4/21/22 Update: The University of Toronto EdX program should be getting way more attention than it is getting. There could be my own bias, but I believe that this also reinforces previous constructions/assumptions of the quantum sparse matrix - with the blending of Descartes a bit.

I imagine the applications of these algorithms can be very beneficial, and should be shared.

Old content (approx 3/20/22):

The sparse matrix I am going to choose to implement is the quantum sparse matrix. The applications of this idea are endless

Essentially - the purpose of a precision-recall curve is to add a condensed heat center along the True positive and True negative values, in order to optimize the vision of a given matrix. Such as a rubix code, is it plausible that an algorithm could be constructed that pulls elements into a state equivalent to a quantum version of RREF, which accounts for seasonality/fluidity/ non egalitarian.

However, this algorithm can also be applied to larger matrices, such as a linear regression where you would like to find the best r^2, and non binary values.

Usages:

- 1. This sparse matrix can be applied to how we think about the world and our lives. I think that data is fluid and not linear, and this idea can be applied to a lot of different scenarios.
- Can change the way we think about pivots. Pivoting can be done with 4 elements at a time
 instead of 2 (as long as the elements are non-zero). In real life, there is constant pivoting of
 elements.

Efficiency Issues:

- I think that a sparsity level of 1.0 (full RREF) is probably unrealistic. Also, I imagine that in a real life matrix, the sparse matrix values likely interact with each other. 1.0 is not likely in that sense, either.
- This means that this quantum matrix is likely anti-linear, and that breaks a few linear algebra rules that the rows and columns should sum exactly to 1.
- Likely not an efficient way to think, as this could lead to a re-evaluation of a lot of linear algebra rules.
- The easiest way I like to think about this is subjectivity. Two individuals looking at the same image are likely to interpret it differently.
- -NA values could throw off calculations, and should probably be omitted.

Some of my viewpoints:

- 1. https://quantumcomputing.stackexchange.com/questions/12706/quantum-operations-as-sparse-matrices
- 2. Precision-recall curves what are they and how are they used?
- 3. Quantum Precision Recall Curves
- 4. Quantum Pivoting, like a rubix cube
- 5. Quantum Algorithms



I'm interested in the thoughts of highly advanced developers. Do they notice that in computer vision, sometimes exact summation to 1 in both rows and columns is not likely? I like to acknowledge fluidity. Thanks for reading!:)

Comment: Ethan, I like how you found a way to use a new computing technology to come up with a unique data structure! I admit I'm not that great with quantum computing despite having a module in it for Computer Organization last semester. Please bare with my ignorance!

n your analysis, you discuss efficiency issues. What would be the O notation complexity for this?

From what I gathered, it sounds like there is an issue with how sparse a sparse matrix can be. After reading the StackOverflow post, it seems like its a function of how many Qubits the computer has. It looks like its like this, where n is the number of qubits the computer, the number of nonzero elements must be at least f(n) = 2^n for a 2^n x 2 ^n matrix. Wouldn't this get hard to represent of a non-unitary matrix of mxn size?

Thanks for baring with me, this is a very new field for me to understand.

Good point, and questions. For effiency, I was tinking in terms of economic efficiency, not necssarily mathematical effiency. For O notation complexity, I am not sure. Maybe, https://science.howstuffworks.com/math-concepts/fibonacci-nature.htm, maybe this fits for both, not sure

The matrix could still remain sparse (especially at the beginning), but I agree that as the matrix expands, it would be unitary*, just with decentralized product spaces to allow for scalability in the long run, and protect the sparseness - with connectedness to the central core.

A good picture for this is with cryptocurrency. Cryptocurrency can start with just a few members with close-knit bonds, but as more transactions occur (perhaps new entries to a matrix), a need for devices such as smartphones can process transactions by themselves, with the data eventually flowing back to the same source. For example, when individuals are born they are ikely not connected to a power greater than themselves (I like to refer this as the null vector).

however, with the help of globalization this can lead to more individuals being connected to the null space, and lead to a global sense of interconnectedness.

This would facilitate: trust, higher level of equity, peace, a focus on more environmental goals once in a unitary state, and serve as a great public good. However, there will probably always be variability, which is why linear matrix is likely unrealistic for this model. Within this matrix, we could even consider unresolved goals notated as non-zero values. The task would be to solve these goals, and continue to grow the matrix, while preserving the sparseness.

t is a very new field to me as well, so please let me know if you notice any questions, or would ike to discuss this further

references* = <u>https://en.wikipedia.org/wiki/Unitary_operator</u> & https://en.wikipedia.org/wiki/Inner_product_space

most recent discussion post on null vector in DEPTH: https://github.com/EthanNorton/Research-Projects/blob/main/Power%20Pop%2C%20anyone .pdf

4/21/2022 updates:

DEEPER INTO INNER PRODUCT

From Maria Schuld (Info)

Inner product (or the core of the entity) can be calculated with her precise calculations found in the info video. Then, KNN or kernels can be applied to the matter around the object (can even be applied to dark matter!). Such as

- 1. overlap of two quantum states.
- 2. Look into variational quantum kernels with respect to quantum time series applications of seasonality.
- 3. Data entanglement to encode new data as it is introduced into the matrix (produces density matrix).
 - a. Strategies: Apply Eigenvalues, have different types of sampling.
 - b. Can invert the matrix **quadratically faster**.