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The Next Applied

Quantum Computing & Quantum Machine Learning

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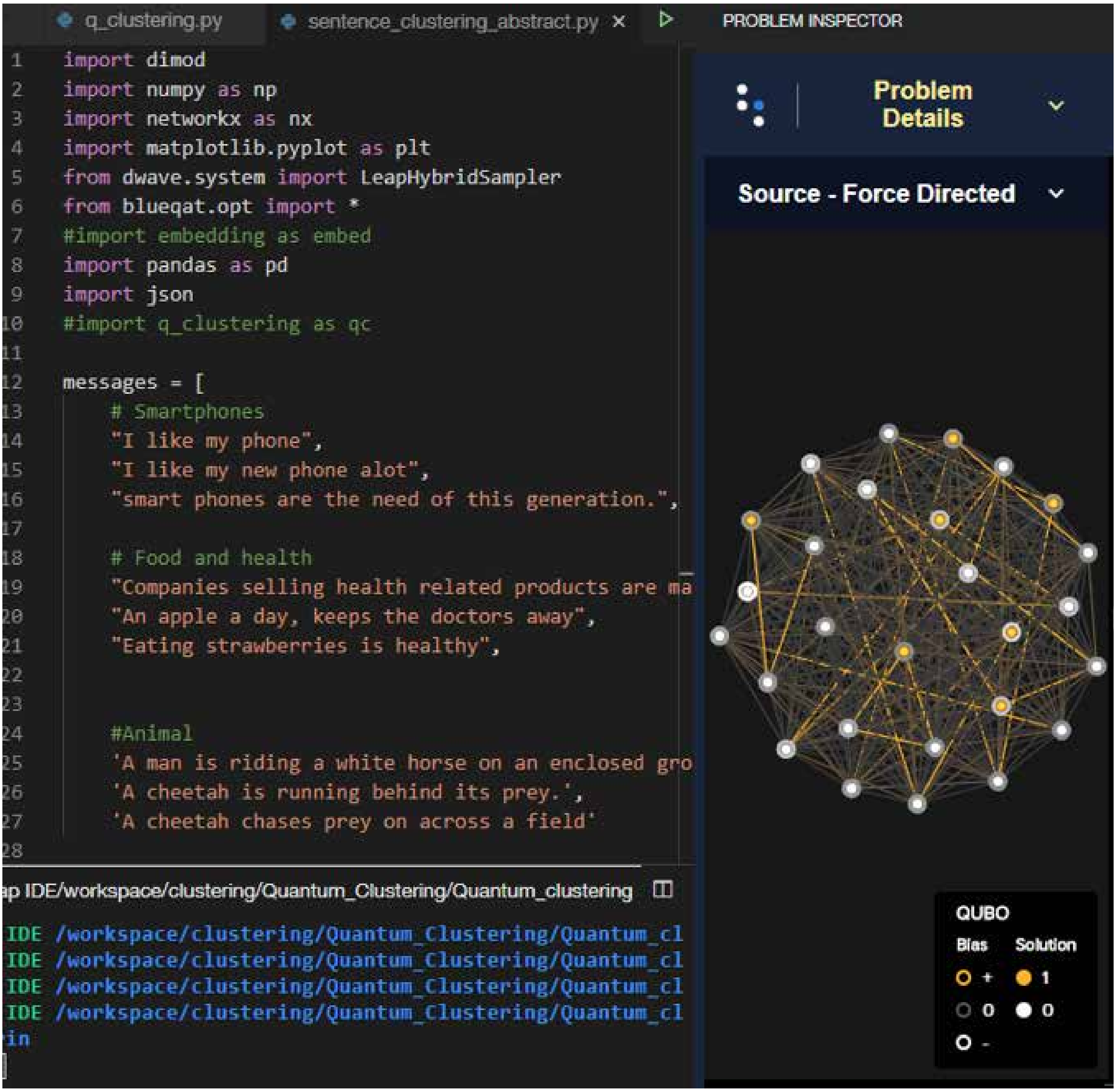

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Introduction

Machine learning is enabling businesses in cognitive automation of decision processes through adaptive learning algorithms, which create self-learn patterns from the data, without much manual intervention or explicit coding. The algorithms try to find the most optimal parameter values, which helps the model provide the right decision for a given user input. If the algorithm's performance deteriorates over time due to external factors or changing decision scenarios, the model can be retrained to handle the shortcomings and provide more accurate results.

Although deep learning has the said advantages, productionizing machine learning models is still a very difficult task. The time required to train a model is considerable and can go into multiple days, due to a large number of training parameters. The trained deep learning model is susceptible to variations in the input data as even a slight variation in the data can result in a different model. Another key drawback occurs due to the algorithm used to arrive at the optimal value for the learnable parameters. The stochastic gradient descent algorithm doesn't provide the most optimal solution for non-convex problems. Even for convex problems, the algorithm may not converge to a local minimum.

Quantum Machine Learning (QML) helps address the shortcomings of both the traditional and the deep learning approach. Quantum computing speeds up the training time, as it uses quantum properties of coherence, superposition and entanglement, making the processing faster. QML manages more complex network topology, as quantum adiabatic computing approach for deep learning network implementation can handle it with minimal constraint in the training time complexity. QML performs complex matrix manipulation at a very high speed, as the entire construction of quantum methods can be mathematically represented as matrix computation. The logical construction in matrix manipulation in classical machine is sequential in nature, whereas in quantum, it is represented in a single matrix and can use parallel mechanism of quantum computation. QML uses quantum tunneling as compared to the classical computers that use local and deterministic approach for searching the space for optimal solution. They are more prone to ending up in local minima and take a longer convergence time. Quantum optimization mechanism, on the other hand, leverages quantum tunneling effect, which helps the optimization process to tunnel through the hills in the cost function, because of its stochastic nature. This increases the probability of reaching global minima with less convergence time.

2.
Why Use Quantum Computing?

Quantum computing helps machine learning to leap over the barriers, enabling widespread application of deep learning. It reduces the training time for the algorithms significantly. The principles of quantum superposition and entanglements lead to much higher degree of parallelism, which helps the algorithms to arrive at the most optimal value of the learnable parameters efficiently and faster. Quantum annealing and tunneling help the algorithms to avoid high energy spots and jump to lower energy, and work for both convex and non-convex problems effectively.

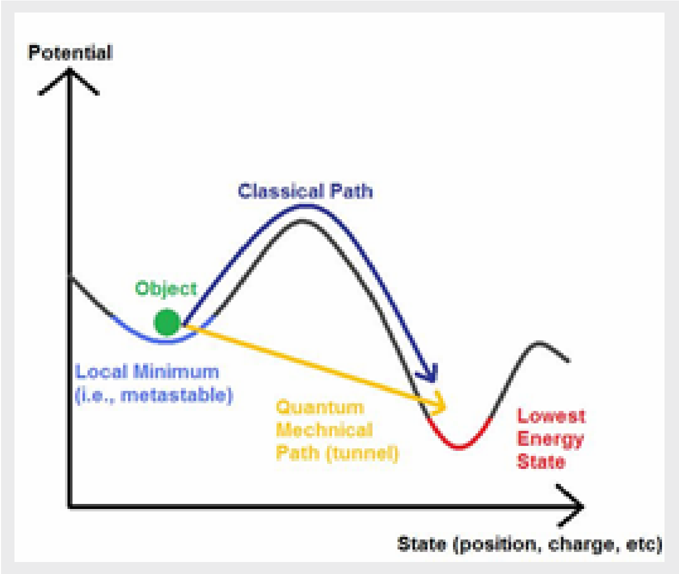

Figure 1: Quantum tunneling
(Source: Wikimedia Commons)

Quantum computing uses complex number representation, which reduces the search space dimensions significantly. Typically, each quantum state can be represented on a Bloch sphere and this has two significant advantages. First, the number of parameters necessary are significantly reduced. Second, the search space for the quantum model parameter can be reduced if the algorithm is properly designed. Since the number of model parameters and the search space are reduced, the amount of time needed to train the model is significantly lowered.

3.
What is Quantum Computing?

In classical computing, the data is stored in the form of bits - zero or one. These states are mutually exclusive, which means if the bit is zero, it cannot be one and vice versa. This mutual exclusivity of bits is eliminated with quantum computing, which uses the physical properties of smaller scale physical interactions among molecules, so that the bits (or qubits, for short) are a linear combinations of both classical bits zero and one. This allows more data to be stored in a qubit than a bit.

The power of quantum computation comes from the expansive permutations, which make quantum computers twice as memory-full of the addition of each qubit. To be more precise, for N bits classical bits system, N bits of binary numbers are necessary. From N-qubit quantum system, 2N bits of classical information can be derived.

Qubit Theory

To understand quantum machine learning, the underlying concept of how a bit is represented, popularly known as qubit or qbit, needs to be understood. Qbit, the basic unit of quantum information, is the quantum version of classical binary bit. It can be considered as a dual spin phenomenon of an electron, i.e., up and down spins. Another example can be a photon state of polarization, i.e., vertical polarization or horizontal polarization. The state in which a qbit exists at an instance of time, is probabilistic in nature. This concept is represented as superposition in quantum theory. Superposition can be understood to be combination of possible qbit configurations, each being represented as a complex number.

Therefore, Dirac's representation can be used to represent the existence of quantum information in 2 superposition basis states of |0> and |1>. And the representation looks like:

$$c_0|0\rangle + c_1|1\rangle$$

Where square root of $C_0^2 + C_1^2 = 1$

Quantum Representation of Classical Data

Quantum bits can store the information in their complex number components of the 2-basis superposition system. Classical information needs to be translated to fit into quantum framework of information. Quantum embedding represents classical data into quantum states in a Hilbert's space via quantum feature map.

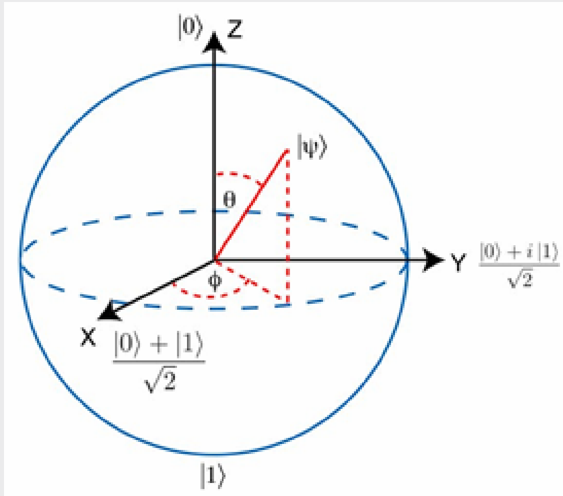

Figure 2: Bloch sphere for qubit representation
(https://en.wikipedia.org/wiki/Qubit#/media/File:Bloch_sphere.svg)

The states in a quantum bit can be represented by Bloch's sphere. Every single point on the sphere can be considered as a single state and every state is a superposition of basis states. It is evident from the above diagram that any state in the Bloch's sphere can be achieved by manipulating either the amplitude or the angle, w.r.t to axis in the sphere. Therefore, there are 3 major kinds of embedding to represent or transform classical data into quantum states namely, Basis Embedding, Amplitude Embedding and Angle Embedding.

To illustrate the embedding, quantum entanglement is used. A group of particles are said to be entangled if they interact or behave in such a way that quantum state of each of those particles cannot be described independently. For example, let us entangle two qubits, one in zero state: $[1\ 0]^T$ and another in excited state: $[0\ 1]^T$

$$|0\rangle \otimes |1\rangle = \begin{pmatrix}1\\0\end{pmatrix} \otimes \begin{pmatrix}0\\1\end{pmatrix} = \begin{pmatrix}1 \cdot \begin{pmatrix}0\\1\end{pmatrix}\\ 0 \cdot \begin{pmatrix}0\\1\end{pmatrix}\end{pmatrix} = \begin{pmatrix}1 \cdot 0\\1 \cdot 1\\0 \cdot 0\\0 \cdot 1\end{pmatrix} = \begin{pmatrix}0\\1\\0\\0\end{pmatrix}$$

Analytically, it is a tensor multiplication of two matrices, and the entangle result is as follows:

$C_1|00\rangle + C_2|01\rangle + C_3|10\rangle + C_4|11\rangle$, Where: $C_1^2 + C_2^2 + C_3^2 + C_4^2 = 1$

Quantum entanglement is extensively used in embedding operations for conversion of classical data in quantum states.

4.

What is Quantum Machine Learning?

Quantum machine learning comes under the umbrella of quantum computing, where principles like superposition and entanglement are directly baked into machine learning algorithms. This enables the algorithms to outperform their classical counterparts, allowing them to process a vast number of calculations simultaneously, and thus performing mathematical computation efficiently.

Like deep learning networks, quantum information can be learnt using quantum circuits. It is evident from the above example that qubits can be represented in the form of matrices, and thus matrix manipulation operation can be performed in quantum mechanics. These manipulations are done using unitary operations on the qubit states, and the resultant of each operation is a new state of qubits. The entire workflow can be represented as a quantum circuit.

The objective of machine learning is to learn a generalized mathematical equation from the data to perform prediction or classification operations. This mathematical equation is a combination of series linear or nonlinear small operations, performed simultaneously or sequentially. Analogous to this, quantum circuits are designed to identify a specific state of qubits, which is generalized in nature and can reflect a specific required operation on the input data. It can be extended for development of regression or classification models using quantum circuits. One such Bloch sphere image for a binary classification model can be visualized below.

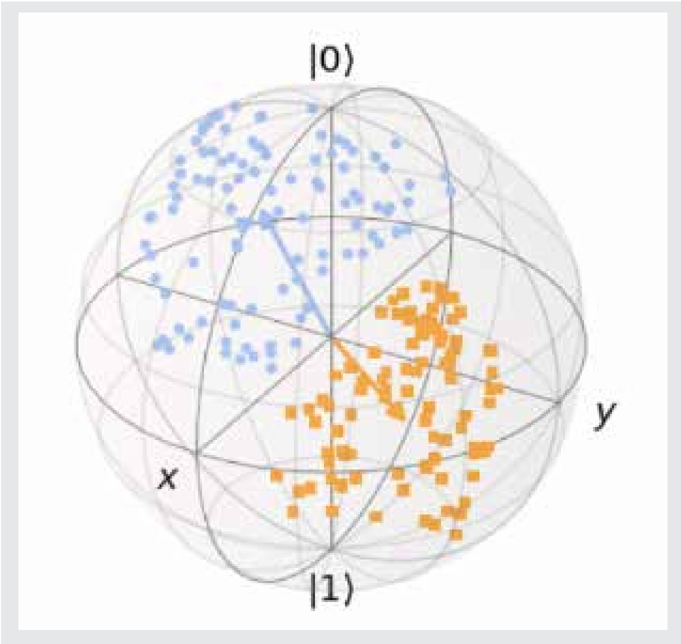

Figure 3: Reference from tensor flow for quantum paper
(source: https://medium.com/@amit02093/review-tensorflow-quantum-tfq-whitepaper-part1-416290828320)

In classical supervised machine learning, defining accurate decision boundary for non-linearly separable data points is critical. Kernel trick is used for this purpose to project these data points into much higher dimensions until a linear hyperplane can be found to separate them. When data points are projected in higher dimensions, it is hard for classical computers to compute through such large computations. In contrast to a classical machine learning algorithm like SVM, the advantage of quantum algorithm is that quantum kernel machine performs the evaluation directly in the higher dimensional space.

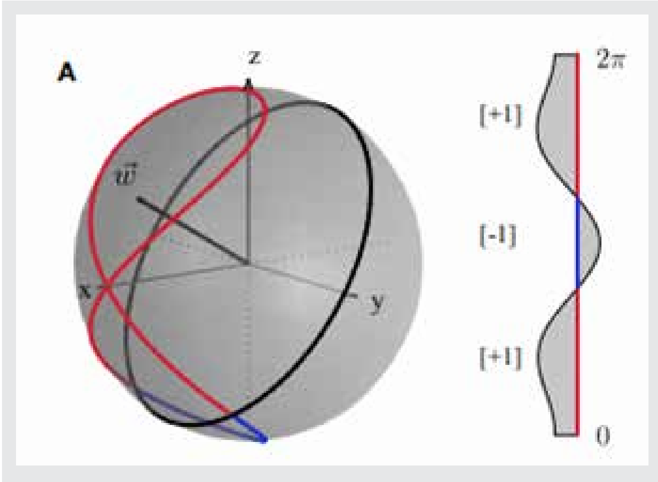

Figure 4: Feature map representation for a single qubit. A classical dataset in the interval Ω = (0, 2π] with binary labels (a, right) can be mapped onto the Bloch sphere (red / blue - lines) by using the non-linear feature map
(Source: Supervised learning with quantum enhanced feature spaces, Nature, 2018)

An important difference between classical and quantum circuit computation is that the entire quantum circuit can be represented as a single matrix, by computing the product of all the components of the circuit. This single matrix then can be multiplied by the input qubit matrix at a single attempt. The strength of quantum computing enhances the learning rate and time complexity of the quantum circuit, making the computation seems parallel in nature. This helps quantum computing in efficiently solving the NP-hard problems.

5.
Issues with Using Quantum Computing for Machine Learning

The current state of quantum computing has several limitations. The number of qubits available are not significant to leverage the advantages of quantum computing for machine learning. Another drawback is that quantum systems are not very good at handling the noise present in the data. Also, when using quantum devices, a protocol needs to be established to send data to the quantum device from a classical device. These protocols are not very clearly defined, and there is no established standard, to perform the handshake efficiently and effectively. Quantum algorithms do not perform very well, when tried to force fit into certain constraints.

When using quantum computing, the data needs to be preprocessed so that it can be ingested by the quantum hardware. One of the popular preprocessing algorithms is amplitude embedding. However, these algorithms are not very well developed. Quantum state embedding can handle discrete values/variables very well. The number of qubits needed to encode these values are manageable, but while embedding continuous values, the number of qubits required can overshoot the qubits currently supported on quantum hardware. Due to these limitations, quantum computing cannot directly replace the machine learning/deep learning algorithms.

6.
Applications of Quantum Machine Learning

Quantum machine learning is theoretically superior to classical machine learning, and hence can be used in place of traditional classical algorithm to solve lingering problems. Also, some of the existing problems can be rephrased to provide quantum machine learning an edge over classical machine learning. There can be two broad areas where quantum machine learning can see early adoption: non-convex optimization and combinatorial optimization.

Generative model optimization is a wide area of opportunity for quantum machine learning approach. Generative models are unsupervised in nature, as they attempt to learn multivariate probability distribution involved in the problem by observing the data points with some prior probabilistic assumptions and update the assumptions by inferencing over the data points. In context of deep learning, generative models have many layers of unobserved stochastic/ hidden variables. The hidden variables can learn the multi-modal distribution in a high dimensional space. Multi-modal distribution parameter learning requires high computation power as they need to infer for each observed data point to capture the expectation values for server quantities under the multi-modal distribution. Monte Carlo Markov Chain algorithms are used to compute these expectation values which are computationally expensive. Quantum computing capability to efficiently sample multi-model distributions and evaluate expectation values can be a game-changer in this space. This enables following business problems easily tractable:

- Micro-segmentation of customer on high dimensional large datasets
- Text categorization on large document corpus
- Rare event classification such as anomaly detection, fraud identification
- Content generative frameworks such as Natural Language Generators, Image Generators, Music Generators, Code Generators, etc.

Quantum systems are better suited for stochastic process-based model designs due to their inherent probabilistic nature of particle representation. Quantum can offer a natural computational environment for dynamic state space modelling that typically deals with time evolution dynamics, Markov process models, etc. The capability of quantum systems to effectively handle stochastic dynamical systems enable business problems such as:

- Next best action prediction in business processes
- Failure prediction in complex systems
- Event driven stock price forecasting

7.
Ecosystems Available for Quantum Machine Learning

Currently, different ecosystems are available to execute the quantum algorithms, such as:

Simulator/Devices

- IBM Q quantum processor: Introduced by IBM in 2019, IBM Q is a 20-qubit quantum computer housed in a 9 x 9 x 9 ft air-tight glass cube that maintains the environment variables.
- Rigetti Forest: An 8-qubit computer, Rigetti Forest has 5 components which are useful for its functioning: the outer casing called the shell, the nerves which carry the measurements to-and-fro, the skeleton which keeps the device cool, the heart which diffuses the heat, and the brain the QPU device.
- Microsoft Azure Quantum Simulator: Microsoft QDK comes with two tools: Toffoli and a resource estimator. These components allow the user to simulate device with up to 30-qubits.
- Xanadu Quantum: A photonic quantum computer which can be accessed from Xanadu cloud platform.
- D-wave: Equipped with Pegasus P16 which provides 5640 qubits. The Pegasus quantum topology allows embedding of larger problems with fewer physical qubits.

Frameworks

- IBM Qiskit: An opensource SDK for working with Open QASM and IBM Q quantum computer
- Google Cirq: A software library for writing, manipulating and optimizing quantum circuits
- Rigetti pyQuil SDK: Rigetti Forest development kit includes pyQuil, the Quil Compiler (quilc) and the quantum virtual machine (qvm)
- Microsoft QDK: Microsoft quantum development kit provides an open source platform to interact with, and program the Microsoft azure quantum simulator

8.
Conclusion

Quantum computing is ready to bring in a new realm of faster computing and change the way we construct and develop the algorithm in machine learning domain. We are now ready to move ahead and solve the age-old problems which are unsolved because of their high-end complexity; we can now fix issues that reside in non-polynomial domain of time complexity. Faster results will let us help in getting to better strategies quicker to cope up with constantly changing and drifting data.

Authors

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Dr. Udayaadithya Avadhanam has multiple granted patents and international publications to his credit. His research interests include quantum machine learning, complex systems, agent-based simulations and AI policy. Udayaadithya has a PhD from Indian Institute of Science (IISc, Bangalore) in artificial societies and complex systems.

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With 5+ years of experience in data science, Ashutosh Vyas is part of Mphasis NEXT Labs. He has built various solutions across domains including information retrieval from unstructured documents, simulation models for IT infrastructure machine failure prediction, FMCG price prediction and sales forecasting, customer sales pitch price optimization for advertisements in television and print media recommender system, among others.

His technical expertise spans generative machine learning, Bayesian statistics, generative deep learning, quantum hybrid modelling, deep learning, agent-based modelling, simulation designs and energy-based generative network design and modelling. Ashutosh holds a Master of Technology degree in Information Technology from IIIT-B and Bachelor of Engineering from SKIT Jaipur, Rajasthan Technical University.

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Rohit Kumar Patel has over 11 years of experience in IT, with 5+ years of experience at Mphasis. His responsibilities include client engagement, pre-sales, process analysis for cognitive automation opportunity identification, AI-ML solution design, development and management. His current areas of work include process mining, quantum machine learning and optimization. He holds an MBA degree in Finance from Great Lakes Institute of Management, Chennai.

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Rajendrakumar Mishra's areas of expertise include machine learning, deep learning, natural language processing and image processing. His recent work at NEXT Labs involves research and development of several projects, transforming the way software development process was approached. He has built multiple Intellectual Properties at Mphasis and has been granted US patent for Autocode.AI. Rajendra has also worked in Smart Assistant and Chatbot domain, and automated Digital Content Generation. He holds an M.Tech in IT from International Institute of Information Technology, Bangalore.

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About Mphasis

Mphasis (BSE: 526299; NSE: MPHASIS) applies next-generation technology to help enterprises transform businesses globally. Customer centricity is foundational to Mphasis and is reflected in the Mphasis' Front2Back™ Transformation approach. Front2Back™ uses the exponential power of cloud and cognitive to provide hyper-personalized (C = X2C$^{2}_{TM}$ = 1) digital experience to clients and their end customers. Mphasis' Service Transformation approach helps 'shrink the core' through the application of digital technologies across legacy environments within an enterprise, enabling businesses to stay ahead in a changing world. Mphasis' core reference architectures and tools, speed and innovation with domain expertise and specialization are key to building strong relationships with marquee clients. To know more, please visit www.mphasis.com

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