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Big Data and Deep Learning in the Defense Acquisition Visibility Environment (DAVE)

7 December 2016

Dr. Ying Zhao, Research Associate Professor

Graduate School of Operational & Information Sciences

Naval Postgraduate School

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Abstract

I have been studying Department of Defense (DoD) acquisition decision-making since 2009. The U.S. DoD acquisition process is extremely complex. There are three key processes that must work in concert to deliver capabilities: determining warfighters' requirements and needs, planning the DoD budget, and procuring final products. Each process produces large amounts of information (Big Data). There is a critical need for automation, validation, and discovery to help acquisition professionals, decision-makers, and researchers understand the important content within large data sets and optimize DoD resources throughout the processes. I have been applying Lexical Link Analysis (LLA), Collaborative Learning Agents (CLA), and System Self-Awareness (SSA) to reveal and depict—to decision-makers—the correlations, associations, and program gaps across all acquisition programs (including their subsets) examined over many years. This enables strategic understanding of data gaps and potential trends, and can inform managers about the areas that might be exposed to higher program risk, and about how resource and big data management might affect the desired return on investment (ROI) for projects.

In last year's research, I extended LLA/CLA/SSA in the context of quantum games and quantum intelligence, which can help the systems of systems, such as DoD acquisition systems, reach Nash Equilibrium and at the same time be Pareto optimal. This theory is capable of making the competitive systems cooperate in terms of systems of systems, such as DoD acquisition systems, for example, the theory can be applied to the current acquisition research to select systems of systems by balancing the expertise attributes (i.e., the system attributes that help to reach Nash Equilibrium) and authoritative attributes (i.e., the system attributes that help to reach Pareto optimal).

I also co-supervised a Naval Postgraduate School (NPS) thesis using LLA and data from the Defense Acquisition Visibility Environment (DAVE) and discovered the characteristics of the success of software-intensive acquisition systems.

Keywords: Lexical Link Analysis, big data, big acquisition data, big data architecture, big data analytics, quantum computing, quantum mechanics, quantum game theory and quantum intelligence.

Acknowledgments

I thank Mr. Robert Flowe from OUSD(AT&L)/ARA/OS&FM, who provided sponsorship to access the Defense Acquisition Visibility Environment (DAVE) along with relevant questions and many insightful discussions.

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About the Author

Dr. Ying Zhao is a research associate professor at the Naval Postgraduate School and a frequent contributor to DoD forums on knowledge management and data sciences. Her research and numerous professional papers are focused on knowledge management approaches such as data/text mining, Lexical Link Analysis, system self-awareness, Collaborative Learning Agents, search and visualization for decision-making, and collaboration. Dr. Zhao was principal investigator (PI) for six contracts awarded by the DoD Small Business Innovation Research (SBIR) Program. Dr. Zhao is a co-author of a few U.S. patents in knowledge pattern search from networked agents, data fusion, and visualization for multiple anomaly detection systems. She received her PhD in mathematics from MIT and is the co-founder of Quantum Intelligence, Inc.

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Executive Summary

I have been studying DoD acquisition decision-making (Gallup, MacKinnon, Zhao, Robey, & Odel, 2009; Zhao, Gallup, & MacKinnon, 2010, 2011, 2012, 2013a, 2013b, 2015) since 2009. The U.S. DoD acquisition process is extremely complex. There are three key processes that must work in concert to deliver capabilities: definition of warfighters' requirements and needs, DoD budget planning, and procurement of products, as shown in Figure 1. Each process produces increasingly large volumes of information (Big Data). The need for automation, validation, and discovery is now a critical need, as acquisition professionals, decision-makers, and researchers grapple to understand data and make decisions to optimize DoD resources.

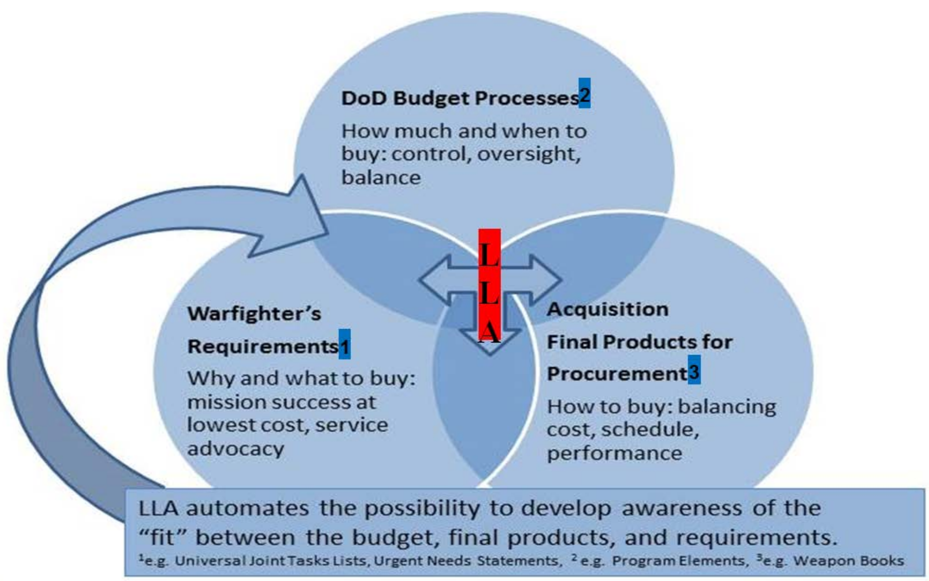


Figure 1. DoD Acquisition Decision-Making

I have been working on the problem of how the interlocking systems processes, their fit between DoD programs and warfighters' *needs,* and how gaps of non-fit can be revealed. Moreover, in the performance of DoD acquisition processes, each functional community is required to review only the particular information for which they are responsible, further exacerbating the problem of lack of fitness. For example, the systems engineering community typically only examines the engineering documents and feasibility studies, the test and evaluation community looks only at the test and evaluation plans, and the acquisition community looks only at acquisition strategies. Rarely do these stakeholders review each other's data or jointly discuss the core questions and integrated processes together as depicted in Figure 1.

In last year's research, we extended the Lexical Link Analysis (LLA), Collaborative Learning Agents (CLA), and System Self-Awareness (SSA), or LLA/CLA/SSA in the context of quantum games and quantum intelligence, which can help the systems of systems, such as DoD acquisition systems, reach Nash Equilibrium and at the same time be Pareto optimal.

The LLA/CLA/SSA is a new paradigm of quantum computing. We called it quantum intelligence for the following aspects of innovations that capture the essence of the quantum game theory:

- To satisfy a Nash's Equilibrium, each system should optimize a total reward locally and for itself. The LLA/CLA/SSA optimization scheme executes locally in a single agent. The Expertise component in such a system contributes to the increase of the competitiveness.
- To be Pareto optimal, systems need to be quantum entangled or correlated while one system optimizes total reward for itself, it simultaneously optimizes the total reward or social welfare of the whole system. The correlation among players (or systems); e.g., the Authority component in the whole system, contributes to the increase of the efficiency of the whole system, which can lead to a Pareto superior or optimal system.
- The recursive scheme is the key to perform a global optimization (i.e., Pareto optimal for multiple players) via simultaneous local optimizations. This theory is capable of making the competitive systems cooperate in terms of systems of systems, such as DoD acquisition systems, for example, the theory can be applied to the current acquisition research to select systems of systems by balancing the expertise attributes (i.e., the system attributes that help to reach Nash Equilibrium) and authoritative attributes (i.e., the system attributes that help to reach Pareto optimal).

I also co-supervised an NPS thesis using LLA and data from the Defense Acquisition Visibility Environment (DAVE) and discovered the characteristics of the success of software-intensive acquisition systems.

Background

This project is a continuing effort to the prior awards which resulted in the Lexical Link Analysis (LLA) implemented within the Collaborative Learning Agents (CLA) tool which has been installed in the DAVE test bed.

Motivated by the lack of fit and horizontal integration in the DoD acquisition process, we have been applying Lexical Link Analysis (LLA), a data-driven automation technology and methodology across DoD acquisition processes to

- identify themes and their relationships across multiple data sources
- discover high value areas for investment
- compare and correlate data from multiple data sources
- sort and rank important and interesting information

As a motivating example from past work, we conducted a detailed examination of the research, development, test and evaluation (RDT&E) budget modification practice from one year to the next, over the course of 10 years and 450 DoD program elements. We found a pattern revealing that the programs with fewer links (measured by LLA) to warfighters' requirements, received more budget reduction in total but less on average, indicating that budget reduction may have focused mainly on large and expensive programs rather than perhaps cutting all the programs that do not match warfighters' requirements. Furthermore, the programs with more links to each other received more budget reduction in total, as well as on average, indicating a pattern of good practice of allocating DoD acquisition resources to avoid overlapping efforts and to fund new and unique projects. These findings were useful as validation and guidance for future decision processes for automatically identifying programs to match warfighter's requirements, limit overall spending, maximize efficiencies, eliminate unnecessary costs, and maximize the return on investment.

LLA is a data-driven method for pattern recognition, anomaly detection and data fusion. It shares indexes, not data, and is therefore feasible for parallel and distributed processing, adaptive to Big Data Architecture and Analytics (BDAA) and capable of analyzing Big Acquisition Data.

This year, continued efforts in the context of the state-of-the-art Big Data and Deep Learning furthered the concept, implementation, and benefits of LLA for the Big Acquisition Data in the DoD acquisition decision process. Specifically, we extended LLA in the context of quantum games and quantum intelligence, which can make the systems of systems, such as DoD acquisition systems, reach Nash Equilibrium and at the same time be Pareto optimal.

Methodology

Big Data and Deep Learning (BDDL)

One important trend in Big Data is Deep Learning, including unsupervised machine learning techniques (e.g., neural networks) for recognizing objects of interest from Big Data, for example, sparse coding (Olshausen & Field, 1996) and self-taught learning (Raina, Battle, Lee, Packer, & Ng, 2007). The self-taught learning approximates the input for unlabeled objects as a succinct, higher-level feature representation of sparse linear combination of the bases. It uses the Expectation and Maximization (EM) method to iteratively learn coefficients and bases. Deep Learning links machine vision and text analysis smartly. For example, text analysis Latent Dirichlet Analysis (LDA; Blei, Ng, & Jordan, 2003) is a sparse coding where a bag of words is used as the sparsely coded features for text (Olshausen & Field, 1996). Our methods, Lexical Link Analysis (LLA), System Self-Awareness (SSA), and Collaborative Learning Agents (CLA) can be viewed as unsupervised learning or Deep Learning for pattern recognition, anomaly detection, and data fusion.

Recent Relevant Research

In the past, we have explored using LLA to compare and find gaps and opportunities within information categories (Zhao et al., 2010, 2011, 2012, 2013a, 2013b, 2015). LLA is related to the Latent Dirichlet analysis (LDA). LDA uses bags of words to model topics and concepts. LLA uses word pairs, bi-gram networks, and network communities to model topics and concepts, which is an innovation of LLA in terms of the theory of system self-awareness. LLA ranks the word pair clusters (themes) according to the theory that one is able to filter features of a data source that best represent the data source’s unique and expert value.

- Spark (http://spark.apache.org/): Map/Reduce is an analytic programming paradigm for Big Data. It consists of two tasks: (1) the “Map” task, where an input dataset is converted into key/value pairs; and (2) the "Reduce" task, where outputs of the “Map” task are combined to reduced key-value pairs. Apache Spark could replace Map/Reduce for its speed and in-memory computation.
- Bayesian Networks with R and Hadoop (Mendelevitch, 2015) is a data-driven learning of conditional probability or structure learning. It is a supervised learning method but works best for Big Data with low dimensions. It is an approximate inference good for Big Data and Hadoop implementation.

System Self-Awareness Towards Deep Learning and Discovering High-Value Information

This year we published a paper (Zhao & Zhou, 2016) in *Proceedings of the Seventh IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference*. In this paper, we summarized the System Self-Awareness concept and theory, which can be used to discover authoritative and popular information as well as emerging and anomalous information when traditional connections among information nodes (e.g., hyperlinks or citations) are not available. The different categories of information can be all high-value depending on the application requirements. A System Self-Awareness is a data-driven framework, modeled and measured using the recursive distributed infrastructure of Collaborative Learning Agent (CLA) and Lexical Link Analysis (LLA) that has been used in this research over the years. The combination of the three allows Deep Reinforcement Learning and Swarm Intelligence to be extended and enhanced in a completely new perspective.

Quantum Computing

Recently, quantum mechanics concepts such as quantum superposition and quantum entanglement have not only inspired quantum computing models and making of physical quantum computers, but also information processing in computer science domain as well as in biology.

For instance, the concept of quantum superposition and entanglement was applied to Genetic Algorithm (GA; Narayanan & Moore, 1996), Evolutionary Algorithm (EA; Han & Kim, 2002) and Quantum-Inspired Cuckoo Search Algorithm (QICSA; Yang, Cui, Xiao, Grandomi, & Karamanoglu, 2013). Quantum mechanics also lends insight into biological and chemical processes.

Quantum information was applied to game theory (Eisert, Wilkens, & Lewenstein, 1999; Du et al., 2002; Pawela & Sładkowski, 2013). The Prisoner's Dilemma has been extended into quantum domain by Eisert et al. (1999).

This year, I discovered an interesting connection between the LLA/CLA/SSA computing theory and quantum game theory.

Quantum Bits (Qubits), States, and Superposition

There are many references on these topics and definitions. We first summarize them here before we focus on quantum game theory. A classical computer has a memory made up of bits, where each bit is represented by either a one or a zero. A quantum computer maintains a sequence of quantum bits or qubits. A single qubit can represent a one, a zero, or any quantum superposition of those two qubit states; a pair of qubits can be in any quantum superposition of four states, three qubits in any superposition of eight states, and n qubits in superposition of 2^n states. In general, quantum computer with qubits can be in an arbitrary superposition of states simultaneously in contrast to a normal computer that can only be in one of these states at any one time. Figure 2 shows qubit states can be represented in a Bloch sphere.

Qubit states

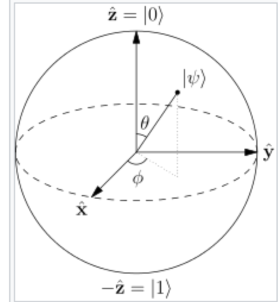
A pure qubit state is a linear superposition of the basis states. This means that the qubit can be represented as a linear combination of $|0\rangle$ and $|1\rangle$:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle,$$

where α and β are probability amplitudes and can in general both be complex numbers.

When we measure this qubit in the standard basis, the probability of outcome $|0\rangle$ is $|\alpha|^2$ and the probability of outcome $|1\rangle$ is $|\beta|^2$. Because the absolute squares of the amplitudes equate to probabilities, it follows that α and β must be constrained by the equation

$$|\alpha|^2 + |\beta|^2 = 1.$$



Bloch sphere representation of a qubit. The probability amplitudes in the text are given by $\alpha = \cos\left(\frac{\theta}{2}\right)$ and $\beta = e^{i\phi}\sin\left(\frac{\theta}{2}\right)$.

Bloch sphere

It might at first sight seem that there should be four degrees of freedom, as α and β are complex numbers with two degrees of freedom each. However, one degree of freedom is removed by the normalization constraint $|\alpha|^2 + |\beta|^2 = 1$, which can be treated as the equation for a 3-sphere embedded in 4-dimensional space with a radius of 1 (unit sphere). This means, with a suitable change of coordinates, one can eliminate one of the degrees of freedom. One possible choice is that of Hopf coordinates:

$$\alpha = e^{i\psi}\cos\frac{\theta}{2},$$

$$\beta = e^{i(\psi+\phi)}\sin\frac{\theta}{2}.$$

Additionally, for a single qubit the overall phase of the state $e^{i\psi}$ has no physically observable consequences, so we can arbitrarily choose α to be real (or β in the case that α is zero), leaving just two degrees of freedom:

$$\alpha = \cos\frac{\theta}{2},$$

$$\beta = e^{i\phi}\sin\frac{\theta}{2}.$$

Figure 2. Qubit States in a Bloch Sphere

The points on the surface of the sphere correspond to the pure qubit states, whereas the interior points correspond to the mixed states:

- A pure state can be written as a superposition of quantum basis vectors (e.g., kets) |0> and |1>, where the coefficient is a complex number.
- A mixed state is a superposition of pure states, represented by a positive-semidefinite density operator matrix.

Figure 3 shows qubits in pure and mixed states or superposition.

Given an orthonormal basis, any pure state $|\psi\rangle$ of a two-level quantum system can be written as a superposition of the basis vectors $|0\rangle$ and $|1\rangle$, where the coefficient or amount of each basis vector is a complex number. Since only the relative phase between the coefficients of the two basis vectors has any physical meaning, we can take the coefficient of $|0\rangle$ to be real and non-negative. We also know from quantum mechanics that the total probability of the system has to be one: $\langle\psi|\psi\rangle = 1$, or equivalently $\||\psi\rangle\|^2 = 1$. Given this constraint, we can write $|\psi\rangle$ using the following representation:

$$|\psi\rangle = \cos\left(\frac{\theta}{2}\right)|0\rangle \, + \, e^{i\phi}\sin\left(\frac{\theta}{2}\right)|1\rangle = \cos\left(\frac{\theta}{2}\right)|0\rangle \, + \, (\cos\phi + i\sin\phi)\,\sin\left(\frac{\theta}{2}\right)|1\rangle, \text{ where } 0 \le \theta \le \pi \text{ and } 0 \le \phi < 2\pi.$$

Except in the case where $|\psi\rangle$ is one of the ket vectors $|0\rangle$ or $|1\rangle$, the representation is unique. The parameters θ and ϕ, re-interpreted in spherical coordinates as respectively the colatitude with respect to the *z*-axis and the longitude with respect to the *y*-axis, specify a point

$$\vec{a} = (\sin\theta\cos\phi,\ \sin\theta\sin\phi,\ \cos\theta) = (u, v, w)$$

on the unit sphere in $\mathbb{R}^3$.

For mixed states, one needs to consider the density operator. Any two-dimensional density operator ρ can be expanded using the identity I and the Hermitian, traceless Pauli matrices $\vec{\sigma}$:

$$\rho = \frac{1}{2}(I + \vec{a}\cdot\vec{\sigma}) = \frac{1}{2}\begin{pmatrix} 1+w & u-iv \\ u+iv & 1-w \end{pmatrix},$$

where $\vec{a} \in \mathbb{R}^3$ is called the **Bloch vector** of the system. It is this vector that indicates the point within the sphere that corresponds to a given mixed state. The eigenvalues of ρ are given by $\frac{1}{2}(1 \pm |\vec{a}|)$. As density operators must be positive-semidefinite, we have $|\vec{a}| \le 1$. For pure states we must have

$$\mathrm{tr}(\rho^2) = \frac{1}{2}\left(1 + |\vec{a}|^2\right) = 1 \quad \Leftrightarrow \quad |\vec{a}| = 1$$

in accordance with the previous result. Hence the surface of the Bloch sphere represents all the pure states of a two-dimensional quantum system, whereas the interior corresponds to all the mixed states.

(a)

Mixed states

See also: Density matrix

A *pure quantum state* is a state which can be described by a single ket vector, as described above. A *mixed quantum state* is a statistical ensemble of pure states (see quantum statistical mechanics). Mixed states inevitably arise from pure states when, for a composite quantum system $H_1 \otimes H_2$ with an entangled state on it, the part H_2 is inaccessible to the observer. The state of the part H_1 is expressed then as the partial trace over H_2.

A mixed state *cannot* be described as a ket vector. Instead, it is described by its associated *density matrix* (or *density operator*), usually denoted ρ. Note that density matrices can describe both mixed *and* pure states, treating them on the same footing. Moreover, a mixed quantum state on a given quantum system described by a Hilbert space H can be always represented as the partial trace of a pure quantum state (called a purification) on a larger bipartite system $H \otimes K$ for a sufficiently large Hilbert space K.

The density matrix describing a mixed state is defined to be an operator of the form

$$\rho = \sum_s p_s |\psi_s\rangle\langle\psi_s|$$

where p_s is the fraction of the ensemble in each pure state $|\psi_s\rangle$. The density matrix can be thought of as a way of using the one-particle formalism to describe the behavior of many similar particles by giving a probability distribution (or ensemble) of states that these particles can be found in.

(b)

Figure 3. Qubit Pure and Mixed States (Superposition)
(Source: https://en.wikipedia.org/wiki/Quantum_state)

Quantum Entanglement

Whereas a pair of classical bits must be in one of the four states (00, 01, 10, 11), a pair of qubits can be in a state which cannot be factorized into two separate pure qubit states. The interdependence remains even when the two qubits are far apart—this is the origin of “non-local” effects in quantum mechanics.

Two quantum systems A and B can be entangled as follows: a state of System A, which can be a pure state or mixed states, is given by a unit vector in a Hilbert space H_A; a state of System B, which can be a pure or mixed state, is given by a unit vector in a Hilbert space H_B; the Hilbert space of the composite system is the tensor product of H_A and H_B.

Figure 4 shows two qubits entangled.

Consider two noninteracting systems A and B, with respective Hilbert spaces H_A and H_B. The Hilbert space of the composite system is the tensor product

$$H_A \otimes H_B.$$

If the first system is in state $|\psi\rangle_A$ and the second in state $|\phi\rangle_B$, the state of the composite system is

$$|\psi\rangle_A \otimes |\phi\rangle_B.$$

States of the composite system which can be represented in this form are called *separable states*, or (in the simplest case) *product states*.

Not all states are separable states (and thus product states). Fix a basis $\{|i\rangle_A\}$ for H_A and a basis $\{|j\rangle_B\}$ for H_B. The most general state in $H_A \otimes H_B$ is of the form

$$|\psi\rangle_{AB} = \sum_{i,j} c_{ij} |i\rangle_A \otimes |j\rangle_B.$$

This state is separable if there exist vectors $[c_i^A],[c_j^B]$ so that $c_{ij}=c_i^A c_j^B$, yielding $|\psi\rangle_A=\sum_i c_i^A|i\rangle_A$ and $|\phi\rangle_B=\sum_j c_j^B|j\rangle_B$. It is inseparable if for any vectors $[c_i^A],[c_j^B]$ at least for one pair of coordinates c_i^A,c_j^B we have $c_{ij}\neq c_i^A c_j^B$. If a state is inseparable, it is called an *entangled state*.

For example, given two basis vectors $\{|0\rangle_A,|1\rangle_A\}$ of H_A and two basis vectors $\{|0\rangle_B,|1\rangle_B\}$ of H_B, the following is an entangled state:

$$\frac{1}{\sqrt{2}} \left(|0\rangle_A \otimes |1\rangle_B - |1\rangle_A \otimes |0\rangle_B \right).$$

If the composite system is in this state, it is impossible to attribute to either system A or system B a definite pure state.

Figure 4. Two Qubits Entangled
(Source: https://en.wikipedia.org/wiki/Quantum_entanglement)

Measurements of physical properties such as position, momentum, spin, and polarization, performed on entangled particles are found to be appropriately correlated. Quantum entanglement is an area of extremely active research by the physics community, and its effects have been demonstrated experimentally with photons, neutrinos, electrons, molecules the size of buckyballs, and even small diamonds. Research is also focused on the utilization of entanglement effects in communication and computation.

Although the effect of quantum entanglement cannot directly transfer information, it has been identified as a crucial resource in quantum communication, quantum computation and error-correction, and some forms of quantum cryptography (Bennett & DiVincenzo, 2000). Here we will see that when the resources controlled by competing agents are entangled, they can cooperate to perfectly exploit their environment (i.e., the game), and to prevent one another from "defecting" in so-called Prisoners' Dilemma game.

Quantum Game Theory

Game theory is a field of applied mathematics. It formalizes the conflict between competing players or agents and has found applications ranging from economics to biology (Rasmusen, 1995; Nowak & Sigmund, 1999).

Quantum information is a young field of physics in terms of physical implementation of quantum mechanics which that requires ultimately a physical quantity (e.g., measurement), rather than a mathematical abstraction (Bennett & DiVincenzo, 1999). However, various problems, even in quantum information processing, can be usefully thought of as games. Quantum cryptography, for example, is readily cast as a game between the individuals who wish to communicate, and those who wish to eavesdrop (Ekert, 1991). Quantum cloning has been thought of as a physicist playing a game against nature (Werner, 1998) and indeed even the measurement process itself may be thought of in these terms (Deutsch, 1999). Furthermore, Meyer (1999) has pointed out that the algorithms conceived for quantum computers may be usefully thought of as games between classical and quantum agents. Against this background, it is natural to seek a unified theory of games and quantum mechanics (Ball, 1999; Peterson, 1999; Collins, 2000).

The Prisoners' Dilemma game is one of the well-known games, having implications in a wide range of disciplines. In a Prisoners' Dilemma game, two players simultaneously decide their strategy C (cooperator) or D (defector). For mutual cooperation, both players receive a payoff, i.e., a reward to be free from jail, R and receive P upon mutual defection, i.e., a reward to stay in jail with a shorter period of time. If one cooperates and the other defects, then the cooperator gains payoff S, and the traitor gains temptation T. The payoff rank for the Prisoners' Dilemma game is given by T>R>P>>S. In a Prisoners' Dilemma game, the best strategy for both players is to defect regardless of the others decision. Figure 5 shows Alice and Bob playing the game with T=5; R=3; P=1; S=0.

(Alice, Bob)	C	D
C	(3,3)	(0,5)
D	(5,0)	**(1,1)**

Nash equilibrium: selfish/local best; dominant strategies; evolutionary stable; no players are motived to change decisions; a degree of stability – for example, no player can improve her expected payoff by unilaterally changing her strategy

Non Pareto optimal: players could gain without lessening the other player's expected pay-off, e.g., (C,C)=(3,3)

Figure 5. A Classic Prisoners' Dilemma Game

In a classic Prisoners' Dilemma, a player has a dominant strategy if this strategy yields a higher payoff than any alternative, regardless of the strategies adopted by other players. A rational player will inevitably adopt such a strategy – even when we allow free communication with other players. Most games do not possess dominant strategies. If every player has a dominant strategy, then the game's inevitable outcome is the dominant-strategy equilibrium. The Prisoners' Dilemma game has the dominant-strategy equilibrium (D,D). Either player reasons thus: "If my partner were to cooperate, my best action would be to defect. If he were to defect, my best action is still to defect. Thus I have a dominant strategy: 'always defect.'" The players face a dilemma since rational reasoning in such a situation dictates the players to defect, although they would both benefit from mutual cooperation. As Alice is better off with defection regardless of Bob's choice, she will defect. The game being symmetric, the same argument applies to Bob.

In a quantum version of the game, two qubits are prepared by an arbiter in a particular initial state, the qubits are sent to the two players who have physical instruments at hand to manipulate their qubits in an appropriate manner. Finally, the qubits are sent back to the arbiter who performs a measurement to evaluate the payoff. The two qubits have to be entangled with the unitary matrix shown in Figure 6.

Here, Alice and Bob both have strategies s_A and s_B from Hilbert space H_A and H_B. $H = H_A \otimes H_B$ is combined state space S(H). A quantum operation is a unitary matrix, as shown in Figure 6, applied to a quantum state. Quantum strategies or Q-strategies s_A and s_B of Alice and Bob are local quantum operations acting in H_A and H_B respectively. In a generalized set up of quantum Prisoners' Dilemma, the only Nash equilibrium invariant by applying a new Q-strategy and exchange of the strategies of the players yields a payoff PA(H,H) = PB(H,H) = 2.25. This is the solution of the game using the most general case of quantum operations (i.e., unitary matrix) shown in Figure 6. Both players could in principle do better although the solution still lacks Pareto optimality. The efficiency of this focal equilibrium is much higher than the equilibrium in dominant strategies of the classical game.

$$U(\theta,\phi)=\begin{pmatrix} e^{i\phi}\cos(\theta/2) & \sin(\theta/2) \\ -\sin(\theta/2) & e^{-i\phi}\cos(\theta/2) \end{pmatrix}$$

with $\theta \in [0,\pi]$ and $\phi \in [0,\pi/2]$.

Classical pure strategies:

$$C \sim U(0,0) \quad \text{and} \quad D \sim U(\pi,0).$$

The previous Nash equilibrium is no longer and a new Nash equilibrium as given by (Q,Q), The Q-strategy is associated with the matrix

$$Q \sim U(0,\pi/2)=\begin{pmatrix} i & 0 \\ 0 & -i \end{pmatrix}.$$

(Q,Q)=(3,3), is also Pareto optimal: No players could gain without lessen others' pay-off. In the classical game only mutual cooperation is Pareto optimal, but this pair of strategies does not correspond to a Nash equilibrium.

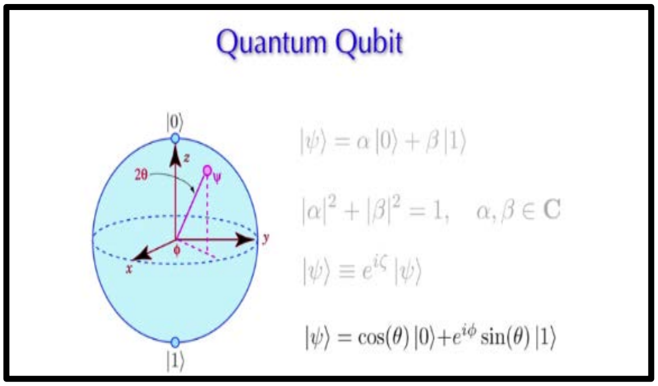
ϕ Is the entanglement degree of the two qubits

Figure 6. Quantum Operation as Presented as a Unitary Matrix Used in Quantum Prisoner's Game (QPD)

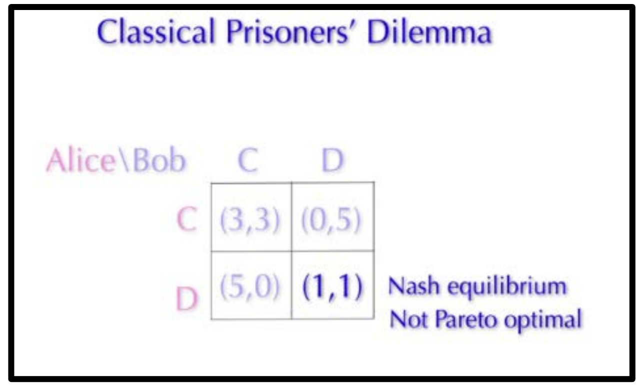
Hence, in this most general case, both players gain from using quantum strategies. Figure 7 shows the sequence of QPD when choosing a special case quantum operation which has the maximum quantum entanglement of the two players.

$$Q \sim U(0,\pi/2)=\begin{pmatrix} i & 0 \\ 0 & -i \end{pmatrix}$$

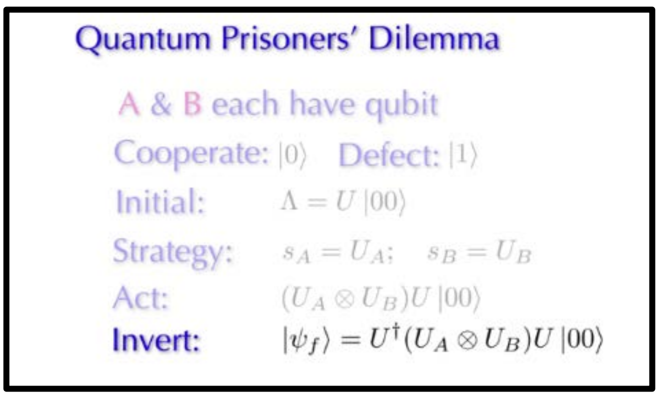
The solution yields a payoff PA(Z,Z) = PB(Z,Z) = 3. It is both Nash equilibrium invariant and Pareto optimal! It effectively eliminates the Prisoners' Dilemma effect.


Quantum Qubit
$|0\rangle$
2θ
z
ψ
y
x
ϕ
$|1\rangle$
$|\psi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle$
$|\alpha|^2 + |\beta|^2 = 1, \quad \alpha, \beta \in \mathbf{C}$
$|\psi\rangle \equiv e^{i\zeta}\,|\psi\rangle$
$|\psi\rangle = \cos(\theta)\,|0\rangle + e^{i\phi}\sin(\theta)\,|1\rangle$

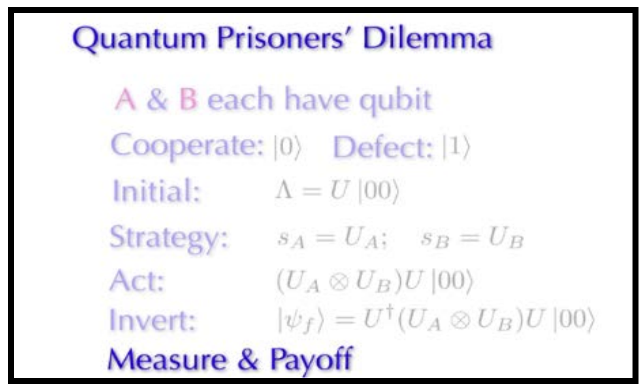
(a)


Classical Prisoners' Dilemma
Alice\Bob C D
C (3,3) (0,5)
D (5,0) (1,1)
Nash equilibrium
Not Pareto optimal

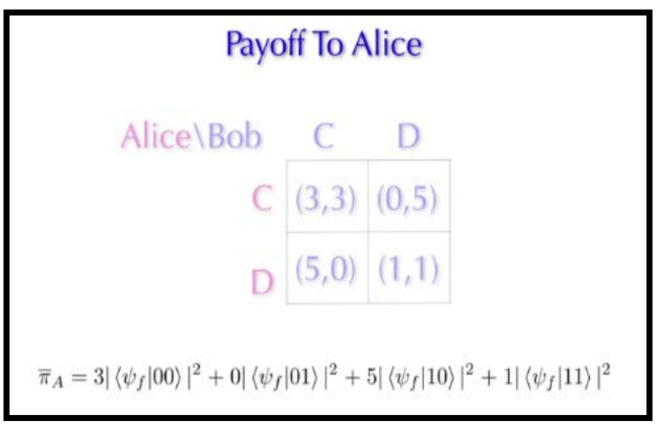
(b)


Quantum Prisoners' Dilemma
A & B each have qubit
Cooperate: $|0\rangle$ Defect: $|1\rangle$
Initial: $\Lambda = U\,|00\rangle$
Strategy: $s_A = U_A; \quad s_B = U_B$
Act: $(U_A \otimes U_B)U\,|00\rangle$
Invert: $|\psi_f\rangle = U^\dagger(U_A \otimes U_B)U\,|00\rangle$

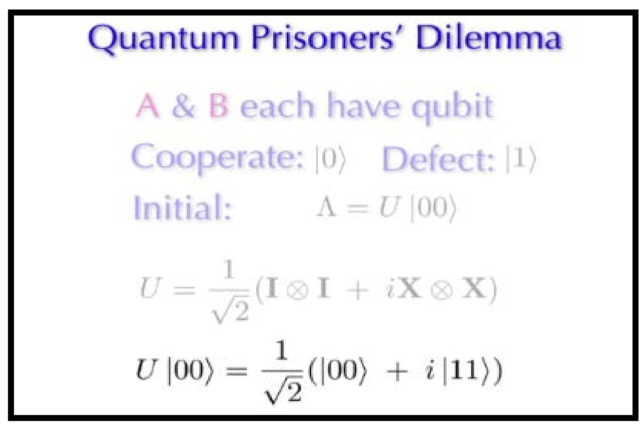
(c)


Quantum Prisoners' Dilemma
A & B each have qubit
Cooperate: $|0\rangle$ Defect: $|1\rangle$
Initial: $\Lambda = U\,|00\rangle$
Strategy: $s_A = U_A; \quad s_B = U_B$
Act: $(U_A \otimes U_B)U\,|00\rangle$
Invert: $|\psi_f\rangle = U^\dagger(U_A \otimes U_B)U\,|00\rangle$
Measure & Payoff

(d)


Payoff To Alice
Alice\Bob C D
C (3,3) (0,5)
D (5,0) (1,1)
$\overline{\pi}_A = 3|\langle\psi_f|00\rangle|^2 + 0|\langle\psi_f|01\rangle|^2 + 5|\langle\psi_f|10\rangle|^2 + 1|\langle\psi_f|11\rangle|^2$

(e)


Quantum Prisoners' Dilemma
A & B each have qubit
Cooperate: $|0\rangle$ Defect: $|1\rangle$
Initial: $\Lambda = U\,|00\rangle$
$U = \frac{1}{\sqrt{2}}(\mathbf{I}\otimes\mathbf{I} + i\mathbf{X}\otimes\mathbf{X})$
$U\,|00\rangle = \frac{1}{\sqrt{2}}(|00\rangle + i\,|11\rangle)$

(f)

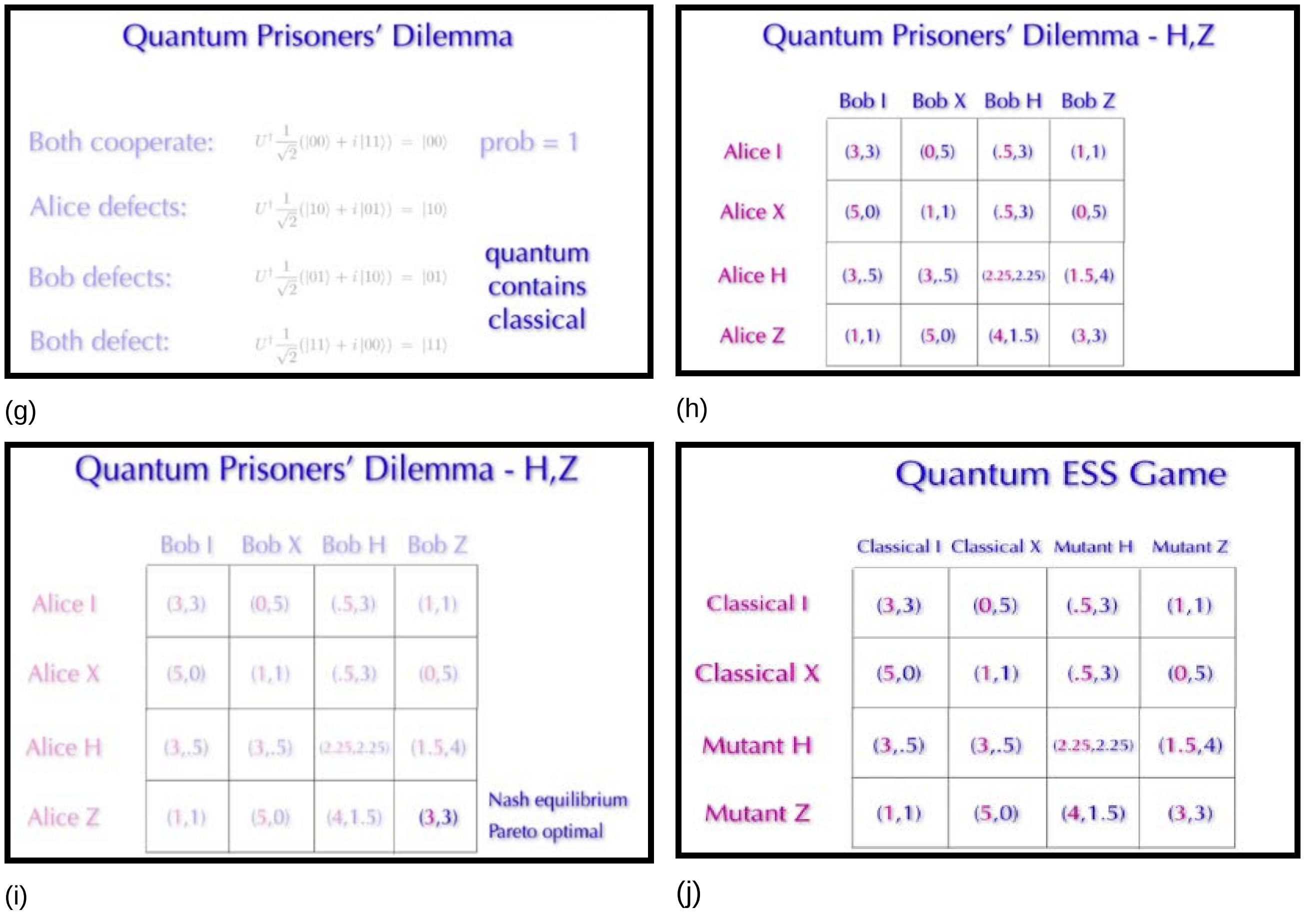


Figure 7. Quantum Prisoners' Dilemma Game

This shows that the players can by taking advantage of appropriate quantum strategies so that more Pareto efficient equilibria could be reached. In certain sets of strategies, even the maximally efficient solution—the Pareto optimum—was attainable.

Quantum Intelligence

It has been a longstanding challenge and interest to understand the emergence and convergence (or guaranteed emergence) of cooperation of games on networks and the principles behind how to make competing systems to cooperate. Quantum strategies allow a new type of Nash's equilibrium for the whole system to be more Pareto efficient. In other words, Emergence of cooperation from competing systems is both Pareto optimal and in Nash's equilibrium.

It is shown the quantum strategies are also different from the mixed strategies with probabilities in the traditional games. The real reason that there are quantum strategies that can be in Nash's equilibrium as well as Pareto optimal is due to the fact that a quantum game allows a quantum entanglement of players' choices that can have the effect of preventing players from profiting from pure defecting actions. For example, Alice forces Bob to choose a quantum strategy Q if Bob wants to maximize his payoff at the same time. When both Alice and Bob choose Q, the payoffs of both players and the total game are maximized.

This year I further extended the theoretical aspect of the recursive data fusion methodology in LLA/SSA/CLA to analyze the data in the DAVE as follows:

- An agent *j* represents a sensor and operates on its own like a decentralized data fusion, however it does not communicate with all other sensors but only with the ones that are its peers. A peer list can be specified by the agent.
- An agent *j* includes a learning engine CLA that collects and analyzes, from its domain, specific data knowledge base *b(t,j)*, for examples; *b(t,j)* may represent the statistics for bi-gram feature pairs (word pairs) computed from LLA.
- An agent *j* also includes a fusion engine SSA with two algorithms, SSA1 and SSA2, that can be customized externally. SSA1 integrates the local knowledge base *b(t,j)* to the total knowledge base *B(t,j)* that can be passed along to its peers and used globally in the recursion in Figure 6. SSA2 assesses the total value of the agent *j* by separating the total knowledge base into the categories of patterns, emerging and anomalous themes based on the total knowledge base *B(t,j)* and generates a total value *V(t,j) as follows:*
    - *Step 1: B(t,j) = SSA1(B(t-1, p(j)), b(t,j));*
    - *Step 2: V(t,j) = SSA2(B(t,j))*

Where *p(j)* represents the peer list of agent *j*.

- The total value *V(t,j)* is used in the global sorting and ranking of relevant information.

In this recursive data fusion, the knowledge bases and total values are completely data-driven and automatically discovered from the data. Each agent has the exact same code of LLA, SSA, and CLA, yet has its own data apart from other agents. This agent work has the advantages of both decentralized and distributed data fusion. It performs learning and fusion simultaneously and in parallel. Meanwhile, it categorizes the patterns and anomalous information.

The uniqueness of a CLA that each agent can self-aware of its global position or authority and also its unique strength (i.e., innovation or expertise).

We formulate a model as follows:

A single agent only ingests domain specific data or content input x_t. A value function or a utility function $b_j(x_t)$ can be derived (learned) from the input x_t for Expertise $\boldsymbol{j}$, i.e. Content x_t is mapped to Expertise j with a value $b_j(x_t)$.

There are different types of expertise across different domains or agents; a link matrix r_{ij} is used to describe how one Expertise $\boldsymbol{i}$ is linked to another Expertise $\boldsymbol{j}$.

Each agent analyzes its own input or content data in parallel. An agent has one or multiple types of expertise, topics or themes (used interchangeably in this paper). Agents that share knowledge and different types of expertise are collaborative or cooperative.

Here we describe how to use the Expectation and Maximization (EM) method to compute the correlation or affinity between an input content *x* and the type of Expertise *j* being implemented.

Let $b_j(x)$ be a likelihood function representing the likelihood of producing content *x* if an agent possesses Expertise *j.* A joint likelihood of multiple agents given all the parameters associated with a model λ can be represented as $f(x|\lambda)$ and

$f(x|\lambda) = \sum_{all\ s} \prod_{t=1}^{T-1} r_{s_{t-1}s_t} b_{s_t}(x_t)$ where *t=1, … T* are samples, s_t is the expertise used at sample *t* based on the observable input (content) x_t..

In mathematical terms, the learning part of a CLA system refers to finding the model parameters λ to maximize the likelihood $f(x|\lambda)$. It is difficult to maximize $f(x|\lambda)$ directly, due to the interlocking of the parameters of all the agents. By introducing a *Q*-function (e.g., *Kullbuk-Leibler* Statistic method), this problem can be transformed into two relatively simpler problems than maximizing $f(x|\lambda)$ directly.

Let $Q(\lambda,\overline{\lambda})$ be a utility function when

$$Q(\lambda,\overline{\lambda}) \geq Q(\lambda,\lambda) \Rightarrow f(x|\overline{\lambda}) \geq f(x|\lambda)$$

$$Q(\lambda,\overline{\lambda}) = \sum_{o \in n^T} \frac{f(x,o|\lambda)}{f(x|\lambda)} \log f(x,o|\overline{\lambda})$$

Maximizing $Q(\lambda,\overline{\lambda})$ with respect to $\overline{\lambda}$, referred as the Expectation step of the EM methodology, leads to the maximization of $f(x|\lambda)$.The Maximization step of the EM methodology involves looking for a joint set of states, in this case, a set of expertise that maximize the joint likelihood function, which can be viewed as a total value for a multi-agent system. The overall value *R(t, j)* is the total value of a multi-agent system up to sample *t* if the ending expertise is *j*. The overall value function can be computed recursively, as shown Figure 3. The overall value comes from a combination of the accumulative authority from the past *R(t-1, i)* and an individual expertise at sample t, i.e., $b_j(x_t)$.

It is evident that traditional search engine algorithms only consider the accumulative authority part of the recursion (e.g., using the Power method to compute the largest eigenvector). We introduce the expertise part of the recursion as the total value of collaborative learning agents. The resulted information ranking mechanism when weighting expertise more than authority values new and unique information more than authoritative and popular information. The tradeoff between authority and expertise is controlled by the coefficients w_1 and w_2, as shown in Figure 8.

To summarize, LLA/CLA/SSA is a new paradigm of quantum computing defined as quantum intelligence for the following aspects that capture the essence of the quantum game theory, or leverage the metaphor measurement of quantum entanglement for the relationship between competing systems:

- To satisfy a Nash's Equilibrium, each system should optimize a total reward locally and for itself. Figure 8 is the optimization scheme that executes locally in a single agent. The expertise of a system, e.g., the Expertise component in Figure 8 contributes to the increase of the competitiveness of the system.
- To be Pareto optimal, systems need to be quantum entangled or correlated therefore while a player optimizes total reward for itself, it simultaneously optimizes the total reward or social welfare of the whole system. The correlation among players (or systems), e.g., the Authority component in Figure 8 contributes to the increase of the efficiency of the whole system.
- The recursive scheme is the key to perform a global optimization (i.e., Pareto optimal for multiple players) via simultaneous local optimizations.
- This paradigm is capable of making the competitive systems to cooperate in terms of systems of systems such as DoD acquisition systems.

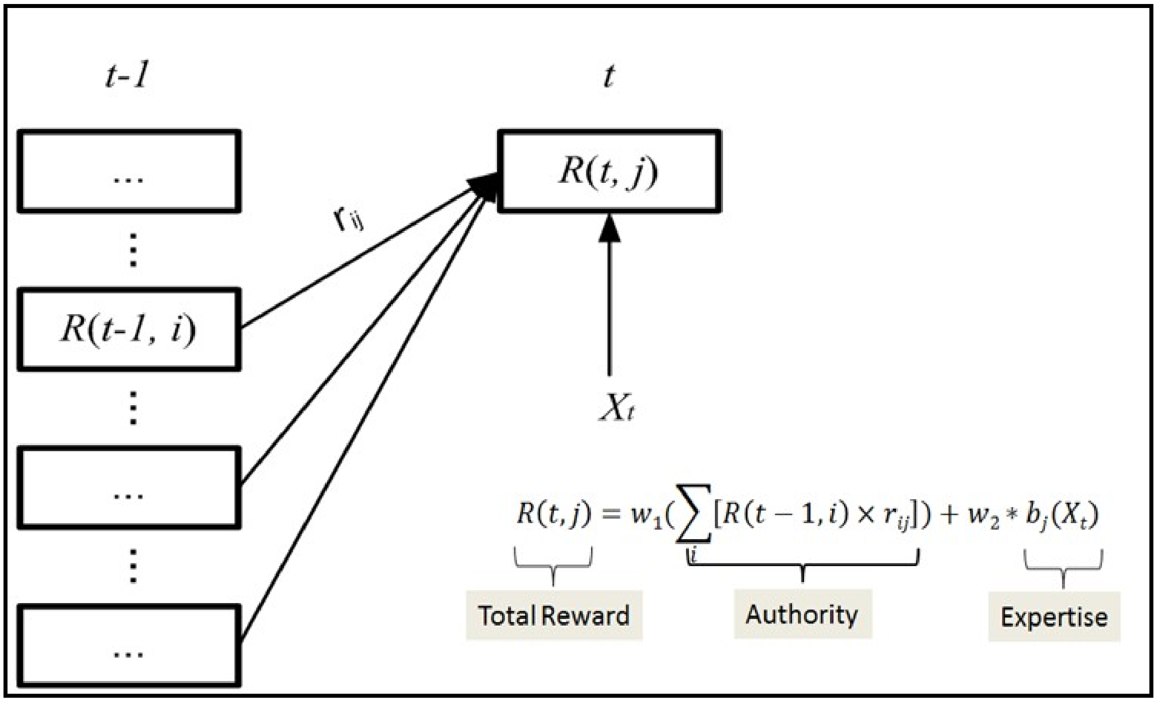


Figure 8. Quantum Intelligence Recursive Algorithm to Optimize Systems of Systems Locally and Globally

Research Results

In this section, we describe the research results for the following two tasks completed this year.

Task 1: Develop a training class and work with potential analysts in OUSD(AT&L) to use the installed LLA/CLA. Explore and provide evidence on how to use LLA jointly with Big Data and Deep Learning tools for improving the DoD Acquisition Process.

AT&L eBusiness Center Service Certification

We continuously worked with the OUSD(AT&L) to certifiy the LLA/CLA system as a web service in the Defense Acquisition Visibility Environment (DAVE) test bed via the AT&L eBusiness Center Service. The process is expected to be complete in 2/2017.

We also provided evidence of using the recursive data fusion methodology in LLA/SSA/CLA and to analyze the data in the DAVE. As shown in the Methodology section, we have linked LLA/SSA/CLA to an innovative concept of quantum intelligence.

Task 2: Examine how to use the DAVE Big Data to gain business insights with the following specifics of research interests from domain experts proposed as follows:

- In the current acquisition process, a small delay or anomaly in the contract negotiation process can have a huge impact on its performance, and, therefore, cost the government a lot of money downstream. For example, the following is a potential list of studies that can leverage LLA/CLA/SSA methods and the DAVE Big Data
    - Study Prime and subcontractor relationships
    - Study the Director, Operational Test and Evaluation (DOT&E) annual reports for horizontal analysis
    - Compare DOT&E and DAES: What did the OT result say and did issues surface?
    - Perform Time series analysis
    - Compare budget data and contracts data
- It will be very useful to apply LLA/CLA/SSA for pattern recognition and anomaly detection for these kind of problems and make early warnings and predictions to prevent the downstream risks.
- The Big Acquisition Data might include programs' costs, SAR, DAMIR, tech data, and even outside economic environment data, if access is possible.
- The causes of the deviations from the normal behaviors for the programs/contracts might be modeled using physics (e.g., fluid dynamics theories).

Last year, we met with Mr. Mark E. Krzysko, Deputy Director, Acquisition, Resources and Analysis Enterprise Information at the OUSD(AT&L). In that discussion, we agreed that future work will also include installing LLA at the Defense Manpower Defense Center (DMDC)—a federally funded research and development center (FFRDC)—and setting up a BDAA consortium, whereby DAVE could provide an authoritative yet secure data throughput to the DMDC and NPS students, faculty, and acquisition research professionals. This, in turn, can inspire a large community of researchers and NPS students, who may be future leaders of the DoD acquisition community, to use the Big Data tools and analytics like LLA to access the DAVE data to answer important research questions and advance the state-of-the-art of DoD acquisition.

As a proof-of-concept, I worked with Kyle Opel, a master's thesis student, on his thesis titled *Unlocking Secrets of Successful Software-Intensive Systems*. The following is the executive summary of Opel's (2016) thesis.

Abstract and Findings of the Master's Thesis of Kyle Opel (2016, pp. vi, pp. 99-102)

Abstract

The increasing volume and unstructured nature of digital data provide both a monumental headache to, and opportunity for, analysis. Standard analytic tools do not possess the capabilities needed to extract the full value from such data. Data associated with Defense Acquisition System (DAS) documentation requirements provide significant resources to which new big data analytic tools can be applied. Software-Intensive Systems (SIS) rely heavily on detailed and stable requirements to deliver timely, cost effective, and capable systems to end users. Unplanned software redesign and system requirements changes are frequently blamed for cost and schedule overruns, as well as system-performance shortfalls.

This thesis analyzes DAS-delivered SIS through the implementation of Lexical Link Analysis (LLA) to explore how requirements language structure, specific requirements language, and underlying requirements language themes or patterns may identify successful systems. Our findings indicate that successful SIS appear to maintain a focus on program requirements through use of requirements-focused language throughout program documentation when major programs changes do not occur during program development. Program restructuring appears to have a minor effect in language patterns, but not enough to force significant changes in documentation language subsequent to such a restructure.

This research explored whether Defense Acquisition System (DAS) program data, the majority of which is unstructured, could be analyzed to identify successful Software-Intensive Systems (SIS). The increase in variety and volume of data, especially associated with DAS programs, provides significant opportunities for value extraction. The existence of patterns within the data was also analyzed in an effort to uncover relationships between documentation types/functional areas within successful SIS. Findings from this research are discussed below with respect to each of the two research questions.

Research Question One

- Can requirements language be analyzed to uniquely identify successful Software-Intensive Systems?

We propose the answer is yes. While our research is limited in its ability to apply a broad, DoD-wide generalization, Lexical Link Analysis (LLA) appears to be capable of ingesting unstructured DAS program data and is supportive of unlocking value in the data through multiple visualizations when analyzed.

Prior to application of the LLA tool to our five selected systems' program data, extracting value from the various program documents, would have required brute force to read and analyze hundreds of pages of data. LLA and the capabilities it provides exponentially compresses the time required to read all program data and produce readable output from which potentially valuable conclusions can be drawn.

Research Question Two

- Is there a requirements-language structure or specific requirements-language that is associated with successful SIS development?

As previously discussed, while we cannot make DAS-wide generalizations about all successful SIS, there appears to be a pattern in language used within document types/functional areas of our five selected successful SIS.

Recommendations

As discussed in the Introduction, this thesis is more qualitative than quantitative in nature, making specific recommendations unsupportable; however, general recommendations with respect to overall program management can be made in a limited capacity.

While different program documents have different focus areas, such as cost, testing, and development strategy, an overall focus on user requirements as identified in Requirements Documentation (ICD, CDD, and CPD) should drive generation of subsequent program documents, such as the ICD, CDD, and CPD surrogate documentation as used in this research. When creating new program documents, returning to original requirement documentation may support the inclusion of real user needs into future program documentation. This will also help mitigate the erosion of a Requirements' focus over time.

Requirements engineering should be a formal process that supports identification of real user requirements. Gaps between real and stated requirements may exist due to the lack of technological feasibility of the stated requirements, the cost-prohibitive nature of meeting the stated requirement, or the failure to review and refer to stated requirements when attempting to capture the real user requirement(s). Maintaining open lines of communication between key stakeholders, users and designers and developers, may support closing the gap between what users state as a need and what is ultimately delivered by the DAS process.

This research focused on finding value within DAS SIS program documentation. Drawing conclusions and making recommendations would not be possible without access to the data. Continuing to make data available for not only research, but generation of new program documentation can support learning from previous programs and may support more focused program documentation from such learning. Application of the LLA tool to programs under-development may also support identification of well-documented and developing programs as well as those that may need additional support to ensure meeting of user requirements. Data availability and possible application of LLA to documents may provide a quantitative measure to support what can be seen as a highly qualitative success definition.

Future Research

Our definition of a successful SIS was derived from research that included significant effort placed into using questionnaires as the primary means of defining success. These questionnaires were directed mostly at key stakeholders involved in system development. To more accurately capture the true definition of a successful DoD SIS, future research could include building a definition of a successful SIS through key DoD program stakeholder input in the same questionnaire format.

The conclusions and findings in this thesis are specific and limited to a handful of successful DoD Software-Intensive Systems. The conclusions should be tested against additional successful systems to validate the findings. Furthermore, analysis of unsuccessful systems, once defined, should be undertaken to see if patterns exist inside documentation language of those systems. Comparisons between both successful and unsuccessful systems should be examined as well.

Additional data sources should be sought out to increase the data from which analyses are done and conclusions are drawn. An increase in the volume of data analyzed may support conclusions drawn in this thesis, and may also lead to other findings outside the scope of our research. The AIR and DTIC R&E Gateway have shown to be supportive sources for DoD SIS documentation. Efforts should be made to increase data availability in each system through work with program offices to support increased SIS data analyses. Application of LLA to volumetrically large (big data sized) data sets may yield additional insight with more bytes from which to perform analysis.

Task 3: I delivered an NPS Acquisition Research Program sponsored technical report and Maj. Opel participated in the ***13th Annual Acquisition Research Symposium***

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