NPS-AM-18-012

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Big Data and Deep Learning for Defense Acquisition Visibility Environment (DAVE)—Developing NPS Student Thesis Research

21 December 2017

Dr. Ying Zhao, Research Professor

Graduate School of Operational & Information Sciences

Naval Postgraduate School

Prepared for the Naval Postgraduate School, Monterey, CA 93943.

The research presented in this report was supported by the Acquisition Research Program of the Graduate School of Business & Public Policy at the Naval Postgraduate School.

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Abstract

The U.S. Department of Defense (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. Lexical link analysis (LLA) and collaborative learning agents (CLAs) have been applied to reveal and depict—to decision-makers—the correlations, associations, and program gaps across acquisition programs examined over many years. This enables strategic understanding of data gaps and potential trends, and it can inform managers which areas might be exposed to higher program risk and how resource and big data management might affect the desired return on investment (ROI) among projects.

In last year's research, a Naval Postgraduate School (NPS) thesis started using LLA and data from the Defense Acquisition Visibility Environment (DAVE). The goal of the thesis was to discover the correlation of the vendors' capabilities and the requirements of a logistics application. LLA also used visualization capabilities, which was planned to be used in the student thesis. In the same time, a conference paper about discovering high-value information using LLA and the associated new visualizations was published.

There is an interesting connection between the LLA and CLA computing theory and quantum game theory. LLA/CLA/SSA was introduced in the context of quantum game and quantum intelligence, which is an interesting connection that can help systems of systems, such as DoD acquisition systems, reach stable states of Nash equilibria and at the same time be Pareto optimal. This theory is capable of making competitive systems cooperate, 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 authoritative attributes (i.e., the system attributes that help to reach Nash equilibrium) and expertise attributes (i.e., the system attributes that help to reach Pareto optimality).

Keywords: Lexical Link Analysis, big data, big acquisition data, big data architecture, big data analytics, big data platform, logistics application, quantum mechanics, superposition, quantum game, game theory, quantum intelligence

About the Authors

Dr. Ying Zhao is a research professor at the Naval Postgraduate School (NPS) and 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; big data analytics; deep learning techniques, such as lexical link analysis (LLA) and collaborative learning agents (CLAs); machine learning (ML); and artificial intelligence (AI) methods, such as reinforcement learning for search, visualization, and large-scale cognitive modeling for decision-making. Since joining NPS, Dr. Zhao has been a principal investigator (PI) on 21 contracts awarded for DoD research projects. Dr. Zhao is a co-author of four 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.

Dr. Ying Zhao
Information Sciences Department
Naval Postgraduate School
Monterey, CA 93943-5000
Tel: (831) 656-3789
Fax: (831) 656-3679
E-mail: yzhao@nps.edu

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Executive Summary

Researchers 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 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. The interlocking systems and processes that connect DoD program to the needs of warfighters present many challenges. How can gaps of non-fit be revealed? Moreover, in the performance of DoD acquisition processes, each functional community is required to review only the particular information for which it is 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.

In last year's research, a Naval Postgraduate School (NPS) thesis started using Lexical Link Analysis (LLA) and data from the Defense Acquisition Visibility Environment (DAVE). The goal of the thesis was to discover the correlation of the vendors' capabilities and the requirements of a logistics application. LLA was improved through the use of visualization capabilities, which was planned to be used in the student thesis. A conference paper about discovering high-value information using LLA and the associated new visualizations was published.

There is an interesting connection between the LLA and CLA computing theory and quantum game theory. LLA and CLA was introduced in the context of quantum game and quantum intelligence, which is an interesting connection and theory that can help systems of systems, such as DoD acquisition systems, reach stable states of Nash equilibria and at the same time be Pareto optimal. This theory is capable of making the competitive systems cooperate, 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 authoritative attributes (i.e., the system attributes that help to reach Nash equilibrium) and expertise attributes (i.e., the system attributes that help to reach Pareto optimality).

Background

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

- surface 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 annual research, development, test, and evaluation (RDT&E) budget modification practice, over the course of 10 years and 450 DoD program elements. We found a pattern of programs with fewer links (measured by LLA) to warfighters' requirements receiving more budget reductions in total but less on average, indicating that budget reduction may have been focused mainly on large and expensive programs rather than on cutting all the programs that did 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 the good practice of allocating DoD acquisition resources to avoid overlap 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, limiting overall spending, maximizing efficiencies, eliminating unnecessary costs, and maximizing 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.

In 2017, the state-of-the-art big data and deep learning techniques such as the Big Data Platform (BDP) were also explored. These tools have been useful to the NPS students as they conduct their thesis research.

Methodology

Lexical Link Analysis

In the past, we have applied LLA as a data-driven automation technology and methodology across the DoD acquisition process, as shown in Figure 1.

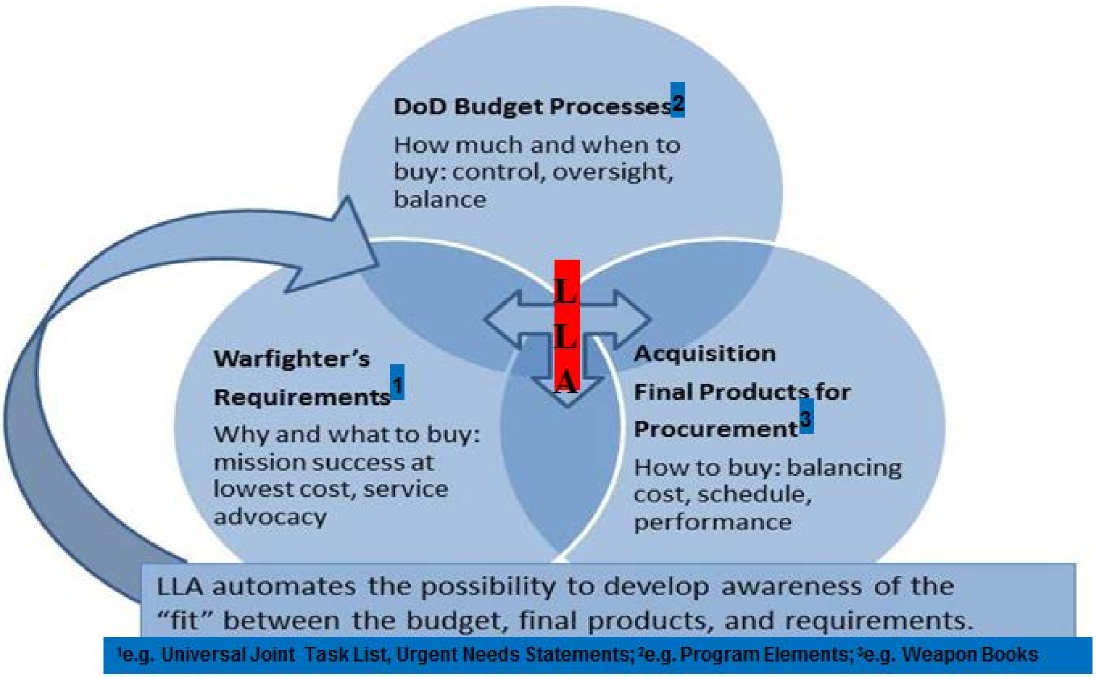


Figure 1. LLA Applied to Acquisition Processes

The LLA core algorithm, as shown in Figure 2, includes the following language-independent processing steps:

1. Extract word pairs (bigram) in context, connect them as word networks (text-as-networks).
2. Group word networks into clusters /themes (by color).

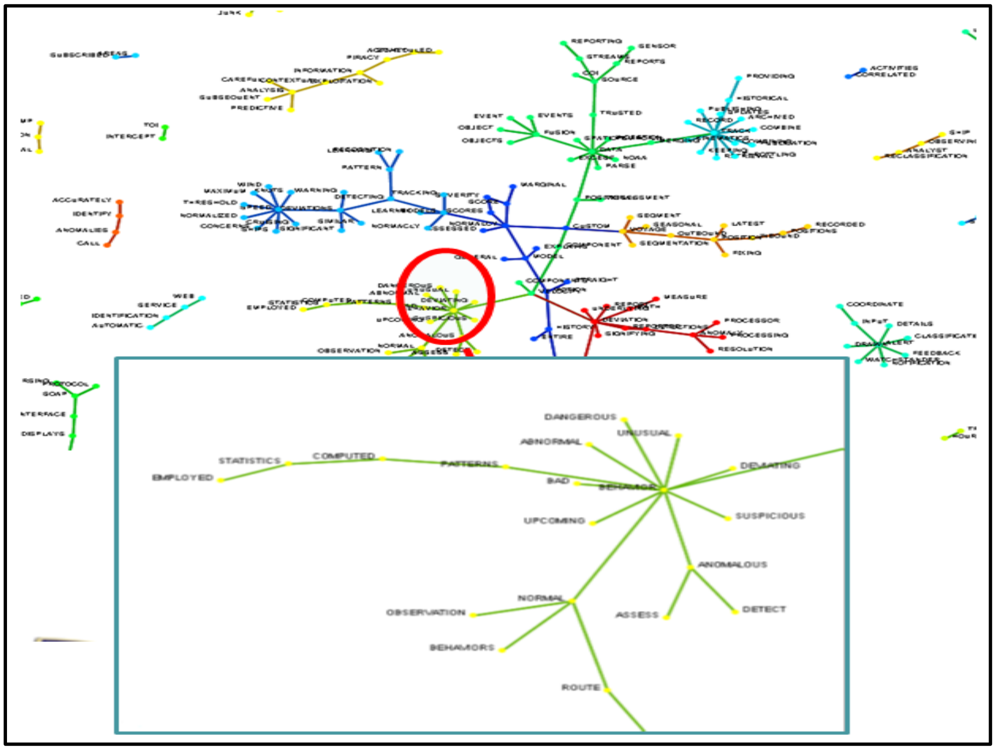


Figure 2. LLA Core Algorithm

The optional language-dependent pre-processing steps via Stanford NLP (Stanford Natural Language Processing Group [SNLP], 2015) include the following:

- Stop-word removal: Leave out stop words (e.g., a, of, the).
- Named entity (NE) extraction: Leave in/out people, places, and organizations; focus on semantics; use NE in social networks.
- Parts of speech tagging (Manning & Schütze,1999): Use only nouns and verbs.
- Stemming: Use only word roots.

Example LLA reports and visualizations are shown in Figure 3.

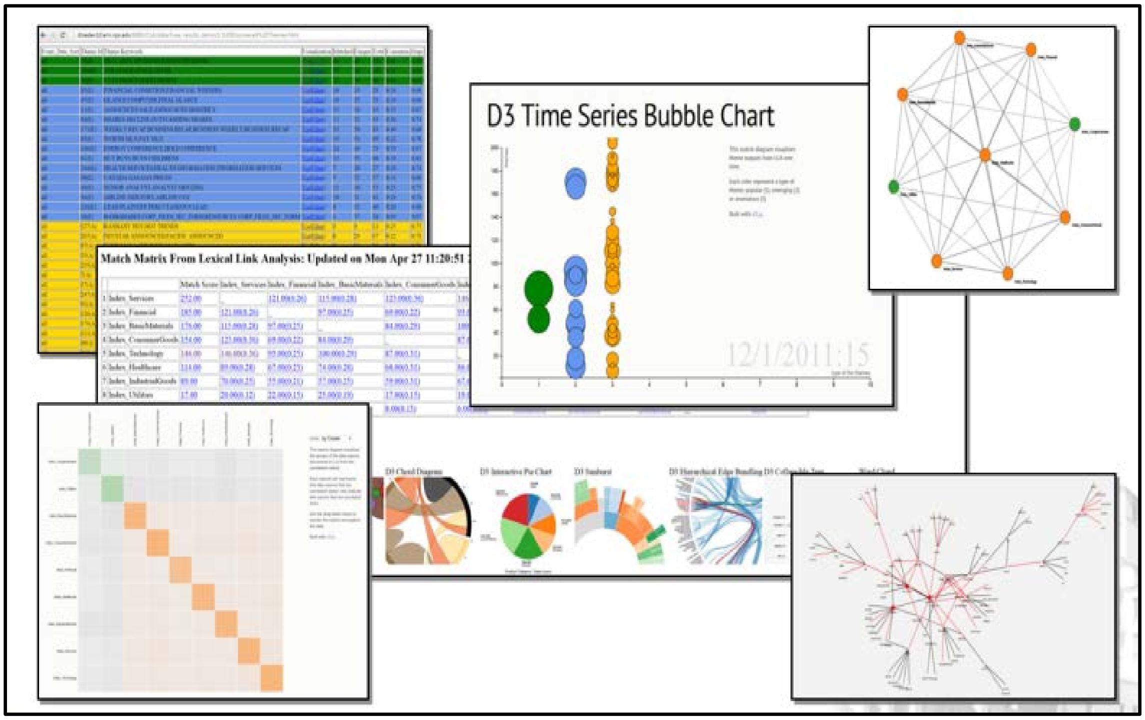
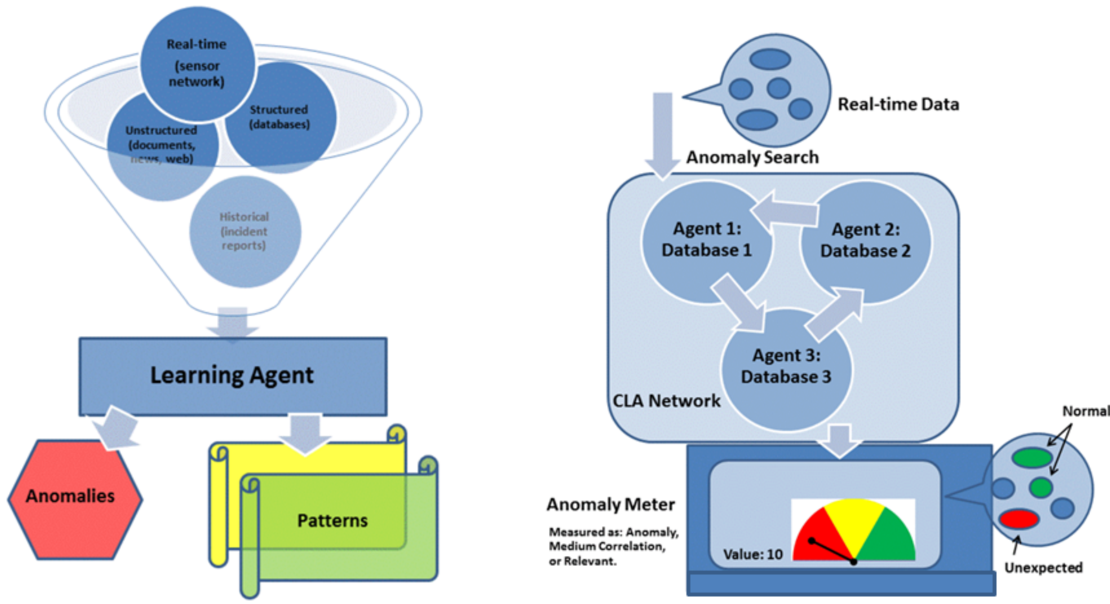


Figure 3. Examples of LLA Reports and Visualizations

Some of the functions of LLA are

- to surface themes and their relationships across multiple data sources,
- to compare/correlate data from multiple data sources,
- to sort/rank and compare/correlate data from multiple data sources to reveal important and interesting information, and
- to discover high value areas for investment.

Lexical link analysis (LLA) is implemented using collaborative learning agents (CLAs), as shown in Figure 4, which can be viewed as unsupervised learning and deep learning for data fusion, pattern recognition, and anomaly detection.



(a) A single Collaborative Learning Agent (CLA) where patterns and anomalies are separated

(b): Agent Collaboration

- System and Method for Knowledge Pattern Search from Networked Agents (US patent **8,903,756**) Zhao et al., Quantum Intelligence, Inc. (www.quantumii.com)
- Multiple Domain Anomaly Detection System and Method using Fusion rule and Visualization (US Patent **9,323,837)** Zhao et al., Quantum Intelligence, Inc. (www.quantumii.com)
- Zhao, Y. & Zhou, C. (2016). System Self-Awareness Towards Deep Learning and Discovering High-Value Information. In the Proceedings of The 7th IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference, Oct. 20-22, New York, USA. Page 109-116

Figure 4. Collaborative Learning Agents

Big Data and Deep Learning (BDDL)

In this past year, we explored a BDDL tool called Big Data Platform (BDP 2.3.8), as shown in Figure 5. The BDP provides a common computing solution capable of ingesting, storing, processing, sharing, and visualizing multiple petabytes of DoD data. The tool includes standard big data tools such as Hadoop Cloudera CDH4, Apache Accumulo, and Spark (http://spark.apache.org/). It primarily focuses on the integration of end user visualization tools that provide greater query and statistical capabilities for business intelligence. For example, R and Shiny servers provide the ability to display statistical analytic results in a graphical format.

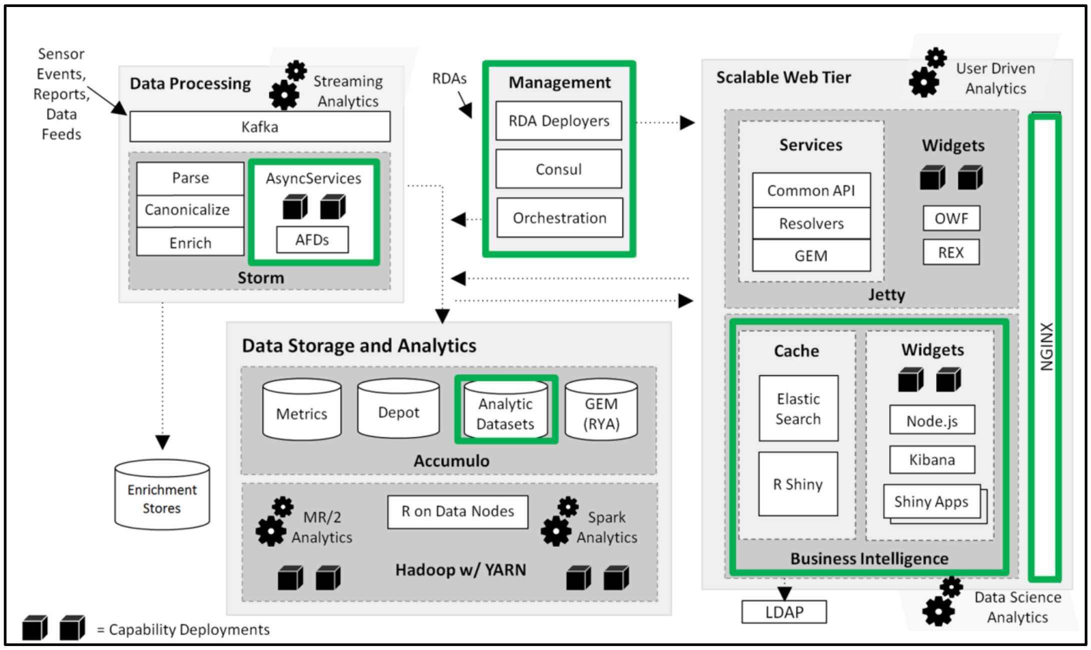


Figure 5. Big Data Platform (BDP), Including Standard Big Data Tools and Visualization Tools

Recent Relevant Research Summary

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 instance, 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, latent Dirichlet analysis (LDA; Blei, Ng, & Jordan, 2003) is a sparse coding in which a bag of words is used as the sparsely coded features for text (Olshausen & Field, 1996). LLA can be viewed an unsupervised deep learning for pattern recognition, anomaly detection, and data fusion.

LLA is implemented in the parallel and distributed fashion of CLA. LLA uses bi-gram word pairs, which, compared to LDA, are potentially more meaningful than sparse coded features. In practice, one can argue that a spammer might adapt to fit the described features or authoritative information and might promote its own ranks by simply copying and pasting the text of top-ranked information. In this case, the hyperlinks-based ranking may be more successful because the links convey a notion of endorsement by others, which is harder to manipulate in a large scale. However, one can still use the CLA and LLA methods by filtering out the popular themes (i.e., the ones that are already known or in the public conscience and awareness) and then focusing only on emerging and anomalous themes for sorting and ranking the authority and expertise.

Research Results

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

Task 1: One NPS thesis was started using LLA and related big data and deep learning to develop research questions to advance DoD acquisition research.

In the proposal, we stated that the following topics could be interesting and important, but that students' thesis research questions should not be limited to these questions:

1. Examine and compare the important acquisition data sources to gain business insights to accomplish the following:
    - 1.1 Study correlation between DoD requirements and vendors' solutions.
    - 1.2 Study prime and subcontractor relationships.
        - 1.2.1 Analyze Director of Operational Test and Evaluation (DOT&E) annual reports using horizontal analysis.
        - 1.2.2 Compare DOT&E and DAES: What did the OT results reveal and did issues surface?
        - 1.2.3 Did these issues show up somewhere in DAES earlier?
    - 1.3 Perform time series analysis.
        - 1.3.1 Can LLA look at program ratings over time?
    - 1.4 Compare budget data and contracts data.
2. Other areas of big data exploration may include the following:
    - 2.1 Understanding how, in the current acquisition process, a small delay or anomaly in a contract negotiation process can have a huge impact onan acquisition program's performance, therefore costing the government a lot of money downstream
    - 2.2 Applying BDAA such as LLA for pattern recognition and anomaly detection for these kind of problems to enable early warnings and predictions to prevent the downstream risks
    - 2.3 Leveraging big acquisition data to include programs' cost, SAR, DAMIR, technical data, and to perhaps include outside economic environment data if access is possible

2.4 Learning causes of the deviations from the normal behaviors for the programs/contracts and how to use models arising from physics (e.g., fluid dynamics theories)

2.5 Exploring LLA's network perspectives and social dynamics found among the nodes and the System Self-Awareness (SSA) theory and how they may be used to lay out the academic rigor for business processes, for example, to answer the following questions:

2.5.1 Are some nodes drawn towards some other nodes because the other nodes are more powerful, for instance, the powerful nodes can represent the organizations with more decision-makers?

2.5.2 Should the growth pattern be attached to popular existing ideas (i.e., preferential attachment) or innovative ideas (i.e., expertise growth)? How are the forces of the nodes modeled and mapped into the social network settings and actual business processes?

Student Thesis Topic: Logistics Software Acquisition

The student thesis, titled *Systems Engineering Management (SEM) Implementation to Portfolio Management of U.S. Marine Corps Logistics Chain Management (LCM) Information Technology (IT)*, will use LLA and DAVE data sources for research. The synopsis of the thesis is as follows:

> A critical warfighting requirement in military superiority is the ability to deliver the right equipment at the right time and place. As weapon systems become more complex and require higher operational tempos and operational availability, the demands placed on warehouse management for accuracy and responsiveness for order fulfillment increase commensurately. In the past, the USMC pursued an enterprise resource planning (ERP) solution to consolidate and modernize its logistics chain management (LCM) operations.
>
> Increment 1 of the ERP-based Global Combat Support System–Marine Corps (GCSS-MC), comprising supply and maintenance, has been fielded. The remaining increments including tactical warehouse management are under review by USMC senior leadership to determine if an ERP-based solution for future increments is cost-effective within the USMC’s defense budget given the time and cost expended to field Increment 1. Recent industry initiatives move away from ERPs in favor of leaner and more agile application-based business process modeling (BPM) solution sets.

> The primary question is whether a common architecture framework enabling DoD-wide warehouse management operations can exist.
>
> This thesis will analyze the system functions, operational architectures, and varying implementation solutions across DoD warehouse management operations. A technical analysis of the systems under review and their common architectural frameworks will be performed in order to determine how each is able to satisfy common requirements. The goal of this thesis will be to determine, through engineering analysis, whether there is enough commonality in order to increase re-use of systems and reduce the number of unique solution sets.
>
> The technical analysis to address the questions, for example, comparing gaps and overlaps of the systems with the requirements or comparing systems with each other, will also include using data-driven approaches such as Lexical Link Analysis and visualizations implemented using data-driven documents (D3).

This thesis will be completed in 2018. The thesis student is in the process of extracting authoritative and authentic data sources from DAVE from documents from the Oracle data warehouse solutions and GCSS-MC requirements. The student will apply LLA and other tools to compare Oracle solutions with requirements, addressing Research Questions 1.1 and 1.3, listed previously.

I (the researcher) will also use the data to address the methodologies regarding Research Questions 2.1 and 2.3. We researched the methodologies regarding Questions 2.5 which is summarized in the following section.

Quantum Game, Learning, and Intelligence Theory for Nash Equilibria and Pareto Optimal Systems of Systems

Last year, I introduced LLA, CLA and system-self awareness (SSA) in the context of quantum game and quantum intelligence, which is an interesting connection and theory that can help systems of systems, such as DoD acquisition systems, reach stable states of Nash equilibria and at the same time be Pareto optimal. This theory is capable of making competitive systems cooperate, 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 authoritative attributes (i.e., the system attributes that help to reach Nash equilibrium) and expertise attributes (i.e., the system attributes that help to reach Pareto optimality). The following section describes part of the new development regarding quantum game, learning, and intelligence theory for Nash equilibria and Pareto optimal systems of systems this year.

Game Theory

Game theory is a field of applied mathematics. It formalizes the conflict between competing players or agents and has applications ranging from economics to biology (Nowak & Sigmund, 1999; Rasmusen, 1995). Quantum information is a young field of physics related to physical implementation of quantum mechanics. Various problems, even in quantum information processing, can be usefully thought of as games. Meyer (1999) has pointed out that the algorithms for quantum computers can be modeled as games between classical and quantum agents. By applying quantum mechanics to game theory, it is shown that when the resources controlled by competing agents are entangled (or correlated, overlapped), the agents can cooperate to exploit their environment, such as preventing both from "defecting" in the prisoners' dilemma (PD) game. Using quantum mechanics, the PD game can reach both Nash equilibrium and Pareto optimality, effectively eliminating the classical PD effect; that is, Nash equilibrium and Pareto optimality cannot be achieved simultaneously.

Pure and Mixed Strategies in Classic Game: In game theory (Fudenberg & Tirole, 1991), a player or an agent or a system (used interchangeably below) applies a strategy that can be any of the options she can choose in a setting in which reward depends not only on her own actions but also on the action of others. A pure strategy provides a complete definition of how a player will play a game. In particular, it determines the move a player will make for any situation she could face. A player's strategy set is the set of pure strategies available to that player. Table 1 shows a reward matrix for two players and two pure strategies (C or D). The row player gets the reward as the first number of the pair.

Table 1. Reward Matrix for Two Players, Two Pure Strategies

	C	D
C	*(r,r)*	*(s,t)*
D	*(t,s)*	*(p,p)*

A mixed strategy is an assignment of a probability to each pure strategy. It allows for a player to randomly select a pure strategy. Since probabilities are continuous, there are an infinite number of mixed strategies available to a player. For example, the row player and column player can play (C,C), (C,D), and (D,C) with a probability of 1/3.

Nash Equilibrium: In classic game theory, a strategy profile is at Nash equilibrium if no player can do better by unilaterally changing her strategy. In other words, the player's strategy is optimized for her own reward and the whole system converges to a fixed point. Nash (1950, 1951) proved that if mixed strategies are allowed, every game with a finite number of players and a finite number of pure strategies has at least one Nash equilibrium. The key assumption here is that every player in the games is perfectly rational when selecting strategies to maximize her reward. Rationalizability is a central solution concept of game theory.

Pareto Efficiency and Optimality: Pareto efficiency, or Pareto optimality, is a state of resource allocation in which it is impossible to make one individual better off without making at least one individual worse off. When considering a multiple variable optimization with constraints, the Pareto optimality is the whole curve that separates feasible and infeasible solutions. For example, as shown in Figure 6, if the reward for two agents has the constraint $R^2_1 + R^2_2 = 1$, the Pareto optimal solutions are the points on the curve satisfying the constraint.

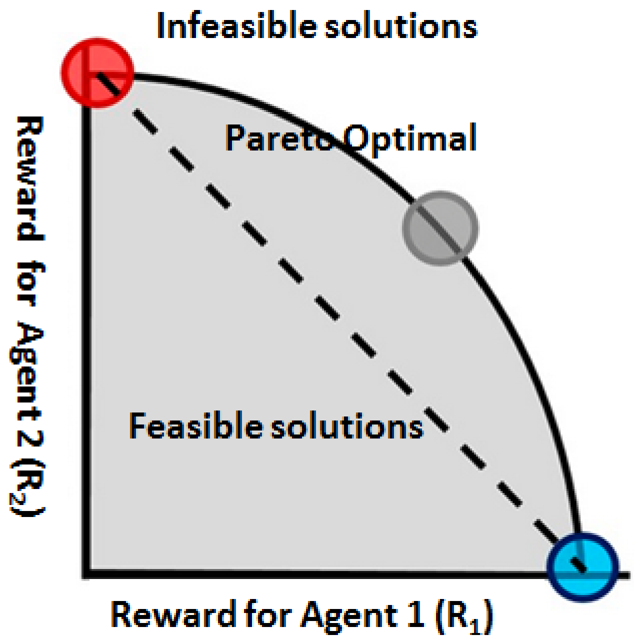


Figure 6. Pareto Efficiency and Pareto Optimality

<u>Games on Networks:</u> Consider a finite set of players (1, ..., *N*) who are connected in a network (Jackson & Zenou, 2014). The network (or graph) consists of *N* nodes representing the game's interaction structure and indicating other players who impact a given player's reward through their interactions (links). r_{ij} is the correlation matrix where player *i* is linked to *j* with relationship intensity r_{ij} . In our research, for example, the r_{ij} can be computed using LLA, as shown in Figure 7.

$$r_{ij} = \frac{(\#\ of\ Overlapped\ Lexical\ Features\ for\ Agent\ i\ and\ j)}{\sqrt{(\#\ of\ Lexical\ Features\ for\ Agent\ i) * (\#\ of\ Lexical\ Features\ for\ Agent\ j)}}$$

Figure 7. Computing the Correlation Between Two Agents Using LLA

In a game network, a player chooses an action, and the rewards of each player are determined by those of her neighbors. Traditional network game theory has focused on games of strategic complements (cooperative or collaborative) and strategic substitutes (competitive). With strategic complements, a player's incentives to choose a strategy increase with the number of correlated agents who also choose the strategy. With strategic substitutes, the opposite incentives are in place.

Prisoner's Dilemma (PD) Game: The prisoner's dilemma is one of the most well-known games with implications in a wide range of disciplines. In the PD, two players simultaneously decide their strategy to be a cooperator (C) or a defector (D). For mutual cooperation, both players receive a reward R, that is, being freed from jail. For mutual defection, both players receive a reward 1, that is, staying in jail for a shorter period of time. If one player cooperates and the other defects, the cooperator gains reward 0, and the defector gains 5. The best strategy for both players is to defect regardless of the other's decision. Table 2 shows the game reward matrix. In traditional game theory, a player has a dominant strategy if it yields a higher reward than any alternative, regardless of the strategies adopted by other players. When a player decides on a dominant strategy, she is considered rational. The PD game has the dominant-strategy or Nash equilibrium (D,D), in which a selfish/local optimal and stable solution can be reached regardless of the other player's strategies. However, (D,D) is not Pareto optimal because the players face a dilemma since rational reasoning dictates that the players defect even though they would both benefit from mutual cooperation.

Table 2. Prisoner's Dilemma (PD) Game Reward Matrix

	Cooperation	Defect
Cooperation	*(3,3)*	*(0,5)*
Defect	*(5,0)*	*(1,1)*

In a quantum version of the PD game, each move corresponds to a quantum operation, or a Q-strategy, that is, a unitary positive definite complex matrix. There is evidence that a quantum operation such as this does exist, with the correct amount of initial degree of entanglement or correlation of two players, in which the Q-strategy is both at Nash equilibrium and Pareto optimal.

Chicken Game: The chicken game (CG) is an anti-coordination game in which two chickens chose "dare" to cross the street or "chicken out" and not cross the street. According to the reward matrix shown in Table 3, it is mutually beneficial for the players to play different strategies. In this sense, the chicken can be thought of as the opposite of a coordination game such as the PD game. The concept underlying the CG is that players use a shared resource. In coordination games, sharing the resource creates a benefit for all, whereas in anti-coordination games, the shared resource comes at a cost.

In the classic setting, CG has two pure Nash equilibria—(1,6) and (6,1)—as shown in Table 3. The existence of two Nash equilibria causes a dilemma. The players, without communicating with each other, cannot decide on which Nash equilibrium to choose. Furthermore, there is another mixed Nash equilibrium in which the probabilities to play (C,C), (C,D) and (D,C) are 1/3. By applying quantum mechanics to the chicken game, one can also achieve both Nash equilibrium and Pareto optimality.

Table 3. Chicken Game Reward Matrix

	Chicken	Dare
Chicken	*(4,4)*	*(1,6)*
Dare	*(6,1)*	*(0,0)*

SSA/CLA/LLA Game Theory Models

A SSA/CLA/LLA model combined with game theory, or a quantum intelligence game, can be modeled as a CG with a reward matrix, as shown in Table 4.

Table 4. Chicken Game Reward Matrix

	Authority (A)	Expertise (E)
Authority (A)	$1-R_j, R_j$	$0, b_j$
Expertise (E)	$b_j, 0$	$0,0$

In the matrix, the row player is *j* and all other agents are the column player, as in a network game. There are two pure strategies, Authority or Expertise, for each agent *j.* The game is similar to a strategic complement game such as the CG game in which the authority strategy is similar to the chicken out (C) strategy and the expertise strategy is similar to the dare (D) strategy. Therefore, the CG has two Nash equilibria: (A,E) and (E,A) if $b_j > R_j$.

Baseline Model

As a baseline model, shown in Figure 8, if a network of agents decide an action based only on authoritative information, the resulting Nash equilibrium is s a total value 1 distributed among the agents associated with the eigenvector corresponding to the maximum eigenvalue of the correlation matrix r_{ij}, as shown in Figure 7. The eigenvector can be computed from the following iteration:

$$\vec{R}(t+1) = \lambda r \vec{R}(t)$$

$$\vec{R} = \begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_N \end{bmatrix} \qquad R_1^2 + R_2^2 + ... + R_N^2 = 1.$$

where $\lambda > 1$, r denotes the correlation matrix r_{ij} and N is the number of agents. R converges to the eigenvector of the maximum eigenvalue of r when for any small ϵ and $|\vec{R}(t+1) - \vec{R}(t)| < \epsilon$

Figure 8. Nash Equilibrium With Only Authority Used

Mixed Strategies Model

Here, we first discuss the mixed strategies for the authority and expertise game, in which a collection of agents uses a strategy built on both authority and expertise as shown in Figure 9.

$$\hat{R}_j = w_1 R_j + w_2 b_j$$

$$w_1 > 0 \ \& \ w_2 > 0; w_1 + w_2 = 1$$

Figure 9. Mixed Strategies for the AE Game

In Figure 9, w_1 *and* w_2 represent the probabilities of authority and expertise knowledge an agent decides to apply, respectively. The recursive process in Figure 8 converges to the distribution of the total authority reward 1 among the *N* agents.

The authority reward for Agent *j is* R_j *and* b_j is the expertise reward. The reward for Agent *j* is (w_1R_j+w_2b_j) with the conditions: $w_1R_j+w_2b_j>R_j$ *and* $1>w_1+w_2b_j>b_j$. Agent *j*'s fraction of the total reward R_{max} is shown in Figure 10.

$$R_{max} = \frac{w_1 R_j + w_2 b_j}{w_1 + w_2 b_j} = R_j + \frac{w_2 b_j (1 - R_j)}{w_1 + w_2 b_j}$$

Figure 10. Agent j's Fraction of the Total Reward R_{max} > R*j* in the Mixed Strategies Game

The mixed strategies AE game overcomes the limitation of being Pareto efficient. Given an initial selection of expertise for a set of agents, choosing a different expertise that makes at least one agent better off without making any other agent worse off is called a Pareto improvement. Here, *better off* is often interpreted as having a higher reward or being in a preferred position, for example, more central or with a higher degree. If no Pareto improvement can be made in a system, the system is Pareto efficient. The total reward of the multi-agent system at one of the equilibria is $w_1 + w_2b_j$, which is more than the total value of another pure strategy equilibrium b_j reward when using expertise alone (i.e., $w_1 = 0$). Therefore, the mixed authority and expertise strategies can generate Pareto superior solutions.

The new paradigm can also be explained in term of the Pareto index. In economics, the Pareto index is a measure of the breadth of a value (e.g., reward) distribution. The index is one of the parameters specifying a Pareto distribution and embodies the Pareto principle. The Pareto principle, or the “80-20 rule,” says that 80% of the effects (e.g., cumulative value or reward) come from 20% of the causes (e.g., cost or population; Rootzén & Tajvidi, 2006). The Pareto distribution is a power law probability distribution that is used in description of social, scientific, geophysical, actuarial, and many other types of observable phenomena in which a competitive, small percentage of the population represents most of the total value of a system. Figure 11 shows the Pareto index curve using the mixed strategies (i.e., the purple curve).

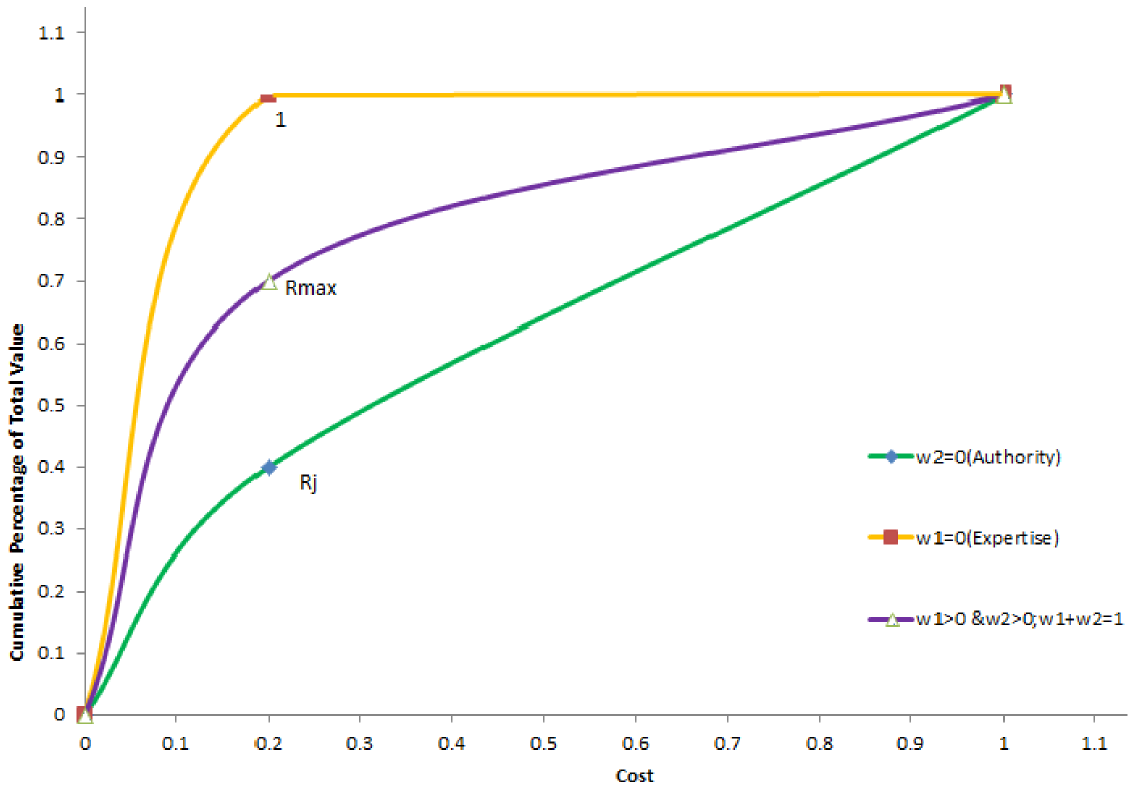


Figure 11. Pareto Index of the Mixed Strategies AE Game

Quantum Intelligence Model

Classical probability theory assumes that decisions and of actions of an agent are based on a definite state of accumulated reward. However, modern behavior research (Kvama, Pleskacb, Yua & Busemeyerc, 2015)may suggest that actions and rewards are more likely to be in the fashion of superpositions of cumulated reward for the potential actions, up to the point that the measurement has to be made, the final action is selected, and the final reward is determined. During the process, the agents in the system go through a quantum process that they may not be aware of but that does exist so the system can converge to an equilibrium state. The following are three elements in quantum mechanics that can be simulated and applied to a quantum intelligence AE model:

1. Game players must be in an entangled initial state, or in a correlated initial state, as in the correlation matrix shown in Figure 7.

2. Game players do not communicate with each other. Each agent tries to maximize her own reward via the process of reaching a Nash equilibrium: When each individual agent's reward is maximized and the whole system converges to a stable state, then each agent cannot unilaterally improve herself This is an iterative and recursive process in which players in a multi-agent game take turns and play with each other
3. Game players use superposition quantum strategies, not mixed or pure strategies. Quantum entanglement in quantum mechanics is simulated with the mathematics of superpositions of the authority and expertise strategies. Players or agents (CLA) in a network are entangled or correlated because their knowledge contents overlap. The degree of correlation or entanglement between two agents is determined using LLA.

In Figure 12, the *r is* a non-negative matrix with the properties related to the Perron theorem for non-negative matrix, namely its dominant eigenvalue value, that is, eigenvalue with the maximum magnitude, $r_{max}>0$. To illustrate the quantum effect, we consider a multi-agent system in which if Agent *j* has an expertise valued b_j, then the whole system's reward matrix is superpositioned between the system without b_j (pure strategy authority only) and b_j (pure strategy expertise) only.

$$\hat{r} = \begin{bmatrix} \frac{1}{\lambda_{max}} r & 0 \\ 0 & 1 \end{bmatrix}$$

r's eigenvector corresponding to the maximum eigenvalue is

$$R_1^2 + R_2^2 + \ldots + R_N^2 = 1.$$

$$\begin{bmatrix} R_1 \\ \vdots \\ R_N \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} \hat{R}_1 \\ \vdots \\ \hat{R}_N \\ \hat{R}_{N+1} \end{bmatrix} = \begin{bmatrix} \sqrt{1-b_j^2}R_1 \\ \vdots \\ \sqrt{1-b_j^2}R_N \\ b_j \end{bmatrix}$$

$$\hat{R}_1^2 + \hat{R}_2^2 + \ldots + \hat{R}_N^2 = 1$$

$$\hat{R}_j^2 = (1-b_j^2)R_j^2 + b_j^2 > R_{max}^2$$

$$b_j > \sqrt{\frac{R_{max}^2 - R_j^2}{1-R_j^2}}$$

Figure 12. Quantum Intelligence Game and Conditions of Superpositions of Authority and Expertise

In summary, Figure 13 shows the possible emergence of a higher value component and higher Pareto index among other Pareto optimal solutions. The expertise signals that are used to reinforce the system converge to an equilibrium in which every agent's reward is maximized, while the system is also Pareto optimal, meaning the combined reward for all agents is 1 and not less than 1. This is similar to the normalized summary of probability amplitudes of all the eigenstates in quantum mechanics.

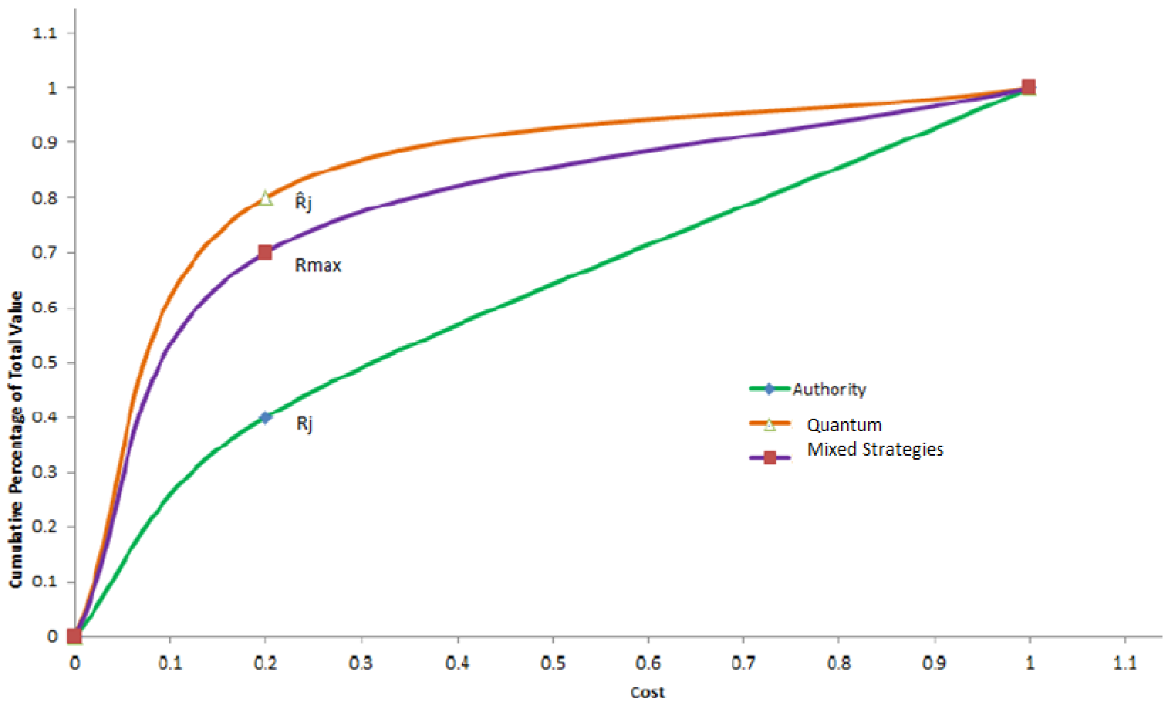


Figure 13. Quantum Strategies AE Game Generating Better Pareto Index

Task 2: The thesis student also explored LLA and other big data and deep learning tools, such as the Big Data Platform, to answer thebusiness questions proposed in the students' thesis research.

In the past year, we also explored other big data and deep learning (BDDL) tools for data fusion, pattern recognition, and anomaly detection.

Student Thesis Tools

We brought a couple of NPS students to a BDP training class. The BDP has a standalone installation CD or requires an Amazon web service (AWS, or Rapid Analytic Deployment and Management Framework [RADMF]).

Install and Access BDP Core Capabilities

We attended a three-day class of the BDP RADMF that was hosted and taught by Enlighten IT Consulting, LLC, a MacAulay-Brown company, in which we were able to learn the BDP installation, configuration, and capabilities in an Amazon AWS implementation. The key characteristics of BDP include the following:

- 99% open source big data tools such as APACH Accumulo, Storm, Spark, and R Shiny, as shown in Figure 5 are included in the BDP.
- Fast and large-scale data ingestion tool called Kronos, which is a time-series event-based parsing tool for various big data. There are several common catalogs (attributes) and pre-defined tools to load commonly used data sources. A data ingestion timeline can be ordered by the data sources.
- Customized interface and analytics can be built on the data requirements (e.g., the so-called RDA process can be used to load a new analytic capability; Java, Spark, R or Python code can be run in the BDP platform implemented in an AWS environment). Students and faculty can access free AWS computing resources at NPS; therefore, it is a good platform for thesis students to be familiar with. Spark jobs can be customized for analytics. For example, Unity is a business intelligence type of tool in BDP for big data sets that allows users to query and slice-dice big data according to the values of the data attributes.

Use Improved LLA

In the past year, we have made some improvements to LLA tools, as described in the following sections.

Visualization—Time Series Bubble Plot

We implemented a few new data-driven document (D3) visualizations. We applied the improved LLA to the use case of the eight years of research report data for the NPS Acquisition Research Program. There were 740 publications (from 2003–2010) from the website http://www.acquisitionresearch.net (Zhao, Gallup & Mackinnon 2012). Figure 14 shows the distribution of anomalous, popular, and emerging themes over time as a bubble plot. The size of the radius of a bubble is proportional to the number of the LLA word pairs in a theme at a particular time point. The color indicates the type of theme (orange indicates anomalous, green indicates popular, and blue indicates emerging). Table 5 shows the average size for three types of themes for the first half (6/1/2003–12/1/2007) and second half of the time period (1/1/2008–12/10/2010). Only the average sizes of the bubbles for the popular themes decrease statistically significantly (*p*-value = .04), as shown in Table 5. the other two categories' average sizes are not changed statistically significantly. In other words, the emerging and anomalous themes are persistently carried out in the time period.

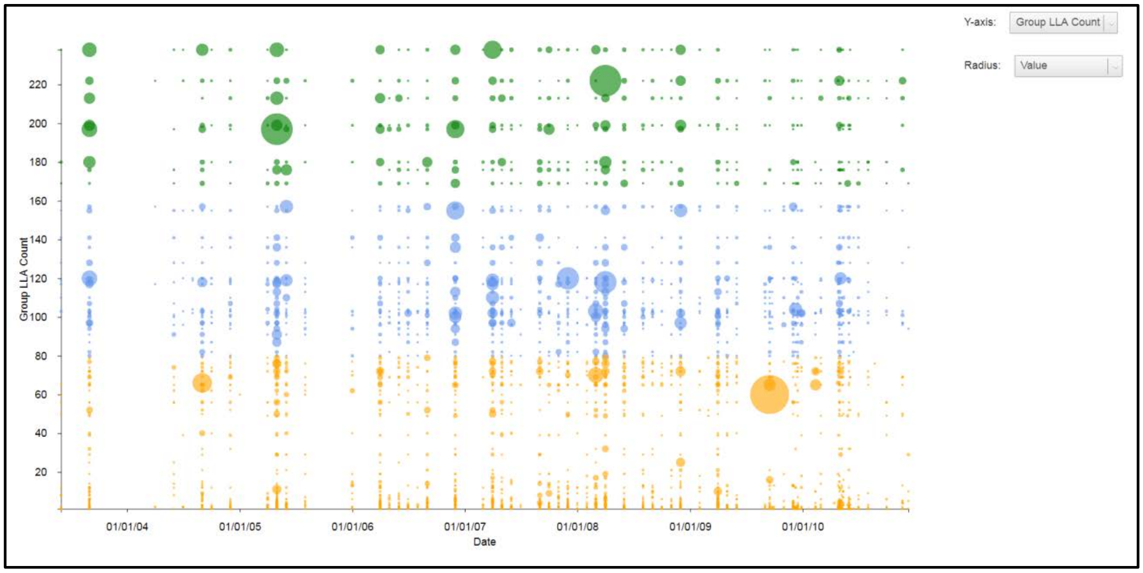


Figure 14. Emerging and Anomalous Themes Persistently Carried Out in the Time Period

Table 5. Average Sizes of Bubble Plots

Average Sizes of Bubble Plots	Anomalous	Popular	Emerging
6/1/2003–12/1/2007	1.067	0.470	0.785
1/1/2008–12/10/2010	0.997	0.375	0.730
p-value	.126	.041	.201

Visualization—Power-Law

Figure 15 is a bar chart showing the number of word pairs, the number of themes, and the total word pairs for the following six types of themes:

- A1: anomalous themes with only one word pair
- A2: anomalous themes with only two word pairs

- A3: anomalous themes with only 3–9 word pairs
- A4: the rest of anomalous themes
- E: emerging themes
- P: popular themes

The red bars show the characteristics of a scale-free network that observes the power-law (Bak, 1997). The green bars show the total number of word pairs in the six types of themes. Table 6 shows the data used in Figure 15. Figure 16 is a Pareto index graph showing that 7% of themes with types A4 and E contain 57% of the total word pairs in the whole data set.

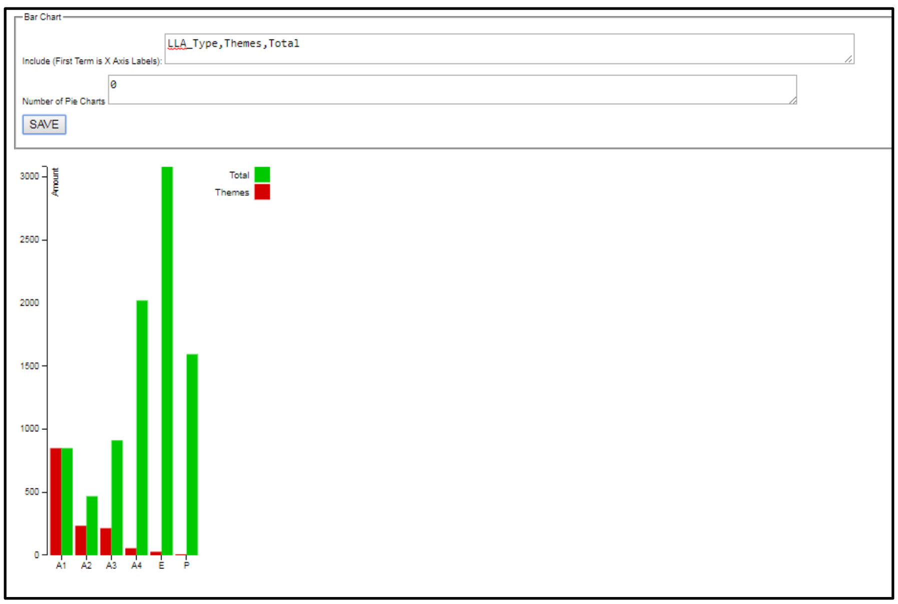


Figure 15. Bar Chart Showing Power-Law

Table 6. Power-Law Graph Data

LLA Type	# of Word Pairs	# of Themes	Total
A1	1	849	849
A2	2	234	468
A3	3-9	215	911
A4	10-79	56	2020
E	80-157	28	3080
P	157-238	8	1594

Visualization—Pareto Graph

Table 7 shows the data used in Figure 8.

Table 7. Pareto Graph Data

	# of themes	# of word pairs	Cumulative % of themes	Cumulative % of word pairs
E	56	3080	0.040	0.345
A4	84	5100	0.060	0.572
P	92	6694	0.066	0.750
A3	307	7605	0.221	0.852
A1	1156	8454	0.832	0.948
A2	1390	8922	1	1

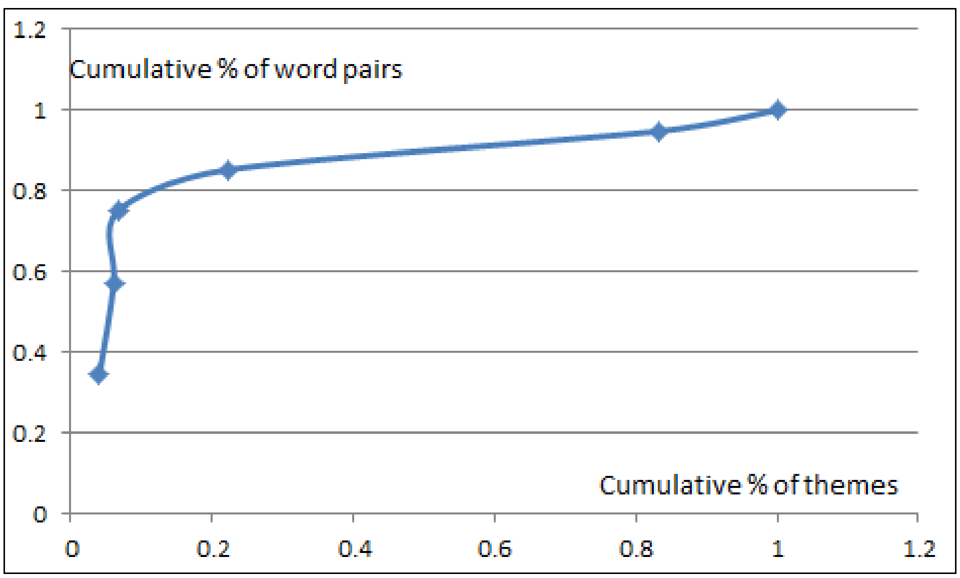


Figure 16. Theme Type E and A4 Contain 57% of the Total Word Pairs

In summary, combining Table 6 and Figure 16, A4 and E are the theme types that contain the most interesting information. The pattern of high-value information discovery was also observed in other data sets using the new visualization capabilities and summarized in Zhao, MacKinnon, and Zhou (2017).

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