Introduction to Quantum Computing – Quantum Applications

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July 28, 2022

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The goal for today's lecture is to discuss how some applications/algorithms for quantum computers work and can be implemented. We will discuss the following topics:

- Quatum Fourier Transform (QFT) Fourier Transform, DFT, FFT, ...
- Shor's Algorithm



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- Quatum Fourier Transform (QFT) Fourier Transform, DFT, FFT, ...
- Shor's Algorithm

Material based on Xanadu's codebook and PennyLane documentation.



Please stop me if you have a question.



Recap Quantum Gates

Recap Quantum Gates

Gate	Matrix	Circuit element(s)	Basis state action
x	$\begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}$	-X $ -$	$\begin{array}{l} X 0\rangle = 1\rangle \\ X 1\rangle = 0\rangle \end{array}$
Н	$\frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$	-H	$\begin{split} H 0\rangle &= \frac{1}{\sqrt{2}} \left(0\rangle + 1\rangle \right) \\ H 1\rangle &= \frac{1}{\sqrt{2}} \left(0\rangle - 1\rangle \right) \end{split}$
z	$\begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$		$\begin{array}{l} Z 0\rangle = 0\rangle \\ Z 1\rangle = - 1\rangle \end{array}$
s	$\begin{pmatrix} 1 & 0 \\ 0 & i \end{pmatrix}$	<u>S</u>	$egin{array}{llllllllllllllllllllllllllllllllllll$
Т	$\begin{pmatrix} 1 & 0 \\ 0 & e^{i \pi/4} \end{pmatrix}$		$egin{array}{ll} T 0 angle= 0 angle\ T 1 angle=e^{arepsilon n/4} 1 angle$
Y	$\begin{pmatrix} 0 & -i \\ i & 0 \end{pmatrix}$		$egin{array}{llllllllllllllllllllllllllllllllllll$
RZ	$\begin{pmatrix} e^{-i\frac{\beta}{2}} & 0 \\ 0 & e^{i\frac{\beta}{2}} \end{pmatrix}$	$-R_z(\theta)$	$egin{aligned} RZ(heta) 0 angle = e^{-irac{t}{2}} 0 angle \ RZ(heta) 1 angle = e^{irac{p}{2}} 1 angle \end{aligned}$
RX	$\begin{pmatrix} \cos\left(\frac{\delta}{2}\right) & -i\sin\left(\frac{\theta}{2}\right) \\ -i\sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$	$R_{\pi}(\theta)$	$\begin{split} RX(\theta) 0\rangle &= \cos\frac{\theta}{2} 0\rangle - i\sin\frac{\theta}{2} 1\rangle\\ RX(\theta) 1\rangle &= -i\sin\frac{\theta}{2} 0\rangle + \cos\frac{\theta}{2} 1\rangle \end{split}$
RY	$\begin{pmatrix} \cos\left(\frac{\theta}{2}\right) & -\sin\left(\frac{\theta}{2}\right) \\ \sin\left(\frac{\theta}{2}\right) & \cos\left(\frac{\theta}{2}\right) \end{pmatrix}$	$-R_y(\theta)$	$\begin{split} RY(\theta) 0\rangle &= \cos\frac{\theta}{2} 0\rangle + \sin\frac{\theta}{2} 1\rangle \\ RY(\theta) 1\rangle &= -\sin\frac{\theta}{2} 0\rangle + \cos\frac{\theta}{2} 1\rangle \end{split}$

Gate	Matrix	Circuit element(s)	Basis state action
CNOT	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$		CNOT[00] = 00 CNOT[01] = 01 CNOT[10] = 11 CNOT[11] = 10
CZ	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -1 \end{pmatrix}$		$\begin{array}{l} CZ(00) = 00\rangle \\ CZ(01) = 01\rangle \\ CZ(10) = 10\rangle \\ CZ(11) = - 11\rangle \end{array}$
CRZ	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & e^{-i\frac{\theta}{2}} & 0 \\ 0 & 0 & 0 & e^{i\frac{\theta}{2}} \end{pmatrix}$	$-R_z(\theta)$	$CZ 00\rangle = 00\rangle$ $CZ 01\rangle = 01\rangle$ $CZ 10\rangle = e^{- \tilde{1} } 10\rangle$ $CZ 11\rangle = e^{1\tilde{1}} 11\rangle$
CRX	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \cos\left(\frac{\pi}{2}\right) & -i\sin\left(\frac{\pi}{2}\right) \\ 0 & 0 & -i\sin\left(\frac{\pi}{2}\right) & \cos\left(\frac{\pi}{2}\right) \end{pmatrix}$	$-R_{s}(\theta)$	$\begin{array}{l} CRX(\theta)(00) = 00\rangle \\ CRX(\theta)(01) = 01\rangle \\ CRX(\theta) 10\rangle = \cos\frac{\theta}{2} 10\rangle - i\sin\frac{\theta}{2} 11\rangle \\ CRX(\theta) 10\rangle = \cos\frac{\theta}{2} 10\rangle + \cos\frac{\theta}{2} 11\rangle \end{array}$
CRY	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \cos\left(\frac{\pi}{2}\right) & -\sin\left(\frac{\pi}{2}\right) \\ 0 & 0 & \sin\left(\frac{\pi}{2}\right) & \cos\left(\frac{\pi}{2}\right) \end{pmatrix}$	- <u>R_y(0)</u> -	$ \begin{array}{l} CRY(\theta) 00\rangle = 00\rangle\\ CRY(\theta) 01\rangle = 01\rangle\\ CRY(\theta) 10\rangle = \cos\frac{\theta}{2} 10\rangle + \sin\frac{\theta}{2} 11\rangle\\ CRY(\theta) 11\rangle = -\sin\frac{\theta}{2} 10\rangle + \cos\frac{\theta}{2} 11\rangle \end{array} $
CU	$\begin{pmatrix} I_3 & 0 \\ 0 & U \end{pmatrix}$		$\begin{array}{l} CU(00) = 00\rangle \\ CU(01) = 01\rangle \\ CU(10) = 1\rangle \otimes U 0\rangle \\ CU 11\rangle = 1\rangle \otimes U 1\rangle \end{array}$
SWAP	$\begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$	_ *	$\begin{array}{l} SWAP(00) = 00)\\ SWAP(01) = 10)\\ SWAP(10) = 01)\\ SWAP(11) = 11) \end{array}$
TOF	$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$	$\stackrel{+}{\stackrel{+}{\mapsto}}$	$\begin{array}{l} TOF(060) = [010] \\ TOF(001) = [001] \\ \vdots = \vdots \\ TOF(101) = [101] \\ TOF(101) = [111] \\ TOF(111) = [110] \end{array}$



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Intro to Quantum Computing – Applications

and some special cases...

$$\begin{split} & \text{Special cases of } RZ: \ Z, S, T \\ & |\psi\rangle = \alpha \left|0\right\rangle + \beta \left|1\right\rangle \Rightarrow \boxed{RZ(\omega) \left|\psi\right\rangle = \alpha \left|0\right\rangle + \beta e^{i\omega} \left|1\right\rangle} \\ & \overline{RZ(\omega) = \begin{bmatrix} e^{-i\frac{\omega}{2}} & 0 \\ 0 & e^{i\frac{\omega}{2}} \end{bmatrix} \sim \begin{bmatrix} 1 & 0 \\ 0 & e^{i\omega} \end{bmatrix}} \quad RZ^{\dagger}(\omega) = RZ(-\omega) \\ & \overline{Z = RZ(\omega = \pi) = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}} \quad ZZ = Z^2 = I, Z^{\dagger} = Z \\ & \overline{S = RZ(\omega = \frac{\pi}{2}) = \begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix}} \quad SS = Z, SSSS = ZZ = I, S^{\dagger} = SSS \\ & \overline{T = RZ(\omega = \frac{\pi}{4}) = \begin{bmatrix} 1 & 0 \\ 0 & e^{i\frac{\pi}{4}} \end{bmatrix}} \quad T^{\dagger} = T^{7}} \end{split}$$

When implementing your quantum circuits, you will need to READ the $\ensuremath{\mathsf{DOCUMENTATION!}}$

https://pennylane.readthedocs.io/en/stable/code/qml.html



Fourier Transform

- Let $oldsymbol{f}$ be a function of some variable $oldsymbol{x}$
- The FT is defined as,

$$\mathcal{F}(f(x))\equiv \hat{f}(k)\propto \int f(x)e^{\pm ik\cdot x}dx$$

Inverse transformation,

$$\mathcal{F}^{-1}(\hat{f}(k))\equiv f(x)\propto\int\hat{f}(k)e^{\mp ik\cdot x}dk$$

- The overall idea is that any function (under certain conditions) can be expressed as a harmonic series
- The FT is a mathematical expression of that
- Constitutes a linear (basis) transformation in *function space*.
- Transforms from spatial to wavenumber, or time to frequency, etc.
- Constants and signs are conventions.



FT – Examples & Applications

Examples

- Double sided exponential: $f(x) = e^{-a|x|}(a > 0) \Rightarrow \hat{f}(k) = rac{2a}{a^2 + k^2}$
- Rectangular pulse: $f(t) = \begin{cases} 1 & -T \le t \le T \\ 0 & |t| > T \end{cases} \Rightarrow \hat{f}(\omega) = 2 \frac{\sin(\omega T)}{\omega}$

• Unit impulse:
$$f(t)=\delta(t)\Rightarrow \hat{f}(\omega)=1$$

Applications

- Solve differential equations, integration, polynomials multiplication, ...
- Communications, Signal processing, sampling.
- Harmonic analysis, principal modes, ...



Discrete Fourier Transform (DFT)

- Given a set of n function values on a regular grid: $f_j = f(j\Delta x)$
- Fourier-transform these *n* values (Fourier series),

$$\hat{f}_k = \sum_{j=0}^{n-1} f_j e^{\pm 2\pi i j k/n}$$

• Easy to inverse-transform (revert),

$$f_j = rac{1}{n}\sum_{j=0}^{n-1} \widehat{f}_k e^{\mp 2\pi i j k/n}$$

- Discrete Fourier transform is a linear transformation.
- In particular, it's a matrix-vector multiplication.
- Slow: naively, costs ${\cal O}(n^2)$

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Fast Fourier Transform (FFT) i

- Derived in partial form several times before and even after Gauss, because he'd just written it in his diary in 1805 (published later).
- Rediscovered (in general form) by Cooley and Tukey in 1965.

Basic Idea

- Write each n-point FT as a sum of two n/2 point FTs.
- Do this recursively $\log n$ times.
- Each level requires $\sim n$ computations: $\mathcal{O}(n \log n)$ instead of $\mathcal{O}(n^2)$. Could as easily divide into 3, 5, 7, ... parts



Fast Fourier Transform (FFT) ii

- Define $\omega_n = e^{(2\pi i)/n}$.
- Note that $\omega_n^2 = \omega_{rac{n}{2}}$.
- DFT takes form of matrix-vector multiplication: $\hat{f}_k = \sum_{j=0}^{n-1} \omega_n^{kj} f_j$
- Rewriting this, assuming n is even, $\hat{f}_k = \underbrace{\sum_{j=0}^{\frac{n}{2}-1} \omega_{\frac{n}{2}}^{kj} f_{2j}}_{j=0} + \omega_n^k \underbrace{\sum_{j=0}^{\frac{n}{2}-1} \omega_{\frac{n}{2}}^{kj} f_{2j+1}}_{j=0}$

FT of even samples



FT of odd samples

• Inverse DFT is similar to forward DFT, up to a normalization: almost just as fast.

$$f_j = rac{1}{n}\sum_{k=0}^{n-1} \hat{f}_k e^{\mp 2\pi i j k/n}$$

Inverse DFT is similar to forward DFT, up to a normalization: almost just as fast.

- FFT allows quick back-and-forth between x and k domain (or e.g. time and frequency domain).
- Allows parts of the computation and/or analysis to be done in the most convenient or efficient domain.



Polynomial Multiplication

Let's consider two polynomials,

$$A(x) = x^2 + 2x + 1$$

 $B(x) = 3x^2 + 2$



Polynomial Multiplication

Let's consider two polynomials,

$$egin{aligned} A(x) &= x^2 + 2x + 1 \ B(x) &= 3x^2 + 2 \end{aligned}$$

To compute $C(x) = A(x) \cdot B(x)$, we can use the distribute property,

$$\begin{array}{rcl} C(x) &=& (x^2+2x+1)\cdot(3x^2+2)\\ &=& x^2\cdot(3x^2+2)+2x\cdot(3x^2+2)+1\cdot(3x^2+2)\\ &=& 1+2x+4x^2+6x^3+3x^4 \end{array}$$

Coefficient representation: $C(x) \rightsquigarrow [1,2,4,6,3]$



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How difficult is multiplying two polynomials?

Given two polynomials of degree d,

$$A(x) = a_0 + a_1 x + a_2 x^2 + \dots + a_d x^d = \sum_{n=0}^d a_j x^j$$

 $B(x) = b_0 + b_1 x + b_2 x^2 + \dots + b_d x^d = \sum_{n=0}^d b_j x^j$

 $\Rightarrow C(x) = A(x) \cdot B(x)$ is a polynomial with degree 2d,

$$C(x) = c_0 + c_1 x + c_2 x^2 + \dots + c_{2d} x^{2d} = \sum_{n=0}^{2d} c_j x^j$$

Using the distribute property, we end up with a complexity $\sim {\cal O}(d^2)$



Faster polynomials multiplication

Polynomials can be multiplied faster when they are represented using values (a set of $n \ge d+1$ points representing a d-degree polynomial) instead of using coefficients

Polynomials can be converted from the *coefficient representation* to the *value representation* using the Discrete Fourier transform.

Evaluation: coeffs. \rightarrow values

$$A(x) = \{(x_0, A(x_0), (x_1, A(x_1)), \dots, (x_{2d+1}, A(x_{2d+1}))\}$$

$$B(x) = \{(x_0, B(x_0), (x_1, B(x_1)), \dots, (x_{2d+1}, B(x_{2d+1}))\}$$

Multiplication in the values representation

$$C(x) = \{(x_0, A(x_0) \cdot B(x_0), (x_1, A(x_1) \cdot B(x_1)), \dots, (x_{2d+1}, A(x_{2d+1}) \cdot B(x_{2d+1}))\}$$

$$\sim \mathcal{O}(d) \parallel \parallel$$

Alternative Algorithm for Multiplying Polynomials

- 1. Selection: choose a set of $n \geq 2d+1$ points to represent both our polynomials. \sim constant linear time
- 2. *Evaluation*: convert the two polynomials from the coefficient representation to the value representation.

 \sim linear time and that we have to evaluate the polynomial at $n \geq 2d + 1$ points \Rightarrow quadratic running time for evaluating and multiplying both the polynomials

3. *Multiplication*: multiply element-wise to get the value representation of the product of the polynomials.

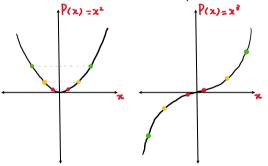
 $\sim \mathcal{O}(d)$

4. *Interpolation*: convert the value representation back to the coefficient representation.



Divide-and-Conquer

The FFT algorithm is an elegant technique that uses the *divide-and-conquer* approach to make evaluation and interpolation faster.



 $P(x) = x^2$ is an even function; only needs to evaluate the polynomial at only n/2 points – P(x) = P(-x) $P(x) = x^3$ is an odd function; P(x) = -P(-x)

(Credit: Xanadu)

In general, any given polynomial could be partitioned into an even and odd part, $P(x)=P_{even}(x)+P_{odd}(x)$



Eg. $P(x)=1+2x+4x^2+6x^3+3x^4$



Eg.
$$P(x) = 1 + 2x + 4x^2 + 6x^3 + 3x^4 \Rightarrow P(x) = \underbrace{(1 + 4x^2 + 3x^4)}_{P_e(x)} + x\underbrace{(2 + 6x^2)}_{P_o(x)}$$



Eg.
$$P(x) = 1 + 2x + 4x^2 + 6x^3 + 3x^4 \Rightarrow P(x) = \underbrace{(1 + 4x^2 + 3x^4)}_{P_e(x)} + x \underbrace{(2 + 6x^2)}_{P_o(x)}$$

 $u\equiv x^2$,



17 / 48

Eg.

$$P(x) = 1 + 2x + 4x^2 + 6x^3 + 3x^4 \Rightarrow P(x) = \underbrace{(1 + 4x^2 + 3x^4)}_{P_e(x)} + x \underbrace{(2 + 6x^2)}_{P_o(x)}$$

$$u\equiv x^2$$
 , $egin{array}{c} P_e(u)=1+4u+3u^2\ P_o(u)=2+6u \end{array} \Rightarrow P(x)=P_e(x^2)+xP_o(x^2) \end{array}$

We can think of polynomials of x^2 (rather than x) with a degree $d \leq 2$, we can evaluate them at fewer points.

We are not reducing the number of points, rather just the number of evaluations based on the relationship between positive and negative pairs of points.



For a general polynomial,

$$P(x) = P_e(x^2) + x P_o(x^2) \ P(-x) = P_e(x^2) - x P_o(x^2)$$

To evaluate a polynomial of degree (n-1), we need to evaluate it at n points.

Recursively, we can evaluate $P_e(x^2)$ and $P_o(x^2)$ at each $[x_1^2, x_2^2, \ldots, x_{n/2}^2] \rightarrow$ using the parity relations between the polynomials, we end up with two polynomials evaluated at $\frac{n}{2}$ points.

However, the $\{x_i^2\}$ points posse a problem... if $x_i \in \mathbb{R} \Rightarrow \{x_i^2\} > 0$



The way to fix the issue of being left out of negative numbers can be solved by considering the *n*-th roots of the eqn. $\boxed{x^n = 1}$.

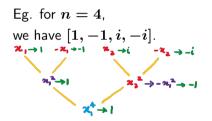


The way to fix the issue of being left out of negative numbers can be solved by considering the *n*-th roots of the eqn. $x^n = 1$.

Eg. for n = 4,



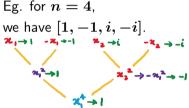
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(Credit: Xanadu)

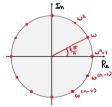


The way to fix the issue of being left out of negative numbers can be solved by considering the *n*-th roots of the eqn. $\boxed{x^n = 1}$. In general, for $x^n = 1$, there are *n* complex roots: $[\omega^0, \omega^1, \dots, \omega^{(n-1)}]$



(Credit: Xanadu)

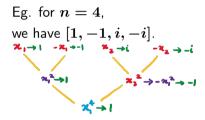
complex roots: $[\omega^0, \omega^1, \dots, \omega^{(n-1)}]$ where $\omega = e^{\frac{2\pi i}{n}} = \cos(\frac{2\pi}{n}) + i\sin(\frac{2\pi}{n})$ For any polynomial of degree d, we choose $n \ge (d+1)$ roots of unity so that the polynomial can be evaluated at these points – with n a power of 2.



(Credit: Xanadu)



The way to fix the issue of being left out of negative numbers can be solved by considering the *n*-th roots of the eqn. $x^n = 1$.

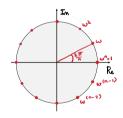


(Credit: Xanadu)

Some properties:

In general, for $x^n = 1$, there are n complex roots: $[\omega^0, \omega^1, \ldots, \omega^{(n-1)}]$ where $\omega = e^{rac{2\pi i}{n}} = \cos(rac{2\pi}{n}) + i\sin(rac{2\pi}{n})$ For any polynomial of degree d, we choose n > (d+1) roots of unity so that the polynomial can be evaluated at these points – with n a power of 2.

 $\sum_{k=0}^{n-1} \omega^{xk} = 0$, for $x \neq 0$



(Credit: Xanadu)

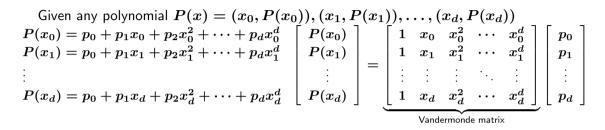
 $\omega^0 + \omega^1 + \ldots + \omega^{(n-1)} = 0$

Given any polynomial
$$P(x) = (x_0, P(x_0)), (x_1, P(x_1)), \dots, (x_d, P(x_d))$$

 $P(x_0) = p_0 + p_1 x_0 + p_2 x_0^2 + \dots + p_d x_0^d$
 $P(x_1) = p_0 + p_1 x_1 + p_2 x_1^2 + \dots + p_d x_1^d$
 \vdots
 $P(x_d) = p_0 + p_1 x_d + p_2 x_d^2 + \dots + p_d x_d^d$



20 / 48





20 / 48

$$\begin{array}{l} \text{Given any polynomial } P(x) = (x_0, P(x_0)), (x_1, P(x_1)), \dots, (x_d, P(x_d)) \\ P(x_0) = p_0 + p_1 x_0 + p_2 x_0^2 + \dots + p_d x_0^d \\ P(x_1) = p_0 + p_1 x_1 + p_2 x_1^2 + \dots + p_d x_1^d \\ \vdots \\ P(x_d) = p_0 + p_1 x_d + p_2 x_d^2 + \dots + p_d x_d^d \end{array} \begin{bmatrix} P(x_0) \\ P(x_1) \\ \vdots \\ P(x_d) \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & x_0 & x_0^2 & \dots & x_0^d \\ 1 & x_1 & x_1^2 & \dots & x_1^d \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_d & x_d^2 & \dots & x_d^d \end{bmatrix}}_{\text{Vandermonde matrix}} \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_d \end{bmatrix}$$

Evaluating in the set of $n \geq (d+1)$ points as the n-th roots of unity,



Given any polynomial
$$P(x) = (x_0, P(x_0)), (x_1, P(x_1)), \dots, (x_d, P(x_d))$$

 $P(x_0) = p_0 + p_1 x_0 + p_2 x_0^2 + \dots + p_d x_0^d$
 $P(x_1) = p_0 + p_1 x_1 + p_2 x_1^2 + \dots + p_d x_d^d$
 $P(x_d) = p_0 + p_1 x_d + p_2 x_d^2 + \dots + p_d x_d^d$
 $P(x_d) = p_0 + p_1 x_d + p_2 x_d^2 + \dots + p_d x_d^d$
Evaluating in the set of $n \ge (d+1)$ points as the *n*-th roots of unity,
 $\left[\begin{array}{c}P(\omega^0)\\P(\omega^1)\\\vdots\\P(\omega^{n-1})\end{array}\right] = \left[\begin{array}{cccc}1 & 1 & 1 & \dots & 1\\1 & \omega & \omega^2 & \dots & \omega^{n-1}\\\vdots & \vdots & \vdots & \ddots & \vdots\\1 & \omega^{n-1} & \omega^{2(n-1)} & \dots & \omega^{(n-1)(n-1)}\end{array}\right] \left[\begin{array}{c}p_0\\p_1\\\vdots\\p_{n-1}\end{array}\right]$
DFT matrix

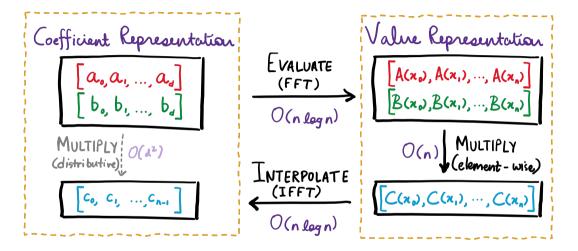


Unitary DFT Matrix & IDFT

- Interpolation, as matrix-vector multiplication $\rightsquigarrow \mathcal{O}(n^2) \Rightarrow \mathsf{FFT} \sim \mathcal{O}(n \log n)$
- The DFT matrix, is unitary up to a factor of n, i.e. $U_{DFT}U_{DFT}^{\dagger}=nI$
- The DFT matrix is invertible, $U_{DFT}^{-1} = rac{1}{n} U_{DFT}^{\dagger}$
- The Inverse Discrete Fourier transform (IDFT) is essentially just the DFT but with a factor of $\frac{1}{n}$ and the inverse roots of unity

$$U_{DFT} = egin{bmatrix} 1 & 1 & 1 & \cdots & 1 \ 1 & \omega & \omega^2 & \cdots & \omega^{n-1} \ dots & dots & dots & dots & dots \ 1 & \omega^{n-1} & \omega^{2(n-1)} & \cdots & \omega^{(n-1)(n-1)} \end{bmatrix} \ U_{IDFT} = rac{1}{n} egin{bmatrix} 1 & 1 & 1 & \cdots & 1 \ 1 & \omega^{-1} & \omega^{-2} & \cdots & \omega^{-(n-1)} \ dots & dots & dots & dots & dots & dots \ 1 & \omega^{-(n-1)} & \omega^{-2(n-1)} & \cdots & \omega^{-(n-1)(n-1)} \end{bmatrix}$$









Numpy FFT implementation of Polynomials Multiplication i

Given a polynomial in its coefficient representation, convert it into a value representation using NumPy's DFT/FFT module.

```
def coefficients_to_values(coefficients):
      """Returns the value representation of a polynomial
2
3
4
      Args:
           coefficients (array[complex]): a 1-D array of complex
5
               coefficients of a polynomial with
6
7
               index i representing the i-th degree coefficient
8
9
      Returns:
           array[complex]: the value representation of the
10
               polvnomial
11
       . . . .
13
      # applv FFT
      return np.fft.fft(coefficients)
14
15
16
  A = [4, 3, 2, 1]
18 print(coefficients_to_values(A))
```



Numpy FFT implementation of Polynomials Multiplication ii

Given a polynomial in its value representation, use the NumPy's DFT/FFT module to convert from the value representation to the coefficient representation.

```
def values_to_coefficients(values):
       """Returns the coefficient representation of a polynomial
2
3
4
       Args:
            values (array[complex]): a 1-D complex array with
5
6
                the value representation of a polynomial
7
8
       Returns:
9
            array[complex]: a 1-D complex array of coefficients
       . . . .
10
11
       # applv inverse_FFT
       return np.fft.ifft(values)
13
14
15
  A = [10.+0.j, 2.-2.j, 2.+0.j, 2.+2.j]
print(values_to_coefficients(A))
16
17
```



Numpy FFT implementation of Polynomials Multiplication iii

Implement a helper function nearest_power_of_2 that calculates a power of 2 that is greater than a given number.

```
def nearest_power_of_2(x):
       """Given an integer, return the nearest power of 2.
2
3
4
      Args:
5
           x (int): a positive integer
6
7
      Returns:
8
           int: the nearest power of 2 of x
9
       ......
10
      return int(2**np.ceil(np.log2(x)))
11
```



Numpy FFT implementation of Polynomials Multiplication iv

Given two polynomials in their coefficient representation, write a function to multiply them both using the functions coefficients_to_values, nearest_power_of_2, and values_to_coefficients

```
def fft_multiplication(poly_a, poly_b):
       """Returns the result of multiplying two polynomials
2
3
4
      Args:
5
           poly_a (array[complex]): 1-D array of coefficients
6
           poly_b (array[complex]): 1-D array of coefficients
7
8
      Returns:
9
           array[complex]: complex coefficients of the product
10
               of the polvnomials
       . . . .
11
12
13
      # Calculate the number of values required
      # polvnomial degree
14
      d = (len(polv_a) - 1) + (len(polv_b) - 1) + 1
16
      # Figure out the nearest power of 2
17
      d=nearest_power_of_2(d)
```

Numpy FFT implementation of Polynomials Multiplication v

```
# Pad zeros to the polynomial
20
      # padding: 2nd arg a list with nbr of elements before and after
21
      pad_poly_a=np.pad(poly_a,(0,d-len(poly_a)), 'constant', constant_values=(0))
22
      pad_poly_b=np.pad(poly_b,(0,d-len(poly_b)),'constant',constant_values=(0))
23
24
25
      # Convert the polynomials to value representation
      polv_a_values = coefficients_to_values(pad_polv_a)
26
      poly_b_values = coefficients_to_values(pad_poly_b)
27
28
29
      # Multiply
      result = np.multiply(poly_a_values, poly_b_values)
30
31
32
      # Convert back to coefficient representation
33
      return values_to_coefficients(result)
```



Quantum Fourier Transform

Quantum Fourier Transform

The Quantum Fourier transform (QFT) is the quantum version of the discrete Fourier transform (DFT).

The transformation is applied to the amplitudes of a quantum state, rotating the state vectors from any given basis (e.g., the computational basis) into the Fourier basis.

$$U_{QFT} = rac{1}{\sqrt{N}} \left[egin{array}{ccccccccc} 1 & 1 & 1 & \cdots & 1 \ 1 & \omega & \omega^2 & \cdots & \omega^{(N-1)} \ 1 & \omega^2 & \omega^4 & \cdots & \omega^{2(N-1)} \ dots & dots & dots & dots & dots \ 1 & \omega^{(N-1)} & \omega^{2(N-1)} & \cdots & \omega^{(N-1)^2} \end{array}
ight]$$

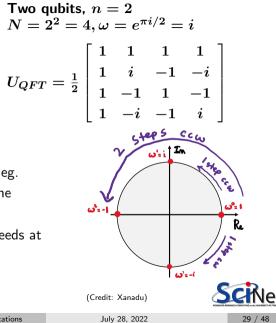
with $N=2^n, \omega=e^{rac{2\pi i}{N}}.$



$$\begin{array}{l} \text{One qubit, } n = 1 \\ N = 2^1 = 2, \omega = e^{\pi i} = -1 \\ U_{QFT} = \frac{1}{\sqrt{2}} \left[\begin{array}{c} 1 & 1 \\ 1 & -1 \end{array} \right] \end{array}$$

Looking at the structure of the QFT matrix, eg. consider the columns, its values are cycling the roots of unity.

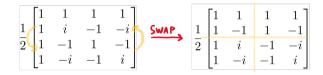
The particular columns represent different speeds at which we cycle around.



Qn: which gate operations will result in operator/matrix as the QFT one?

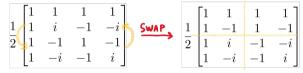


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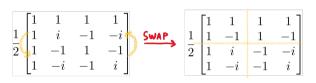


Qn: which gate operations will result in operator/matrix as the QFT one? the two upper blocks \rightsquigarrow Hadamard





Qn: which gate operations will result in operator/matrix as the QFT one?

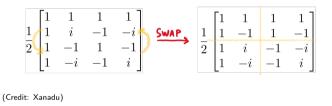


the two upper blocks \rightsquigarrow Hadamard

bottom:



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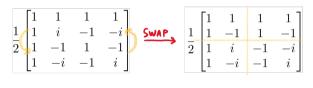


bottom:
$$HS =$$

 $\frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix} =$
 $\begin{bmatrix} 1 & i \\ 1 & -i \end{bmatrix}$



Qn: which gate operations will result in operator/matrix as the QFT one?

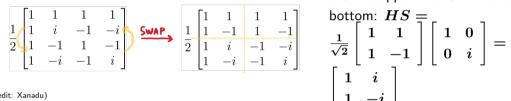


$$\Rightarrow egin{array}{c} U_{QFT} = rac{1}{\sqrt{2}} \left[egin{array}{c} H & H \ HS & -HS \end{array}
ight] \end{array}$$

bottom:
$$HS = \begin{bmatrix} 1 & 1 \\ \sqrt{2} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & i \end{bmatrix} = \begin{bmatrix} 1 & i \\ 1 & -i \end{bmatrix}$$



Qn: which gate operations will result in operator/matrix as the QFT one? the two upper blocks \rightsquigarrow Hadamard



(Credit: Xanadu)

$$\Rightarrow egin{array}{c} U_{QFT} = rac{1}{\sqrt{2}} \left[egin{array}{c} H & H \ HS & -HS \end{array}
ight] \end{array}$$

 $\Rightarrow U^{S}_{OFT} = (I \otimes H)(I \otimes |0\rangle \langle 0| + S \otimes |1\rangle \langle 1|)(H \otimes I)$



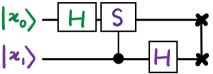
$$U^{S}_{QFT} = (I \otimes H) (I \otimes \ket{0} ra{0} + S \otimes \ket{1} ra{1}) (H \otimes I)$$



31 / 48

$$U^{S}_{QFT} = (I \otimes H) (I \otimes \ket{0} ra{0} + S \otimes \ket{1} ra{1}) (H \otimes I)$$

Since we swapped the inner rows, we need to swap them back!



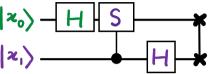
(Credit: Xanadu)



31 / 48

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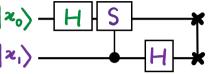
(Credit: Xanadu)

It's possible to show that the SWAP-gate applied to $U^S_{QFT} \rightsquigarrow U_{QFT}$, i.e. $U_{QFT} = SWAP \cdot U^S_{QFT}$



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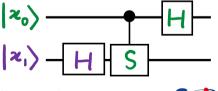
Since we swapped the inner rows, we need to swap them back!



(Credit: Xanadu)

It's possible to show that the SWAP-gate applied to $U^S_{QFT} \rightsquigarrow U_{QFT}$, i.e. $U_{QFT} = SWAP \cdot U^S_{QFT}$

An alternative, to reduce the circuit depth, is reversing the operations on the first and the second qubit to get rid of the SWAP-gate





Properties of the QFT



Unitarity QFT (more generally the discrete Fourier transformation matrix) is unitary



Unitarity

QFT (more generally the discrete Fourier transformation matrix) is unitary

Convolution-Multiplication

Given an *n*-qubit state: $[\alpha_0, \alpha_1, \ldots, \alpha_{(N-1)}] \xrightarrow{QFT} [\beta_0, \beta_1, \ldots, \beta_{(N-1)}]$ a new vector in the Fourier basis, with prob. $|\beta_j|^2$

If input amplitudes are shifted cyclically, the output distribution remains the same



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If input amplitudes are shifted cyclically, the output distribution remains the same

Periodicity

For periodic functions, $|lpha
angle=(lpha_0,lpha_1,\ldots,lpha_{(N-1)})$, whose period r divides N

$$\Rightarrow |\alpha\rangle = (\alpha_0, \alpha_1, \dots, \alpha_{(r-1)}, \alpha_0, \alpha_1, \dots, \alpha_{(r-1)}, \cdots)$$

$$\Rightarrow |lpha
angle = \sqrt{rac{r}{N}}\sum_{j=0}^{rac{N}{r}-1}|jr
angle \implies$$
 the QFT is also **periodic** with period $rac{N}{r}$



QFT – Hands-on i

Implement the circuit that performs the single-qubit QFT operation, i.e., for n = 1.

```
dev = qml.device("default.qubit", wires=1)
  @gml.gnode(dev)
  def one_qubit_QFT(basis_id):
4
      """A circuit that computes the QFT on a single qubit.
5
6
7
      Args:
           basis_id (int): An integer value identifying
8
               the basis state to construct.
9
11
      Returns:
           arrav[complex]: The state of the qubit after applying QFT.
12
       .. .. ..
13
      # Prepare the basis state |basis_id>
14
      bits = [int(x) for x in np.binary_repr(basis_id, width=dev.num_wires)]
15
      gml.BasisStatePreparation(bits, wires=[0])
16
17
18
      ### YOUR CODE HERE ###
```



QFT – Hands-on ii

```
dev = qml.device("default.qubit", wires=1)
2
  Qaml.anode(dev)
  def one_qubit_QFT(basis_id):
4
      """A circuit that computes the QFT on a single qubit.
5
6
7
      Args:
8
           basis_id (int): An integer value identifying
9
               the basis state to construct.
      Returns:
11
          arrav[complex]: The state of the qubit after applying QFT.
12
       .....
13
14
      # Prepare the basis state |basis_id>
      bits = [int(x) for x in np.binary_repr(basis_id, width=dev.num_wires)]
16
      gml.BasisStatePreparation(bits, wires=[0])
17
      # The QFT on a single qubit can be performed using the Hadamard gate.
      gml.Hadamard(wires=0)
20
      return gml.state()
21
```



QFT – Hands-on iii

Implement a circuit that performs the two-qubit QFT operation.

```
n \text{ bits} = 2
  dev = qml.device("default.qubit", wires=n_bits)
3
4
  @qml.gnode(dev)
  def two_gubit_QFT(basis_id):
      """A circuit that computes the QFT on two qubits using qml.QubitUnitary.
6
7
8
      Args:
           basis_id (int): An integer value identifying the basis state to construct.
9
11
      Returns:
12
           array[complex]: The state of the qubits after the QFT operation.
       .....
13
14
      # Prepare the basis state |basis_id>
      bits = [int(x) for x in np.binary_repr(basis_id, width=dev.num_wires)]
16
      gml.BasisStatePreparation(bits, wires=[0, 1])
17
      ### YOUR CODE HERE ###
```



QFT – Hands-on iv

```
n_bits = 2
1
  dev = qml.device("default.qubit", wires=n_bits)
3
  @qml.qnode(dev)
5
  def two_qubit_QFT(basis_id):
      """A circuit that computes the QFT on two qubits using qml.QubitUnitary.
7
8
      Args:
          basis_id (int): An integer value identifying the basis state to construct.
9
11
      Returns:
12
          array[complex]: The state of the qubits after the QFT operation.
      .....
13
14
      # Prepare the basis state |basis_id>
15
      bits = [int(x) for x in np.binary_repr(basis_id, width=dev.num_wires)]
16
      gml.BasisStatePreparation(bits, wires=[0, 1])
17
      # define U QFT matrix for n=2
      U_QFT=0.5 * np.array([[1,1,1,1], [1,1],-1,-1]], [1,-1,1,-1], [1,-1],[1,-1,1]])
20
21
22
      # Applv U_QFT
      qml.QubitUnitary(U_QFT,wires=[0,1])
23
```

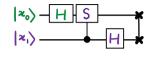
QFT – Hands-on v

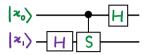
24
25 return qml.state()



EXERCISE I: TO BE COMPLETED AND SUBMITTED!

Implement the two-qubit QFT using a combination of gates (without using gml.QubitUnitary).



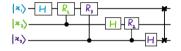


```
dev = qml.device("default.qubit", wires=2)
  @qml.qnode(dev)
3
  def decompose_two_qubit_QFT(basis_id):
      """A circuit that computes the QFT on two qubits using elementary gates.
      Args:
           basis_id (int): An integer value identifying the basis state to
8
               construct.
9
10
      Returns:
11
          array[complex]: The state of the qubits after the QFT operation.
       .. .. ..
      # Prepare the basis state |basis_id>
13
      bits = [int(x) for x in np.binary_repr(basis_id, width=dev.num_wires)]
14
      qml.BasisStatePreparation(bits, wires=[0, 1])
15
16
      ### YOUR CODE HERE ###
```



```
# print/draw circuit
# print(qml.draw(decompose_two_qubit_QFT,show_all_wires=True)(2))
# https://pennylane.readthedocs.io/en/stable/code/api/pennylane.draw.html
```







https://pennylane.ai/blog/2021/05/

how-to-visualize-quantum-circuits-in-pennylane/



Hadamard Transform/QFT

The Quantum Fourier transform (QFT) is closely related to the Hadamard transform. The Hadamard transform takes a system of qubits from the computational basis (for represented as a unitary matrix, example) to the Hadamard basis, . .

$$egin{aligned} H^{\otimes n} \ket{x} &= rac{1}{\sqrt{N}} \sum_{y=0}^{N-1} (-1)^{x \cdot y} \ket{y} \ N &= 2^n \end{aligned}$$

The Quantum Fourier transform can be

$$U_{QFT} \ket{x} = rac{1}{\sqrt{N}} \sum_{y=0}^{N-1} \omega^{x \cdot y} \ket{y}$$

$$\omega=e^{rac{2\pi i}{N}},N=2^n$$



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$$A = 2^{n}$$
About representations
$$|x\rangle = \underbrace{|110\rangle}_{binary} = \underbrace{|6\rangle}_{decimal} \mapsto |1\rangle \otimes |1\rangle \otimes |0\rangle$$

A bitstring,
$$x_1, x_2, \ldots, x_n \rightsquigarrow$$

 $x_1 2^{n-1} + x_2 2^{n-2} + x_3 2^{n-3} + \ldots + x_n 2^0 = \sum_{k=1}^n x_k 2^{n-k}$

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$$\omega=e^{rac{2\pi i}{N}},N=2^n$$



Α

- $1. \ \mbox{For a single qubit, the QFT}$ is performed just using the Hadamard gate.
- 2. For n>1 qubits, we may need to apply a Hadamard gate to produce a superposition, along with some kind of rotations to account for the added phases $\omega^{x\cdot y}$



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it is possible to write the QFT in a way that is tensor-factorized,

$$\begin{array}{lll} U_{QFT} \ket{x_1 x_2 \dots x_n} & = & \frac{1}{\sqrt{N}} \left[& \left(\ket{0} + e^{2\pi i 0.x_n} \ket{1} \right) \left(\ket{0} + e^{2\pi i 0.x_{n-1}x_n} \ket{1} \right) \cdots \\ & & \cdots \left(\ket{0} + e^{2\pi i 0.x_1 x_2 \dots x_n} \ket{1} \right) \right] \end{array}$$

with fractional binary, $rac{x_l}{2}+rac{x_{l+1}}{2^2}+\ldots+rac{x_m}{2^{m-l+1}}\equiv 0.x_lx_{l+1}\ldots x_m$



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with fractional binary, $\frac{x_l}{2} + \frac{x_{l+1}}{2^2} + \ldots + \frac{x_m}{2^{m-l+1}} \equiv 0.x_l x_{l+1} \ldots x_m$

One can prove,
$$\Rightarrow \left| U_{QFT} \left| x_1 x_2 \dots x_n \right\rangle = rac{1}{\sqrt{N}} \bigotimes_{k=1}^n \left[\left| 0 \right\rangle + e^{rac{2\pi i}{2^k} x} \left| 1 \right\rangle \right]$$



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- 2. For n>1 qubits, we may need to apply a Hadamard gate to produce a superposition, along with some kind of rotations to account for the added phases $\omega^{x\cdot y}$

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QN: which gates will produce this state?

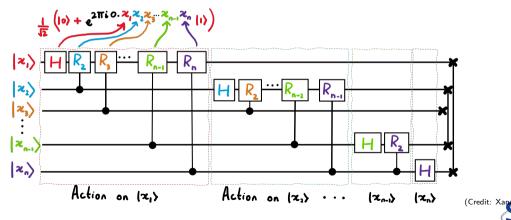
M.Ponce



41 / 48

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et

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$$N=2^n \Rightarrow n=\log(N) \Rightarrow \mathcal{O}((\log(N)\log(N)))$$



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n-qubits, $N=2^n$ amplitudes

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 $\mathcal{O}((\log(N)\log(N)))$

The transformation is encoded into the amplitudes of the qubits; \Rightarrow measuring in an arbitrary basis state



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n-qubits, $N=2^n$ amplitudes

$$N = 2^n \Rightarrow n = \log(N) \Rightarrow$$

 $\mathcal{O}((\log(N)\log(N)))$

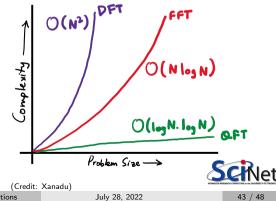
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an arbitrary basis state

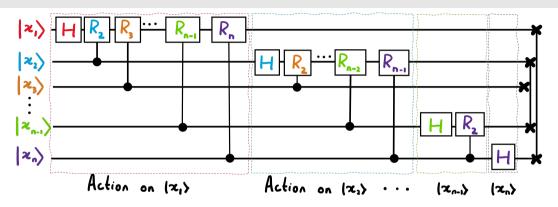
Using the Fourier basis, we can solve

classically intractable problems such as

factoring in polynomial time.



QFT – Hands-on i



(Credit: Xanadu)



QFT – Hands-on ii

Implement the QFT for three qubits.

```
dev = qml.device("default.qubit", wires=3)
2
  @gml.gnode(dev)
  def three_qubit_QFT(basis_id):
4
      """A circuit that computes the QFT on three qubits.
5
6
7
      Args:
           basis_id (int): An integer value identifying the basis state to
8
               construct.
9
10
      Returns:
          array[complex]: The state of the qubits after the QFT operation.
11
      .....
12
13
      # Prepare the basis state |basis_id>
      bits = [int(x) for x in np.binary_repr(basis_id, width=dev.num_wires)]
14
15
      gml.BasisStatePreparation(bits, wires=[0, 1, 2])
```



QFT – Hands-on iii

2

3

45

6

8

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12

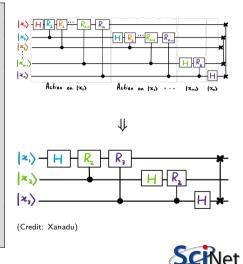
14

15 16

18 19

20

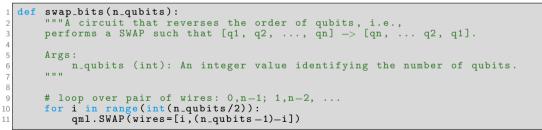
```
# Rk gates // NOT used!
R2=np.array([[1,0],[0,np.exp(np.pi*0.5j)]])
R3=np.array([[1,0],[0,np.exp(np.pi*0.25j)]])
# R2 -> TT -> S
# R3 -> T
# R2R3 -> TTT -> ST
# on |0>
qml.Hadamard(wires=0)
aml.ctrl(gml.S,control=1)(wires=0)
qml.ctrl(qml.T,control=2)(wires=0)
# on |1>
gml.Hadamard(wires=1)
qml.ctrl(qml.S,control=2)(wires=1)
# on |2>
qml.Hadamard(wires=2)
qml.SWAP(wires=[0,2])
return qml.state()
```





Implement a circuit that reverses the order of n qubits using SWAP gates. $Action on (x_1)$ Action on (x_2) \dots (x_{n-1}) $(x_{n-1$

(Credit: Xanadu)



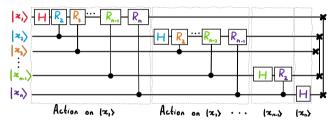


EXERCISE II: TO BE COMPLETED AND SUBMITTED!

Implement the *n*-qubit QFT using the circuit that performs the Hadamards and controlled rotations on *n* qubits using qml.ControlledPhaseShift. Recall that you must read the documentation, e.g. see

https://pennylane.readthedocs.io/en/stable/code/api/

pennylane.ControlledPhaseShift.html



(Credit: Xanadu)

