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Using Data Analytics to Detect Bridge Contracts

David I. Gill—Procurement Data Scientist, Analytics, Research and Technology Division, Office of the Chief Procurement Officer, Internal Revenue Service. [david.gill@irs.gov]

Dr. Timothy G. Hawkins—Senior Subject Matter Expert, Procurement Data and Analytic Solutions, Inc. [Hawkins@DASconsultants.com]

Jinsu Elhance—Junior Data Scientist, Data and Analytic Solutions, Inc. [Elhance@DASconsultants.com]

Robert Carlson—Technical Manager/Lead Data Scientist, Data and Analytic Solutions, Inc. [RCarlson@dasconsultants.com]

Abstract

Bridge contracts—temporary contract actions that enable continued contractor performance until a replacement contract can be awarded—are not controlled and are suspected to be overused. While facilitating continued mission achievement, bridge contracts reduce competition, result in higher prices paid, and increase transaction costs. Yet, few agencies have a means to identify bridge contracts, meaning the extent of their use is unknown. Thus, most agencies do not identify, analyze, and monitor the risk associated with achieving statutory competition objectives. This research develops a data analytic methodology to identify bridge contracts, which can quantify the magnitude of the problem and serve as a starting point to enact policy to mitigate usage.

Keywords: Bridge Contract; Competition; Acquisition Planning

Disclaimer: The content of this article is the opinion of the writer and does not necessarily represent the position of the Internal Revenue Service.

Introduction

U.S. government contracts in 2020 accounted for over $682 billion (Bloomberg Government, n.d.). The U.S. government represents the single largest and unique business customer in the world; as such, it exerts an enormous economic importance (Boland & Godsell, 2021). Nevertheless, the business-to-government (B2G) market remains grossly understudied (Josephson et al., 2019). The public availability of data for the millions of contract actions annually has attracted recent scholarly attention of researchers and editors from top academic journals.

Although federal government agencies often have continuing needs for procured goods and services in order to meet mission needs, their contracts are time-bound. To meet agency needs, new contracts must be awarded in time to prevent a gap in coverage. However, given the long lead time for source selections, the complexity of the contracting process, budget uncertainties, an occasional lack of advance planning, personnel workloads, a lack of experience, and turnover, new contract awards are sometimes delayed (GAO, 2014; GAO, 2016). As a contingency, agencies utilize *bridge contracts*—"an extension to an existing contract beyond the period of performance (including option years), or a new, short-term contract awarded on a sole-source basis to an incumbent contractor to avoid a lapse in service caused by a delay in awarding a follow-on contract" (GAO, 2016, p. 4). Two defense agencies estimated their 2014 bridge contracts each exceeded $1 billion (GAO, 2016). Another study of the Department of Defense (DoD) identified 18 bridge contracts valued at $9 billion covering 2007–2011 (GAO, 2012). A study by the Institute for Defense Analysis estimated that over 23% of contracts reviewed were bridge contracts (Williams et al., 2012). A memorandum by the Undersecretary of Defense (AT&L) in 2018 reported 1,100 bridge contracts worth $13.7 billion awarded during 2015 (Longo, 2020).

While meeting mission needs, awarding bridge contract actions brings deleterious effects such as: reduced competition, potentially paying higher prices, and increased transaction costs (GAO, 2016). Such actions also delay or deny business opportunities to prospective suppliers. Despite these effects, currently, there is no mechanism to assess the frequency of the practice. Bridge contract actions are not reported in the Federal Procurement Data System-Next Generation (FPDS-NG; GAO, 2016). Since we do not know the frequency of bridge contracts, we also do not know the magnitude of the consequences or the antecedents (including their relative order of influence). Until the most prevalent causes are identified, agencies will be unable to manage and control the practice.

The purpose of this research, therefore, is to develop a data-analytic methodology—using natural language processing and graph network theory—to reliably identify bridge contract actions. Once applied, the model results will address two research questions.

(1) How prevalent is the practice of bridge contracts?

(2) Are there any discernable patterns in bridge contract use?

Based on the findings, the developed analysis methodology can serve as an internal control tool (per requirements of GAO/AIMD-00-21.3.1 [1999]) for agencies to mitigate overuse of bridge contracts. Findings could ultimately lead to policy changes that control the causal factors resulting in reduced usage. The DOD's use of "tripwires" for bridge contract length (Lucyshyn & Quist, 2019) and early policy by the Navy and Defense Logistics Agency resulted in reduced usage of bridge contracts (GAO, 2016). Consequently, competition rates should increase, opportunity should increase, and excessive prices and transaction costs should be avoided.

The remainder of this article is organized as follows. It begins with a review of the relevant literature surrounding competition, bridge contracts, and relevant theory. Next, the study presents the methodologies of quantitative data collection and analysis to explore the research questions. Lastly, discussions, limitations, implications, future research directions, and conclusions are offered.

Literature Review

Competition

Competition is the bedrock of federal acquisition (FAR 1.102(b)(1)(iii)). Perhaps chief among all of the benefits of competition is its instilled fairness—the ability to provide equal opportunity to all responsible suppliers (Doke, 1995). Absent fair opportunity, suppliers will cease pursuit, thereby decreasing competition (Doke, 1995). Competition also reduces the cost of procured goods and services, resulting in savings (GAO, 2016); increases return on investment for the taxpaying public; improves contractor performance; reduces fraud (GAO, 2012); and promotes innovation (Jackson & Alerding, 1997). Competition rates for the DoD in 2011 for all goods and services was 58%. The competition rate for non-research and development (R&D) service contracts was 78%, while the rate for R&D services was 59%. The competition rate for products was 41% (GAO, 2012).

Full and open competition is required by the Competition in Contracting Act (CICA) of 1984, with some exceptions. The most commonly cited exception for service contracts—excluding R&D—was "only one responsible source" (which includes unique capabilities, unsolicited proposals, particular follow-on contracts, intellectual property rights, standardization programs, and utilities). The second-most common exception was "authorized by statute" (e.g., Small Business Administration's 8(a) program, Federal Prison Industries, AbilityOne Program, HUBZONE Act, Veterans Benefits Act, and WOSB program). Other exceptions include: (1) an "unusual and compelling urgency" situation that does not afford adequate time to traverse the source selection process, (2) “industrial mobilization” to maintain a facility or manufacturer in the case of a national emergency, (3) “engineering, developmental, or research capability” to maintain essential services provided by education or non-profit institutions or by a federally funded research and development center, (4) “expert services” to support litigation or disputes, (5) “international agreement” for acquisitions reimbursed by a foreign government or wherein a treaty or agreement specifies or limits sources, (6) “national security” in cases in which disclosure of the need would compromise security, and (7) “public interest” (FAR 6.302). When the agency uses multiple-award indefinite delivery/indefinite quantity (IDIQ) contracts, orders must be competed unless an exception applies. Exceptions include: (1) urgency, (2) only one capable source, (3) economy and efficiency (including a logical follow-on order), (4) satisfying a guaranteed minimum dollar amount of the parent IDIQ award, (5) statutory requirement, and (6) small business programs. While there are several legitimate reasons to not compete requirements, some situations do not offer relief. There is no exception to competition available for situations wherein: (1) an agency fails to adequately plan for a contract action, (2) uncertainty about funds availability, or (3) expiring funds (e.g., at fiscal year-end). Notably, the exception due to a logical follow-on is used frequently—46% of all of the DoD’s exceptions to fair opportunity cited this reason.

In addition to the situations identified as exceptions, other factors can affect competition such as program officials with preferences for particular contractors (e.g., incumbents), overly restrictive requirements, and unanticipated events such as bid protests (GAO, 2012). Unanticipated delays have also been attributed to program official turnover, requirements definition, expansion of requirements, late completion of pre-award documentation, workload, delays in source selection, an inexperienced workforce, budget uncertainties, and acquisition strategy approvals (GAO, 2014; GAO, 2016). These delays sometimes result in bridge contracts (GAO, 2012; GAO, 2016).

Bridge Contracts

A bridge contract is a useful tool to avoid a lapse in services (GAO, 2016), to preclude substantial duplication of costs, and avoid unacceptable delays (Jackson & Alerding, 1997). Bridge contracts are not a new phenomenon. Several comptroller general decisions of protests in the late 1980s prescribed their permissible usage under CICA (Jackson & Alerding, 1997), highlighting the care that agencies must exercise in using bridge contracts in order to avoid a CICA-based protest. Bridge contracts are used for a variety of services ranging from repair and maintenance of equipment, research and development, housekeeping, information technology and telecommunications, and professional administrative and management support, with the latter two accounting for half of bridge contracts (GAO, 2016).

The government awarded contracts worth $3 billion in Fiscal Year (FY) 2013 non-competitively on the basis of urgency (GAO, 2014). Noncompetitive contract actions using the urgency exception are limited in duration to: (1) the time needed to award a competitive contract, and (2) a maximum of one year unless a high-level approval is obtained (i.e., the head of the contracting activity or a designee). However, a study of DoD, Department of State, and the U.S. Agency for International Development revealed non-competitive contract awards based on urgency extending beyond one year in 10 of 34 contracts inspected—eight of which were later extended via modification to exceed the one-year limit (GAO, 2014). A separate study found six such contracts (out of 29 examined) that exceeded three years (GAO, 2016). Also noteworthy is that bridge contracts are sometimes (20/29 examined) succeeded by one or more additional bridge contracts (GAO, 2016) —one as many as five times increasing the projected value of the bridge by 264%.

The GAO (2014) found that justification and approval documents (J&A) did not always contain the required signatures, were sometimes ambiguous in supporting facts (e.g., the serious injury—financial or other—to the government) and were sometimes publicly posted to the FedBizOpps site late (beyond 30 days of award). These discrepancies can reduce the public's confidence in a fair and transparent contracting system—its fundamental goals (FAR 1.102(b)(3)).

As of 2016, agencies (DoD, Health and Human Services, and Justice) were unaware of the extent of their uses of bridge contracts (GAO, 2016). In fact, omitted from the FAR, agencies did not have a consensus definition of bridge contracts, and thus, most had no policy to manage and control their use.

Theoretical Foundation

The standard for determining that an agency did not adequately plan for an acquisition—an unallowable basis for an exception to competition—is low. "The GAO probably will find advance planning lacking only when there has been virtually no advance planning" (Jackson & Alerding, 1997, p. 218). Importantly, most of the causes of delays in sources selections—with proper planning—can be accommodated in acquisition milestones (e.g., review times, requirements documentation); however, some of them cannot, such as budget uncertainty, bid protests, and personnel turnover. "The practice of compliance is inherently a probabilistic activity due to administrative resource constraints, managerial error, misinterpretation and at times evasion" (Orozco, 2020, p. 258). Law and regulation will have varying degrees of uncertainty attributed to vagueness in language and weak regulatory enforcement (Orozco, 2020). Thus, a theory (or theories) explaining and predicting the use of bridge contracts must encompass: (1) a lack of adequate planning, and (2) uncertainty.

Agencies have taken advantage of the exceptions to competition. For example, the NSA used a bridge contract for installation and logistics services in 2013, allegedly to afford time to plan for a competition. Then, three weeks before its expiration—and thereby creating an urgent situation—the NSA awarded another sole source 8(a) contract (NSAIG, 2021). According to Marshall Doke, a prominent attorney in public contracting:

> Government agencies at least pay lip service to competition, but the actual users of supplies or services usually would prefer no competition at all and chafe at the rules and "red tape" of procurement procedures. The government users usually know the vendor they want or prefer, and describing their requirements adequately for competition in specifications or statements of work often is not a high priority. It is not surprising that specifications written around the product of a particular vendor are frequently developed. Nor is it surprising that government officials "split" a requirement to get below a specified dollar threshold for full competition.

A rule is "a statement of general applicability and future effect that implements, interprets, or prescribes law or policy or the organization, procedures, and standards for practice before an agency" (Rossi, 1995, p. 275). Rules help citizens and governments operate on the basis of common, predictable norms and conditions that will prevail (Rossi, 1995). However, rules cannot perfectly address all nuanced cases, nor can all values be formulated into rules. Thus, tension in law between rules and equity will persist. The principle of *regulatory equity* infuses equity into the regulatory process via an administrative exceptions process, which relieves a person or organization subject to a valid statutory or administrative rule from the legal obligation to comply. A challenge, then, is the case wherein the exception becomes the rule. At what point are exceptions to policy overused, and has this happened with respect to bridge contract actions?

Lindenberg's goal framing theory (GFT) serves as a basis for compliance theory (Etienne, 2011). Although more oriented toward the citizen regulatee, its principles can apply to bureaucrats who are charged with compliance. GFT posits that actors, in deciding whether to comply, pursue multiple different goals simultaneously. Three categories of goals are: hedonic goals (i.e., attaining pleasure or stimulation in task accomplishment), gain goals (i.e., to maintain or increase resources, commonly evaluated as cost versus benefits), and normative goals (i.e., to act appropriately). The three types of goals can operate in both noncompliant and compliant behaviors and can operate simultaneously. However, "for action to occur, one of these multiple goals takes precedence while the other goals take a secondary role, although not necessarily a negligible one" (Rossi, 1995, p. 306).

Per GFT, before taking action, a person evaluates the available options and prioritizes them according to their ability to attain goals. "Planned compliance or noncompliance epitomizes the intentional pursuit of various goals, such as to maximize one's utility, fulfill a moral obligation such as duty or trust, or dispose of one's fear of sanctions" (Rossi, 1995, p. 307). "Making a profit hinges on costs and benefits; it is consequentialist, whereas acting appropriately is not and instead hinges on whether the options available are congruent with internalized norms" (Rossi, 1995, p. 308). The most influential goal holds one's attention, referred to as the goal frame. Any other weaker goals are not top of mind.

In the context of public procurement, bureaucrats very likely trade off two goals—*gain* and *normative*. The gain goals pertain to organizational effectiveness. Whether a requiring activity is judged as effective may hinge on its ability to obtain and retain contractors supporting the mission. Source selections introduce risks of unknown contractors and risks of delays due to bid protests. They consume substantial human resources (Hawkins et al., 2016), effort that could otherwise be directed toward attaining organizational performance goals. While bureaucrats may know of the intent of regulation to promote competition, they may trade off normative compliance in order to gain on behalf of their organization, and, thus, their own performance appraisal in pursuit of job security or promotability. The exceptions afforded by FAR 6.302 give them an "out." Contracting communities, in the interest of customer support and mission impact, may be complicit in prioritizing gain goals (e.g., not forcing advance planning for a source selection or not denying customers contract coverage) over normative goals (e.g., promoting competition). In the absence of sanctions, rules violations may become ubiquitous because rule followers may feel cheated (hedonic goals) and that resources are wasted (gain goals), thereby suppressing normative goals (e.g., to do one's duty). In an experiment, visible evidence of [non]compliance influenced subjects to [not] comply (Keizer et al., 2008). Exposed to wall graffiti and a "no graffiti" sign, 68% littered. In the orderly situation (not exposed to graffiti), only 33% littered. This finding suggests that social acceptance can elevate utilitarian gain goals (e.g., avoiding a source selection) ahead of normative goals (e.g., promoting competition), a phenomenon not uncommon in the literature (Rossi, 1995).

Compliance has also been explored from the theoretical lenses of general deterrence theory (GDT; Malloy, 2003), which is grounded in classic criminology. "Classic Deterrence theory focuses on formal (legal) [and informal] sanctions and posits that the greater the perceived certainty, severity, and celerity (swiftness) of sanctions for an illicit act, the more individuals are deterred from that act" (D'Archy & Herath, 2011, p. 644). Nevertheless, to invoke GDT, the perpetrator must perceive the threat of a sanction. This may not be the case with bridge contracts. Alternatively, if GDT is relevant, the requiring activities and contracting personnel may not perceive a high certainty or severity of sanctions, if any. "Lack of enforcement is one general reason for failure of regulations to promote their underlying objectives" (Malloy, 2003, p. 453). Consistent rule enforcement is also important. According to Doke (1995, p. S-15), "In most cases, a bad rule is better than no rule, and consistent application and enforcement of a bad rule often is better than discretionary application and enforcement of a good rule."

A third theory potentially explaining bridge contract use is the *compliance norm*—that a firm, or as applied here, an agency, is a "law-abiding actor, struggling in good faith to comply with increasingly complicated and contradictory laws and regulations" rather than a pure profit maximizer (Malloy, 2003, p. 454). An extension of this theory considers firm compliance as vulnerable to its organizational routines. Here, the firm is "a system for allocating and managing resources necessary to achieve [its] goals" (Malloy, 2003, p. 458). "In this 'systems' view of the firm, noncompliance is seen as a management problem: it is the complexity of the firm, rather than just the complexity of the regulations, that lies at the root of regulatory violations" (Malloy, 2003, p. 459). Organizations are plagued by their complex functional organizational structures that disperse information, resources, and accountability. An example in a government context is the functional separation of contracting, requiring activities, and accounting and finance. The contracting organization might "own" responsibility for competition compliance, while requiring activities may not have competition incorporated into their processes. These "deficient routines" prevent an organization from being able to comply. Without adequate processes, requiring activities succumb to more uncertainty (i.e., unplanned events such as understaffing, turnover, lack of training, and changing budgets) that cause a need for contract extensions.

Methodology

This research relied upon multiple data analysis methodologies. We use natural language processing (NLP) to prepare the data. Then we apply two machine learning algorithms via random forest regression to predict likely bridge actions—one for bridge modifications and one for bridge contracts. The remainder of this section explains assumptions made, the data sources, data preparation, and model construction.

Advanced analytics techniques are helpful, but not perfect, in detecting bridge contracts. Network analysis is a branch of integrated analysis techniques that allows one to explore relationships between interconnected agents or parties. A network is an operative analytical tool that applies the mathematical language of graph theory and linear algebra and outlines connections. This approach provides insights into the nature of relationships that a particular agency has with specific vendors. In each network, like the one shown in Table 1, each party/agent/person is represented as a node and their interactions amongst each other are represented as edges. Note that an interaction can be any point of relation, like a recipient of a contract or a type of contract and the vendors that can fulfill it. Additionally, fuzzy matching principles are important in connecting bridges with predecessors. Exact or approximate matches in some, but not all, relevant data fields may be sufficient to identify bridges and predecessors. Variation was observed in the timing of original contract end dates and bridge start dates. Other relevant data fields varied occasionally too (e.g., new PSC code selected, new Funding Office codes established).

Table 1. Example of a matching relationship with some matching and non-matching fields (Source: FPDS.gov)

Field	**Original Contract (Predecessor)**	**Bridge Contract**
PIID	TIRNO11D000160019	2032H518F00765
POP Start Date	09/30/2016	09/26/2018
Ultimate Completion Date	09/29/2018	09/26/2019
Contract Length	2 Years	1 Year
Contract Value	$35,787,420.44	$27,555,770.14
Funding Office Name	Commissioner	Commissioner
Vendor UEI	CKV2L9GZKJK3	CKV2L9GZKJK3
Number of Offers	2	1
Product/Service Code Description	SUPPORT- PROFESSIONAL: PROGRAM EVALUATION/REVIEW/DEVELOPMENT	SUPPORT- PROFESSIONAL: OPERATIONS RESEARCH/QUANTITATIVE ANALYSIS
Award Description	OCA Compliance and Data Analytics Support Services	Compliance and Data Analytics Support Services
Extent Competed	Full and Open Competition	Full and Open Competition (*miscoded)
Fair Opportunity / Limited Sources	Fair Opportunity Given	Urgency

IRS contract documents and a FY2021 Navy bridge contract report were used as a source of ground truth to assess the model. Model precision, the proportion of algorithmically identified putative bridge contracts that are actually bridges was calculated. The formula for precision is True Positives / (True Positives + False Positives).

Methodology Assumptions

At the inception of this research, we outlined a list of assumptions about bridge contracts, bridge modifications, and the data, which were used as a basis in the development of the algorithm.

1. A bridge contract will have the same vendor name, funding office, and department as the contract it is bridging (i.e., its predecessor).
2. Procurement instrument identification numbers (PIID) —contract numbers—were considered erroneous if less than four characters.
3. A bridge modification will share the same award PIID as its modified award.
4. Service contracts can be unilaterally extended for up to six months via modification under the authority of FAR 52.217-8. The scope of this research includes extensions under the authority of FAR 52.217-8, which is consistent with the GAO's definition of bridge contracts and is a common mechanism used (GAO, 2016). Notably, not everyone agrees that a bridge contract encompasses an extension under FAR 52.217-8 (Longo, 2020).

Data Source and Preparation

Contract Award Data was downloaded from USASpending.gov and used to develop and train the model. The Navy provided a report of bridge contracts and modifications from FY2021 which was used to classify entries in the data. Additionally, IRS procurement documents and standard forms (Standard Form [SF] 1012 Limited Sources Justification, SF 1013 Justification for Other Than Full and Open Competition (JOFOC), SF 1014 Justification for an Exception to Fair Opportunity (JEFO)) were scanned using NLP techniques to identify bridge keywords, providing additional labels for the data. A total of more than five million contract actions were compiled for analysis covering the period from FY2010 to FY2022.

Both the Bridge Contract Classifier and Bridge Modification Classifier were framed as problems within the conceptual framework of graph theory. Essentially, a graph can be thought of as a collection of objects called “vertices” and relationships between those objects, called “edges.” Bridge actions, whether contracts or modifications, are heavily context-dependent occurrences. Consequently, creating a network that captures how data entries are related to one another offers an advantage in the task of identifying anomalies. Both classifiers made use of a “directed” graph structure, wherein edges can be thought of as arrows, linking an award A to an award B but not award B to award A. Otherwise, the structure of the network differed slightly between each classifier to better suit the classification task.

Certain column values needed to be transformed to be fed into our random forest models. Product or service codes were categorized into one-hot encodings which indicated whether the award was for knowledge-based services, logistics or transportation services, operations services, or medical services/supplies.

Bridge Contract Classifier Methodology

As received from the USASpending.gov website, the contract data to be used in the Bridge Contract Classifier needed to be processed. The first step was to aggregate properties of awards over their full life cycles. This was done by chronologically ordering the base award and modifications of a shared PIID and aggregating values such as period of performance and contract value. Any contracts with a PIID of less than 4 characters were seen as erroneously entered and were consequently removed. After this process of simplifying our data and trimming out errors, we were left with a data population (*n*) of 954,218.

To place these data entries into our graph, we represented contracts as vertices, and defined a set of rules governing whether or not an edge should be drawn between them. Creating a set of constraints on which edges can exist prevents the graph from becoming too complex. With fewer edges, there is less computation required to assess whether an edge may be linking a bridge award to its predecessor. The constraints dictated that an edge should only be directed from a potential predecessor to a potential bridge if the two awards shared a vendor, shared a funding office, and were chronologically sequential. The chronological ordering prevented the construction of edges pointing “backwards in time,” as a bridge will never precede its predecessor. Understanding that contract award dates can differ from actual performance dates, we also remove any edges where the period of performance gap is less than seven, meaning the potential bridge began more than seven days before the potential predecessor ended.

The computational complexity of creating a graph which represented chronologically-ordered edges between all awards with the same vendor and funding office required that we train our model on a subset of the data. To do this, we sampled 1,000 vendor-funding office “clusters” from our graph and ensured that the clusters containing our labelled entries were included. This resulted in a final data set size of awards (vertices) = 4,904 and edges = 82,645. Those contract actions flagged as bridge contracts can be verified with additional data from justifications and approvals (J&A) available on SAM.gov or from agency reports that track bridge actions.

We create features using our data that we believe will provide signals for classifying bridges. Plots and descriptions of these features are provided in Figure 1. The first feature we created was similarity of award description. After tokenizing and stemming the award description field of the individual awards, we scored the similarity of descriptions across edges in our graph. Figure 1 shows that bridge edges likely do not share a description similarity distribution with non-bridge edges.

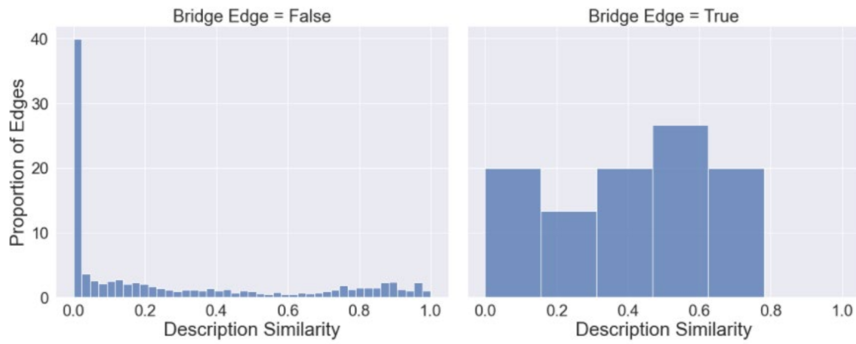

Figure 1. Comparing Award Description Similarity for Bridge and Non-bridge Edges

To follow up on an initial assumption that bridge awards have a similar value per day to their predecessors, we created a feature that flags whether or not the percent change in value per day is greater than 50% and less than 300%. Figure 2 shows the distribution of bridges and non-bridges with similar values per day.

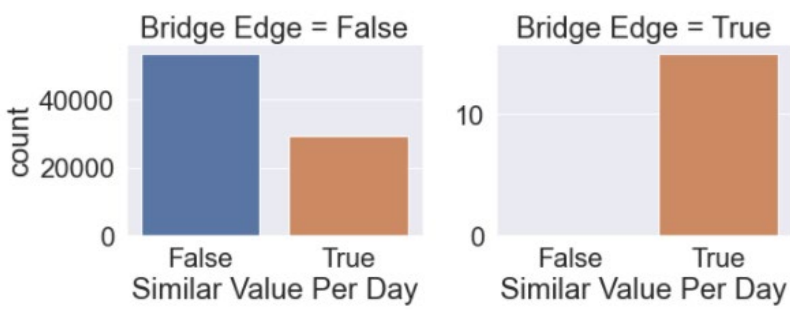

Figure 2. Comparing Edges where 0.5 < Percent Change in Value per Day < 3 for Bridge and Non-bridge Edges

Bridge contracts are typically used as a vehicle for covering a temporary lapse in service at the end of an expiring contract. To capture this, we calculated the number of days between the end of a predecessor's period of performance (PoP) and the beginning of a potential bridge. This is shown in Figure 3.

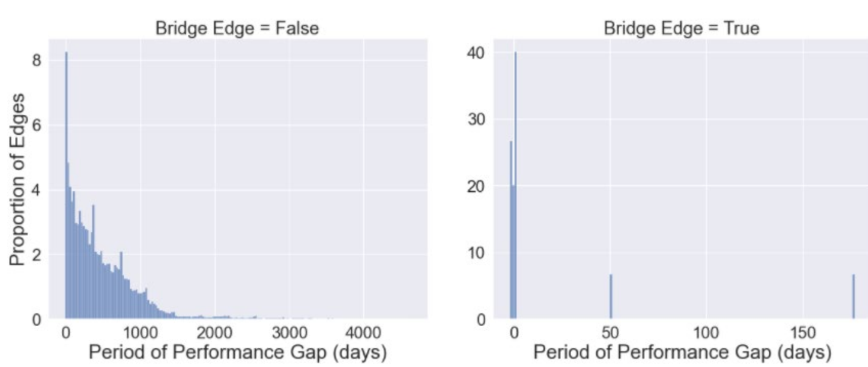

Figure 3. Comparing PoP Gap for Bridge and Non-Bridge Edges

Due to the irregular circumstances presented by the COVID-19 pandemic, funding was specifically allocated to certain awards to maintain service. We have flagged those as shown in Figure 4.

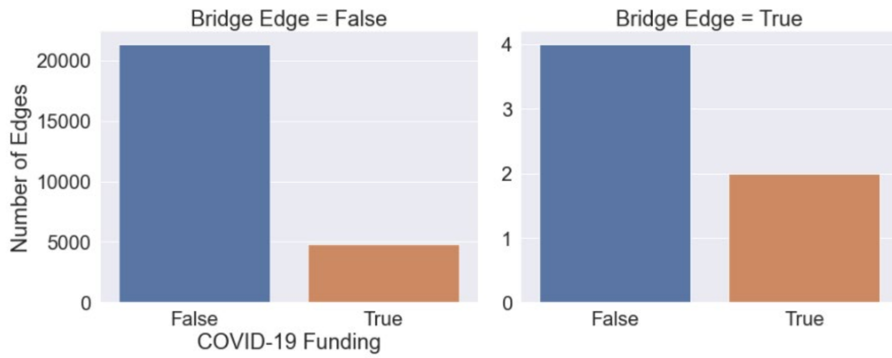

Figure 4. Number of Edges Where Either Award Received Funding Related to COVID-19 (only counts edges where the predecessor's period of performance began in 2019 or later)

The end of the fiscal year could also bring urgency to procurement that encourages the use of bridge contracts. We created a flag for edges where the predecessor expires within the 4th quarter of the fiscal year.

Figure 5. Shows Count of Edges Where Predecessor Expires in 4th Quarter of Fiscal Year

Bridge contracts do not follow proper procedure for allowing potential vendors to compete for the award. As a result, the fair opportunity sourcing code field in USASpending.gov provides an important indicator of how vendor sourcing took place. Table 2 shows the counts for edges wherein the potential bridge was flagged as a "follow on action following competitive initial action." After these features were created, the data was ready for the Random Forest Classifier, which has 50 decision trees.

Table 2. Edge Counts for Bridge Categories and a Fair Opportunity Sourcing Category of Interest

	Bridge Edge	**Non-Bridge Edge**
Follow-on Action after Initial Competition	2	163
Other Fair Opportunity Sourcing Code	13	82467

Bridge <u>Modification</u> Classifier Methodology

The same data set was used for the development of the bridge modification classifier. The graph was created to represent modifications as the vertices with edges pointing backwards in time such that the second modification on an award points to the first modification on the same award, and that first modification points to the base award (mod number = 0). We were able to process a much larger sample of data as the clusters of modifications were significantly smaller due to the fact that edges only existed between modifications that shared an award PIID. Without needing to sample our data as heavily as with our bridge contract data, we were left with vertices = 626,354 and edges = 38,279. The differences in vertices and edges is largely accounted for by awards which have no modifications. This allowed for additional data fields to be defined as shown in Table 3.

Table 3. Data Features for Modification Edges

Feature	Definition
Action Rank	Modification order as determined by action date
Action Value	Change in total dollars obligated
Action Performance Days	Period of performance of a modification (i.e., 1-month extension)
Value Per Day	Total dollars obligated divided by number of days in period of performance
Exercise Rank	The number of times an option has been exercised on an award
Number of Options	An approximation of the number of options available to the award; calculated as the number of years in the period of performance of the initial contract award
Potential End Date Delta	Period of performance extension caused by modification; calculated as difference in period of performance potential end dates

At this point, we have the training data necessary for our model. The model trained is a Random Forest Classifier (as defined in the sklearn.ensemble). We maintain the default parameters for the model and train a set of 50 decision trees.

Results

Bridge <u>Contract</u> Classifier Results

Figure 6 shows the mean decrease in impurity (MDI) for our model for each feature included in the training set. The model was trained and run 100 times and the feature importance plot has taken the mean MDI across those iterations. Features suffixed by an “_x” belong to the potential bridge contract while features suffixed by “_y” belong to the predecessor.

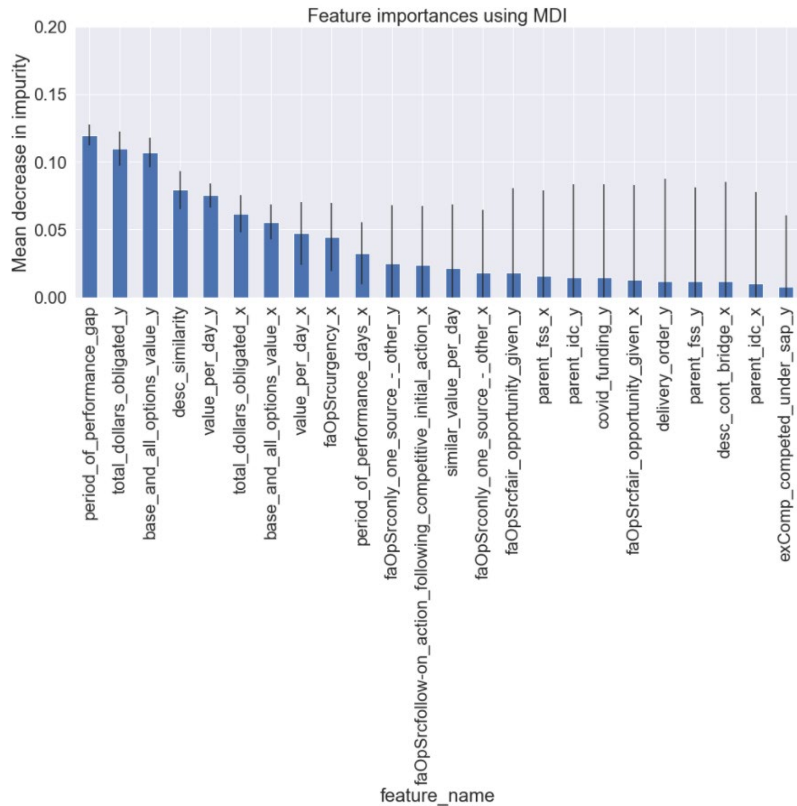

Figure 6. Mean Decrease in Impurity for Top 24 Features Across 100 Iterations

The outputs of our model are dependent upon the threshold we set for its predictions. By default, the model will only classify something as a bridge if more than half of the decision trees agree that it should be labelled as such. This produces Figure 7. The confusion matrix shown in Figure 7 shows that the model produced 13 true positives and 2 false negatives. The precision of the classifier is defined as the number of true positives divided by the total number of predicted positives. Precision can be seen as the accuracy of the model's positive outputs. The recall is calculated as the number of true positives divided by the total number of positives in the test data and describes the probability that a bridge is correctly identified.

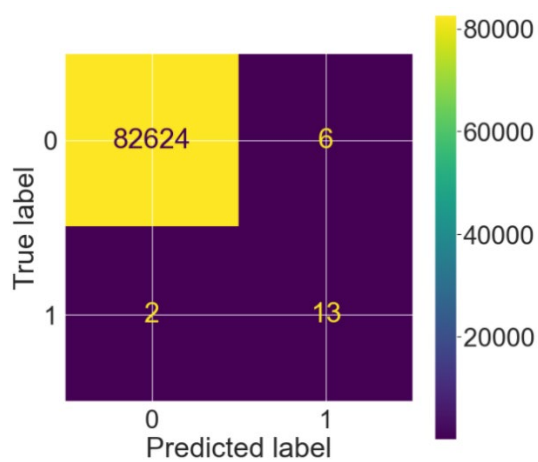

Figure 7. Confusion Matrix From the Random Forest Model's Output Precision=.684, Recall=.868

Bridge Modification Classifier Results

With fewer labelled bridge modifications than bridge contracts, the outputted model ran the risk of becoming highly biased toward the training set. However, the outputs of the model's feature importance align closely with our initial assumptions for important signals of bridge modifications. Figure 8 depicts the feature importance breakdown for the bridge modification random forest. For bridge modification features, "_y" indicates a data point belonging to a preceding modification and "_x" fields belong to the potential bridge mod.

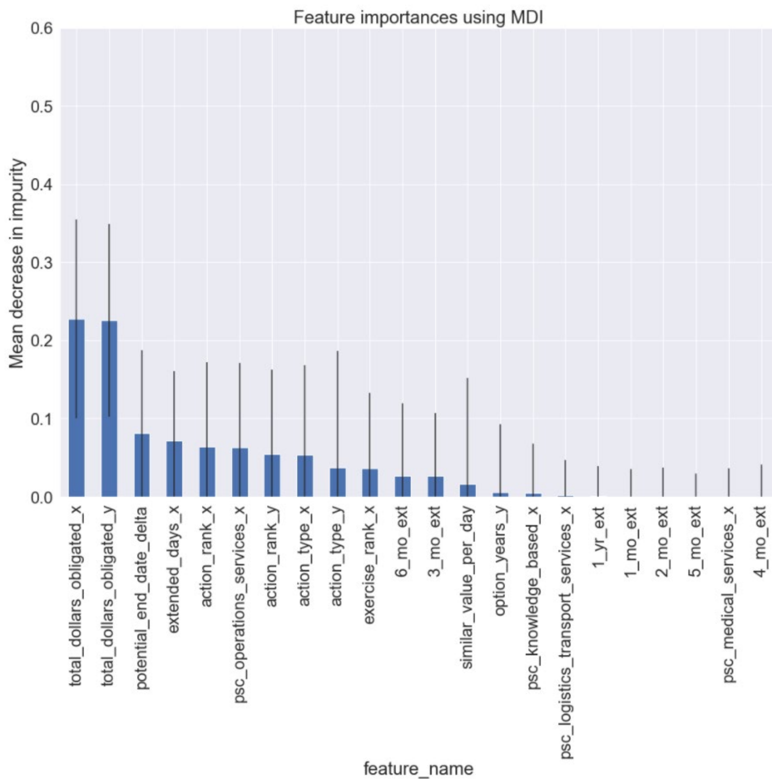

Figure 8. Mean Decrease in Impurity for Top 24 Features Across 100 Iterations

As can be seen in the confusion matrix shown in Figure 9, our model has produced 2 true positives and 2 false negatives. The model's precision indicates that roughly 66% of its positive outputs will be bridges; its recall indicates that there is a 50% chance that a bridge is correctly identified.

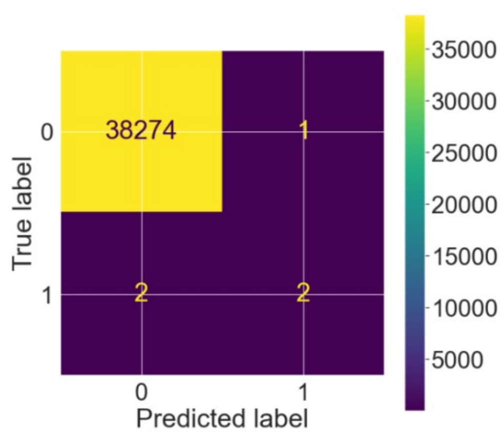

Figure 9. Confusion Matrix From the Random Forest Model's Output Precision = .667, Recall = .5

Results Conclusions

The results of both models are highly biased due to the few labelled bridges that we provided in training. As a result, the models tend to be extremely conservative, claiming that an entry is a bridge only if it has seen a very similar combination of features being labelled as a bridge in the past. However, in their current state, these models output a few potential bridges which are not labelled as bridges but seem to fit the pattern of bridges in the training set (i.e., false positives). To continue to improve the models, these cases should be investigated, and if determined to be bridges, fed back into the models as training data.

Identifying which awards were either bridges or contained a bridge modification within them can be done by closely investigating the model outputs. Each model outputs a table of actions (contracts or modifications) and the model's predicted "probability of being a bridge." Revising these outputs and confirming the model's predictions will be key to the longevity and continued improvement of this analysis. At the moment, the model is already turning up contracts and modifications which appear to be bridges upon closer inspection, but were not labelled as such in the training data.

Assumption Conclusions

Some of our initial assumptions did not hold true. Our assumption that vendor name and contract NAICS code would remain the same between predecessor and bridge contract applied in a majority of cases, but not always (example 1: vendor legally changed name; example 2: a bridge contract was given to a new vendor while a contract award was under protest). However, this was identified to be an outlier case, the final bridge contract edge constraint requires vendor name and NAICS code equivalence. With greater computing power, this edge constraint could be loosened, capturing these edge cases.

Discussion

The purpose of this research was to develop a data-analytic methodology to reliably identify bridge contract actions. The following two research questions were addressed.

(1) How prevalent is the practice of bridge contracts?

(2) Are there any discernable patterns in bridge contract use?

Previous efforts to identify the prevalence of bridge contracts have suggested that the proportion of actions which are bridge actions is greater than the proportion found by our models. This is very likely due to the lack of labelled bridge contracts and modifications in the training data. For example, in our bridge contract model outputs, many of the awards with non-zero probabilities of being bridges actually contained the word "bridge" in their award descriptions. This shows that our model is likely turning up only the most obvious bridge contracts, and those which do not "self-identify" likely slip through the cracks—evidence of a biased model. Consequently, the prevalence of bridge actions may be significantly greater than our model suggests.

As for research question number 2, the most predictive features of bridge contracts include (in order of predictive power): the period of performance gap between the predecessor and bridge contract action, the base and all options value, dollars obligated, similarity in the award descriptions, a consistent value per day among the predecessor and bridge contract action, urgency, period of performance days, competition codes in FPDS, and COVID-19 funding. The most predictive features of bridge modifications include (in order of predictive power): dollars obligated, potential end date, action rank, services, action type, exercise rank, six or three month extension, similar value per day, option year, knowledge-based services, and logistics and transportation services.

Managerial Implications

The GAO routinely cites its "Standards for Internal Control in the Federal Government" (GAO, 1999) to determine that agencies do not "identify, analyze, and monitor risks associated with achieving objectives, and that information needs to be recorded and communicated to management so as to achieve agency objectives" (GAO, 2016, p. 10). Since NLP is instrumental in linking contract action data from USASpending.gov to procurement documents, those documents (e.g., sole source justifications and approvals [J&A], memoranda for record, price negotiation memoranda) should explicitly identify bridge actions. Additionally, since bridge actions are commonly succeeded by another bridge action, documents in the contract file (e.g., sole source J&As) should report the history of prior extensions and identify the original contract extended. Together, this data would enable agencies to efficiently create dashboards to properly track and manage their use of these actions.

Procurement activities should consider using the modelling process developed herein to analyze their contract data to identify potential bridge contract actions. This will require either routinely contracting for the analyses or developing an organic data science capability including natural language processing and machine learning.

Study Limitations

This research is not without limitations. First, federal procurement data in FPDS-NG is riddled with errors. For example, coding of non-competitive contract actions due to urgency in FPDS-NG was found to be grossly erroneous in 2014—45% miscoded (GAO, 2014). Thus, any analyses based on this data is likely faulty to some degree.

We do not have an understanding of the true prevalence of bridge modifications. As a result, no assertions can be made that we have found a representative sample of labelled data for our model to be trained on. This results in a model which is highly biased to very few flagged data points. As more data becomes available on true bridge modifications, the model can be improved through iterative training.

Future Research Directions

Future research could refine the prediction models by adding features to improve predictive accuracy. While omitted from the scope of this study, future research could explore analytical techniques to detect edges between successive bridge actions. This is important since the GAO's analysis (2016) revealed five requirements that were bridged multiple times each (from 3 to 12 times). Future research could apply the methodology developed herein to contract actions of government organizations beyond the IRS and U.S. Navy.

Conclusion

Bridge contract actions pose problems such as impeding competition, paying higher prices, and increased transaction costs. Few agencies rigorously identify and control bridge contracts. This research developed a data analytic methodology to identify bridge contracts. The most predictive features of bridge contracts and bridge modifications include: the period of performance gap between the predecessor and bridge contract action, the base and all options value, dollars obligated, similarity in the award descriptions, a consistent value per day among the predecessor and bridge contract action, urgency, period of performance days, competition codes in FPDS, COVID-19 funding, potential end date, action rank, services, action type, exercise rank, six- or three-month extension, option year, knowledge-based services, and logistics and transportation services. Advanced analytics techniques are helpful, but not perfect, in detecting bridge contracts. With continued development and iterative training the models have the potential to produce more accurate results.

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References

Boland, M., & Godsell, D. (2021). Bureaucratic discretion and contracting outcomes. *Accounting, Organizations and Society*, 88, 1–24.

D'Arcy, J., & Herath, T. (2011). A review and analysis of deterrence theory in the IS security literature: Making sense of the disparate findings. *European Journal of Information Systems, 20,* 643–658.

Doke, M. J., Jr. (1995). Competition requirements in public contracting: The myth of full and open competition. *Federal Contracts Report*. *64*(3), S3-S38. Bureau of National Affairs.

Etienne, J. (2011). Compliance theory: A goal framing approach. *Law & Policy, 33*(3), 305–333.

Federal Acquisition Regulation (FAR).

FAR, 48 C.F.R 1.102(b) (n.d.).

FAR, 48 C.F.R 6.302 (n.d.).

FAR, 48 C.F.R 52.217-8 (n.d.).

GAO. (1999). *Standards for internal control in the federal government* (GAO/AIMD-00-21.3.1). https://www.gao.gov/assets/files.gao.gov/assets/aimd-00-21.3.1.pdf

GAO. (2012). *Competition for services and recent initiatives to increase competitive procurements* (GAO-12-384). https://www.gao.gov/products/gao-12-384

GAO. (2014). *Noncompetitive contracts based on urgency need additional oversight* (GAO-14-304). https://www.gao.gov/products/gao-14-304

GAO. (2016). *Defining and tracking bridge contracts would help agencies manage their use* (GAO-16-15). https://www.gao.gov/products/gao-16-15

Hawkins, T., Gravier, M., & Yoder, E. C. (2016). Federal bid protests: Is the tail wagging the dog? *Journal of Public Procurement, 16*(2), 152–190.

Jackson, A., & Alerding, S. A. (1997). Expanding contracting opportunities without competition. *Public Contract Law Journal, 26*(2), 205–220.

Josephson, B. W., Lee, J. Y., Mariadoss, B. J., & Johnson, J. L. (2019). Uncle Sam rising: Performance implications of business-to-government relationships. *Journal of Marketing, 83*(1), 51–72.

Keizer, K., Lindenberg, S., & Steg, L. (2008). The spreading of disorder. *ScienceXpress, 322*(5908), 1681–1685.

Longo, D. P. (2020). On contracting: Avoid bridges to nowhere. *Army AL&T Magazine*, (Summer). https://asc.army.mil/web/publications/army-alt-magazine/

Lucyshyn, W., & Quist, S. (2019). Evaluating the impact of contracting "tripwires" on service acquisitions (UMD-19-200). University of Maryland Center for Public Policy and Private Enterprise.

Malloy, T. F. (2003). Regulation, compliance, and the firm. *Temple Law Review, 76*(3), 451–531.

National Security Agency Office of the Inspector General. (2021). *Audit of National Security Agency's facilities and logistics service contract* (AU-18-0015). National Security Agency.

Orozco, D. (2020). A systems theory of compliance law. *University of Pennsylvania Journal of Business Law, 22*(2), 244–302.

Rossi, J. (1995). Making policy through the waiver of regulations at the Federal Energy Regulatory Commission. *Administrative Law Review, 47,* 255–301.

Williams, L. M., Rose, S. L, & Rehwinkel, A. S. (2012). Competitiveness in the services sector: Understanding the contracting data. D-4659. Institute For Defense Analyses.

Acquisition Research Program
Naval Postgraduate School
555 Dyer Road, Ingersoll Hall
Monterey, CA 93943

www.acquisitionresearch.net