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The role of quantization in quantum computing

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Summary: Quantization techniques of mathematics could play an important role in the processing of complex data with multi-level information at the atomic level. If the mapped topological space of the quantized pieces of complex data does not perfectly overlap with the atomic structure, then that could lead to uncertainty in the domains of functions through which quantum computing is envisioned. We propose a novel approach that could advance the current experiments on quantum computing and argue that a single method of quantization may not be enough, and we might need an ensemble of techniques. We illustrate our proposed approach through a basic example within a disease-modeling framework. Still, quantum computing is at the proof-of-concept and prototype hardware development stage, and we propose how quantization techniques can reduce the gap in processing complex data into quantum bits.

Keywords: topology of quantum data, continuous transformation, atomic level.

1. Background

Quantization techniques combined with other mathematical tools could be resourceful in quantum computing. Topology of the data transfer from one location to another location has already gained momentum. See for example [1-2]. There are possibilities for the creation of novel hybrid methods involving several branches of mathematics (including probability) in processing and digesting the very large, ever-increasing data sets. Yet there could be uncertainties in providing accurate solutions due to model-based understandings of the structure of an atom. This is despite attempts to see an atom with multimillion times magnification [3-4]. Niels Bohr's vision of an atomic model varies from Max Planck's view of quantum energy. The experiments done independently by J.J. Thompson, E. Rutherford, and J. Chadwick at different time points between 1897 and 1925 led to the building of multiple models of atomic structure. The properties of an atom are generally defined by the number of electrons present within an atom and the structure of these electrons, which follow a random pattern. The random pattern within an atom gives scope to uncertainty. However, the aims of the original experiments on electrons, protons, and neutrons are not meant to take up any computational experiments but instead to build an atomic model.

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2. Qubits

We will briefly describe the essentials of quantum computing in a few paragraphs, and then present our proposed approach, which employs topological spaces, quantization, and mapping to advance the current state of knowledge. The quantum computing idea is about processing high-dimensional complex data through qubits or quantum bits and then performing desired computing according to a required algorithm in hand. These qubits [5] consist of two states, which could be either of two polarizations of a photon or two spin positions of an electron. The state of a qubit for practical purposes is still at a model stage due to several uncertainties described in the understanding of atomic structure, and measurement of a qubit follows a probability approach.

3. Probability Model

In addition to the random pattern of electrons, there is also a question about the positioning of an electron within an atom that led to Heisenberg's uncertainty principle [6-8]. Any data, be it massive or not so massive, sent through an atom might be used for computations, which could lead to erroneous outcomes that we describe here. The recent demonstration of the supremacy of quantum computing in laboratory-level experiments could be a positive beginning, although they were not based on direct comparison with classical computing algorithms [9]. The benchmarking in such experiments was usually done by comparing the partial patterns using some random pattern circuits. Suppose $F(x_i)$ is the cross-entropy benchmarking fidelity [8] of a measurable bitstring, say, x_i; then

$$F(x_i) = 2^n P(x_i) - 1, \tag{2}$$

where $P(x_i)$ is the probability of detecting a bitstring x_i.. When $P(x_i)$ follows a uniform sampling distribution, $F(x_i) \to 0$ (since $P(x_i) \to 1/2^n$). All such above experiments of benchmarking might see real-world implementable quantum computing hardware and software in the future.

4. Quantization Hypothesis

In this article, we propose technicalities of quantization that could be best suited for processing massive data sets at an atomic level by imagining a flexible topological space of massive data, and functional mapping of it to a space in the atom. Such techniques were not discussed in recent experiments using one-qubit and two-qubit proof of concepts.

In the next two subsections, we describe what we mean by flexible topological spaces and the functional mapping of them to a space in the atom.

4.1 Flexible Topological Space

As explained previously, massive data formed by individuals and by society as a whole is continuous, and also such data formation is unavoidable. The key question is, how to optimally process such data sets for faster and more accurate information for the benefit and use of society and individuals. This is where the quantum computing framework could assist.

The massive data can be conceptualized as a topological space containing hidden or visible multilevel information. Quantization can assist in breaking down such a continuous space of data into smaller topological spaces. This breakdown of smaller spaces need not be unique; rather, they depend on the requirements of a given study design and the goals of an experiment. Given a topological space X representing massive data, one can partition it into smaller subspaces that can be processed efficiently by a quantum machine, as illustrated in Figures 1 and 2. The partitioning of massive data demonstrated in Figure 1 is not unique, and it is often study-dependent for which an experiment is conducted.

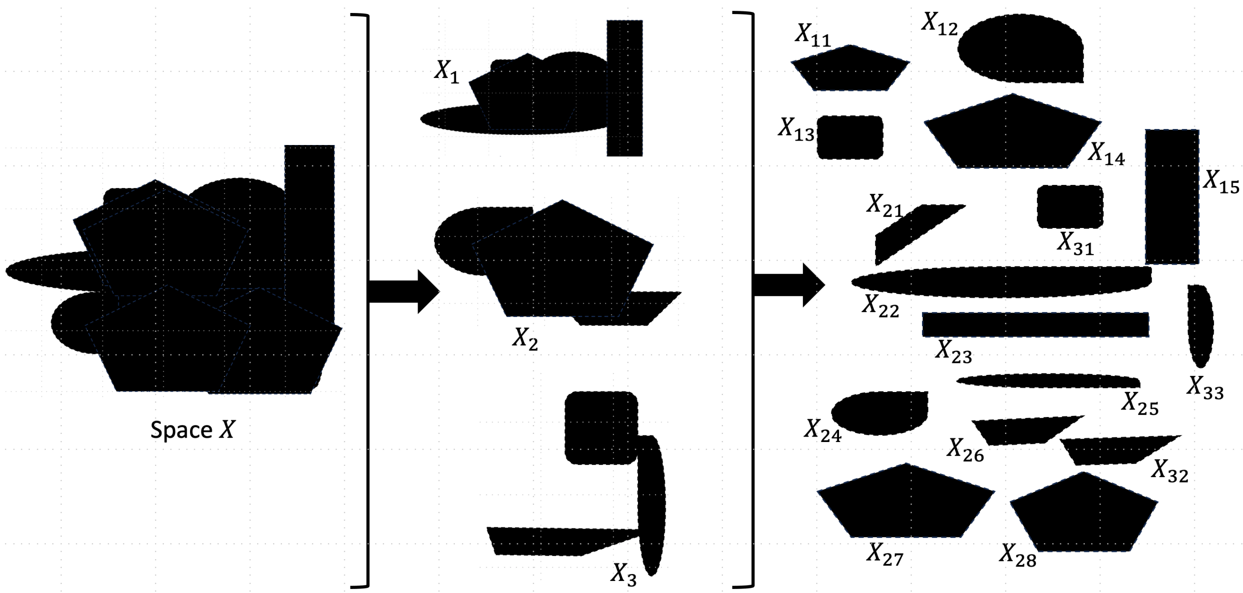

Figure 1. Decomposition of massive topological data X into flexible spaces for processing and modeling. The space X is the union of smaller disjoint subspaces X_1, X_2, and X_3. The subspaces X_{ij}, X_{ik}, and X_{il} for $i = 1, 2, 3$ are themselves union of smaller disjoint subspaces: X_{1j} for $j = 1, \dots, 5$, X_{2k} for $j = 1, \dots, 8$, and X_{3l} for $l = 1, 2, 3$. The advantage of our approach is that the above partitioning of the massive data space is not unique.

4.2 Functional Mapping of Quantized Spaces

Once the data is decomposed into smaller subspaces according to the requirements of a study, it can be used to model the phenomenon of interest. Different quantized subspaces may lead to different forms of individual model equations, allowing the original massive data space to be effectively analyzed. The quantization of the space X into smaller subspaces, as well as the corresponding individual modeling equations processed on a quantum machine, is not unique. This approach enables the advantage of significantly faster computation by reducing the massive data space through quantization. Another advantage, which will be discussed later in the article, is the ability to quantify uncertainty due to quantum computing, which is referred to here as atomic uncertainty. The term atomic uncertainty is explained in Section 5.

The creation of massive complex data sets from various sources of the world and the universe might be challenging to use and process with the present available advanced computational capabilities and existing cloud computing facilities for any time-sensitive research objectives and goals. Each human individual on the planet and other species are leaving enormous data footprints continuously, be it pandemic-related health and scientific information or climate and food-related global information. Such data also varies by individual, region, and several other differential factors. We refer to such data with the terminology-complex multilevel data. Topology of quantum data, here, we mean continuous, wired deformations of multilevel data, where each wire can be imagined representing a space of the quantized data at the atomic level. Such deformations are precisely needed for understanding if any atomic uncertainty exists, a measure proposed in the article. A general idea on quantization can be found in several textbooks, for example, see [10-13].

Quantum computing is perceived as a potential alternative for handling such massive complex data sets and deriving solutions and answers for research goals that require time-sensitive conclusions

5. Atomic Uncertainty

Let us denote by X the space of massive complex multilevel data. Here X could be dynamic over time, and we express it here as

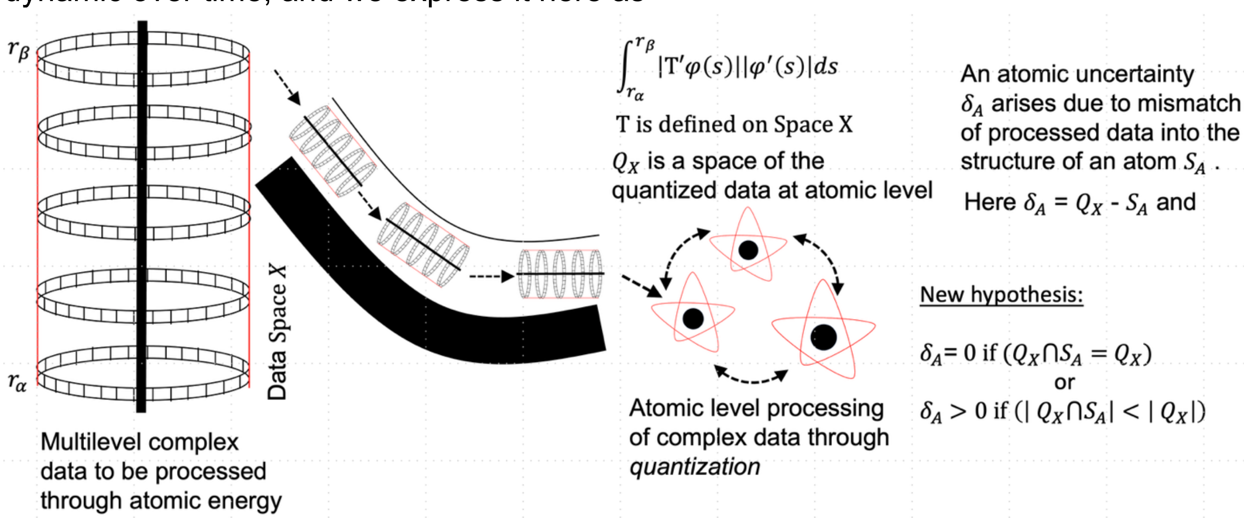

Figure 2. Processing of complex data into an atomic structure, quantization, and the possibility of the creation of uncertainty in the atomic space.

$$X = \bigcup_{i \in A} \int_i X_i di \,, \tag{2}$$

where $X_i \subset X$ and A is the set of different components of data in X that needs quantization while processing them through an atom. We expressed X in (2) as an integral to give the impression that the X_i's are continuous pieces of the total space X. For example, when only three components of the data, say $i, j,$ and k are present in X, then it can expressed as

$$X = \int_i X_i di \cup \int_j X_j dj \cup \int_k X_k dk$$

(3)

Carlsson's methods of data transformation [1] could help us to write X in smaller quantities, and the data can be processed into normal or traditional computing machines (non-quantum type). The continuous data flux can be broken into smaller continuous fluxes of bits of data. Suppose Q_X is a space of the quantized data at the atomic level, then it is rather difficult to establish a one to one correspondence:

$$Q_X \sim X$$

(4)

because the atomic structure is yet to be clear to scientists. Let the atomic structure be denoted by S_A. We propose a new hypothesis:

$$\delta_A = 0 \; if \; (Q_X \cap S_A = Q_X)$$

or

$$\delta_A > 0 \; if \; (|\, Q_X \cap S_A| < |\, Q_X|),$$

(5)

where δ_A = Q_X - S_A, a quantity we define as *atomic uncertainty*. The norm $|\, Q_X \cap S_A|$ indicates the level of matching of quantized data with the atomic structure. Even though quantization techniques can help in providing bits of continuous data flux, the uncertainty in the atomic structure could make quantum computing not fully accurate. Quantum computing can be performed, but the outcomes of such computing due to the uncertainty discussed could lead to not-so-perfect computing outcomes. With the massive data inputs, the errors of quantum computing (until we have clarity on atomic structure) could generate large-scale errors. The random pattern bitstring benchmarking that has assisted in a small-scale proof of concept can be used to measure uncertainty. The quantization techniques proposed, combined with circuits, can help break down complex multilevel data into single-layer data in a faster way. See Figure 3.

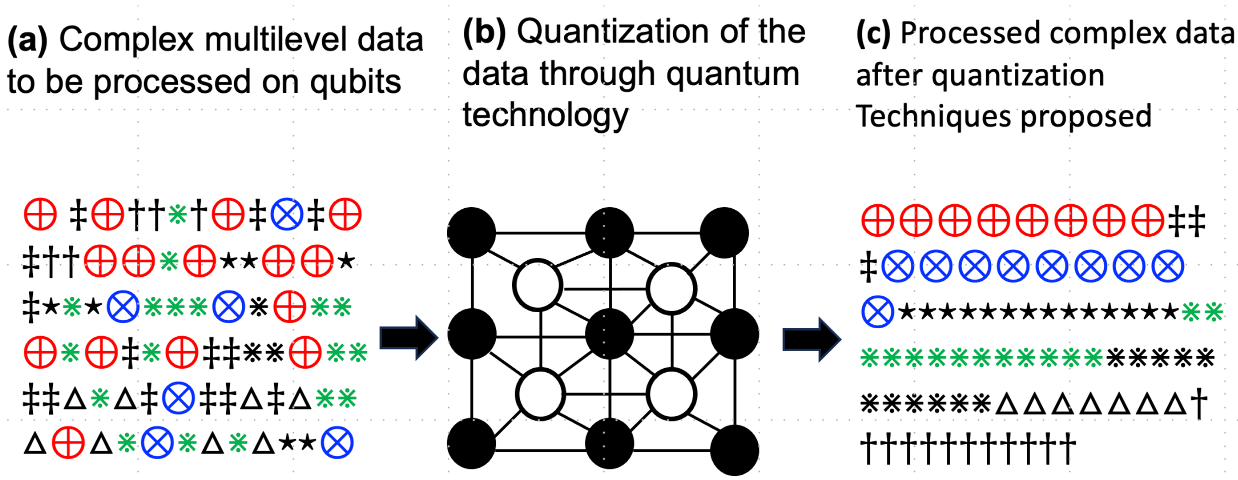

Figure 3. Simplification of the processing of complex data through quantization and qubit circuits

5.1 A Basic Example

Let us try to understand the computation of atomic uncertainty in a disease modeling framework within a population. Let the multilevel data X be formed out of four layers of distinct information, say X_1, X_2, X_3, and X_4, where:

X_1: is basic demographic information of the population (for example, population density among youth, population density by middle-aged, old-age, etc., population density by gender, etc.),
X_2: is socio-economic status of individuals (for example, proportions of low-income, middle-income, high-income, celebrity, academics, politician, business, etc.),
X_3: is infection status of each individual in the population (for example, susceptible, infected, recovered, etc.),
X_4: is living conditions of work and house (for example, condo, individual house, multi-floor office building, sharing accommodation, etc.).

For the sake of illustration, let us assume:

$X_1 = [0.35, 0.45, 0.15]$,
$X_2 = [0.15, 0.25, 0.11, 0, 28, 0.16, 0.21]$,
$X_3 = [0.23, 0.67, 0.10]$,
$X_4 = [0.13, 0.42, 0.15, 0.16, 0.25]$.

The space of X is then given by $X = \cup_{i=1}^{4} X_i = [0.10, 0.11, 0.13, 0.15, 0.16, 0.21, 0.23, 0.25, 0.28, 0.35, 0.42, 0.45, 0.67]$.

Let us obtain Q_X values by quantization to one decimal place of the X values above (i.e. rounding to nearest 0.1). This gives us
Q_{X_1} =[0.4,0.5,0.2],
Q_{X_2} =[0.2,0.3,0.1,0.3,0.2,0.2],
Q_{X_3} =[0.2,0.7,0.1],
Q_{X_4} =[0.1,0.4,0.2,0.2,0.3].

We thus obtain, $Q_X =$
$\cup_1^4 Q_{X_i}$ =[0.4,0.5,0.2,0.2,0.3,0.1,0.3,0.2,0.2,0.2,0.7,0.1,0.1,0.4,0.2,0.2,0.3]

Hence $Q_X = [0.1,0.2,0.3,0.4,0.5,0.7]$.

Let us assume the atomic structure $S_A = [0.05,0.1,0.13,0.35,0.4,0.45,0.6,0.7]$.

The atomic uncertainty δ_A is computed by Q_X - $S_A = [0.2,0.3,0.5] \neq 0$. Since the atomic uncertainty is present, the computation errors are present in understanding the disease spread.

6. Conclusions

Quantization techniques could be of great assistance in processing complex data into a *qubit* that is otherwise not processable through a classical computing approach in a standard *bit*. Quantum computing experiments can be conducted, but there could be atomic uncertainty described due to the random structures and patterns involved. The quantum computing world is still in a proof-of-concept stage and emtails speculation of various kinds of data manipulation at the atomic level. The possible applications of quantum computing are considerable if the hardware eventually becomes available. However, the complex may be the data, eventually, the patterns within the data and patterns of complexity need to be precisely understood to map data into the structure of a multi-partite quantum system. Through this article, we propose the role of quantization that would reduce the gap in decoding the patterns in the data and making it ready to be processed into a qubit.

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