International Journal on Semantic Web and Information Systems
Volume 18 • Issue 1

Longitudinal Study of a Website for Assessing American Presidential Candidates and Decision Making of Potential Election Irregularities Detection

Justin Piper, Drexel University, USA*
https://orcid.org/0000-0002-2646-3375

James A. Rodger, Slippery Rock University, USA

ABSTRACT

The authors employ the concept of word sense disambiguation to determine the inherent meaning of voter intentions regarding possible political candidates from the 2016 Presidential election. They present the findings based on a website (www.presidentselect.com) that they developed, where candidates can be examined and their true assets and competencies in three major areas of eligibility, education, and experience can be deciphered. Data envelope analysis is used to determine underlying word instances for elected and successful outputs. They also utilize the web site results to longitudinally extend these findings for decision making of potential election fraud detection in the 2020 Presidential election, utilizing Benford's Law. The results shed light on these phenomena and provide new insights into the word sense disambiguation literature.

KEYWORDS

Artificial Intelligence, Benford's Law, Data Envelope Analysis, Decision Making, Engineering, Ontological, Word-Sense Disambiguation (WSD)

1. INTRODUCTION

1.1 Examples of How to Pick a Good American President from 2016 Election

This paper begins by investigating the expression "good American president" as an instance of word-sense disambiguation (WSD). Making a prediction of who could become a "good American president" is founded on information discovered while vetting a candidate. The records of previous presidents provide some criteria, including the job model of the presidency, previous presidents' task performance, and behavioral characteristics, such as the profile and measurement of specific actions against expectations. This project examines this in specific, concrete terms. The challenge is daunting, even in simplified examples. However, the harnessed power of information technology, data, mathematical analysis, and algorithms can bring understanding of this phenomenon within reach.

If advanced technology and tools are not used to support voters in a democratic republic, they can be overwhelmed by their responsibility of choosing their government. A good citizen must be

DOI: 10.4018/IJSWIS.305802
*Corresponding Author

actively involved in government at every level, beginning in the town, city, or county, continuing through the district and state, and ultimately finishing with the federal government. It would be a disservice to democracy to make good citizenship sound easy. The denial of adequate support by political parties to voters undermines free rule to an equal extent. That is why research of this kind is essential to improve the system. In our IoT web project, we assess three acting entities: candidate, voter, and website, much like the concepts utilized in IoT transaction processing through cooperative concurrency control on the fog-cloud and the Internet of Medical Things computing environment (Al-Qerem et al. 2020; Masud et al. 2021). This is similar to Cena (2011) who built a model of the user and adapted their services according to their needs and preferences. Fauzi and Belkhatir (2014) investigated the issue of web images and characterized their content with semantic descriptors. In a similar fashion, Motwakel and Shaout (2014) investigated the impact of digital fingerprint image quality on the fingerprint recognition accuracy. Further, Wang et al. (2020) conducted research on visual saliency guided complex image retrieval. Nhi et al. (2022) investigated this phenomenon utilizing a model of semantic-based image retrieval using C-Tree and Neighbor Graph.

This project is conducted to assess and ameliorate the voters' lack of knowledge of their preferred candidate in an upcoming election and the candidates' lack of awareness of how well they fit voter's needs. The guiding goal of the project is to determine how to select future American presidents in an unbiased manner free from fraudulent processes. The first step was to create a set of questionnaires for both the candidate and the voter. These questionnaires are posted on a website created using ASP.NET and C#, and they are to be completed ultimately by the candidates first, followed by the voters. The questions for the candidates are divided into three sections. The first is <u>Legal Eligibility</u>. In this eliminator section, we determine whether the candidate is eligible to contest in the election. If not, the candidate is eliminated and unable to respond the next section of questions. The second section is <u>Basic Bio-data</u>. Here, we build the candidates' resumes through questions on their background, from their name and birth place, to educational qualification and alma mater, to occupational and work history, among other items. This section is useful for voters to learn about the backgrounds of the candidates. The third section is an <u>Intellectual Assessment</u>. This round of questions establishes the knowledge and policies of the candidates in different domain areas (including the environment, education, terrorism, health care, research and development, gun violence, inflation, corruption, and racism) that they would need to face as president. This section is important because a voter might only be considering candidates for president in terms of a limited set of responses to a given range of concerns, while the candidates might be thinking in different terms or might not address the voter's pet issues at all. The responses to this set of questions would benefit both the voter and candidate. In this way, each voter would have a chance to understand the unique thinking of each candidate that will guide that candidate if given a chance to lead the country as president. For their part, in this way, the candidates could come to understand what the voters expect from them, using the equivalent portion of the voter survey. Once the candidates finish their responses, the voters will receive their questionnaires. Of course, the voters' questionnaire is not as complex as the candidates' and is more generic but covers the same domain areas as the candidates' questionnaire. The voters here have the same privilege as the candidates of prioritizing the questions. Once the voters have completed their questionnaires, the website will process the answers and begin matching voters' responses to those provided by the candidates. We have implemented a Data Envelop Analysis (DEA) to provide weighted averages to match the priorities assigned for different questions by the voters and the candidates to indicate which candidate best matches a given voter's answers. This method is used to match the asymmetrical data provided by the two groups. For every question the voter answers, there is more than one question on the same subject answered by the candidate. This is done to obtain more detailed information on the candidate's perspective on the given topic. Because the voters answer fewer questions than the candidates, the matching algorithm must be complex. The weighted average method helps compute the average for all candidates' answers and matches the averages for every question answered by the voter. This will act as a self-assessment for the candidate and a voter–candidate compatibility calculator for the voter.

Leading into the 2020 Presidential Election, then candidate Joe Biden made a Oct. 24 appearance on the podcast named "Pod Save America." It was during this podcast that some of Biden's remarks gained attention for some of the words he spoke. A transcript, overview, and fact check are available at: https://www.factcheck.org/2020/10/viral-posts-take-biden-quote-on-voter-fraud-out-of-context/. The part of Biden's remarks that drew criticism were:

Secondly, we're in a situation where we have put together, and you guys did it for our administration — President Obama's administration before this — we have put together I think the most extensive and inclusive voter fraud organization in the history of American politics. What the president is trying to do is discourage people from voting by implying that their vote won't be counted, it can't be counted, we're going to challenge it and all these things. If enough people vote, it's going to overwhelm the system.

In the aforementioned link, the fact check rationalized that:

When Biden used the phrase "voter fraud organization," he was referring to the systems put into place to help people who have trouble voting. He wasn't admitting to voter fraud.

Here, we take a novel approach in re-visiting whether the statement "we have put together I think the most extensive and inclusive voter fraud organization in the history of American politics" is a perspective, a fact, or open to interpretation as word sense disambiguation by different individuals. For instance, was this a premonition, innocuous, a slip of the tongue, or spur of the moment word choice. We employ Benford's Law to determine if there are any indications that fraud actually did occur in the 2020 presidential election. (Benford, 1938).

Benford's Law states that any random numbers will have a specific result as to which digits appear first in each data set. This makes sense when you analyze a phenomenon from a logarithmic scale perspective. This law can be applied to the distance of the planets from the sun, the distance of the stars from the Earth and even for the Fibonacci numbers. In these examples, each case produces a histogram that is almost identical to those provided by Benford's Law. The logarithmic explanation for this mathematical phenomenon is shown below.

Modulo: a = b mod c if a − b is an integer times c; thus 17 = 5 mod 12, and 4.5 = .5 mod 1. Significand: x = S10(x) · 10k, k integer, 1 £ S10(x) < 10. S10(x) = S10(xe) if and only if x and xe have the same leading digits. Note log10 x = log10 S10(x) + k. Key observation: log10(x) = log10(xe) mod 1 if and only if x and xe have the same leading digits. Thus often study y = log10 x mod 1. Advanced: e 2πiu = e 2πi(u mod 1) .

Neustein (2012) analyzed three different areas of natural language processing (NLP) from a cognitive science perspective, namely, simulation of human language use in spoken dialogue systems, reference generation and referential practices, and WSD. Selvaretnam and Belkhatir (2012) used NLP for information retrieval. Moteshakker Arani (2021) employed NRL to convert semantics into structured information. Dimitrakis et al. (2020) utilized NLP in a Question Answering (QA) system aimed at supplying precise answers to questions, posed by users in a natural language form. In addition, Neustein (2008) rethought the science of NLP by exploring the connection between sense abstractness and semantic activation in WSD. Studies in subjects as varied as finance and medicine have used extractive summation, sentiment classification, and corpus-based stemming techniques, which are taken from this field of study (Arroyo-Fernández, Curiel, & Méndez-Cruz 2019); (Singh & Gupta, 2019); (Xu, Huang, Zhang, & Wang, (2019); (Xing, Cambria, & Zhang, (2019). Kwong (2008) examined the chronological evidence for internal lexicons and suggested that concrete senses are more readily activated than abstract ones and that broad associations are more easily triggered than narrow paradigmatic ones. Ion and Tufis (2009) describe two different WSD systems, one of which is applicable to parallel corpora and the other of which is less knowledge rich. They found that the performance of the two WSD systems could be objectively compared if the same sense inventory was used. They concluded that multilingual WSDs are more precise than monolingual ones. Cristea (2009) examined cohesion as part of the veins theory. He computed strings of discourse units to find the best fit, taking an incremental view of discourse processing, linguistic observations, cognitive short-term memory, and online summarization. Bateman (2010) reviewed recently developed approaches to the semantics of natural language expressions that drew on a new combination of the principles of ontological engineering and natural dialogue system behavior involving spatial information. Witt (2015) proposed a probabilistic response time model to calculate the likelihood of user response at any time that can be used for timeout setting optimization. Ismail et al. (2022) presented a new alignment word-space approach for snipped text similarity. Lakhfif and Laskri (2016) described the design and implementation of a computational model for an Arabic semantic parser that could create a deeper semantic representation of Arabic text. They showed that the integration of WordNet and FrameNet can improve disambiguation accuracy. Cai et al. (2018) looked at semantic similarity using a weighted path distance in WordNet. AlMaayah, Sawalha, and& Abushariah et al. (2016) developed an automatic extraction model for synonyms, which they used to construct their Quranic Arabic WordNet, which uses traditional Arabic dictionaries. This project improved the recall of semantic search for Quranic concepts by 27%. Lu, Liu, Dong, and & Chen (2016) et al. described each (POS) tagger used to classify unannotated natural language words with POS labels for categories such as noun, verb, and adjective. Kadim and Lazrek (2016) proposed a hypothesis for the selection results for a POS tagging implemented for the Arabic language and presented numerous cases where the morphosyntactic state of a word depends on the states of the subsequent words. Alian, Awajan, and Al-Kouz (2016) et al. introduced a vector space to Arabic WSD, utilizing Wikipedia as a lexical resource for disambiguation. This approach was also tested on English words for improved generalizability. Wei et al. (2015) performed a similar approach using text clustering and lexical chains. Spanakis and Siolas (2012) proposed a document Self Organizer (DoSO), an extension of the classic Self Organizing Map (SOM) model, in order to deal more efficiently with a document clustering task. El Mahdaouy, El Alaoui, and Gaussier (2018) et al. developed word embedding semantic similarities and incorporated them into existing probabilistic information retrieval (IR) models for Arabic to deal with term mismatch. Their results showed that extending the IR model can improve the baseline bag-of-words model and that their extensions significantly improve the Arabic WordNet-based semantic indexing approach. Zhang et al. (2020) and Ruas et al. (2019) performed a similar process through definition and usage. Yang and Mao (2016) used word embedding to integrate knowledge. Boudchiche and Mazroui (2018) created an lemmatization, including two modules. They adopted hidden Markov models and validated this approach using a labeled corpus consisting of about 500,000 words.

Krawczyk and McInnes (2018) noted that NLP plays a key role in man–machine interactions, but that there is a challenging subdomain in this area, namely, WSD, defined as the task of identifying the intended sense of an ambiguous word using the context through machine learning and pattern recognition. They proposed a local ensemble learning solution with a one-class decomposition of a multi-class problem that displays robustness for both multi-class skewed distributions and class label noise. Wang, Li, Liu, and Hu (2017) tested the use of a sprinkled semantic diffusion kernel. They employed class knowledge of training documents to supplement co-occurrence knowledge and construct an augmented-term document matrix by encoding class information as additional terms and appending them to training documents. Duque, Martinez-Romo, and Araujo (2016) explored whether multilingualism can help solve problems of ambiguity or the conditions required for a system to improve the results obtained using a monolingual approach, in WSD. They determined the optimal means of generating those useful multilingual resources, and they studied different languages and sources of knowledge. Duque, Stevenson, Martinez-Romo, and Araujo (2018) presented a new graph-based, unsupervised technique to address this problem. They used a knowledge base in the form of a graph built from co-occurrence information on medical concepts as found in scientific abstracts. Similarity, Sydow et al. (2013) utilized graphical entity summaries on knowledge graphs. Sydow et al.

(2013) posit the notion of diversity in graphical entity summarization on semantic knowledge graphs. Izquierdo, Suárez, and Rigau (2009) used a very simple method of deriving a small set of appropriate meanings employing the basic structural properties of WordNet. They empirically demonstrated that this automatically derived set of meanings groups senses into an adequate level of abstraction to perform class-based WSD, with 80% accuracy. Singh and Siddiqui (2015) investigated the role of hypernym, hyponym, holonym, and meronym relationships in Hindi using WSD. They found that maximum improvement in single semantic relationships was obtained using hyponyms, which resulted in an overall improvement in precision of 9.86%. Gutiérrez, Vázquez, and Montoyo (2017) presented an unsupervised approach to the solution of semantic ambiguity based on the integration of the Personalized PageRank algorithm, applying word-sense frequency information. This was supported by a multidimensional network including a set of resources (i.e., WordNet, WordNet Domains, WordNet Affect, SUMO, and Semantic Classes) and the information provided by word-sense frequencies and word-sense collocations, taken from the SemCor Corpus and studies using the SensEval-2, SensEval-3, and SemEval-2013 datasets. Yepes (2017) evaluated several features derived from the context of an ambiguous word and explored MEDLINE using word embeddings, which, utilizing recurrent neural network classifiers and a combination of unigrams and word embeddings, they found improve the performance of more traditional features with a macro accuracy of 95.97 in the MSH WSD dataset. Kehagias and Petridis (2003) investigated word- and sense-based text categorization using several classification algorithms. Li et al. (2012) employed a traditional supervised classifier for text categorization. Hung and Chen (2016) examined three techniques for WOM documents to build WSD-based SentiWordNet lexicons. Their experiments demonstrated that the results improved with this lexicon. Lopez-Arevalo, Sosa-Sosa, Rojas-Lopez, and Tello-Leal (2017) described an approach to domain-specific WSD by selecting a predominant sense for ambiguous words, using two corpora, a domain-specific test corpus and a domain-specific auxiliary corpus, and they tested their approach on sports and finance texts. Corrêa, Lopes, and Amancio (2018) focused on semantic relationships and represented texts as graphs, but they also constructed a structure through which sense discrimination can be achieved. Their learning algorithm outperformed the support vector machine algorithm, in particular cases. Zhu and Iglesias (2018) used knowledge graphs to exploit semantic similarity.

THEORY AND CALCULATION

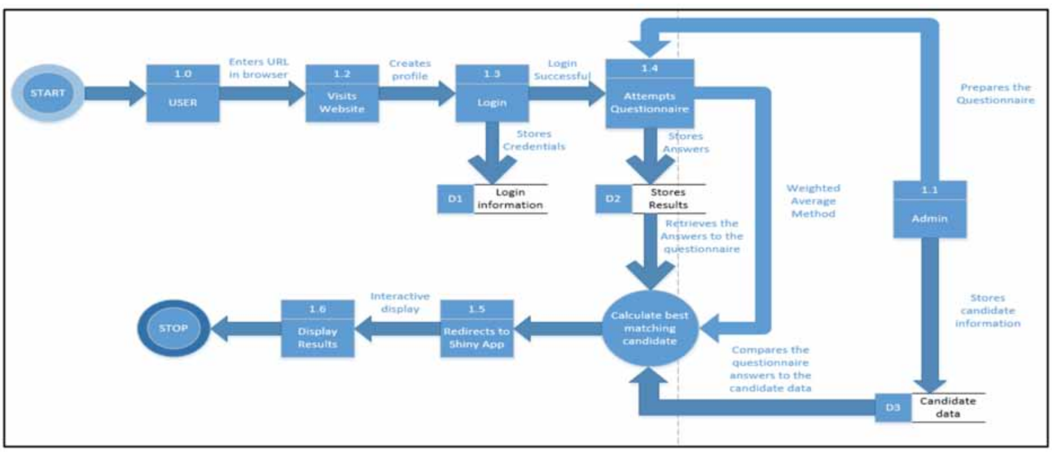
We followed unified modeling language (UML) principles in our website design to guarantee a scientific framework for our analysis. We began this process by creating a use case diagram; at its simplest, such a diagram is a representation of a user's interaction with a system that demonstrates the relationship between the user and the particular use case in effect. The use case diagram of this presidential candidate project contains the actors, administrator, database, voter, and candidate. Each actor is assigned its own associations and events that pertain to it individually.

A data-flow diagram (DFD) is a graphic representation of how data move through an information framework. DFDs can be utilized for the perception of data processing in a structured design. In a DFD, data are shown to flow from an exterior or interior store to internal data store or an external data sink, following an inner process. DFDs include four essential segments that show how data flow within a framework: entity, process, data store, and data flow. Here, an entity is the source or destination of data. Entities and their possible disambiguation are very important in understanding word sense disambiguation and they have been applied to many different outlets. Fernández et al. (2012) looked at entity disambiguation in the news domain. Vashishtha and Susan (2019) investigated social media posts of entity sentiment analysis. Aanen et al. (2015) applied automated product taxonomies to map an ecommerce entity environment. Spina et al. (2013) discovered filter keyword entities for disambiguation of company names in twitter. Seifollahi and Shajari (2019) investigated sentiment entities of news headlines. Tommasel and Godoy (2015) investigated social annotations in Flickr and Delicious. Hunter (2001) indexed documents using entities and keywords for information retrieval of disambiguating words via database queries. Saia and Boratto (2016) exploited entity interactions in a recommender database as a semantic approach.

In order to study word sense disambiguation for selecting an American President, we first need to conceive a logical flow of data within the website. This is illustrated below utilizing a data flow diagram (DFD). Our system is broken down into many process and functions. We can see the user, login information database, results storage database, admin, candidate data stored in database, best-matching candidate process, and results display (using Shiny). Each part of this DFD is given a number from 1.0 to 1.6. The databases are named D1, D2, and D3. The admin maintains the website, adds or modifies questions, and stores candidate information in the database. Finally, the Level 1 DFD is a scaled-up version of the Level 0 DFD. As shown in our literature review, databases are extremely key in semantic disambiguation studies. Gort et al. (2020) showed the importance of semantic-driven watermarking of relational textual databases in semantic disambiguation processes. Therefore, we expanded our DFD to another level. Level 2 shows a decomposition of the process of the Level 1 DFD, and as such there should be an aspect of the Level 2 DFD for every process shown in the Level 1 DFD.

The Level 2 DFD is represented in Figure 1, where it is clear that it is a more refined form of the Level 1 DFD. Here, we describe the repositories of questionnaires in three sections rather than as a single block. The login block in the Level 1 DFD is broken down in the Level 2 DFD into its parts, the user ID and password sections. The remainder of the diagram remains the same. The idea of the DFD levels is to refine the diagram in subsequent levels to develop a more detailed system.

Figure 1. Level two DFD



RESULTS

DEA

In the DEA methodology, a dual model can be employed that shadow prices the primary model developed by Charnes (1978). The constraints that limit efficiency must be less than or equal to 1. Binding constraints have positive shadow prices, which are nonbinding at zero. If a binding constraint unit has an efficiency of 1 in the primary model, then the dual model also has a positive shadow price. The dual model is determined using the ratio of the weighted sum of the outputs to the weighted sum of the inputs. The positive shadow prices in the primary are represented by positive lambda values in the dual model, which are used to identify inefficient units. This is true where the weighting structure is calculated through mathematical programming, and constant returns to scale (CRS) are assumed. In 1984, Banker, Charnes, and Cooper (1984) developed a model focusing on variable returns to scale. In our presidential-candidate site, we used several weight-reflecting, multi-attribute performance measures, such as sensitivity, specificity, bias, and variance of misclassification rate, defined as follows:

Sensitivity = Number of instances that represent a target word (1)
Specificity = Number of instances that represent a context word (2)

where $P(Y_F = y|x)$ is the probability that the outcome of an instance with input x is y and $P(Y_H = y|x)$ is the probability that the outcome of an instance with input x is classified as y.

We used DEA to determine individual weights to assess input-oriented CRS efficiency, output slacks, and efficient output targets. Experience, education, and eligibility were made input classifiers, and elected and successful were output performance indicators. We then found the efficiency scores for each of the decision-making units. Using benchmarking, we determined inefficiencies and used linear programming to find the best weight for v_i to maximize the output.

max ${}^{h}o = å^{v}r\ {}^{y}rm$
$r = 1$

s.t. $_{å}v_r\, y_{rm}$ £ 1 *for* $m = 1,\ldots,M$ (3)

$r = 1$
$v_r = 0,\ s = 1,2,3,4$

The highest efficiency allowed by the constraints leads to output weighting of the outputs. Therefore, $h_o^* = 1$, and the slack constraints were met if and only if word instance o was efficient relative to other instances considered. On the other hand, if $h_o^* < 1$, then the word instance was considered inefficient and therefore was not assigned a higher rating than the reference instance to which it was compared. The use of this methodology led to the results below, including the input-oriented CRS efficiencies, output slacks, and efficient output targets using experience, education, and eligibility as inputs and elected and successful as outputs to determine the corresponding weights.

Table 1. Input-oriented CRS efficiency

		Input-oriented									
		CRS	Sum of		Optimal lambdas						
DMU no.	DMU name	Efficiency	Lambdas	RTS	with benchmarks						
1	good	0.86813	0.756	Increasing	0.244	environment		0.512	violence		
2	fair	1.00000	0.500	Constant	0.500	environment					
3	knowledge	1.00000	0.500	Constant	0.500	environment					
4	fit	0.80700	1.000	Increasing	0.478	environment		0.196	education	0.325	terrorism
5	environment	1.00000	1.000	Constant	1.000	environment					
6	education	1.00000	1.000	Constant	1.000	education					
7	terrorism	1.00000	1.000	Constant	1.000	terrorism					
8	health care	0.26821	0.511	Increasing	0.197	environment		0.293	terrorism	0.021	violence
9	inflation	1.00000	1.000	Constant	1.000	inflation					
10	corrupt	1.00000	1.000	Constant	1.000	corrupt					
11	racism	0.66458	1.129	Decreasing	0.173	environment		0.698	terrorism	0.258	violence
12	R&D	0.74958	1.912	Decreasing	0.135	environment		0.568	education	1.208	terrorism
13	violence	1.00000	1.000	Constant	1.000	violence					

Table 1 provides the data for input-oriented efficiency, together with the corresponding lambdas.

Table 2. Input-oriented CRS model slacks

		Input slacks			**Output slacks**	
DMU no.	**DMU name**	*Experience*	*Education*	*Eligibility*	**Elected**	**Successful**
1	good	0.00000	13.70549	0.00000	0.00000	10.85495
2	fair	26.00000	0.00000	41.00000	0.00000	19.00000
3	knowledge	30.00000	0.00000	30.00000	0.00000	16.00000
4	fit	0.00000	0.00000	0.00000	0.00000	35.42132
5	environment	0.00000	0.00000	0.00000	0.00000	0.00000
6	education	0.00000	0.00000	0.00000	0.00000	0.00000
7	terrorism	0.00000	0.00000	0.00000	0.00000	0.00000
8	health care	0.00000	0.00000	0.00000	0.00000	18.62580
9	inflation	0.00000	0.00000	0.00000	0.00000	0.00000
10	corrupt	0.00000	0.00000	0.00000	0.00000	0.00000
11	racism	0.00000	3.47974	0.00000	0.00000	0.00000
12	R&D	0.00000	0.00000	0.00000	1.82320	0.00000
13	violence	0.00000	0.00000	0.00000	0.00000	0.00000

Table 2 indicates the input-oriented CRS model slacks.

Table 3. Neutral net prediction

Word	Experience	Education	Eligibility	Elected	Successful	$S-successful
Good	17	60	10	1	7	7
Fair	51	1	42	1	5	6.951
Knowledge	55	1	31	1	8	6.75
Fit	42	14	30	2	11	47.434
Environment	50	2	2	2	48	47.672
Education	16	3	77	2	35	46.857
Terrorism	21	30	25	2	51	47.104
Health care	60	40	30	1	6	6.217
Inflation	1	100	21	1	1	7.081
Corrupt	2	9	91	1	10	8.653

The results of the predictive neural network are given in Table 3. The issues of racism, R&D, and violence were removed from the model because they were used to train the neural network. The results demonstrate the validity of using DEA as a tool for WSD in that it uses the entire sample and does not require part of the population to be split off as a training sample. DEA operates on a frontier delimited by constant, decreasing, and increasing RTS. It is not dependent on sheer numbers alone.

Figure 2. Successful and elected

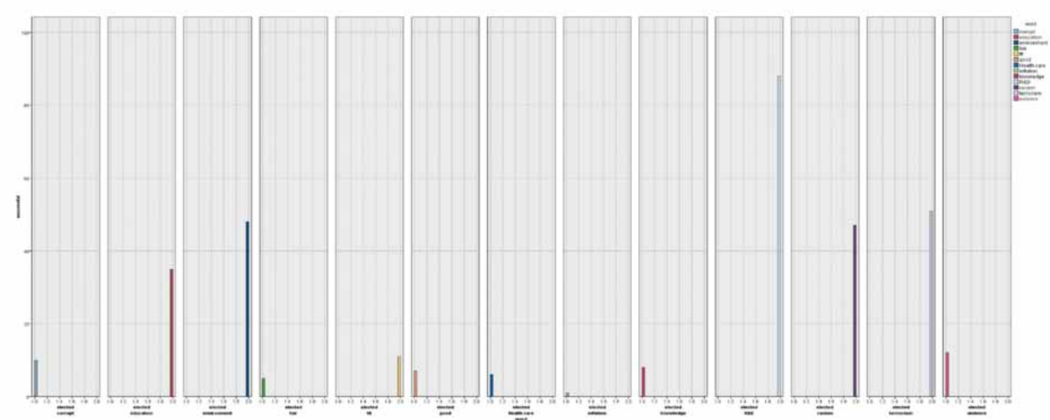


Figure 2 shows a plot of instances of elected against successful, which allows several patterns to emerge. R&D, racism, and terrorism appear much more prevalently where the focus is shifted from increasing returns to sheer numbers. This contrast is important for confirming the value of DEA. The WSD is not a product of numbers alone but rather of increasing returns to scale.

Figure 3. Original word instance visualization

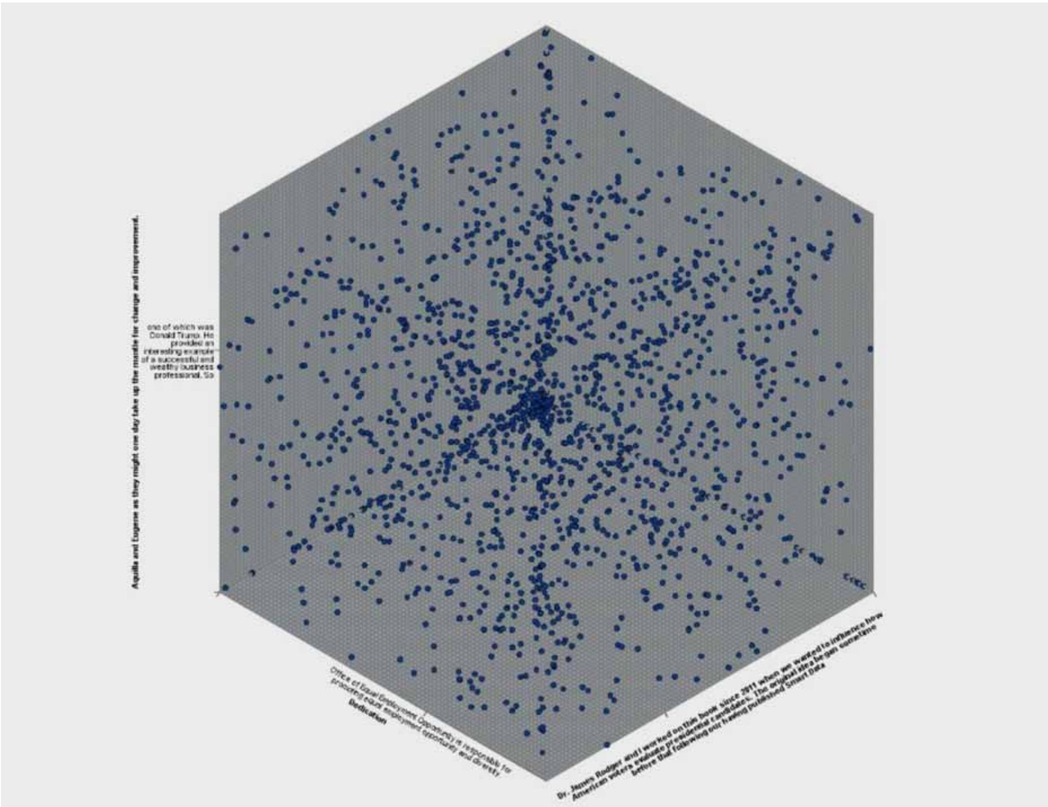


Figure 3 presents a visualization of the original word instances that were text mined for inputting into the DEA analysis. This indicates the thirteen instances analyzed for increasing RTS impact by using Shiny on the results of the responses to the questionnaires.

4.2 Benford Potential Fraud Detection in 2020 Election

For many data sets, such as the Fibonacci numbers, stock prices, street addresses of college employees and election fraud, Benford's Law provides for what percent of the leading digits are

1, 2,3,4,5,6,7,8, and 9. These frequencies are seen in Figure 4.

Figure 4. Benford's Expected Frequencies

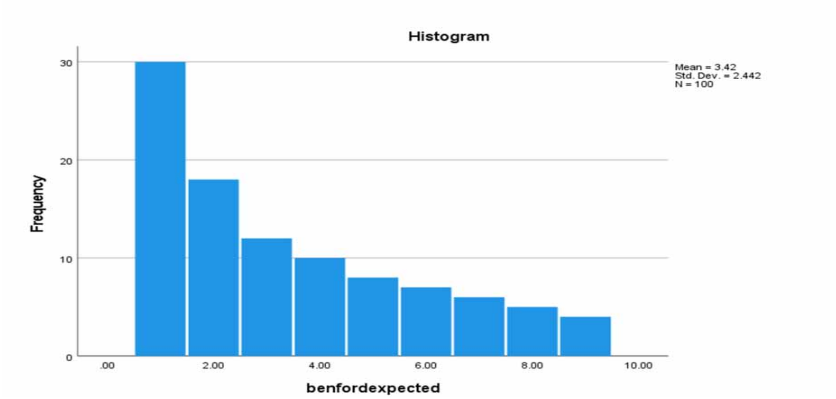


Figure 5. Frequencies

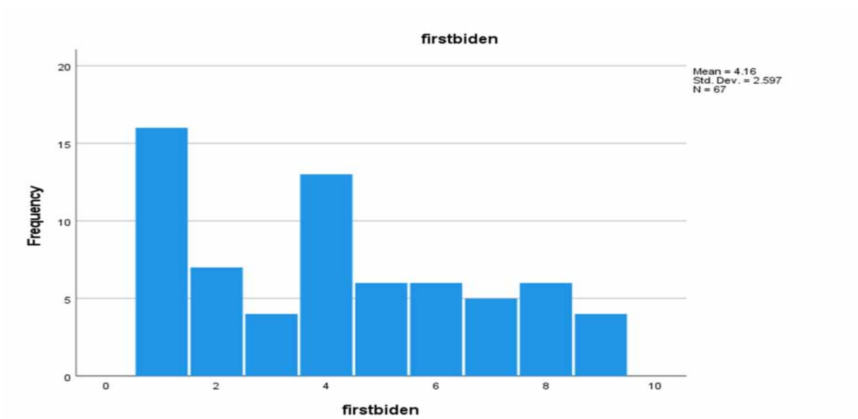


Figure 6. Frequencies

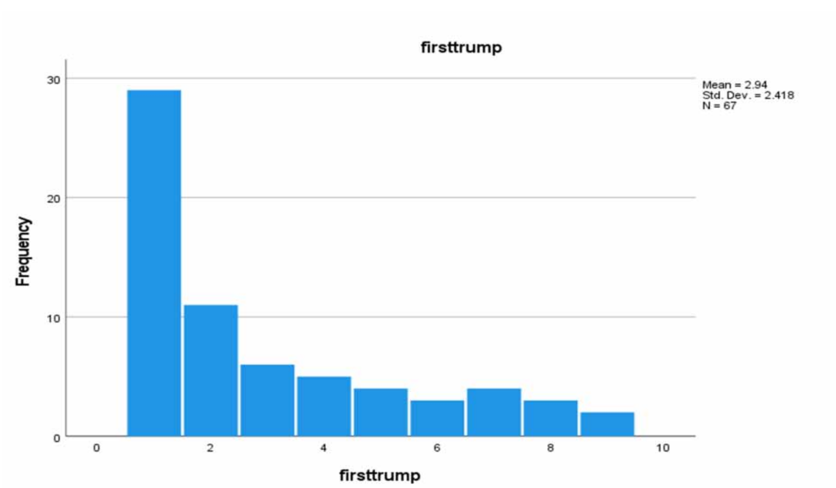


Figure 7. Nearest Neighbor Predictor Space votes

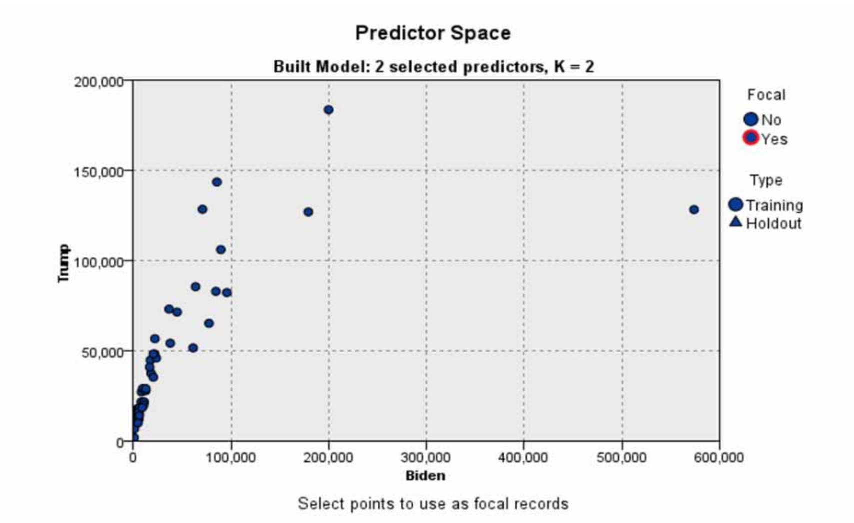


Figure 8. Benford's Law First Number Predictor Space

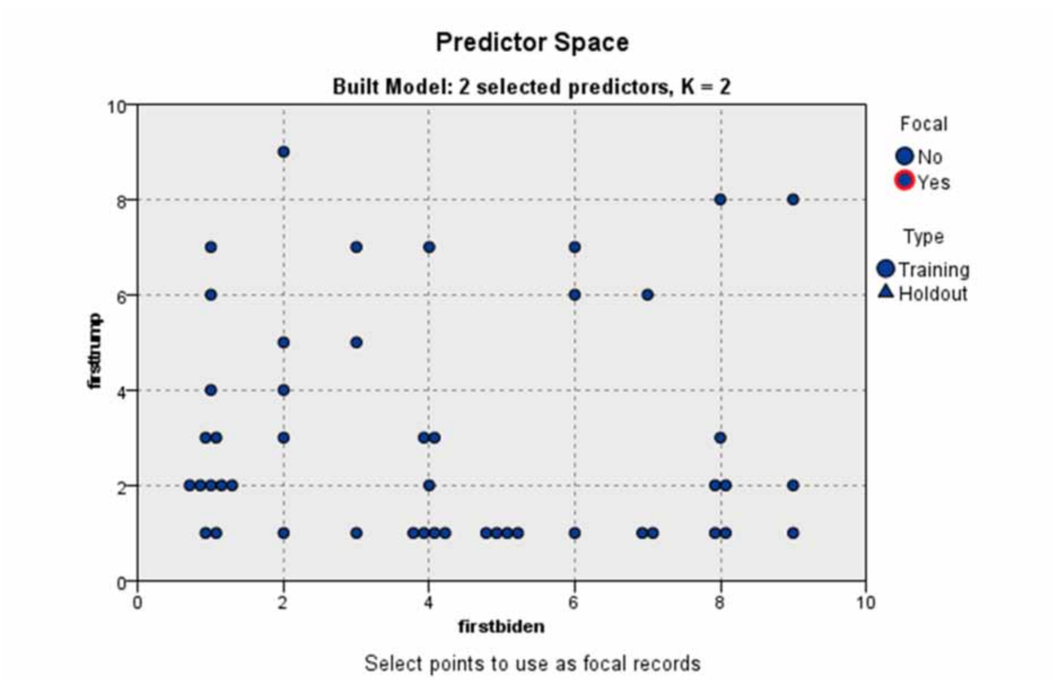


Figure 9. Stacked Pareto Chart

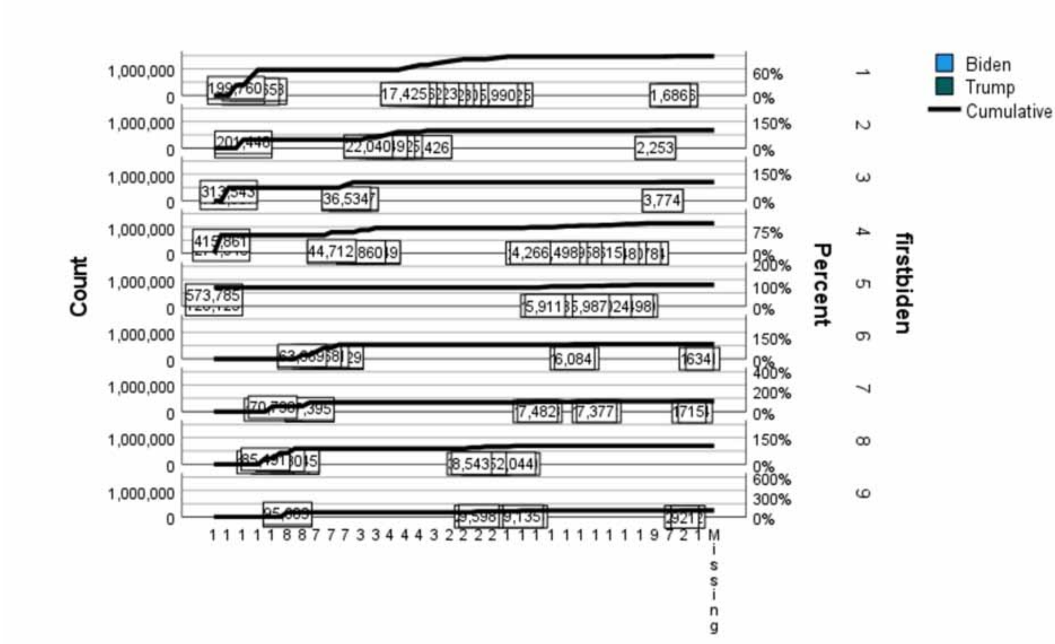
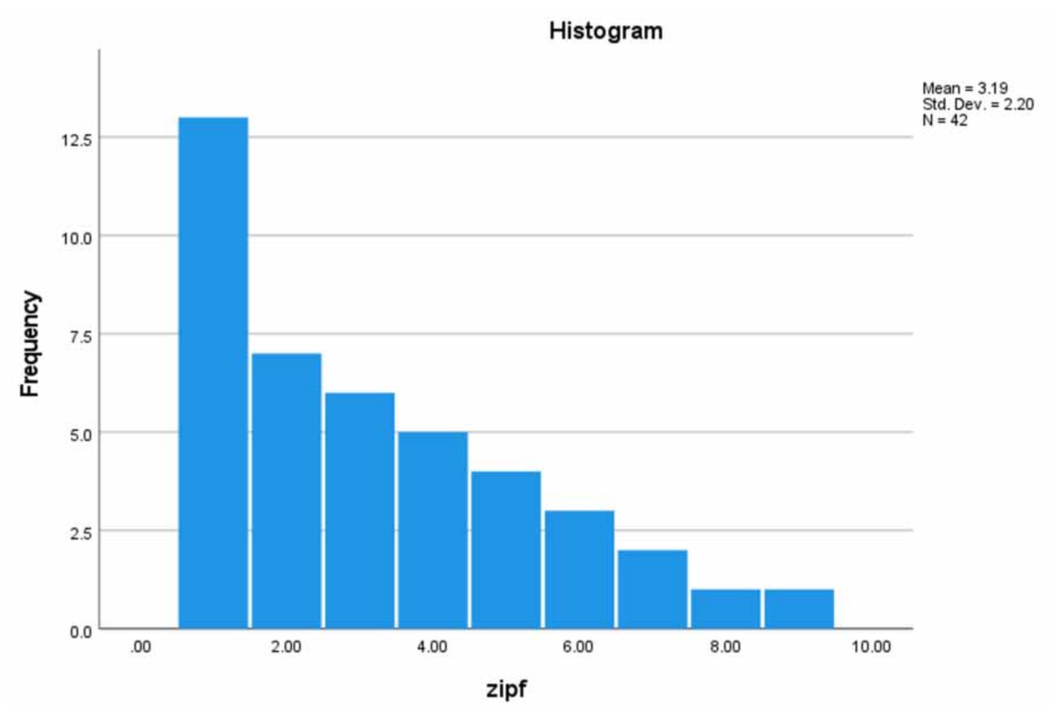


Figure 10. Histogram of Zipf Distribution



Figures 5, 6, 7, 8 and 9 show irregularities in both Benford's Law and Nearest Neighbor predictor space classifications. Figure 10 demonstrates the effect of Zipf's Law from the 2016 election where the frequency of any word is inversely proportional to its rank in the frequency table as the corpus of word sense disambiguation used in our study for experience, education, eligibility and successful variable examples.

Table 5. Discriminant Analysis Classification Results[a,c]

		Winner	Predicted Group Membership		Total
			1.00	2.00	
Original	Count	1.00	11	3	14
		2.00	4	49	53
		Ungrouped cases	0	2	2
	%	1.00	78.6	21.4	100.0
		2.00	7.5	92.5	100.0
		Ungrouped cases	.0	100.0	100.0
Cross-validated[b]	Count	1.00	10	4	14
		2.00	7	46	53
	%	1.00	71.4	28.6	100.0
		2.00	13.2	86.8	100.0

a. 89.6% of original grouped cases correctly classified.

b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

c. 83.6% of cross-validated grouped cases correctly classified.

Table 4. Wilks' Lambda Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.552	37.406	4	.000

Table 4 illustrates that there is a significant relationship indicated (p=.000) with Benford's Law and the winner of each county in Pennsylvania correctly classified (89.6%). However, the misclassification of Type I and Type II errors indicate that irregulates may have occurred in four counties that were predicted to be Biden but went for Trump and 3 counties that were expected to go for Trump, but went for Biden.

DISCUSSION

Table 1 contains raw data of word instances gathered in the initial data collection. Some interesting insights can be gleaned from Table 2. For example, the term good had an input-oriented CRS of 0.868 and an optimal lambda in the return to scale benchmark. Its increasing RTS lambda sum was 0.756, by virtue of the contribution of the environment (.244) and violence (.512). For its part, fit showed an input-oriented CRS of .807 and increasing RTS lambda sum of 1, resulting from environment (.478), education (.196), and terrorism (.325). Likewise, healthcare had an input-oriented CRS efficiency of .268 and an increasing RTS, with a lambda sum of .511 that resulted from the contributions of environment (.197), terrorism (.293), and violence (.021). Racism and R&D had input-oriented CRS efficiencies of 0.665 and 0.750, respectively, and their lambdas were both over 1. The sum of lambdas for racism was 1.129, and the lambda sum for R&D was 1.912. These word instances showed decreasing RTS benchmarks. The remaining word instances for fair, knowledge, environment, education, terrorism, inflation, corrupt, and violence showed constant RTS benchmarks due to input-oriented CRS efficiencies

What ties together our data from the 2016 and 2020 elections is that it has been argued that Benford's law is a special bounded case of Zipf's law, Pietronero et al. (2001). The connection between these two laws occurs when the leading digits of data are satisfied in Zipf's law with $s = 1$ in Benford's law. Zipf's law uses mathematical statistics in terms of quantitative linguistics. It states that given some corpus of language, the frequency of any word is inversely proportional to its rank in the frequency table. Therefore, the most frequent word will occur approximately twice as often as the second most frequent word, and three times as often as the third most frequent word. This is referred to as a rank-frequency distribution and it is an inverse relation. The Zipf distribution is sometimes called the discrete Pareto distribution.

Figures 5, 6 and 7 illustrate some of the irregularities that may have occurred in the 2020 Presidential election as they deviated from both Benford's Law and the Central Tendency Theorem as the vote count increased. Figure 8 demonstrates the predominant deviation from Benford's Law, especially in the categories of 4 and 5 as first numbers in the Biden tally. These results are reinforced by the stacked Pareto charts in Figure 9.

CONCLUSIONS AND FUTURE ISSUES

The application of Benford's Law indicates that voting irregularities occurred in Pennsylvania in the 2020 Presidential election. We cannot tell whether these irregularities are due to an unprecedented mail in voter turn out which, perhaps, could cause anomalies that one would not normally expect to occur. However the Nearest Neighbor Figure 7 gives us insight at another anomaly in Pennsylvania. In Pennsylvania's vote counting history, for the first part of the vote counting process, we see the same pattern for Biden as for Trump and it is a fitted straight line that we would expect. This line shows a relatively stable Biden to Trump ratio that gradually drifts toward Trump up to approximately 50,000 votes. But then as counting continues above this point, the Biden to Trump ratio in ballots inexplicably begin "increasing". Again, this should not happen, because all of the ballots are presumed to be randomly shuffled in the mail system and should not be homogeneous during counting, unless the unprecedented mail in voter turn out can be rationalized to explain such anomalies.

For the 2016 Presidential Election, and based on the theories of word sense ambiguation and ontologies, we have referenced the literature and come to the following conclusions (Wang, Li, Liu, and Hu, 2017) (Lastra-Díaz, Goikoetxea, Hadj Taieb, & García-Serrano, Aouicha, & Agirre, 2019) (Wang, Rao, & QiHuc, 2014) (Huang, Shi, Su, Chen, and Huang, 2015). Our results indicate that the survey administered by the website used in this study is a promising tool for predicting successful presidential candidates. The initial survey was completed by middle class millennials, and it seems clear that voters of this generation would perceive attention to environmental issues and freedom from violence to be 'good.' Likewise, the respondents perceived candidates to be fit in relation to responses to the environment, education, and terrorism. Finally, these voters disambiguated health care from the concept of freedom from the violence and terrorism that has become so prevalent an issue in their lives and the dominant media narratives. Such voters do not appear to see issues of racism and R&D as nearly as important. Further, they consider violence, corruption, inflation, terrorism, education, environment, knowledge, and fairness separate entities unto themselves. For this convenience sample of the younger population, a good, fit, and caring candidate will attend to their concerns for the environment, education, violence, and terrorism, which are the benchmarks in their lives. Future investigation of additional respondents collected through our site will examine a more diverse and nationalized sample to determine how instances of WSD might vary with age, income, and other descriptive statistics.

DATA AVAILABILITY STATEMENT

I confirm I have included a data availability statement in my main manuscript file. This file is called PA County Maps in Excel .xls

CONFLICT OF INTEREST STATEMENT

The authors of this publication declare there is no conflict of interest.

FUNDING INFORMATION STATEMENT

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

Aanen, S. S., Vandic, D., & Frasincar, F. (2015). Automated product taxonomy mapping in an e-commerce environment. *Expert Systems with Applications*, *42*(3), 1298–1313. doi:10.1016/j.eswa.2014.09.032

Al-Qerem, A., Alauthman, M., Almomani, A., & Gupta, B. B. (2020). IoT transaction processing through cooperative concurrency control on fog–cloud computing environment. *Soft Computing*, *24*(8, 2-C), 5695–5711. Advance online publication. doi:10.1007/s00500-019-04220-y

Alian, M., Awajan, A., & Al-Kouz, A. (2016). Word sense disambiguation for Arabic text using Wikipedia and Vector Space Model. *International Journal of Speech Technology*, *19*(4), 857–867. doi:10.1007/s10772-016-9376-y

AlMaayah, M., Sawalha, M., & Abushariah, M. (2016). Towards an automatic extraction of synonyms for Quranic Arabic WordNet. *International Journal of Speech Technology*, *19*(2), 177–189. doi:10.1007/s10772-015-9301-9

Arroyo-Fernández, I., Curiel, A., & Méndez-Cruz, C. F. (2019). Language features in extractive summarization: Huns Vs. Machines. *Knowledge-Based Systems*, *180*, 1–11. doi:10.1016/j.knosys.2019.05.014

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078–1092. doi:10.1287/mnsc.30.9.1078

Bateman, J. (2010). Language and Space: A two-level semantic approach based on principles of ontological engineering. *International Journal of Speech Technology*, *13*(1), 29–48. doi:10.1007/s10772-010-9069-x

Benford, F. (1938). The law of anomalous numbers. *Proceedings of the American Philosophical Society*, *78*, 551–572.

Boudchiche, M., & Mazroui, A. (2018). A hybrid approach for Arabic lemmatization. *International Journal of Speech Technology*, *22*(3), 563–573. doi:10.1007/s10772-018-9528-3

Cai, Y., Zhang, Q., Lu, W., & Che, X. (2018). A hybrid approach for measuring semantic similarity based on IC-weighted path distance in WordNet. *Journal of Intelligent Information Systems*, *51*(1), 23–47. doi:10.1007/s10844-017-0479-y

Cena, F. (2011). Integrating web service and semantic dialogue model for user models interoperability on the web. *Journal of Intelligent Information Systems*, *36*(2), 131–166. doi:10.1007/s10844-010-0126-3

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. doi:10.1016/0377-2217(78)90138-8

Corrêa, E. A. Jr, Lopes, A. A., & Amancio, D. R. (2018). Word sense disambiguation: A complex network approach. *Information Sciences*, *442-443*(C), 103–113. doi:10.1016/j.ins.2018.02.047

Cristea, D. (2009). Motivations and implications of veins theory: A discussion of discourse cohesion. *International Journal of Speech Technology*, *12*(2), 83–94. doi:10.1007/s10772-009-9059-z

Dimitrakis, E., Sgontzos, K., & Tzitzikas, Y. (2020). A survey on question answering systems over linked data and documents. *Journal of Intelligent Information Systems*, *55*(2), 233–259. doi:10.1007/s10844-019-00584-7

Duque, A., Martinez-Romo, J., & Araujo, L. (2016). Can multilinguality improve Biomedical Word Sense disambiguation? *Journal of Biomedical Informatics*, *64*, 320–332. doi:10.1016/j.jbi.2016.10.020 PMID:27815227

Duque, A., Stevenson, M., Martinez-Romo, J., & Araujo, L. (2018). Co-occurrence graphs for word sense disambiguation in the biomedical domain. *Artificial Intelligence in Medicine*, *87*, 9–19. doi:10.1016/j.artmed.2018.03.002 PMID:29573845

El Mahdaouy, A., El Alaoui, S., & Gaussier, O. (2018). Improving Arabic information retrieval using word embedding similarities. *International Journal of Speech Technology*, *21*(1), 121–136. doi:10.1007/s10772-018-9492-y

Fauzi, F., & Belkhatir, M. (2014). Image understanding and the web: A state-of-the-art review. *Journal of Intelligent Information Systems*, *43*(2), 271–306. doi:10.1007/s10844-014-0323-6

Fernández, N., Arias Fisteus, J., Sánchez, L., & López, G. (2012). IdentityRank: Named entity disambiguation in the news domain. *Expert Systems with Applications*, *39*(10), 9207–9221. doi:10.1016/j.eswa.2012.02.084

Gort, M. L. P., & Martina Olliaro, A. (2021, April). Semantic-driven watermarking of relational textual databases. *Expert Systems with Applications*, *167*, 114013. Advance online publication. doi:10.1016/j.eswa.2020.114013

Gutiérrez, Y., Vázquez, S., & Montoyo, A. (2017). Spreading semantic information by Word Sense Disambiguation. *Knowledge-Based Systems*, *132*, 47–61. doi:10.1016/j.knosys.2017.06.013

Huang, Y., Shi, X., Su, J., Chen, Y., & Huang, G. (2015). Using rival penalized competitive learning. *Engineering Applications of Artificial Intelligence*, *1*(C), 166–174. doi:10.1016/j.engappai.2015.02.004

Hung, C., & Chen, S.-J. (2016). Word sense disambiguation based sentiment lexicons for sentiment classification. *Knowledge-Based Systems*, *110*, 224–232. doi:10.1016/j.knosys.2016.07.030

Hunter, A. (2001). A Default Logic Based Framework for Context-Dependent Reasoning with Lexical Knowledge. *Journal of Intelligent Information Systems*, *16*(1), 65–87. doi:10.1023/A:1008741010967

Ion, R., & Tufis, D. (2009). Multilingual versus monolingual word sense disambiguation. *International Journal of Speech Technology*, *12*(2), 113–124. doi:10.1007/s10772-009-9053-5

Ismail, S., Shishtawy, T. E., & Alsammak, A. K. (2022). A New Alignment Word-Space Approach for Measuring Semantic Similarity for Arabic Text. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–18. doi:10.4018/IJSWIS.297036

Izquierdo, R., Suárez, A., & Rigau, G. (2009). An empirical study on class-based word sense disambiguation. *EACL '09 Proceedings of the 12th Conference of the European Chapter of the ACL,* 389–397.

Kadim, A., & Lazrek, A. (2016). Bidirectional HMM-based Arabic POS tagging. *International Journal of Speech Technology*, *19*(2), 303–312. doi:10.1007/s10772-015-9303-7

Kehagias, A., Petridis, V., Kaburlasos, V. G., & Fragkou, P. (2003). A Comparison of Word- and Sense-Based Text Categorization Using Several Classification Algorithms. *Journal of Intelligent Information Systems*, *21*(3), 227–247. doi:10.1023/A:1025554732352

Krawczyk, B., & Mcinnes, B. T. (2018). Local ensemble learning from imbalanced and noisy data for od sense disambiguation. *Pattern Recognition, 78*, 103-119. do:10.1016/j.patcog.2017.10.028

Kwong, O. (2008). Sense abstractness, semantic activation, and word sense disambiguation. *International Journal of Speech Technology*, *11*(3-4), 135–146. doi:10.1007/s10772-009-9041-9

Lakhfif, A., & Laskri, M. (2016). A frame-based approach for capturing semantics from Arabic text for text-to-sign language MT. *International Journal of Speech Technology, 19*(2), 203-228. 10.1007/s10772-015-9290-8

Lastra-Díaz, J. J., Goikoetxea, J., Hadj Taieb, M. A., García-Serrano, A., Ben Aouicha, M., & Agirre, E. (2019). A reproducible survey on word embeddings and ontology-based methods for word similarity: The state of the art. *Engineering Applications of Artificial Intelligence*, *85*, 645–665. doi:10.1016/j.engappai.2019.07.010

Li, J. Q., Zhao, Y., & Liu, B. (2012). Exploiting semantic resources for large scale text categorization. *Journal of Intelligent Information Systems*, *39*(3), 763–788. doi:10.1007/s10844-012-0211-x

Lopez-Arevalo, I., Sosa-Sosa, V. J., Rojas-Lopez, F., & Tello-Leal, E. (2017). Improving selection of synsets on WordNet for domain-specific word sense disambiguation. *Computer Speech & Language*, *41*, 128–145. doi:10.1016/j.csl.2016.06.003

Lu, C., Liu, H., Dong, Y., & Chen, Y. (2016). Corpus based part-of-speech tagging. *International Journal of Speech Technology*, *19*(3), 647–654. doi:10.1007/s10772-016-9356-2

Masud, M., Gaba, G. S., Alqahtani, S. A., Muhammad, G., Gupta, B. B., Kumar, P., & Ghoneim, A. (2021). A Lightweight and Robust Secure Key Establishment Protocol for Internet of Medical Things in COVID-19 Patients Care. *IEEE Internet of Things Journal*, *8*(21), 15694–15703. doi:10.1109/JIOT.2020.3047662

Moteshakker Arani, Z., Abdollahzadeh Barforoush, A., & Shirazi, H. (2021). Representing unstructured text semantics for reasoning purpose. *Journal of Intelligent Information Systems*, *56*(2), 303–325. doi:10.1007/s10844-020-00621-w

Motwakel, A., & Shaout, A.K. (2016). Adnan Impact of digital fingerprint image quality on the fingerprint recognition accuracy, Fingerprint Image Enhancement and Quality Analysis – A Survey. *International Journal of Computer Networks and Security*.

Neustein, A. (2008). Note from the editor: 'Rethinking natural language processing for speech technology'. International Journal of Speech Technology, 11(3-4), 107-108. doi:10.1007/s10772-009-9057-1

Neustein, A. (2012). Think Before You Talk: The Role of Cognitive Science in Natural Language Processing. *NLPCS*: *9th International Workshop on Natural Language Processing and Cognitive Science*, 3-11.

Nhi, N. T., & Le, T. M. (2022). A Model of Semantic-Based Image Retrieval Using C-Tree and Neighbor Graph. *International Journal on Semantic Web and Information Systems*, *18*(1), 1–23. doi:10.4018/IJSWIS.295551

Pietronero, L., Tosatti, E., Tosatti, V., & Vespignani, A. (2001). Explaining the uneven distribution of numbers in nature: The laws of Benford and Zipf. *Physica A*, *293*(1–2), 297–304. doi:10.1016/S0378-4371(00)00633-6

Ruas, T., Grosky, W. I., & Aizawa, A. (2019). Multi-sense emb e ddings through a word sense disambiguation process. *Expert Systems with Applications*, *136*, 288–303. doi:10.1016/j.eswa.2019.06.026

Saia, R., Boratto, L., & Carta, S. (2016). A semantic approach to remove incoherent items from a user profile and improve the accuracy of a recommender system. *Journal of Intelligent Information Systems*, *47*(1), 111–134. doi:10.1007/s10844-016-0406-7

Seifollahi, S., & Shajari, M. (2019). Word sense disambiguation application in sentiment analysis of news headlines: An applied approach to FOREX market prediction. *Journal of Intelligent Information Systems*, *52*(1), 57–83. doi:10.1007/s10844-018-0504-9

Selvaretnam, B., & Belkhatir, M. (2012). Natural language technology and query expansion: Issues, state-of-the-art and perspectives. *Journal of Intelligent Information Systems*, *38*(3), 709–740. doi:10.1007/s10844-011-0174-3

Singh, A. N., & Gupta, M. P. (2019). Information Security Management Practices: Case Studies from India. *Global Business Review*, *20*(1), 253–271. doi:10.1177/0972150917721836

Singh, S. J., & Siddiqui, T. J. (2015). Role of Semantic Relations in Hindi Word Sense Dismbiguation. *Procedia Computer Science*, *46*, 240–248. doi:10.1016/j.procs.2015.02.017

Spanakis, G., Siolas, G., & Stafylopatis, A. (2012). DoSO: A document self-organizer. *Journal of Intelligent Information Systems*, *39*(3), 577–610. doi:10.1007/s10844-012-0204-9

Spina, D., Gonzalo, J., & Amigó, E. (2013). Discovering filter keywords for company name disambiguation in twitter. *Expert Systems with Applications*, *40*(12), 4986–5003. doi:10.1016/j.eswa.2013.03.001

Sydow, M., Pikuła, M., & Schenkel, R. (2013). The notion of diversity in graphical entity summarisation on semantic knowledge graphs. *Journal of Intelligent Information Systems*, *41*(2), 109–149. doi:10.1007/s10844-013-0239-6

Tommasel, A., & Godoy, D. (2015). Semantic grounding of social annotations for enhancing resource classification in folksonomies. *Journal of Intelligent Information Systems*, *44*(3), 415–446. doi:10.1007/s10844-014-0339-y

Vashishtha, S., & Susan, S. (2019). Fuzzy rule based unsupervised sentiment analysis from social media posts. *Expert Systems with Applications*, *138*, 112834. Advance online publication. doi:10.1016/j.eswa.2019.112834

Wang, H., Li, Z., Li, Y., Gupta, B. B., & Choi, C. (2020). Visual saliency guided complex image retrieval. *Change Pattern Recognition Letters.*, *130*(February), 64–67. doi:10.1016/j.patrec.2018.08.010

Wang, T., Li, W., Liu, F., & Hua, J. (2017). Sprinkled semantic diffusion kernel for word sense disambiguation. *Engineering Applications of Artificial Intelligence*, *64*, 43–51. doi:10.1016/j.engappai.2017.05.010

Wang, T., Rao, J., & Hu, Q. (2014). Supervised word sense disambiguation using semantic diffusion. *Engineering Applications of Artificial Intelligence*, *27*, 167–174. doi:10.1016/j.engappai.2013.08.007

Wei, T., Lu, Y., Chang, H., Zhou, Q., & Bao, X. (2015). A semantic approach for text clustering using WordNet and lexical chains. *Expert Systems with Applications*, *42*(4), 2264–2275. doi:10.1016/j.eswa.2014.10.023

Witt, S. (2015). Modeling user response timings in spoken dialog systems. *International Journal of Speech Technology*, *18*(2), 231–243. doi:10.1007/s10772-014-9265-1

Xing, F. Z., Cambria, E., & Zhang, Y. (2019). Sentiment-aware volatility forecasting. *Knowledge-Based Systems*, *176*, 68–76. doi:10.1016/j.knosys.2019.03.029

Xu, J., Huang, F., Zhang, X., Wang, S., Li, C., Li, Z., & He, Y. (2019). Classification with bi-directional multi-level attention networks. *Knowledge-Based Systems*, *178*, 61–67. doi:10.1016/j.knosys.2019.04.018

Yang, X., & Mao, K. (2016). Learning multi-prototype word embedding from single-prototype word embedding with integrated knowledge. *Expert Systems with Applications*, *56*, 291–299. doi:10.1016/j.eswa.2016.03.013

Yepes, A. J. (2017). Word embeddings and recurrent neural networks based on Long-Short Term Memory nodes in supervised biomedical word sense disambiguation. *Journal of Biomedical Informatics*, *73*, 137–147. doi:10.1016/j.jbi.2017.08.001 PMID:28797709

Zhang, H., Du, Y., Sun, J., & Li, Q. (2020). Improving interpretability of word embeddings by generating definition and usage. *Expert Systems with Applications*, *160*, 113633. doi:10.1016/j.eswa.2020.113633

Zhu, G., & Iglesias, C. A. (2018). Exploiting semantic similarity for named entity disambiguation in knowledge graphs. *Expert Systems with Applications*, *101*, 8–24. doi:10.1016/j.eswa.2018.02.011

Justin Piper is an adjunct professor of business law at Drexel University. He received his juris doctorate from the University of California Hastings College of Law in 2017.

James A. Rodger is a Professor of Management Information Systems and Decision Sciences at Indiana University of Pennsylvania (IUP). He received his Doctorate in MIS from Southern Illinois University at Carbondale in 1997. Dr. Rodger has published several journal articles related to these subjects. His work has appeared in the following journals: Computers in Human Behavior, Journal of Computer Information Systems, Issues in Information Systems, IEEE Transactions on Software Engineering, International Journal of Hybrid Intelligent Systems, Information and Software Technology, Information Technology and Management. Annals of Operations Research, Communications of ACM, Computers & Operations Research, Decision Support Systems, Expert Systems with Applications, Lecture Notes in Computer Science, International Journal of Human-Computer Studies as well as several other journals.