ROLE OF BIAS IN INFORMATION WARFARE: CLASSIFYING FAKE NEWS ARTICLES USING NATURAL LANGUAGE PROCESSING

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ABSTRACT

The way that people consume news, entertainment and media has been changed. The print media and even television have started to become obsolete. In this digital age, social media being the biggest news source for the masses has become an issue in terms of security and the manipulation of facts. Add to this the fact that the content is catered towards the audience with respect to what suits the marketers. The consumer is no longer the dictator of what they want to consume but has become a product for the streaming services.

The impact of targeted information propagation is huge and there is a need to study how we can maneuver it. In this paper we see the role that bias plays in an information perception model and how certain words and linguistic patterns can be used to determine if a source of news is authentic or not.

ACKNOWLEDGEMENTS

This paper wouldn't have been possible without the guidance of my advisor Dr. Jeremy Straub. I would also like to thank Mr. Terry Traylor who played a major part in the development of the paper "Classifying Fake News Articles Using Natural Language Processing to Identify In-Article Attribution as a Supervised Learning Estimator". Also, thanks to the fake news team who helped in creating the database of the fake news articles namely Alex Thielen, Zak Merrigan, Brian Kalvoda, Riley Abrahamson, Dibyanshu Tibrewell, William Fleck, Ben Bernard, Brandon Stoick and Bonnie Jan. And last but not the least I would like to thank all my professors at NDSU.

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1. INTRODUCTION

The amount of false information that exists on the internet to support people's confirmation bias is alarming. It is fascinating to see how one can come up with any opinion and can find some form of proof on the internet confirming what they think is true. The alternate opinions are turning into alternate facts. Since it is this powerful, there is a need to study how it works and how we can handle it if need be. In this paper, we are trying to see the bigger picture of what the extent of the impact is and what it can be in the future.

This paper aims to understand how information can be used to manipulate individuals and consequently social groups. The first part of the paper presents an influence model that explains how biases turn into opinions and can result in social and political impact. The next part of it is an extension on another paper [2] which classifies real news articles and fake ones. The last part of the paper discusses the future of the information era.

The 2016 US election is one of the biggest examples of how the propagation of false information can impact the decision making of people [3] on a very large scale. Brexit [4] and the 2019 Indian election [5] are some more instances where we can see the power of what it can do, if leveraged. Alternate opinions turning into alternate facts is now not just limited to politics. The potential that this has is huge and we can already see it in other places like military operations [6] and corporate competition.

Information warfare and influence combined, when targeted at a narrow audience, can make a big impact and bring desirable results for people who take advantage of it. The problem is that the wealthy and the powerful are in a privileged position to carry out influence warfare [7]. Hence, the results are skewed in their favor, which is a threat to democracy. The tremendous progress made in the field of artificial intelligence is also a contributing factor to this information warfare [8] too and makes it even more efficient and hence there is a need to study its impact. Physicists found out that there are two criteria [1] on which social consensus depends. One is how strongly an individual is influenced and the second is how many connections that person has.

The amount of information available to an individual is staggering. It is exponentially more than what the previous generations had access to. This comes with a problem of filtering the noise of what is true and what is just someone's opinion posing as truth.

This paper extends research in the area of media bias analysis. The presented work on opinions formations, influence models (Fig. 1) and bias as an entity (Fig. 2) was done by the author Gurmeet solely. The paper uses results from [2], whose authors are Mr. Terry Traylor, Dr. Jeremy Straub, Nicholas Snell and Gurmeet. The pseudocode for news detection and the outline of the information reception (Fig. 4) was developed by Gurmeet. The statistical analysis and the code for the algorithm was created and run by Terry Traylor. The news corpus was built by a research team of nine different researchers: Alex Thielen, Zak Merrigan, Brian Kalvoda, Riley Abrahamson, Dibyanshu Tibrewell, William Fleck, Ben Bernard, Brandon Stoick and Bonnie Jan. The results and evaluation of the algorithm used was a collective effort by Gurmeet and Terry Traylor. The conclusions of this paper are solely the work of the author Gurmeet.

2. BACKGROUND

The 2016 US election [3] is one of the biggest examples of how propagation of false information and agenda can impact the decision making of people on a very large scale. Brexit and the Indian election are some more instances where the power of what it can do has been witnessed. [3] Information operations and warfare, also known as influence operations, includes the collection of tactical information about an adversary as well as the dissemination of propaganda in pursuit of a competitive advantage over an opponent.

A significant amount of research is occuring in the field of information warfare. There has been some research, like P. Klimek, et al. [6], that shows how opinions and bias can be skewed in the desired direction with influence. As depicted in [1], there is evidence that having a bias as a community can change opinions of all individuals in that community. There are multiple findings that the language we use or that is presented to us through media might be creating biases and consequently opinions.

3. INFLUENCE MODEL

An influence model can be devised in relation to how information shapes the decisions that we make. All the information that we consume goes through a filter of bias. As shown in Figure 1, information that we gather through various sources like family, friends and social media. forms our biases which affects our decisions ultimately making a difference on society as whole.

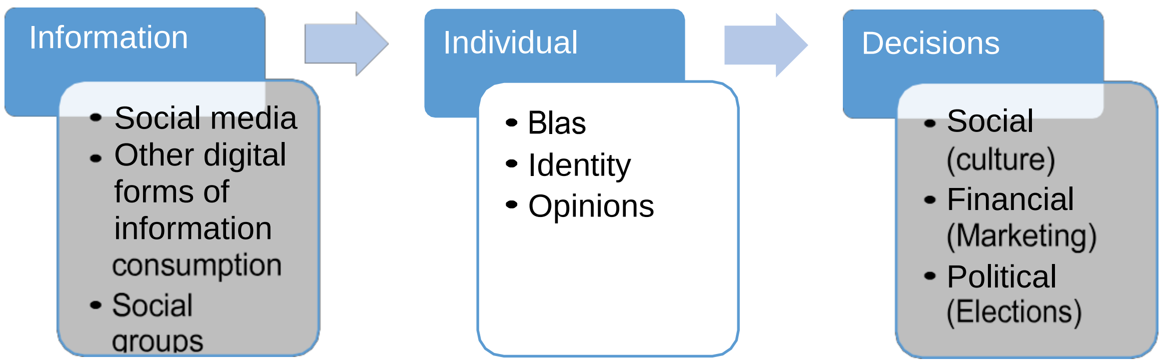

Figure 1. Influence model.

3.1. Cyberspace and the possibilities for influence

Cyberspace, by definition, means the interconnected network of all digital technology. Confirmation bias, by definition [10], means the tendency to search for, interpret, favor, and recall information in a way that confirms one's preexisting beliefs. The term ‘fake news’ [2], as it is commonly known, is a worldwide information accuracy and integrity problem that affects opinion forming, decision making, and voting patterns. Most fake news is initially distributed over social media conduits like Facebook and Twitter [11] and later finds its way onto mainstream media platforms such as traditional television and radio news. The fake news stories that are initially seeded over social media platforms share key linguistic characteristics [12] such as excessive use of unsubstantiated hyperbole and non-attributed quoted content.

3.2. Bias as an entity

The information that we consume is not directly formulated into opinions. The information is manipulated by the different biases that we have. As depicted in Figure 2, some biases are primal instinct whereas other biases are taught by the different social groups that we identify with. Social groups include groups such as religion, nation, political affiliation, hobbies and so forth. Bias is the reason why the same information given to different individuals would formulate different opinions among them. There is always the filter of bias which information has to go through. The idea is that bias can be treated as an entity in a system that consumes information and outputs a decision to mimic how people make political, social and financial decisions. If we can identify and quantify bias, then we can also eliminate it to find out the unbiased information which can help us formulate better decisions. The opposite works for formulating artificial decision making too.

With this great shift there comes the big question of how we can take control of this change. The impact of targeted information propagation is huge and there is a need to study how we can maneuver it.

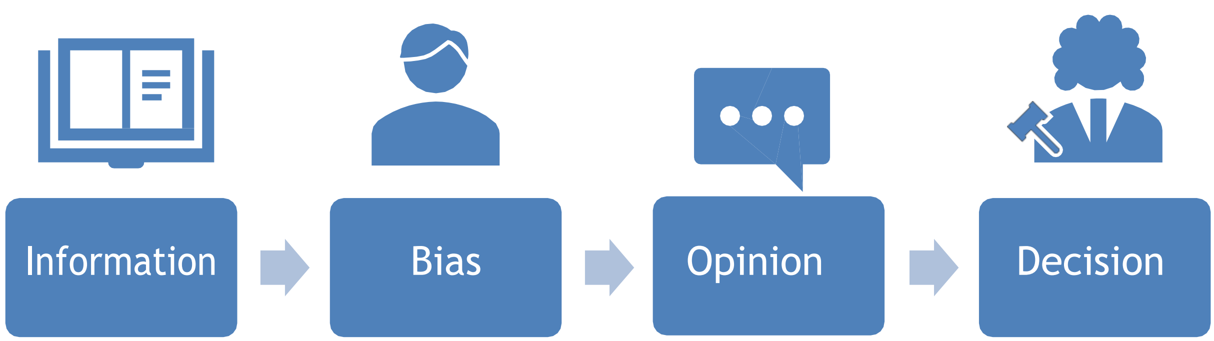

Figure 2. Flow of information.

3.3. Types of cognitive biases

The often-discussed types of cognitive biases described here are confirmation bias, ingroup bias, status-quo bias, negativity bias, false-consensus bias, temporal bias and anchoring.

- Confirmation bias: This [13] is the type of bias where we socially align with people who agree to our point of view, therefore creating a social group of people who have the same opinions on issues.
- In-group bias: Due to a human primal instinct of wanting to be part of the group [16] and not get rejected, we tend to agree with the general consensus of our group and not have a strong individual opinion which might differ from the group. That group can be people with same nationality, religion, economic or social status.
- Status-quo bias: This [15] is the innate bias that we have against change. We tend to avoid change whenever it is possible.
- Negativity bias: Our cognitive attention [16] is heavier on negative opinions because it considers negative feelings more prominent.
- False-consensus bias: This is the false sense of agreement [13] within a larger group, when the support seems inflated and larger than it actually is.
- Temporal bias: The bias [14] that propagates the need of urgency and importance. The news outlets use it to present new changes and provide the immediate gratification of knowing what's important as soon as possible.
- Anchoring bias: This type of bias [13] occurs when somebody uses an initial piece of information to make a subsequent judgement. It involves relying heavily on the initial information and not giving a fair chance to the opposite opinion.

3.4. Opinion formation

P. Klimek, et al, show in [20] if a specified percentage of people around you have the same opinion then you are more likely to have this opinion too. If it is below that specified level, then you are less likely to have the same opinion as the majority. That specified majority has been called the laggard's parameter in [20]. People adopt the opinion held by the majority of their direct neighbors only if the fraction of neighbors exceeds a pre-specified laggard-threshold. The larger this parameter, the more stimulus an individual needs to adapt their opinion to the one of their direct neighborhoods. As the parameter increases, the regions of full consensus shrink.

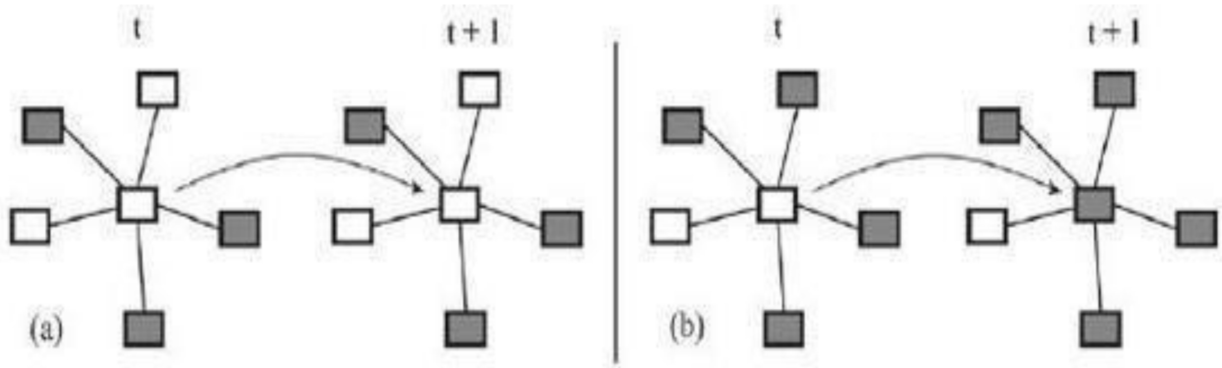

Figure 3. (a) Three out of five neighbors have the same opinion, the threshold is not met, and the node's opinion is unchanged (b) Four out of five neighbors have the same opinion. P. Klimek, et al. [20].

Given the fact that bias can impact decision making and bias is affected by people around us, it makes sense to incorporate bias as an entity in the whole decision-making algorithm if we were to create intelligence artificially and mimic the human decision-making process. The more we study bias, the closer we can recreate the human decision-making process efficiently.

In Figure 4, you can see how a message sent by a person can be treated as a signal that has the message and some noise. The noise can be perceived differently based on the encoder and decoder you use. The internal process decoder depicted here is bias. This bias could be on an individual level, community level or national level.

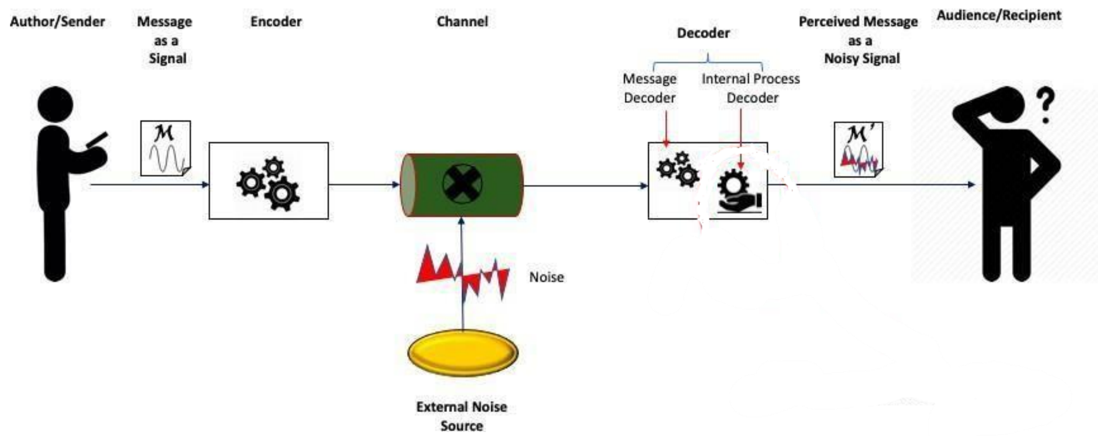

Figure 4. Perception of information by an individual.

4. METHODOLOGY

The methodologies used to research the fake news phenomena, develop the research database and evolve the qualitative model into a quantitative model are reviewed in this section.

4.1. Groundwork and theory development

The research team implemented a mixed-methods approach to study fake news documents, develop a qualitative model for testing, and transform the qualitative construct into a quantitative system. Initial fake news observations and hand-crafted pattern analysis were performed using Glaser and Strauss's grounded theory [22] methods for theory building and coding. Grounded theory is an induction-based social-science research technique that is used to build theories and frameworks from existing data. When researchers use grounded theory to construct an understanding of a phenomena under study, the research team starts by observing the data and looking for patterns, trends, and differences. The trends and patterns that emerge from the analysis are grouped into codes and themes. Over time, the codes and themes become categories and form the basis for a new theory. As a hypothetical example, if one were to notice that all fake news documents started with the phase, 'trust me, I am not lying to you,' the researchers observing this would eventually group enough data documenting this trend and form a hypothesis that all fake news documents start with that phrase. Grounded theory was selected for use to facilitate building a theory inductively based on the data available.

The results of the initial qualitative work unearthed technical linguistic patterns unique to the fake news documents that were reviewed. The linguistic patterns were used to develop a machine learning grammar and hypothesis.

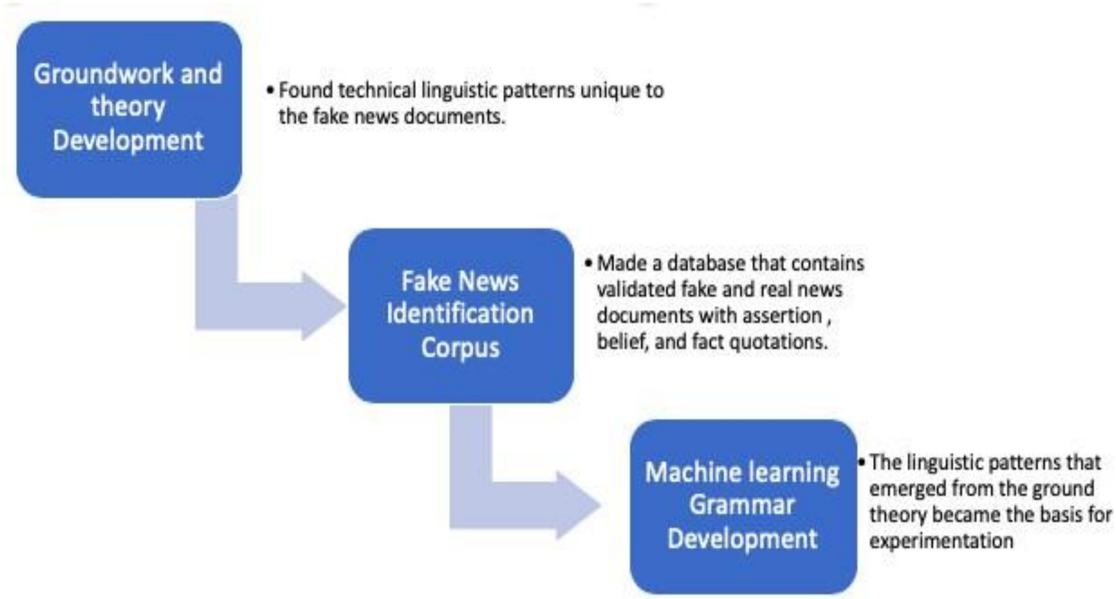

Figure 5. The methodology for the classification of news articles.

4.2. Fake news identification corpus

A new fake news identification corpus was developed in order to study fake news technical linguistic patterns and enable theory testing using a locally generated dataset. The research team constructed and validated the version of the corpus used for this work over a 7- month period. This work was done by a local team of NDSU students.

At the time it was used for this work, the corpus contained 218 documents from different online sources. It contains validated fake and real news documents with assertion, belief, and fact quotations. The corpus was built by a research team of nine different researchers namely Alex Thielen, Zak Merrigan, Brian Kalvoda, Riley Abrahamson, Dibyanshu Tibrewell, William Fleck, Ben Bernard, Brandon Stoick and Bonnie Jan who collected and classified the news articles in the database that was used for this work. Document accuracy (whether or not a document was considered false content or fake news) was reviewed weekly by the research team and evaluated by other researchers on the team for corpus inclusion and acceptance. In short, each document that was added to the corpus was reviewed and accepted by multiple researchers before the document was added to the corpus for future use.

At the time this work was conducted, the corpus contained 421 quotations from documents that the research team classified as either real or fake media documents. While the corpus wasn't originally designed for quote attribution machine learning research, it includes all text inside a document and thus includes quotations. Each document in the corpus is subdivided into header and body parts. Work on a more robust corpus that can be publicly shared is the subject of a future publication.

4.3. Machine learning grammar development

Machine learning grammars were built inductively, and iteratively as technical linguistic patterns emerged from the grounded theory research approach. The emerged grammars became the basis for hypothesis development and experimentation.

Figure 5 on page 10 demonstrates and summarizes the methodology for experimentation and different steps taken to classify the news articles as real or fake.

5. EMERGED TOOL DESIGN

Based on the research team's initial grounded theory work and using the corpus, several key technical linguistic patterns were identified in the fake news documents that were used to develop a classifier model with supporting grammars. These grammars became the base feature extractors for the custom classifier.

5.1. Attribution and key fake news features

Fake news documents exist across many forms of media and are particularly ubiquitous on social media platforms. At the beginning of the research project, 30 false content and 30 real content documents were reviewed to develop an understanding of the phenomena and to begin building theory. These documents were gathered from various news sites like CNN, The New York Times, some right leaning websites and Facebook posts by the local team of NDSU students. Out of the 60 documents reviewed, it was identified that the preponderance of the false content documents (28 of the 30 reviewed documents) included quotes either lacked proper attribution or attributed quotes to non-named entities to assert a fact. While trends continue to be identified across the false content, the most dominant initial false content indicator was the lack of proper attribution. Attribution in the documents that were reviewed and classified as real news documents normally occurred within less than 50-character spaces from the beginning or ending of a direct quote.

These trends and observations in mind, a custom classifier that used attribution as a sole fake news indicator was constructed. The system measures the amount of attribution inside a document and based on a definable attribution tolerance, labels the document as either real or fake.

5.2. Custom attribution feature extraction classifier

The definitions and constructs originally proffered by Pareti, et al. [18] and by O'Keefe, et al. [19] were augmented. Specifically, an attribution for a quote has a source span, cue span, and content span, as defined in Table 1.

Table 1. Pareti, et al. [18] Attribution Model Definitions.

Term	Definitions
Source	The span of text that includes who put forth the quote or who the content is attributed to.
Cue	A verb or verb phrase that lexically links the source to the quote or content.
Content	The span of text that serves as the quote and is attributed

To build the custom attribution machine learning classifier, attribution construct aspects from the work of Muzny, et al. [21] were also implemented. Their quote → mention, mention→ quote, and mention → entity linking attribution constructs helped extend Pareti, et al.'s definitions to build a simple technical attribution classifier shown in Figure 6.

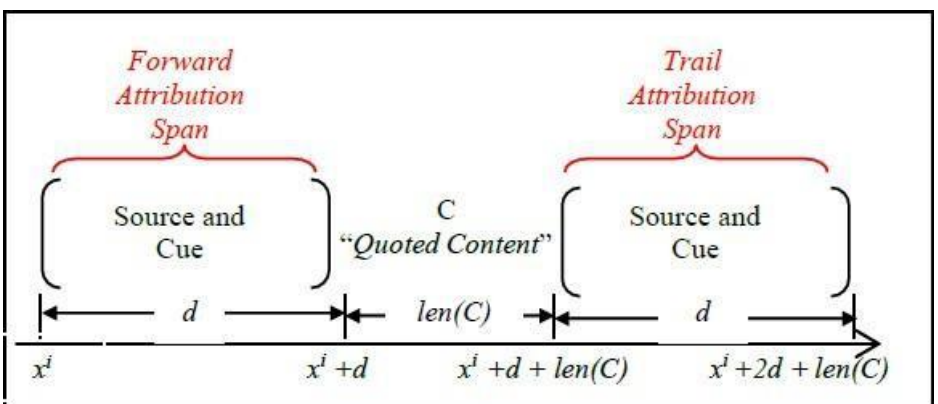

Figure 6. Including the attribution span, attribution span absolute distance 'd', and length of the quote enables simple quote attribution searching for classification. Proposed extensions to the Pareti, et al. [18] definitions. Traylor T., et al. [2].

An attribution to a quote is defined using the following definition, to build the custom feature extractor: Let C be any content span of random span length len (C) for a quote that requires attribution. The attribution span is the absolute distance "d" in character spaces from the beginning or end of a content span marked by double quotes. So, for any properly attributed quote:

$$\exists(S, C) for\ C\ s.t. \begin{cases} (S, C) \leq xi + len(C) + 2d \\ or \\ (S, C) \geq xi \end{cases} \quad \text{(Eq. 1)}$$

The attribution span is divided into two searchable sub-spans called the forward and trail attribution spans. The classifier tool was built to search inside the forward and trail attribution space and to classify the quote as either attributed or not.

The resulting binary classification label is based on the presence of learned source and cue information inside the attribution spans. To identify a source, the custom classifier searched for named-entities or persons or organizations that could be attributed as having made a quote using named-entity recognition methods. Cue identification is based on learning associated cueing verbs or cue information contained inside the training set. Most informative cue words or phrases will be added to a living attribution "bag of words" model. Here, the presence of those words and the repetition of those words matter more than anything else. Hence, the usage of the bag of words model here. Attribution feature extraction comes from applying machine learning algorithms to the forward and trailing attribution spans.

Supervised machine learning is used, which means that it is based on a statistical model. With more data fed into the classifier, it would be more prone to accurately classify using the attributions span along with the performance metric.

5.3. The resultant fake news detection tool

The fake news detection tool uses the outputs from the attribution classifications to assign a final label for the entire document. A simple scoring system, described in the next sub-section, was used to construct a final attribution score (called the attribution or A-score) and assign a fake versus real classification label for every document containing quotes.

5.4. Fake news detection algorithm

The fake news detection algorithm operates as follows. For each document in the document collection, the document's paragraphs are counted and tokenized. Each paragraph is also checked for quotes. If a paragraph has quotes, then these are processed using the custom attribution classifier (which uses the A-score algorithm developed by Terry Traylor). Positive attributions receive a +1 score and negative attribution classifications receive a -1 score. If the overall A-score (the sum of positives and negatives) is greater than or equal to 0, then the document is assigned a label of real. If the A-score is less than 0, then the document is assigned a label of fake. Note that the A-score threshold is, thus, a key area of potential configuration for this algorithm.

The A-score algorithm is used to label quotes as either real or fake based on the results of the machine learning classification. The pseudo code for both of the algorithms is presented in Figure 7.

6. EXPERIMENTAL DESIGN

To test the fake news detection system, the corpus was divided into training (60% of the available data), development (10 % of the available data), and test (30% of the available data) sets. The training process trains the algorithm to recognize words inside the attribution space associated with real or fake news items. Because common word data is not necessary for presentation to the classifier, no additional data preparation is done to the corpus for testing. As can be seen in the pseudo code and algorithm description, it was possible to tune the attribution span during testing, but it was decided to perform a simple run with the attribution space at d=45 for simplicity. Three types of experimental validation were conducted during experimentation. The accuracy of the quote attribution identifier, the custom quote attribution classifier, and finally the overall performance of the one feature fake news detection tool were tested. The pseudo code for both of the algorithms is presented in Figure 7.

Algorithm: Fake News Detector with Attribution Key Extraction Feature

Algorithm: FakeRank Fake News Detector Main

```
For each doc in Documents
pCount ←Σ(number of paragraphs)
Tokenize doc by paragraph
FakeRank ← 0
For each paragraph in doc
  qScore ← Σ (number of quotes)
  if qScore > 0 then
    A-score ← 0
    For each quoteset
      quote_cl classify.naivebayes(quoteset_attribution_space, d)
      If quote_cl
        A-score ← A-score +1
      Else
     A-score ← A-score -1
     return A-score
  FakeRank ← FakeRank + A-score
If FakeRank >=0 then
  docLabel ← real
If FakeRank < 0 then
docLabel ← fake
```

Algorithm: A-Score Fake News Detector Supporting

```
//Prepare quoteset_attribution_space
capture quotes (d)
FWD_A-Span ← quoteset_attribtuion_space-d
TRL_A-Space ← quotest_attribution_space_d
classificationspace ← [ FWD ∪ TRL] - stopwords
  attribution_label ← classify.naivebayes (classificationspace,extractor
      = custom
  return attribution_label
```

Fig 7. Pseudocode for proposed algorithms. Traylor, T., et al. [2].

7. RESULTS AND ANALYSIS

This section summarizes the results of the three tests conducted to support the fake news detection tool. The results of the tests were summarized by Gurmeet and Terry Traylor.

7.1. Quote attribution identifier

The simple Python and Textblob system used to identify quotes in a paragraph worked well. Because the tool looks for the presence of double quotes inside strings, quote or content, identification was simple. The tool identified 96% of the quotes in the training set. We assess that the tool was confused, in limited instances, by complex and malformed quotations.

7.2. Quote attribution classifier

The quote attribution classifier, which is the core of the system, functioned well, but did not perform at an acceptable level. Several runs were needed to properly calibrate the classifier and account for linguistic processing issues such as quotes inside quotes and single quotes inside double quotes. The classifier was calibrated by using the average of repeated results the team generated by running the classifier several times. The classifier also had issues handling multiple quotes within close proximity to each other inside a text. For example, if one quote came right behind another quote and the source and the cue data was within the joint attribution space (in front of or behind a quote) for both quotes, the system encountered challenges processing both quotes. The final overall classifier accuracy is 0.69 and the overall classifier error is 0.31. Additional classifier performance metrics are presented in Table II. While these numbers are subpar for attribution classification work, research is ongoing to improve the performance of the classifier. Tuning the attribution distance and potentially developing a fake news attribution dictionary are methods being used to improve the classifier performance.

Table 2. Classifier Performance Metrics [2].

	Fake	Real
True Positive	0.55	0.88
False Positive	0.13	0.45
True Negative	0.88	0.55
False Negative	0.45	0.13
Precision	0.85	0.61
F-score	0.66	0.72

The metrics in Table 2 are defined as follows. The true and false positive and negative rates are the number correctly (true) or incorrectly (false) identified divided by the total number identified with the relevant classification (positive or negative). For example, the true positive rate is the number of true positives divided by the number of true positives and false negatives. The precision is the number of correctly labeled items divided by the total number of elements belonging to the positive class. The total number of elements in the positive class includes both the true positives or correctly labeled items and the false positives or incorrectly labeled items. The F-score is a metric used in binary classification problems that measures the accuracy of a test. The F-score combines the precision and recall (or true positive rate) for a binary classification problem and is the harmonic mean of the precision and recall.

7.3. Overall fake news detection tool performance

The attribution-based fake news detection tool that uses the quote attribution classifier, performed suitably for a detection tool using only one feature extraction to classify a document; however, like the attribution classifier, it did not perform well enough for production use. After training and configuration, the tool correctly identified 69.4% of the fake and real news documents in the test set. Upon review, some of the missed labels were attributable to fake news documents with no quotations, fake news documents with attributed quotes of inaccurate statements, and fake news documents that quoted or cited other fake news documents. While, the overall performance results for this system are not as strong as desired, the initial performance is generally encouraging. Because fake news is designed to deceive human targets, the initial classification tool with only one extraction feature seems to perform well, given the complexity of the topic and the aims of the project.

8. CONCLUSIONS AND FUTURE WORK

This paper has presented the results of a study that produced a limited fake news detection system. The work presented herein is novel in this topic domain in that it demonstrates the results of a research project that started with qualitative observations and resulted in a working quantitative model. The work presented in this paper is also promising, because it demonstrates a relatively effective level of machine learning classification for large fake news documents with only one extraction feature. Finally, additional research and work to identify and build additional fake news classification grammars is ongoing and should yield a more refined classification scheme for both fake news and direct quotes.

Future planned research efforts involve combining attribution feature extraction with other factors that emerge from the research to produce tools that not only identify potential false content, but influence based content designed to compel a reader or target audience to make inaccurate or altered decision.

Cyberspace is predicted to expand and have presence in more areas of human life. Due to improvements in processors and better system integration [22], there is bound to be a faster and greater level of information propagation. The point here to note is this means the security systems based on previous technologies or minicomputers would become obsolete as people would switch mostly to PC and Linux systems. This raises a question whether we are ready for that move and if the cybersecurity would be up to date. For it to be effective, we need to choose systems and processes that are customizable and migratable from one platform to another.

The more we learn about biases in the fields of medicine, finance and law, the more efficient we can be in those areas and the more efficient algorithms we can make for the future artificial intelligence. Unbiased decision making can be crucial when it comes to these important fields. Various studies [23] have found some form of bias conscious or non-conscious impacting these respective fields.

As stated before, future computers will be faster and more Information will be generated in massive amounts due to improved and faster processors, better system integration, fuzzier boundaries between systems and other advances. This leaves a need to have powerful cybersecurity measures and processes in place.

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