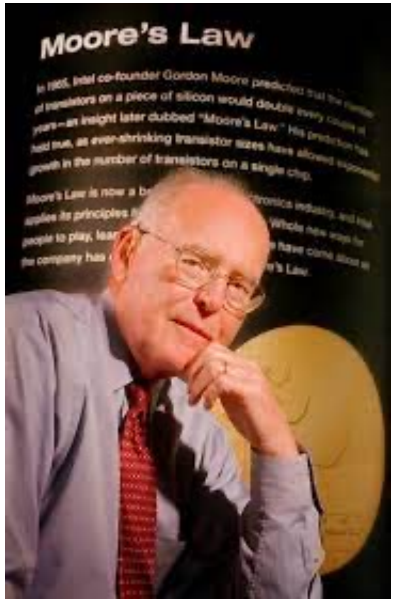


Subject transfer accuracy

Moore’s Law: Deep Learning for BMI/BCI

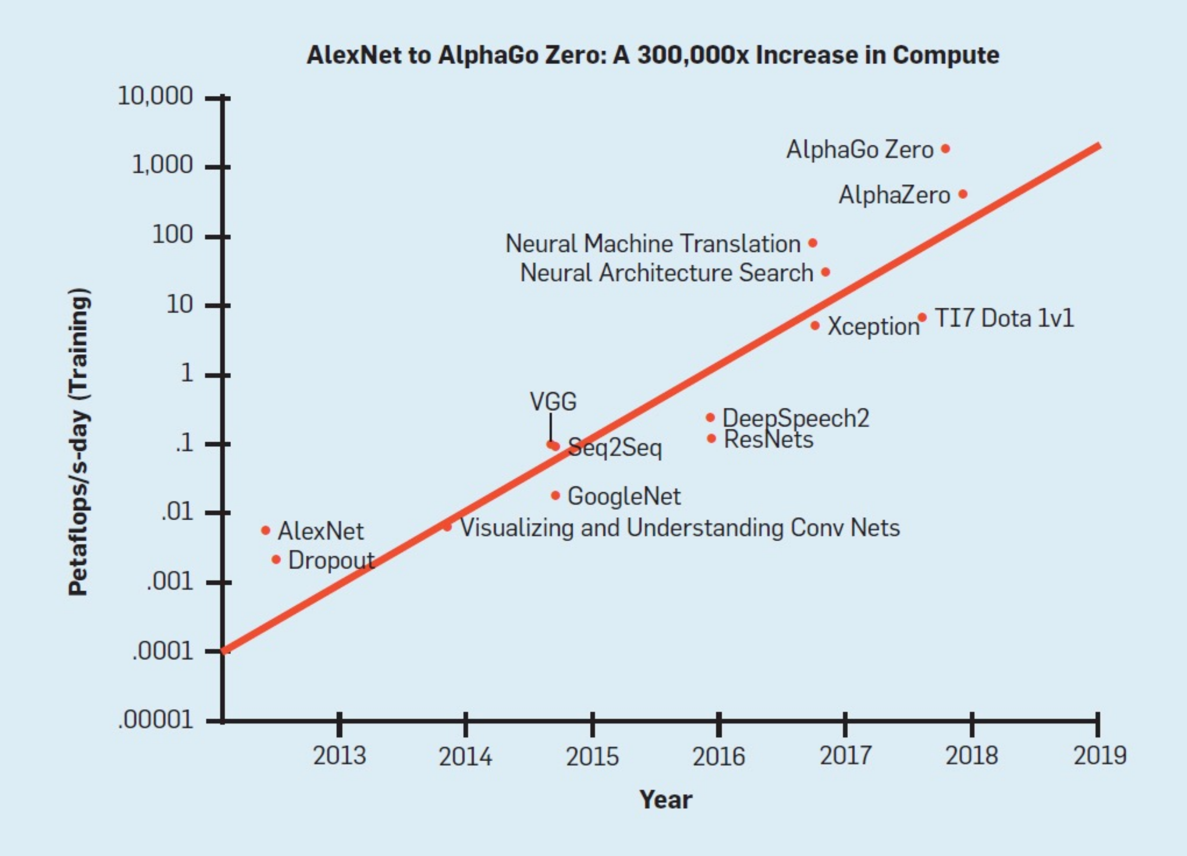
- Number of articles grows exponentially: doubling every year
  - More than 10,000 articles



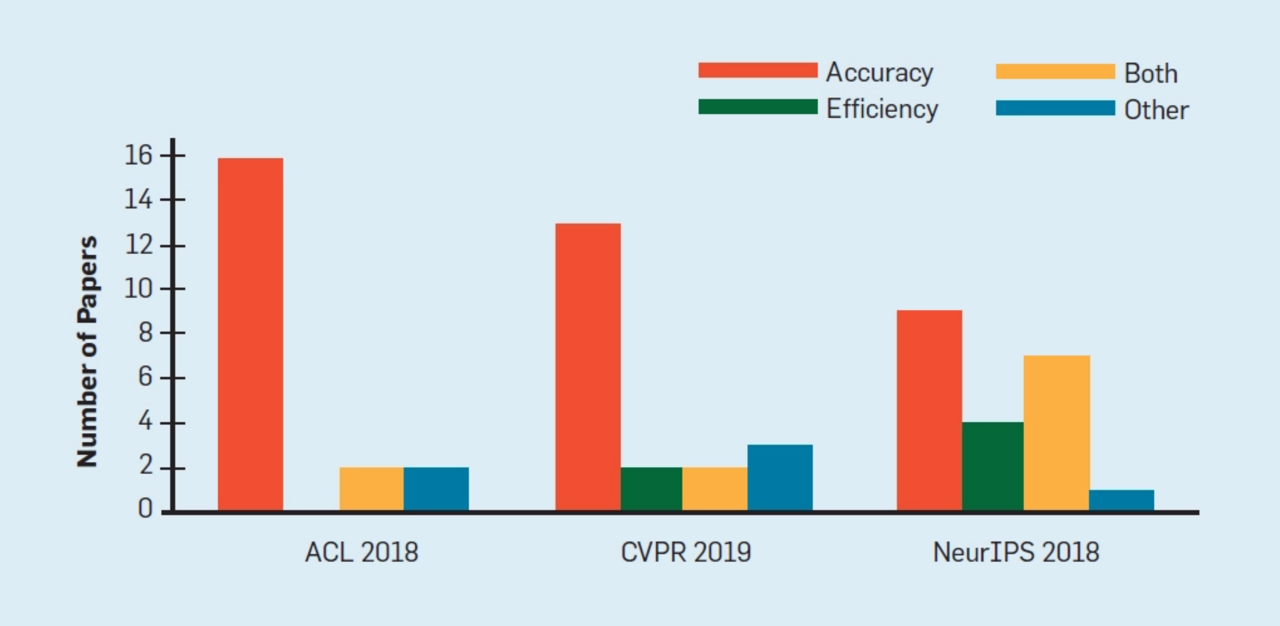


Red AI: Aiming Higher Performance with Higher-Power Computation

- Roy Schwartz, Jesse Dodge, Noah A. Smith, Oren Etzioni, “Green AI”, Communications of the ACM, December 2020, Vol. 63 No. 12, Pages 54-63 10.1145/3381831: https://cacm.acm.org/magazines/2020/12/248800-green-ai/



The amount of compute used to train deep learning models has increased 300,000x in six years



AI papers tend to target accuracy rather than efficiency.

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]
  - 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

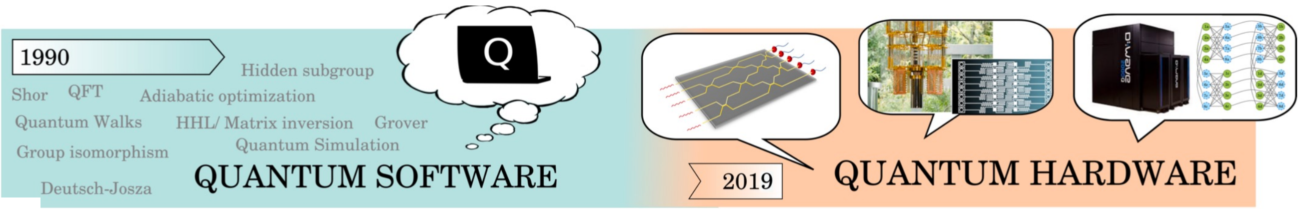
Table 1: Estimated CO_2 emissions from training common NLP models, compared to familiar consumption.[1]

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.

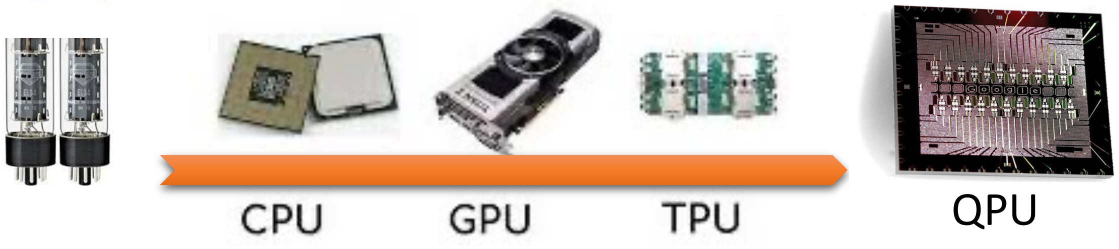
Quantum Computing

- 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



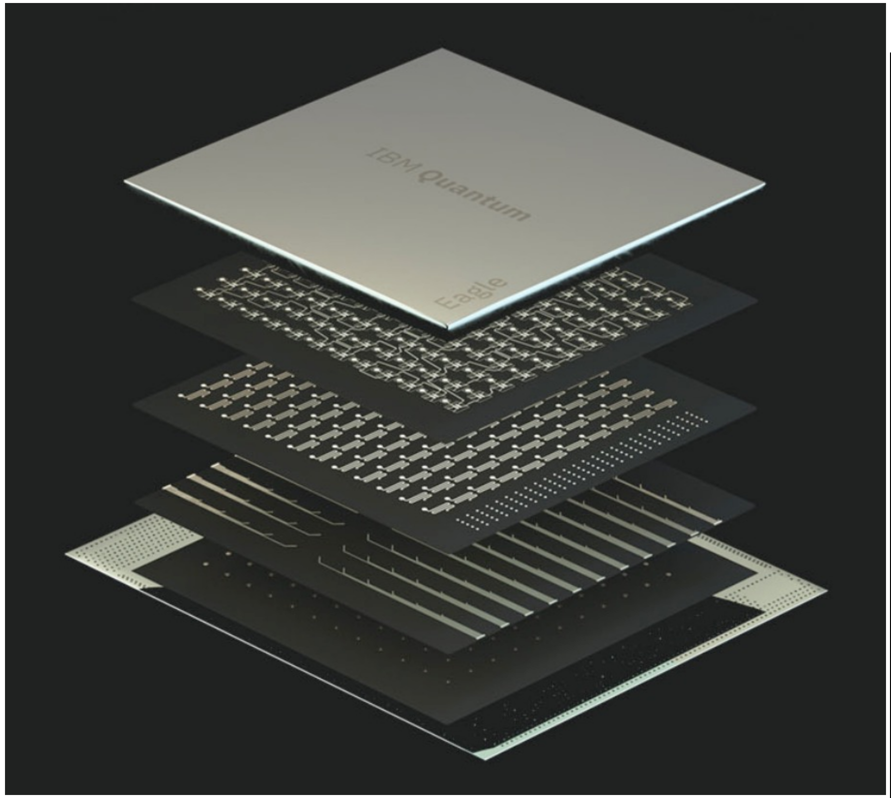
QISKit
Quantum Information Software Kit
PYQUIL
Cirq
QuTiP
Quantum Toolbox in Python
PROJECTQ
PENNYLANE

intel
Microsoft
rigetti
Honeywell
Google
IBM

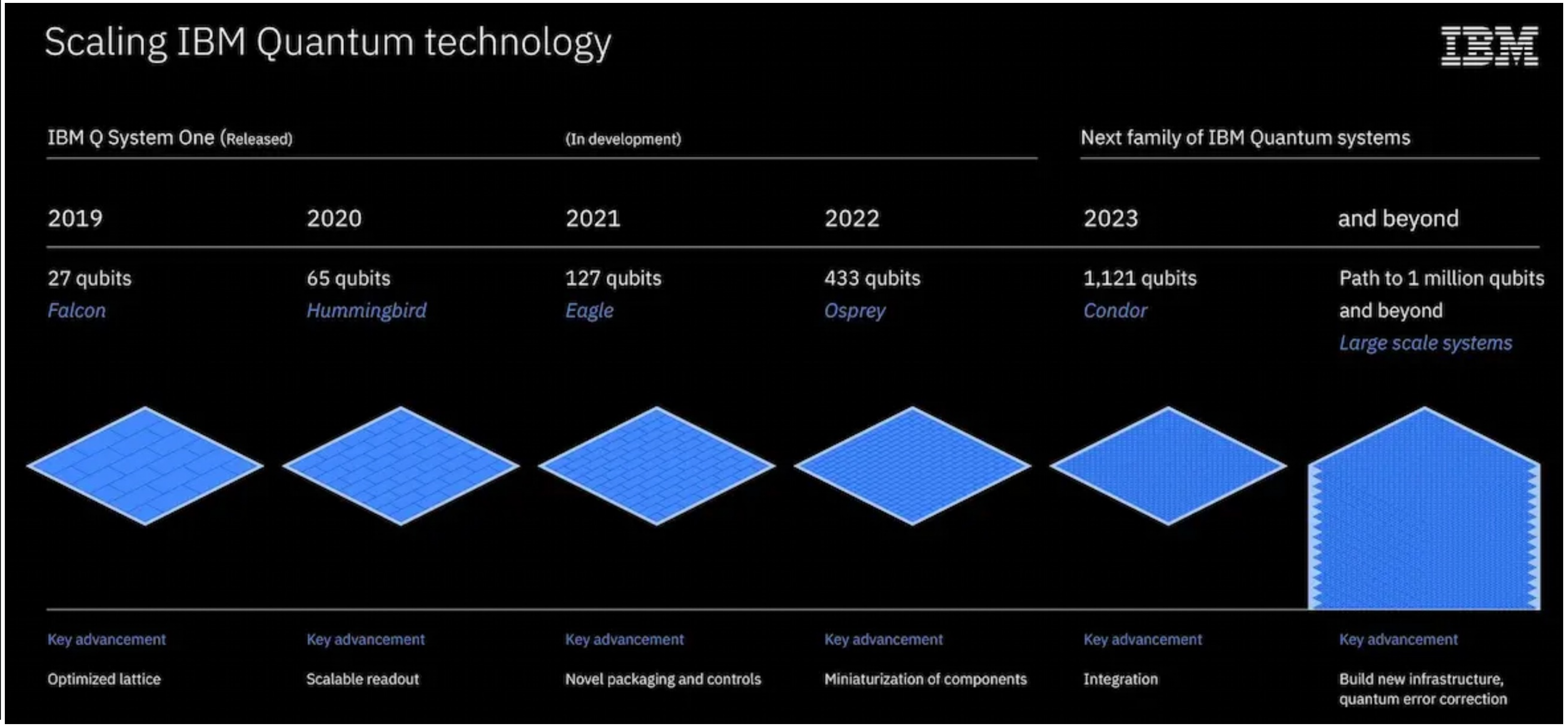


Evolution of Quantum Processing Unit (QPU)

- 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



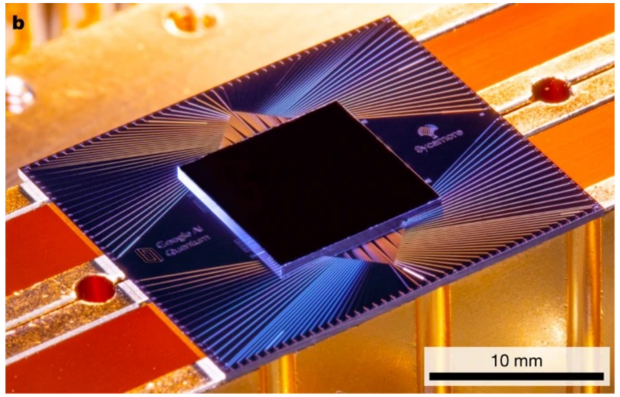
IBM 127-qubit QPU (Nov. 2021)

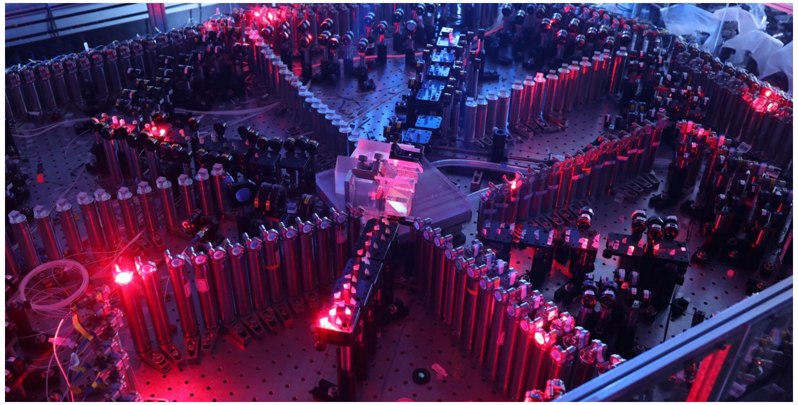


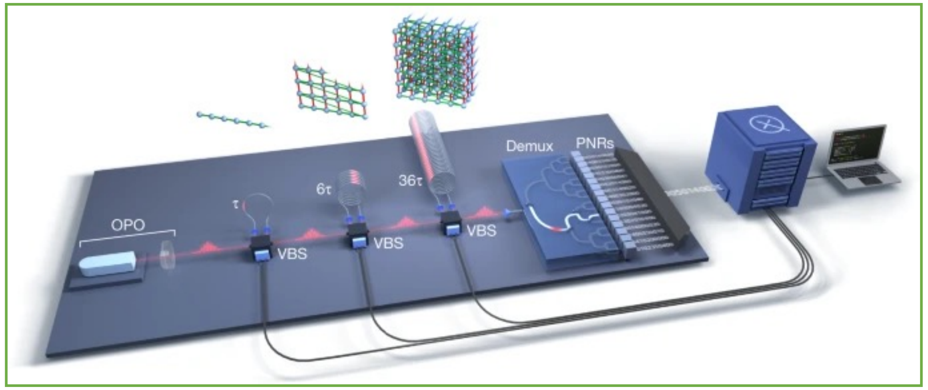
IBM QPU development roadmap (as of 2020)

Quantum Supremacy

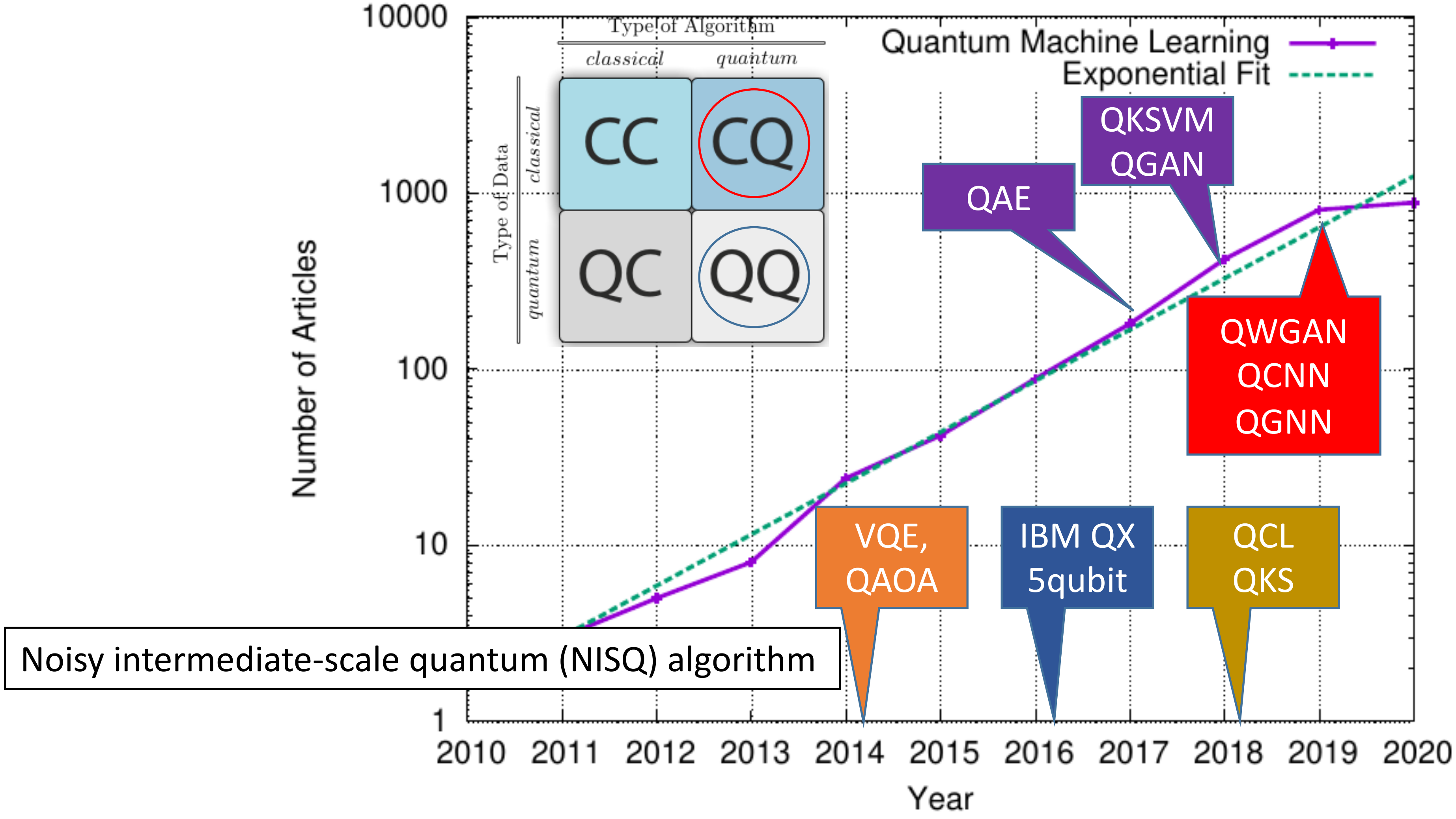
- Some reports claiming to have achieved ***quantum supremacy***:
  - Arute, F., Arya, K., Babbush, R. *et al.* Quantum supremacy using a programmable superconducting processor. *Nature* **574,** 505–510 (2019).
    - 53-qubit QPU: 10^9 faster (200 sec. for 10,000-year job) than classical computers
  - 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
  - Madsen, L.S., Laudenbach, F., Askarani, M.F. et al. "Quantum computational advantage with a programmable photonic processor", Nature 606, 75-81, 2022.
    - Boson sampling: 10^{16} faster (36 usec for 9,000-year job) than classical computers
- Quantum advantage is still argued for general applications







Quantum Machine Learning (QML)

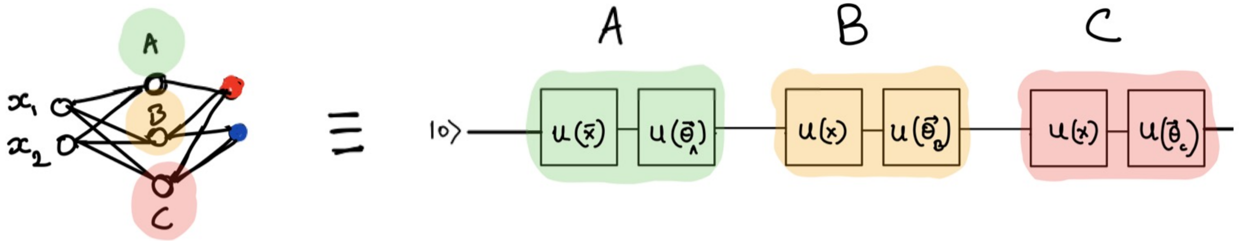


VQE: Variational Quantum Eigensolver, QAOA: Quantum Approximate Optimization Algorithm
QAE: Quantum AutoEncoder, QKSVM: Quantum Kernel Support Vector Machine, Q(W)GAN: Quantum (Wasserstein) Generative Adversarial Network,
QCNN: Quantum Convolutional Neural Network, QGNN: Quantum Graph Neural Net, QX: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

Universal Approximation Theorem/Property (UAT/UAP)

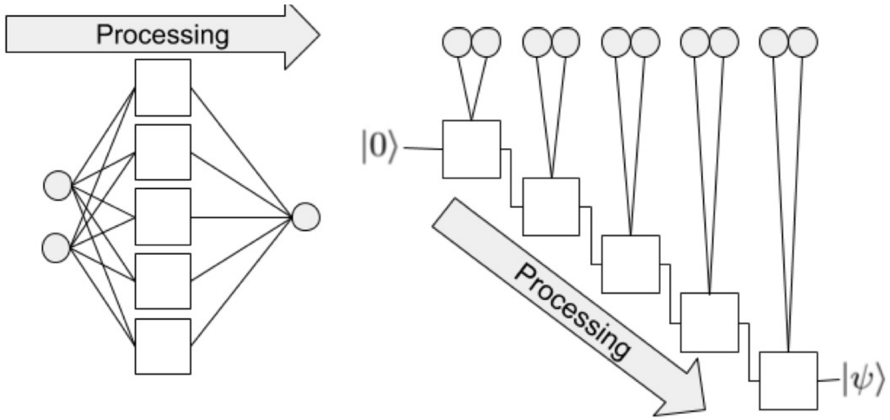
- UAP for classical neural networks:
  - Single hidden neural networks can approximate arbitrary bounded continuous functions [Cybenko 1989]
  - Deep hidden neural networks can asymptoticly approximate arbitrary functions [Zhou 2017]
- UAP still holds for quantum computing [Perez 2019]
  - *Data re-uploading*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

Wider/deeper neurons can reduce approximation error

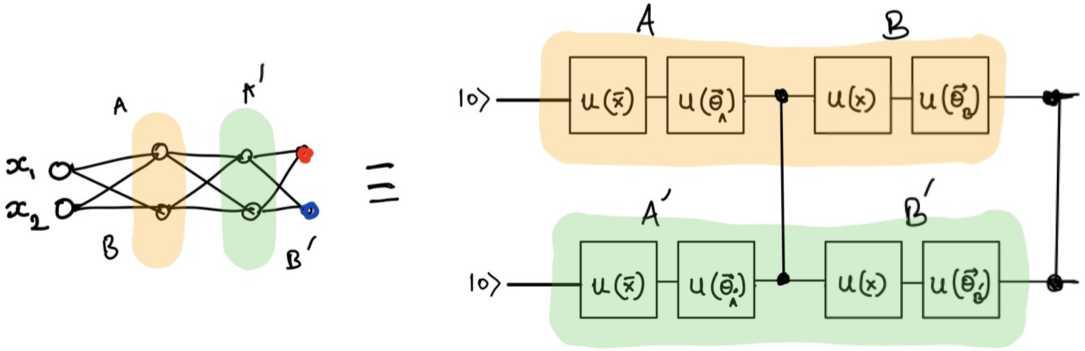


$$h(\vec{x}) = \sum_{i=1}^{N} \alpha_i \; \varphi\left(\vec{w}_i \cdot \vec{x} + b_i\right)$$

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



(a) Neural network (b) Quantum classifier



Wider neuron → More quantum layers
Deeper layer → More qubits

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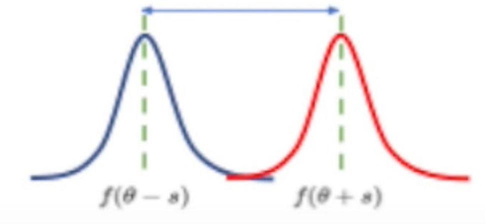
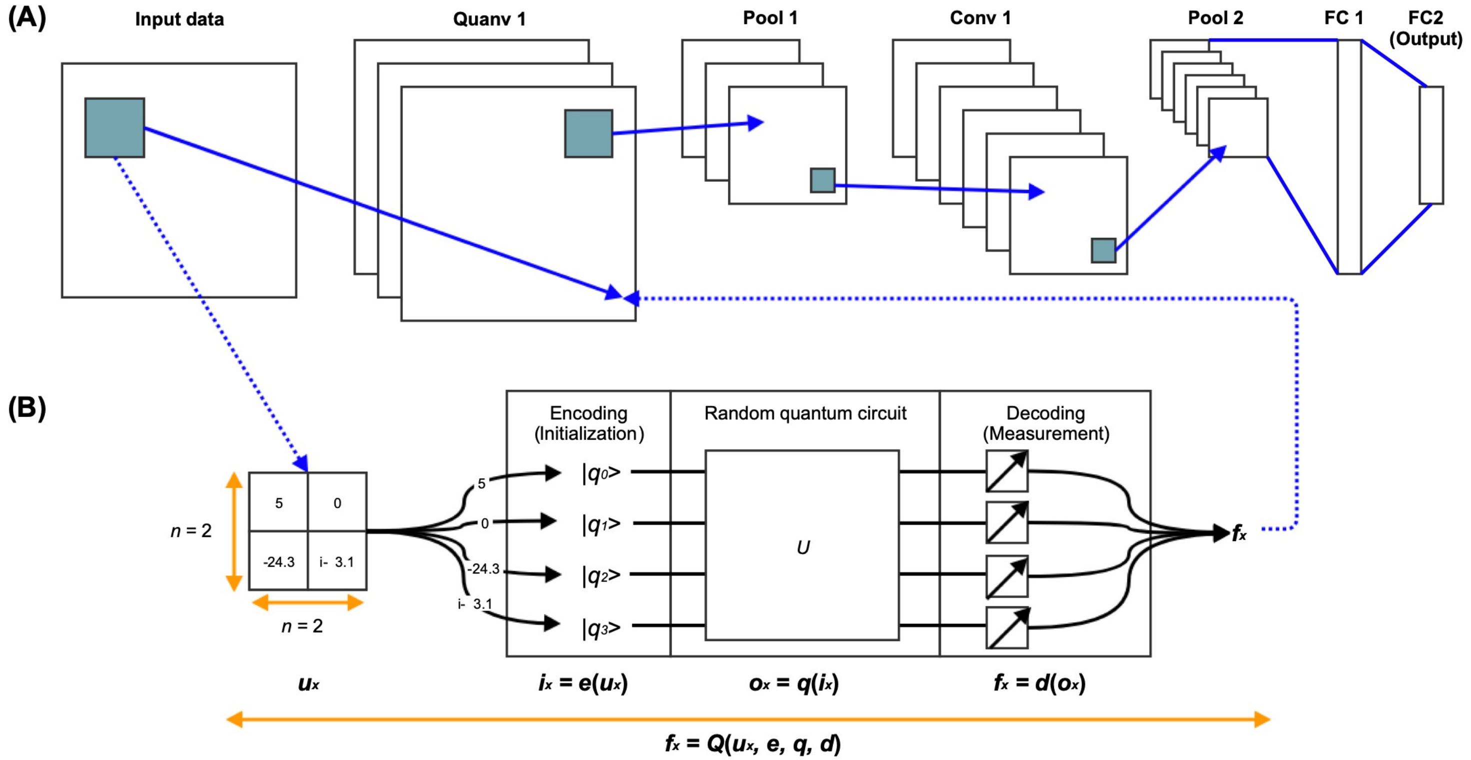
Differential Programming

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

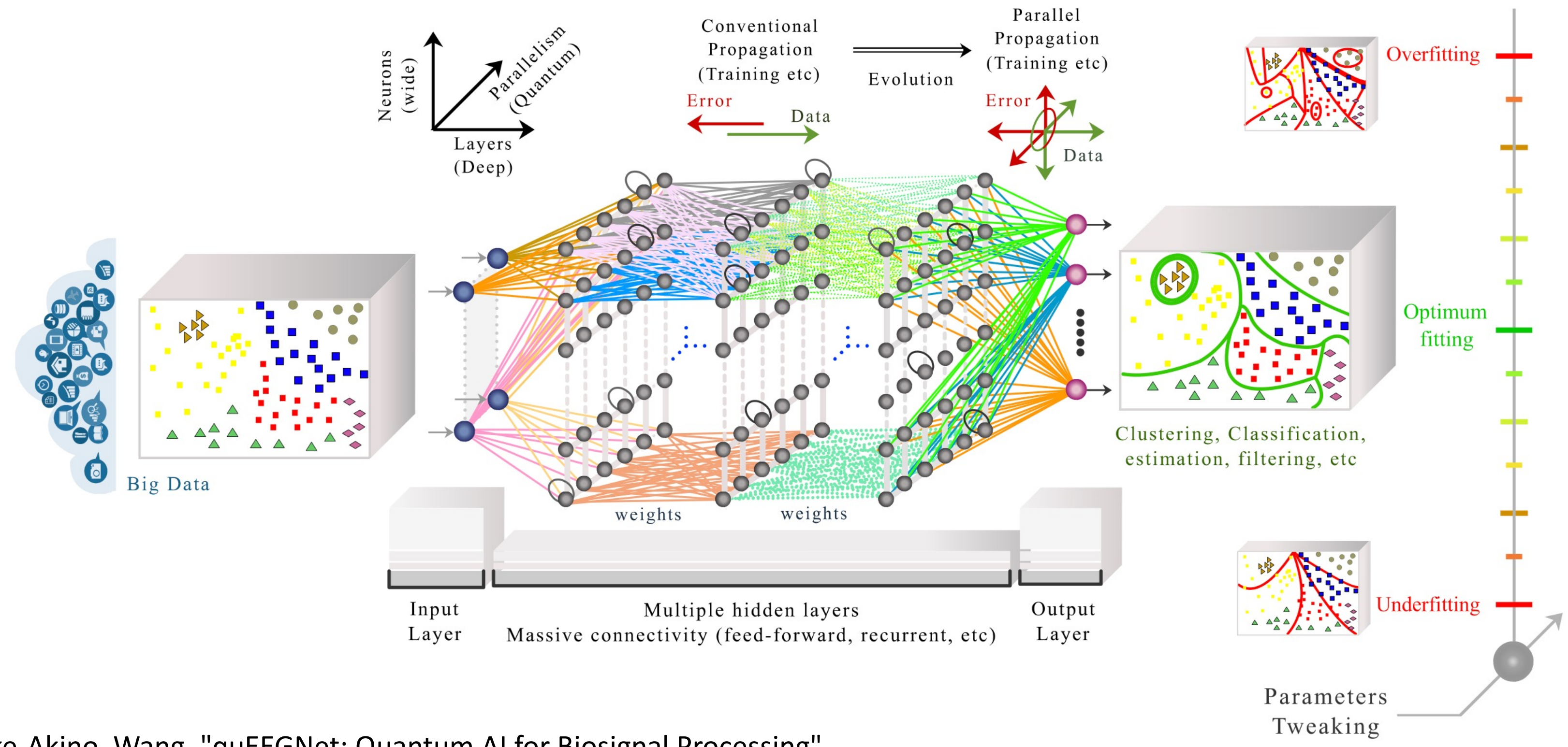
- Quantum operation is differentiable:
  - ***Parameter shift rule*** [Mitarai/Schuld 2018] (exact gradient)
- Backpropagation through hybrid classical/quantum chips
  - Able to integrate ***(implicit) quantum layers*** into DNN models
  - e.g., Quanvolutional Neural Network [Henderson2019]





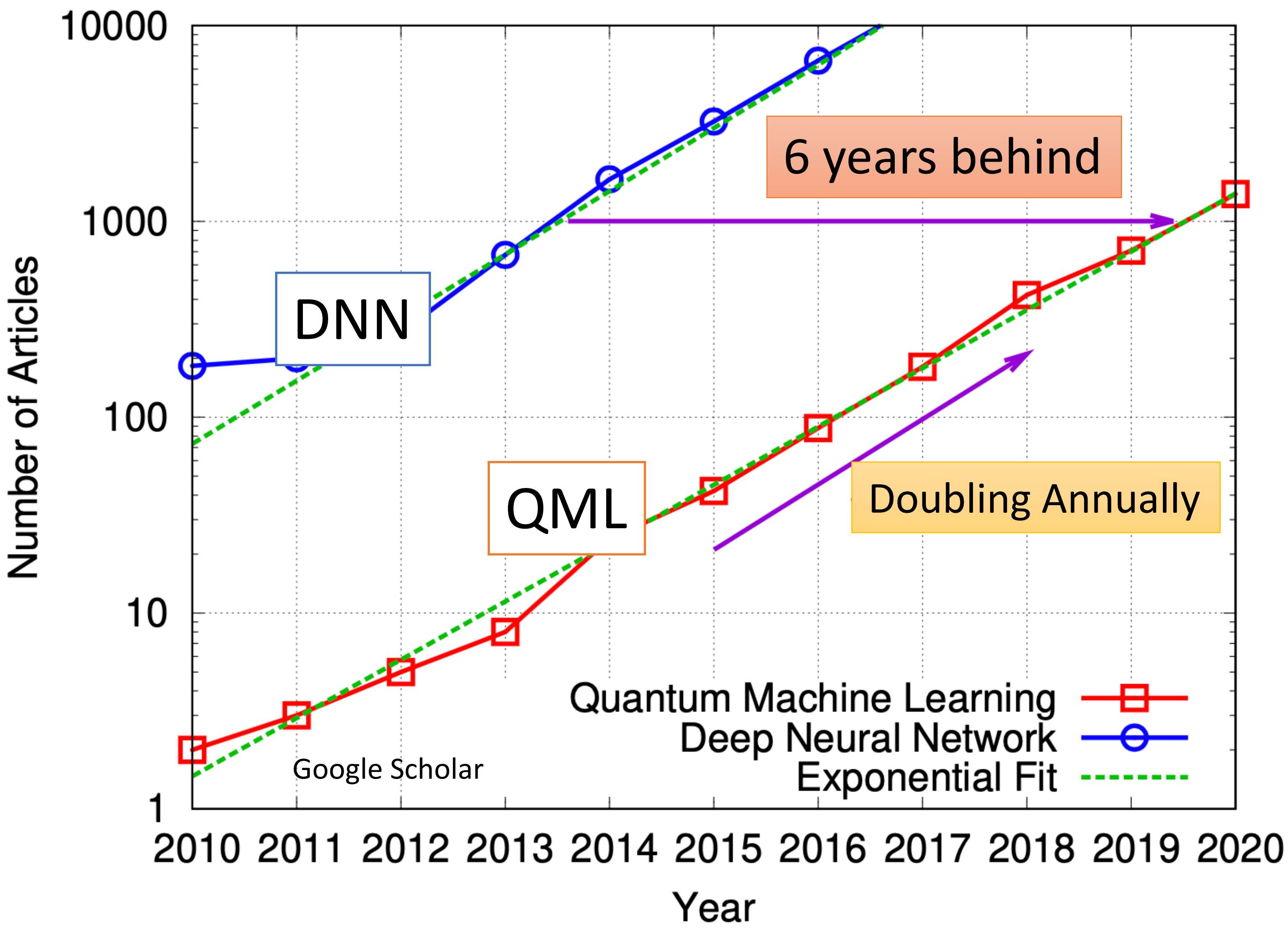
Quantum Neural Network (QNN)

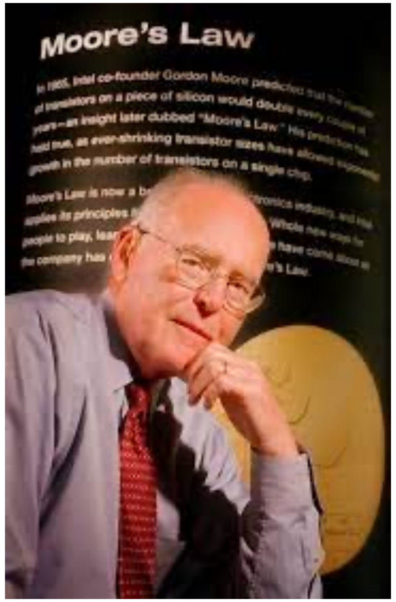
- QML: **Post-deep learning** paradigm
  - QML is a key major driver for **6G applications** [Nawaz et al. Access 2019]
- (Hyped) expectation of QNN advantage:
  - Fewer trainable parameters to support exponentially large quantum states in parallel
  - Parallel ensemble to prevent overfitting and underfitting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



Quantum Machine Learning (QML): Moore's Law

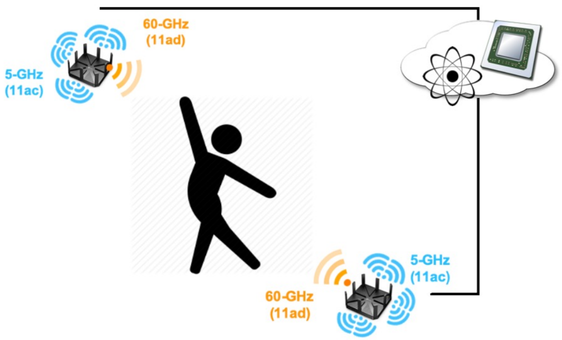
- Number of articles on QML is doubling annually, just **6 years** behind of DNN



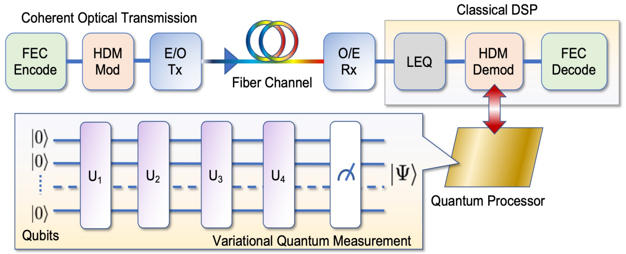


Our Publications: Applied Quantum AI

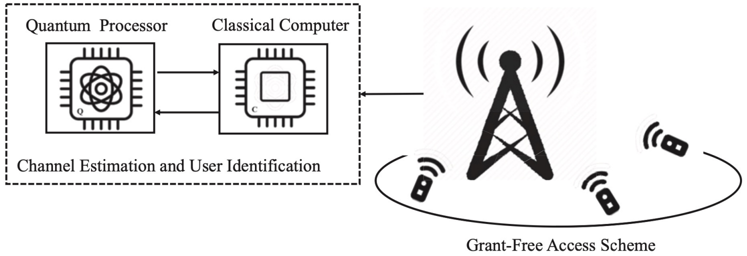
- Variational quantum algorithm for channel decoding [ISIT19]
- Variational quantum algorithm for demodulation [OFC20]
- Quantum neural network (QNN) to WiFi indoor monitoring [ICC22]
- AutoML to optimize ansatz of QNN [SAM22]
- Variational quantum circuit (VQC) to denoising [ICC22]
- Quantum feature extraction for THz imaging [IRMMW22]



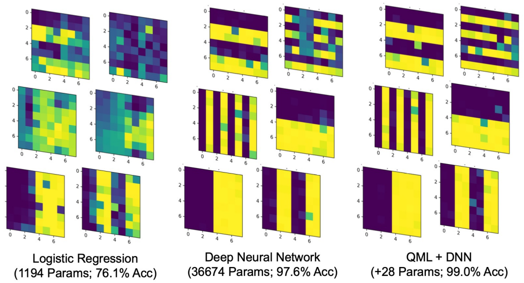
QML for WiFi human monitoring



QML for decoding/demodulation



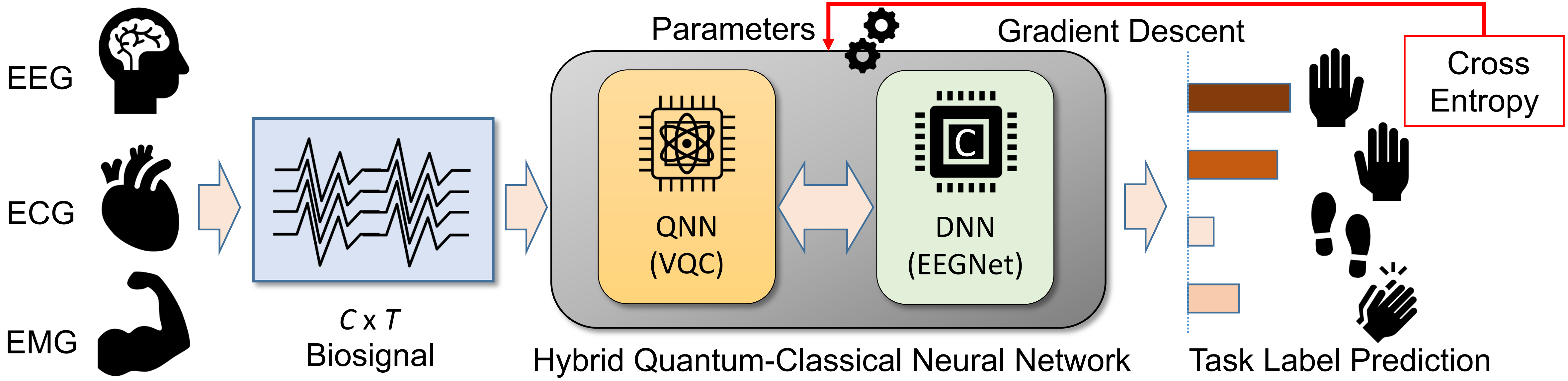
QML for denoising



QML for THz spectroscopy

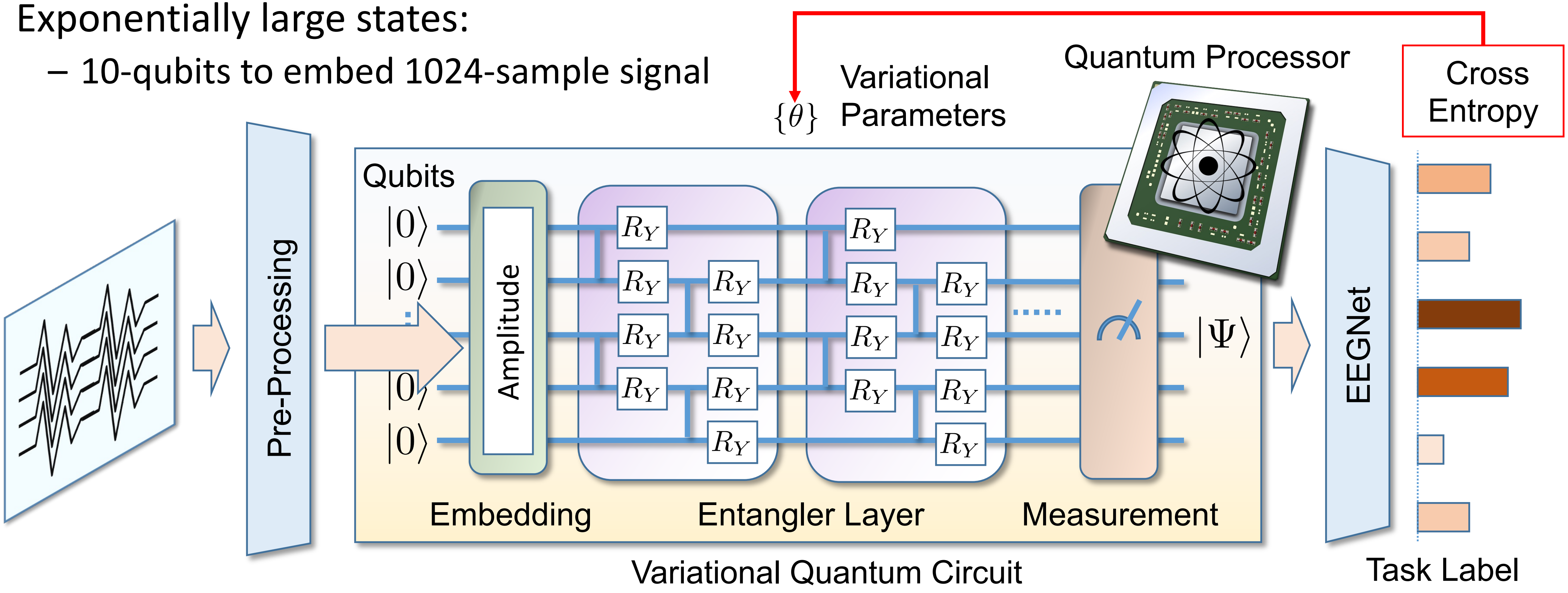
QML Meets Biosignal Processing

- Quantum neural network (QNN) is used to support DNN model (such as EEGNet)
  - We call QNN+DNN for biosignal processing as **quEEGNet** framework for convention



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
- Exponentially large states:
  - 10-qubits to embed 1024-sample signal



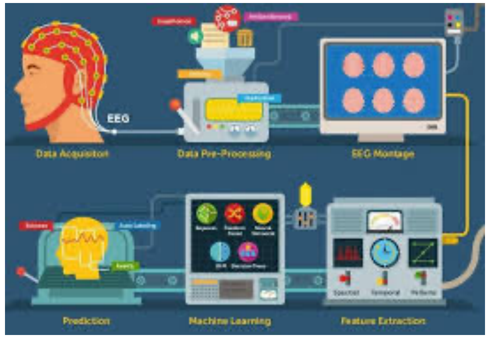
Physiological Datasets for Validation

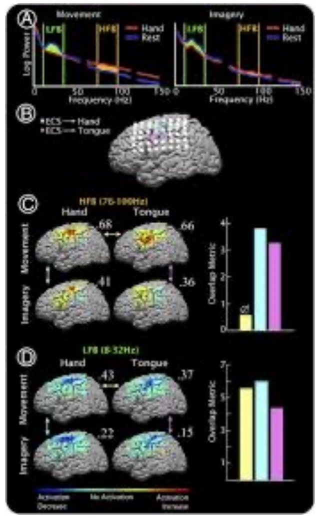
- Stress: temperature, **heart rate**, electrodermal activity, arterial oxygen level, etc. for 4-state stress level measurement
- RSVP: **EEG** for rapid serial visual presentation (RSVP) drowsiness test with 4 tasks
- MI: PhysioNet EEG Motor Imagery (MI) dataset with 4-class tasks
- ErrP: An error-related potential (ErrP) of EEG dataset in spelling task
- Faces: An implanted electrocorticography (**ECoG**) array dataset for visual stimulus.
- ASL: An electromyogram (**EMG**) dataset for fingers motion detection for hand signs.

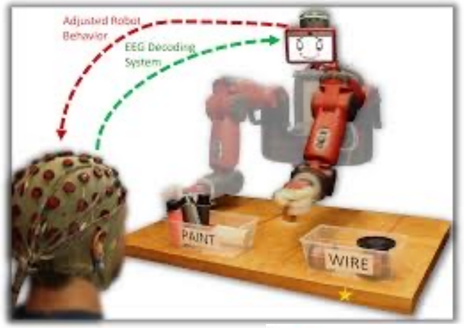

Heart rates


Electrodermal


Oxygen


RSVP EEG


MI EEG



ErrP EEG


ECoG


EMG

Variety of Datasets

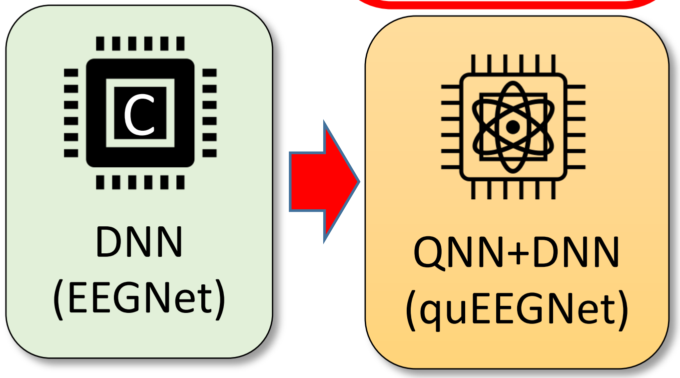
- Publicly available datasets
  - Stress: https://physionet.org/content/noneeg/1.0.0/
  - RSVP: http://hdl.handle.net/2047/D20294523
  - MI: https://physionet.org/physiobank/database/eegmmidb/
  - ErrP: https://www.kaggle.com/c/inria-bci-challenge
  - Faces: https://exhibits.stanford.edu/data/catalog/zk881ps0522
  - ASL: http://hdl.handle.net/2047/D20294523

Dataset	Modality	Dimension	Subjects	Classes	Samples
Stress [48]	Temp. etc.	7×1	20	4	24,000
RSVP [49]	EEG	16×128	10	4	41,400
MI [50]	EEG	64×480	106	4	9,540
ErrP [51]	EEG	56×250	27	2	9,180
Faces Basic [52]	ECoG	31×400	14	2	4,100
Faces Noisy [53]	ECoG	39×400	7	2	2,100
ASL [54]	EMG	16×50	5	33	9,900

Performance Results

- quEEGNet achieves state-of-the-art performance yet having few parameters
- Performance improvement via quantum feature extraction for all physiological datasets

Dataset	EEGNet	quEEGNet
Stress	85.87	87.23
RSVP	93.73	95.12
MI	59.61	60.22
ErrP	74.36	75.92
Faces Basic	63.30	64.92
Faces Noisy	75.94	78.01
ASL	23.64	25.16



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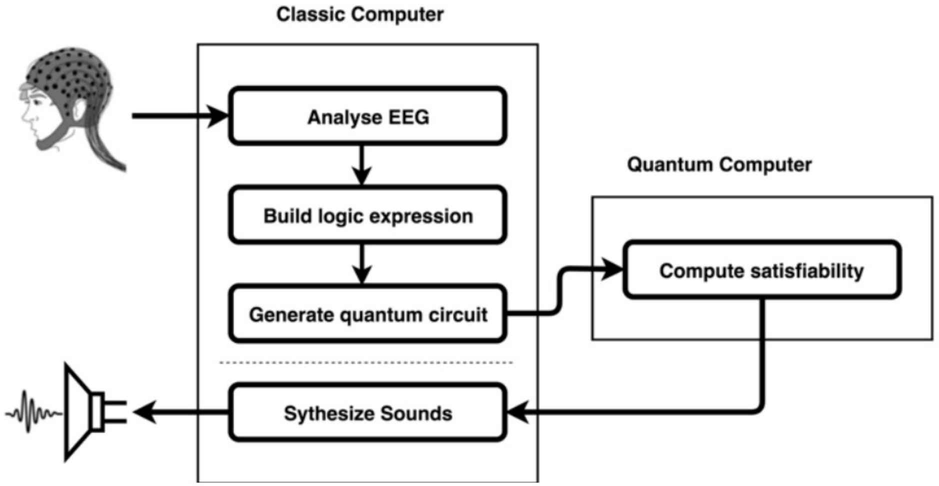
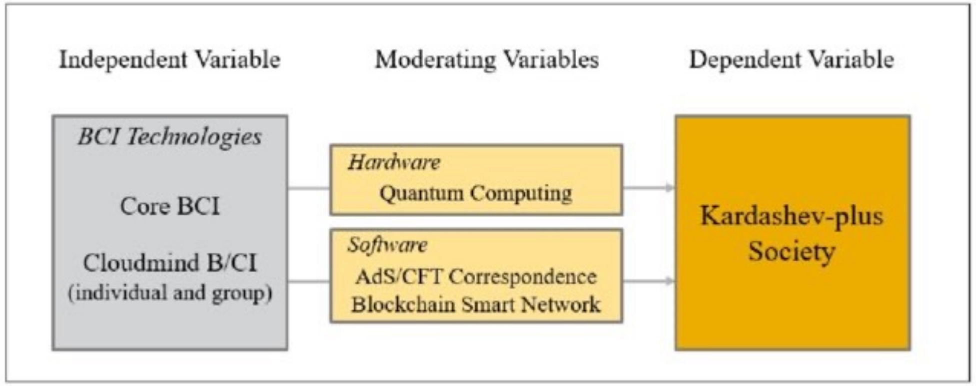
Quantum x Biosignal

- Quantum sensing has been revolutionizing biosensing
  - Superconducting quantum interference devices (SQUID)
- Quantum computing for EEG processing
  - E. R. Miranda, “On interfacing the brain with quantum computers: An approach to listen to the logic of the mind,” *arXiv preprint arXiv:2101.03887*, 2020.
  - M. Swan, “BCI quantum computing IPLD for brain,” *ResearchGate preprint:342184271*, Jun. 2020.
- Our paper is the **very first demonstration** that applied **quantum AI** to BCI

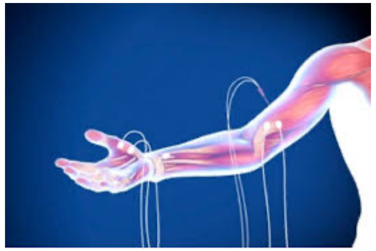




Conclusions

- We showed recent **AI** trends for biosignal processing
- We overviewed recent advancement on **quantum AI (QAI)** as post-deep learning paradigm
- We introduced the use of emerging QAI for **biosignal processing & BCI**
  - Demonstrated the first proof-of-concept study for future quantum-era
  - Showed the feasibility of QAI-assisted biosignal processing
  - Achieved state-of-the-art performance with few-parameter QML
  - 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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