From Quantum Machine Learning (QML) for The Current 5G and Future Modulations of 6G to Condensed Matter Physics[1]

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RESEARCH & INOVATION RECOGNITION

Meraih Klaster Mandiri (Tertinggi) dalam Bidang Penelitian dari Kemenristek / BRIN

1 Pusat Unggulan IPTEK Perguruan Tinggi dan 6 Research Center Telkom Universtiy

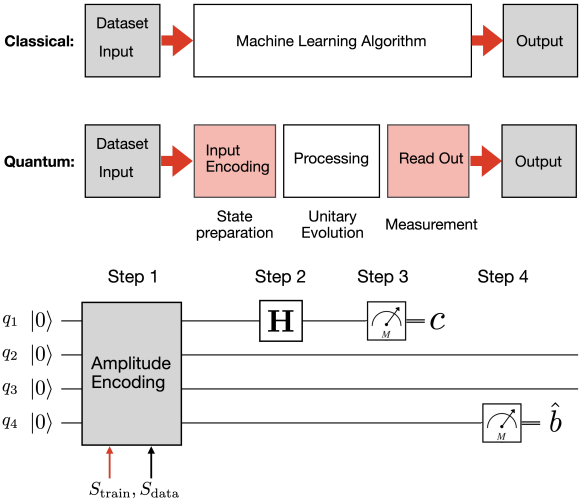
Huawei Beyond 5.5G Research Lab
Telecom Infra Project Lab
Meta Research and Experience Center
AI Center by NVIDIA

Introduction to AICOMS Laboratory

- AICOMS (formerly AdWiTech) established in September 2016 and received funding from national and international funding bodies.

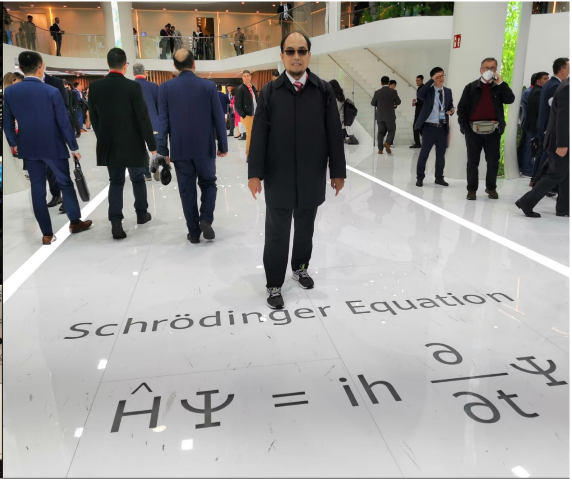
2016	2017	2018	2019	2020	2021	2022	2023
AdWiTech	AdWiTech	AdWiTech	AdWiTech	AICOMS	AICOMS	AICOMS	AICOMS
Est 2016	RP700M	RP2.5B	RP2.5B	RP4B	RP4B	RP5.4B+	RP6.5B
Established since Sept. 2016	• EPSRC UK • Ristekdikti • Internal	• LPDP Rispro • Ristekdikti • Insinas	• LPDP Rispro • Ristekdikti • Insinas	• ASEAN IVO • LPDP Rispro • Ristekdikti • PUI-PT • Kemendikbud	• ASEAN IVO • LPDP Rispro • Kominfo • PUI-PT • Kemendikbud • BRIN	• ASEAN IVO • LPDP Rispro • Kominfo • PUI-PT • BRIN	• Huawei • LPDP Rispro • Kominfo • BRIN

Outline



Classical:
Dataset
Input
Machine Learning Algorithm
Output
Quantum:
Dataset
Input
Input Encoding
Processing
Read Out
Output
State preparation
Unitary Evolution
Measurement
Step 1
Step 2
Step 3
Step 4
q_1 $|0\rangle$
q_2 $|0\rangle$
q_3 $|0\rangle$
q_4 $|0\rangle$
Amplitude Encoding
H
M
c
M
$\hat{b}$
$S_{\text{train}}, S_{\text{data}}$

Updates from MWC2023 Towards 6G: AI and Quantum

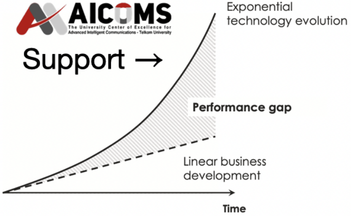


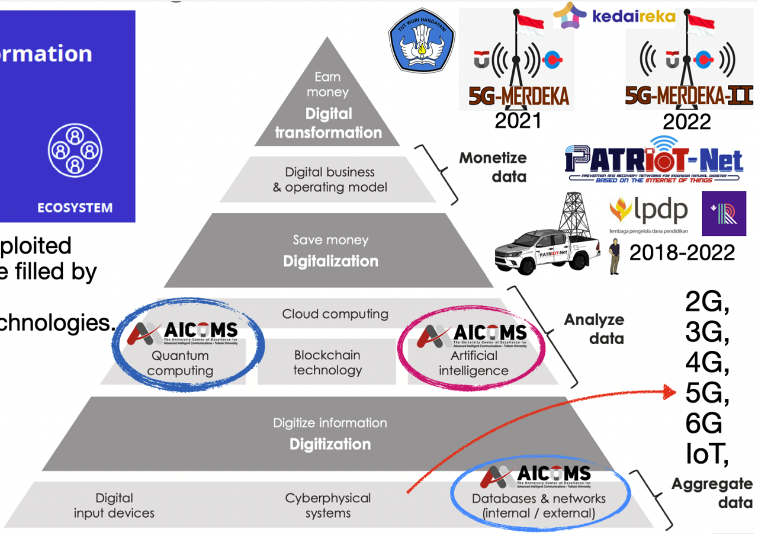
- Mobile World Congress 2023 was held in 27 Feb – 2 March 2023 and followed by 2024.

QML and The Digital Transformation: Aggregate and Analize

AICOMS is supporting that unexploited business opportunities should be filled by innovative university and startup companies that exploit digital technologies.

AICOMS Support →





2G, 3G, 4G, 5G, 6G IoT,

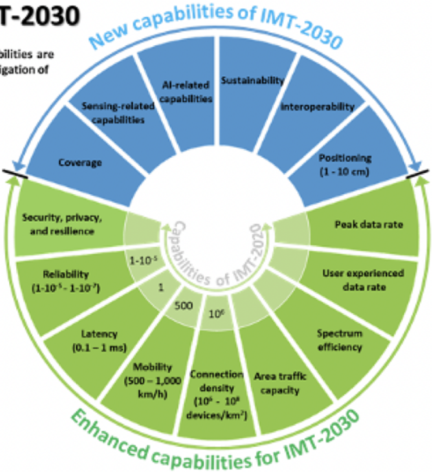
image: Volker Lang, Digital Fluency, Apress, 2021

Capabilities of IMT-2030 (6G)

Capabilities of IMT-2030

NOTE: The range of values given for capabilities are estimated targets for research and investigation of IMT-2030.

- 6G has new and enchanced capabilities
- 6G has 6 use cases, where the new usecases are (1) Integrated AI and communications, (2) Ubiquitous connectivity, and (3) integrated sensing and communications.



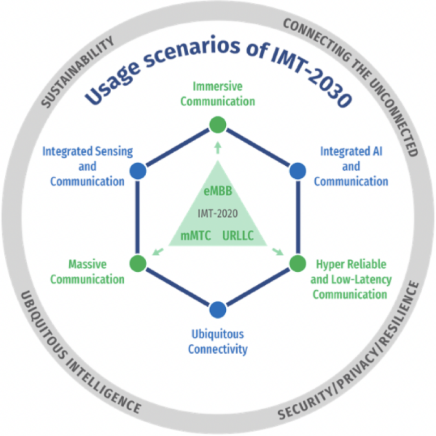
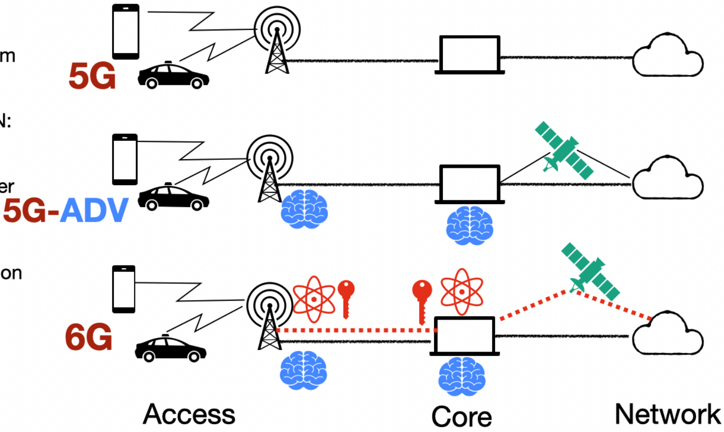


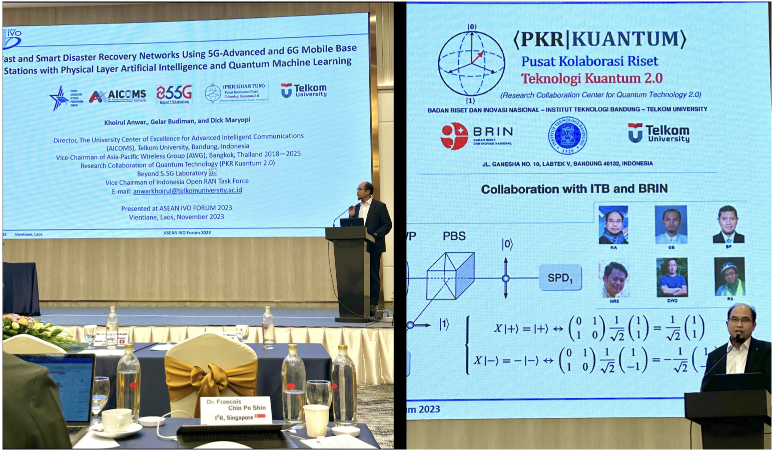
Image: ITU, WP5D

Evolution of 5G to 6G: Possible Implementations

- 5G-Advanced has uniqueness on the artificial intelligence (AI)
- 6G has uniqueness on the AI and Quantum cryptography.
- Quantum Technology with respect to RAN:
  - Physical layer processing of the user data plane in the RAN (quantum Fourier transform and quantum linear solver)
  - Clustering for automatic anomaly detection in network design optimization (quantum K-means algorithm)
  - Prediction of the quality of user experience for video streaming based on device and network level metrics (quantum support vector machine)
  - Database search at the data management layer (Grover's algorithm)



Possible Collaboration for ASEAN Countries



- We are expecting to submit the proposal abstract in September 2024 and complete proposal in December 2024.

System Model

- The system model is following the general structure of QML at the receiver of the classical communications.
- The received signal is

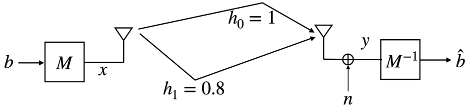
$$\mathbf{y} = \mathbf{H}_c\mathbf{x} + \mathbf{n}, \qquad (1)$$

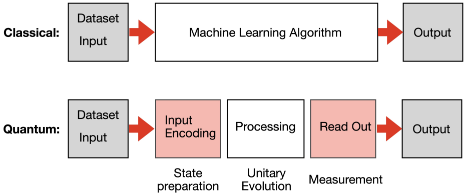
where $\mathbf{H}_c$ is the channel state information (CSI) matrix, $\mathbf{x}$ is the vector of transmit symbols, and $\mathbf{n}$ is additive white Gaussian noise (AWGN) $\mathbf{n} \sim \mathcal{N}(0, \sigma^2)$.

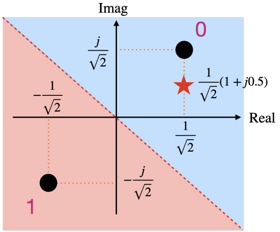
- Since the future modulation mapping of IMT-2030 is not available yet, we use the IMT-2020 (5G-NR) CBPSK, of which the mapped symbol is

$$x(i) = \frac{(1 - 2b(i))}{\sqrt{2}} + j\frac{(1 - 2b(i))}{\sqrt{2}}, \qquad (2)$$

where $b(i)$ is the i-th information bit.







Digital Modulations and Channel Capacity

EM or quantum

Bandwidth

Error correction

Energy

Business

Channels

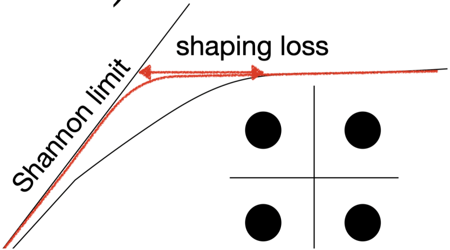
$$C \approx K \cdot n \cdot B \log_2\left(1 + m \cdot R \cdot |h|^2 \frac{E_b}{N_0}\right) \text{ bit/s/Hz/}m^2\text{/Joule/Rp}$$

OAM, qudit

Massive MIMO

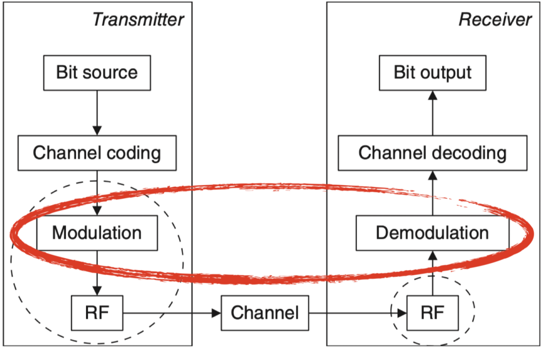
Modulation

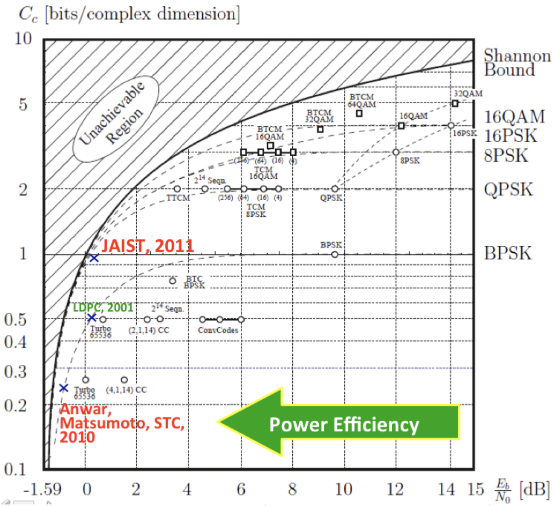
> 1Tbps



- Understanding philosophy for being better in research and teaching

Modulation vs Capacity

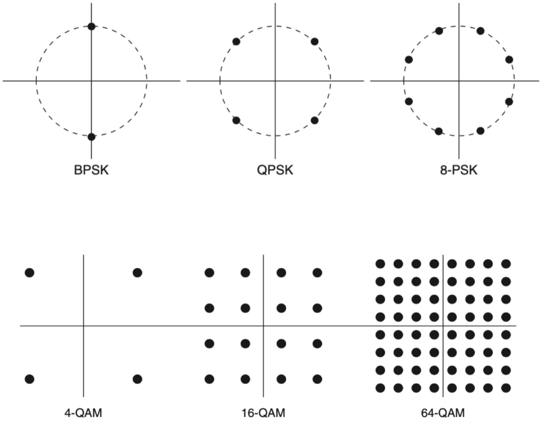




- Shannon capacity does not change

Digital Modulations

- The most fundamental digital modulation techniques are based on keying:
  - Phase-shift keying (PSK): a finite number of phases are used.
  - Frequency-shift keying (FSK): a finite number of frequencies are used.
  - Amplitude-shift keying (ASK): a finite number of amplitudes are used.
  - Quadrature amplitude modulation (QAM): a finite number of at least two phases and at least two amplitudes are used.



The 5G Modulation of 256-QAM

Octuplets of bits $b(8i)b(8i+1)b(8i+2)b(8i+3)b(8i+4)b(8i+5)b(8i+6)b(8i+7)$ are mapped to complex-valued modulation symbol $x(i)$ according to

$$x(i) = \frac{1}{\sqrt{170}}\left(R(i) + jI(i)\right)$$

$$R(i) = (1-2b(8i))[8-(1-2b(8i+2))[4-(1-2b(8i+4))[2-(1-2b(8i+6))]]]$$

$$I(i) = (1-2b(8i+1))[8-(1-2b(8i+3))[4-(1-2b(8i+5))[2-(1-2b(8i+7))]]]$$

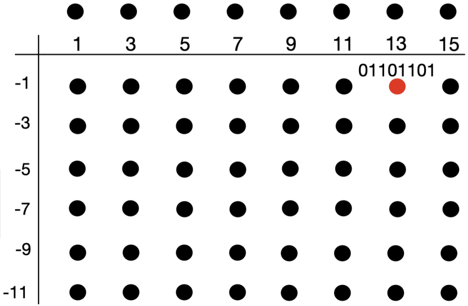
having a modulation index $m = 8$.

Example:

A binary stream $b = [0\ 1\ 1\ 0\ 1\ 1\ 0\ 1]$
is 256QAM modulated into

$$x = \left[\frac{(1)(8-(-1)(4-(-1)(2-1))) + j(-1)(8-1(4-(-1)(2-(-1))))}{\sqrt{170}}\right]$$

$$= \left[\frac{13-j}{\sqrt{170}}\right]$$



Review on the Classical Squared Distance Machine Learning (1/2)

- The classical demapper to obtain the log-likelihood ratio (LLR) is

$$L = \ln \frac{P(b=0|y)}{P(b=1|y)} = \ln \frac{\sum_{x_i \in s_0} \exp\left(-\frac{|y - h \cdot x_i|^2}{\sigma_n^2}\right)}{\sum_{x_i \in s_1} \exp\left(-\frac{|y - h \cdot x_i|^2}{\sigma_n^2}\right)}, \qquad (3)$$

  where s_0 is the set of symbols having label of $b = 0$, while s_1 for $b = 1$.
- Instead of using (3), we use machine learning (ML) to obtain the weight of nearest neighbor for the m-th point as

$$\gamma_m = 1 - \frac{1}{c}|y - x_m|^2 = 1 - \frac{1}{2}|y - x_m|^2 \qquad (4)$$

  with $m = \{1,\ 2, \cdots,\ M\}$. Since the normalization factor $c = 2$ for the modulated symbols of CBPSK in Eq. (2) since $E[x_m] = 1$.

Review on the Classical Squared Distance Machine Learning (2/2)

- Finally, the probability of predicting label of bits $b = 0$ or $b = 1$ is depending on the sum over all weights of all M training data. Therefore, we have the probability of having $b = 0$ as

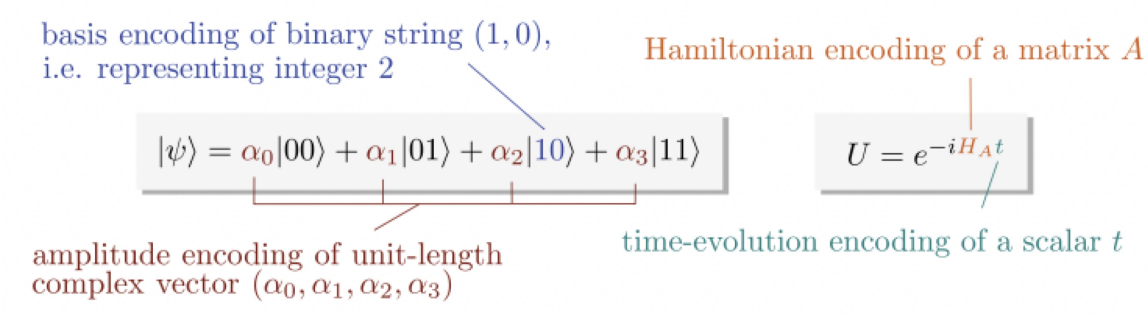
$$p(b = 0|y) = \frac{1}{M} \sum_{m|b=0} \left(1 - \frac{1}{2} |y - x_m|^2 \right) . \tag{5}$$

- Similarly, the probability of having $b = 1$ is

$$p(b = 1|y) = \frac{1}{M} \sum_{m|b=1} \left(1 - \frac{1}{2} |y - x_m|^2 \right) . \tag{6}$$

- We confirm here that $p(b = 0|y) + p(b = 1|y) = 1$ should be satisfied and call this model as the *squared-distance classifier*.
- This method, also called kernel method, works based on the principle that ”similar inputs should have similar outputs”.

Review on Quantum Encoding



[2]

[2] Source: Maria Schuld

The Proposed Quantum Machine Learning (1/2)

- To make the QML possible, we have to make sure that the computation using quantum, which is faster but providing **the same results**.
- Assume that we have only a single training dataset of $M = 1$ symbols as

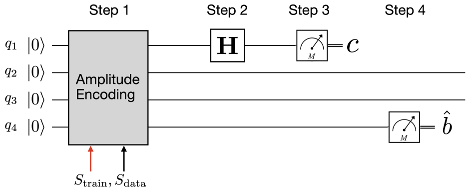
$$x = \frac{a}{\sqrt{2}} + j\frac{c}{\sqrt{2}}, \qquad (7)$$

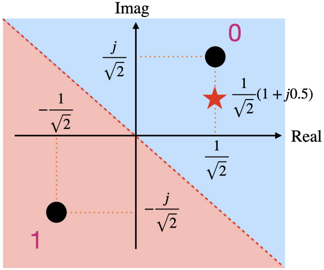
and the received data

$$y = \frac{d}{\sqrt{2}} + j\frac{e}{\sqrt{2}}, \qquad (8)$$

where $a, c, d, e \in \{\pm 1\}$ satisfying

$$a^2 + c^2 = 2 \qquad (9)$$
$$d^2 + e^2 = 2. \qquad (10)$$





The Proposed Quantum Machine Learning (2/2)

- The probability $p(b)$ in Eqs. (5) or (6) can be generally (in classical) expressed as

$$p(b)_K = \frac{1}{2}\left\{\left(1 - \frac{1}{4}|a-d|^2\right) + \left(1 - \frac{1}{4}|c-e|^2\right)\right\}. \quad (11)$$

- Since $p(b)_K$ can not be performed by the quantum computer, we modify the mathematical expression to another expression of $p(b)_Q$ for possible being calculated faster using quantum computer.
- To make a faster computation using quantum computer possible, we need to modify (11) into

$$p(b)_Q = \frac{1}{8}\left(|a+d|^2 + |c+e|^2\right), \quad (12)$$

which is proposed for the QML algorithm in this paper.

How The Proposed QML Works (1/2)

- Assume that the learning is for bit $b = q_3 = 0$ called *amplitude encoding*[3], we then have

$$|\psi\rangle = |q_1 q_2 q_3\rangle = \frac{a}{2}|000\rangle + \frac{c}{2}|010\rangle + \frac{d}{2}|100\rangle + \frac{e}{2}|110\rangle, \tag{13}$$

- Apply a Hadamard gate $\mathbf{H} = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$ on the first qubit to obtain

$$\begin{aligned} |\psi_o\rangle &= (\mathbf{H}\otimes\mathbf{I}\otimes\mathbf{I})|\psi\rangle \\ &= \frac{1}{2\sqrt{2}}\begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & -1 \end{bmatrix}\begin{bmatrix} a \\ 0 \\ c \\ 0 \\ d \\ 0 \\ e \\ 0 \end{bmatrix} = \frac{1}{2\sqrt{2}}\begin{bmatrix} a+d \\ 0 \\ c+e \\ 0 \\ a-d \\ 0 \\ c-e \\ 0 \end{bmatrix}, \end{aligned} \tag{14}$$

[3] Note that in this case qubits q_1 and q_2 can be 0 or 1.

How The Proposed QML Works (2/2)

- With a measurement gate of

$$\mathbf{M}_{10} = \mathbf{M}_0\mathbf{I}\mathbf{I} = |0\rangle\langle 0| \otimes \mathbf{I} \otimes \mathbf{I} \tag{15}$$

  the state $|\psi\rangle$ collapses into

$$|\psi_o'\rangle = \frac{\mathbf{M}_{10}|\psi_o\rangle}{\sqrt{P_{10}}} = \frac{1}{2\sqrt{2P_{10}}} \begin{bmatrix} a+d \\ 0 \\ c+e \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{16}$$

  with probability of qubit q_1 being zero $P_{10} = \langle\psi_o|\mathbf{M}_{10}|\psi_o\rangle = \frac{1}{8}\left(|a+d|^2 + |c+e|^2\right)$.
- Finally, the result is depending on the qubit q_3. Therefore the measurement on q_3 using gate $\mathbf{M}_{30} = \mathbf{I}\mathbf{I} \otimes |0\rangle\langle 0|$ completes the algorithm.

How The Proposed QML Works: The Proof

- The the probability of qubit $q_3 = 0$ is equal to Eq. (12)[4] as

$$p(b=0)_Q = p(q_3=0) = P_{30} = \langle \psi_o' | \mathbf{M}_{30} | \psi_o' \rangle = \frac{1}{8P_{10}} \left(|a+d|^2 + |c+e|^2 \right), \quad (17)$$

$$= \frac{1}{8} \left(|a+d|^2 + |c+e|^2 \right) \quad (18)$$

- The next task is on the proof that Eq. (11) should be equal to Eq. (12) as

$$p(b)_Q = \frac{1}{8} \left(a^2 + 2ad + d^2 + c^2 + 2ce + e^2 \right) = \frac{1}{8} \left(2 + 2ad + 2 + 2ce \right) = \frac{1}{4} \left(2 + ad + ce \right). \quad (19)$$

On the other hand, for the classical ML we can also further derive as

$$p(b)_K = \frac{1}{2} \left(1 - \frac{1}{4}|a-d|^2 + 1 - \frac{1}{4}|c-e|^2 \right) = \frac{1}{4} \left(2 + ad + ce \right). \quad (20)$$

Here, we complete the proof that (19) is equal to (20).

[4] Note that this P_{10} can be ignored because $p(b=1)_Q$ will also contain the same constant. Therefore, comparison between $p(b=0)_Q$ and $p(b=1)_Q$ has no problem with the ignorance of P_{10}.

The Proposed QML for the 5G BCSK Demapper (1/2)

- The qubits q_1 is used to distinguish the training dataset x_m and the data to be tested y, where the qubit $q_1 = 0$ is for training x_m, while qubit $q_1 = 1$ is for data y.
- The qubit q_2 is to distinguish the real part of the dataset symbols $\Re\mathfrak{e}(x_1)$ and $\Re\mathfrak{e}(x_2)$, while qubit q_3 is for the imaginary part of the symbols $\Im\mathfrak{m}(x_1)$ and $\Im\mathfrak{m}(x_2)$.
- The training symbols dataset $S_{\text{train}} = \{x_1,\ x_2\}$

$$x_1 = \frac{1}{\sqrt{2}} + \frac{j}{\sqrt{2}} \ \text{and} \ x_2 = -\frac{1}{\sqrt{2}} - \frac{j}{\sqrt{2}}. \tag{21}$$

  and data to be detected $S_{\text{data}} = y = \frac{1}{\sqrt{2}}(1 + j0.5)$
- The probability of bit $b = 0$ is $p(q_4 = 0) = 0.7845^2 + 0.5883^2 = 0.9615$
- The probability of bit $b = 1$ is $p(q_4 = 1) = 0^2 + (-0.1961)^2 = 0.0385$

Step 1				Step 2	Step 3	Step 4
q_1	q_2	q_3	q_4			
0	0	0	0	$1/\sqrt{2}$	1.0000	0.7845
0	0	0	1	0	0	0
0	0	1	0	$1/\sqrt{2}$	0.7500	0.5883
0	0	1	1	0	0	0
0	1	0	0	0	0	0
0	1	0	1	$-1/\sqrt{2}$	0	0
0	1	1	0	0	0	0
0	1	1	1	$-1/\sqrt{2}$	-0.2500	-0.1961
1	0	0	0	$1/\sqrt{2}$	0	0
1	0	0	1	0	0	0
1	0	1	0	$0.5/\sqrt{2}$	0.2500	0
1	0	1	1	0	0	0
1	1	0	0	0	0	0
1	1	0	1	$1/\sqrt{2}$	-1.0000	0
1	1	1	0	0	0	0
1	1	1	1	$0.5/\sqrt{2}$	-0.7500	0

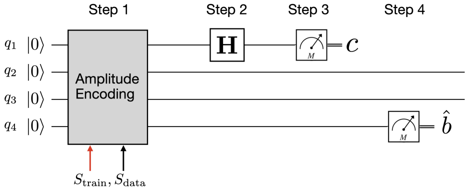
The Proposed QML for the 5G CBPSK Demapper (2/2)

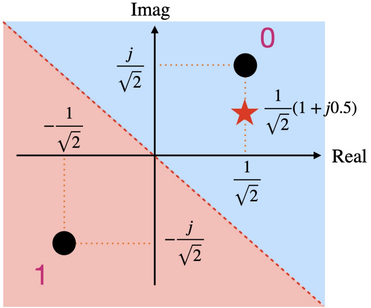
- The qubit state is

$$
\begin{aligned}
|\psi\rangle &= |q_1 q_2 q_3 q_4\rangle \\
&= \frac{1}{\sqrt{2}}|0000\rangle + \frac{1}{\sqrt{2}}|0010\rangle - \frac{1}{\sqrt{2}}|0101\rangle - \frac{1}{\sqrt{2}}|0111\rangle \\
&\quad +\mathfrak{Re}(y)|1000\rangle + \mathfrak{Im}(y)|1010\rangle + \mathfrak{Re}(y)|1100\rangle \\
&\quad +\mathfrak{Im}(y)|1111\rangle, \qquad (22)
\end{aligned}
$$

  where the real and imaginary parts of the received signal y is copied twice since the training symbols dataset contains two symbols x_1 and x_2.

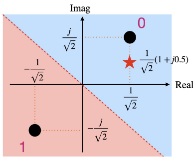
- The mathematical expression of Eq. (22) complies with Table for the received signal $y = \frac{1}{\sqrt{2}} + j\frac{0.5}{\sqrt{2}}$ with marker of "$\star$".
- The qubit q_4 is used to store the final detected information bit $\hat{b}$, which is measured in the last step of the proposed algorithm with gates $\mathbf{IIIM}_0$ to obtain $p(\hat{b}=0)$ or $\mathbf{IIIM}_1$ to obtain $p(\hat{b}=1)$.

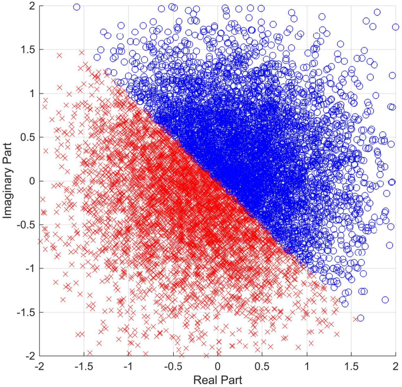




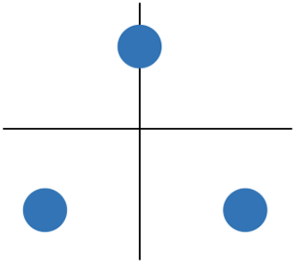
Result of The Proposed QML for the 5G CBPSK Demapper

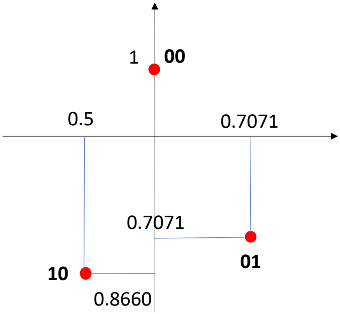
- Bit "0" is mapped to $x_0 = \frac{1}{\sqrt{2}}(1+j)$ and bit "1" to $x_1 = \frac{1}{\sqrt{2}}(-1-j)$.
- We performed quantum measurement following (19) with extention to 4-qubit QML system in Table.
- We use marker of "$\circ$" for the detected bit $\hat{b} = 0$, while marker "$\times$" for bit $\hat{b} = 0$ and plot all possible symbols in this figure.
- The Fig shows clearly that the results can virtually and automatically create a diagonal line crossing the (0,0) point separation marker of "$\circ$" for the detected bit $\hat{b} = 0$, while marker "$\times$" for bit $\hat{b} = 0$.
- This result is expected to be valid for any symbols received with real part larger than 2.0 or less than -2.0 and for imaginary part larger than $j2.0$ or less than $-j2.0$.
- This result is very interesting since only 4 steps are required to calculate the probability $p(b=0)$ and $p(b) = 1$, when quantum machine learning is involved.

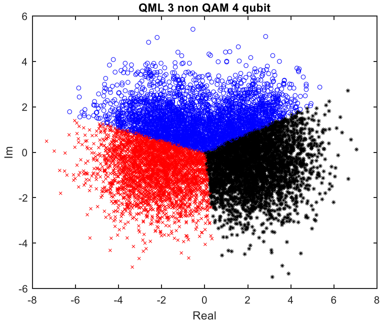




Results on Expected Future Random Modulations (1/2)



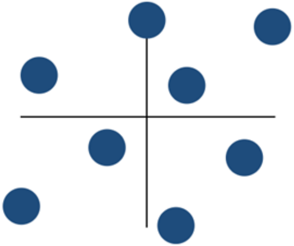


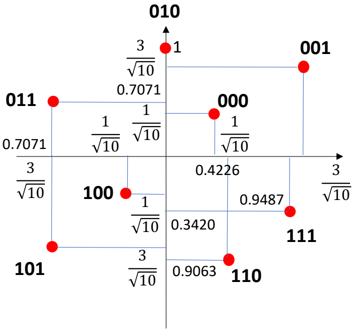


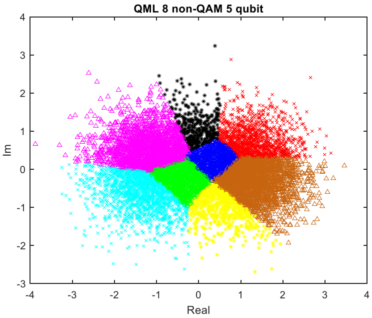
- QML is also working well when the non-QAM is used as modulations.[5]
- Function to distinguish the area of each symbols inherently works well in Non-QAM modulations, which is in general difficult.

5 This work is ongoing with Wahidin for his Master's thesis.

Results on Expected Future Random Modulations (2/2)







- QML still works well for random non-QAM is used as modulations.[6]
- More difficult function to distinguish the area of each symbols can be avoided.

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[6] This work is ongoing with Wahidin for his Master's thesis.

Conclusions

- This talk has demonstrated that quantum machine learning for future any complex demapper, where 5G modulations of both real and complex symbols are used as demonstration purpose.
- The QML is designed to keep the computational complexity low, eventhough the future modulation mapping may involve thousand constellation points.
- We first derived the equality of the equations for the computation used by both classical and quantum machines.
- We then used a series of computer simulations to evaluate and demonstrate the effectiveness of the proposed QML for thousand random CBPSK symbols.
- We found that proposed QML can effectively demap the CBPSK symbols by using only 4 qubits, where virtual regions are automatically identified by the algorithm.
- The design can be extended to any higher order of future constellation, e.g., random modulation, which is theoretically excellent satisfying the the ”Gaussian distribution” that maximize entropy, but difficult in practice.