Chapter 3
Combination of Natural Laws (Benford's Law and Zipf's Law) for Fake News Detection

Abstract With the increase in the number of character assassination and fake news recently happening in Nigeria, we combine Zipf's law and Benford's law to analyse and detect fake news. The problem of fake news has become one of the most prominent issues in Nigeria recently. In this chapter, the challenges fake news poses to Nigeria is briefly presented. Due to these challenges, we propose the combination of Benford's law and Zipf's law in news analysis such that the hybrid of the two laws will obey the Power law for real news and deviate for fake news. We carried out various tests on different real news sources and the result shows that real news obeys the Power law. We, therefore, propose that fake news should not obey the Power law even though we could not test on fake news sources because of the lack of verified fake news dataset.

Keywords Fake news · Benford's law · Zipf's law

Fake news is simply defined as 'a news article that is intentionally and verifiably false [1]'. Fake news is actually difficult to differentiate from real/authentic news. It is even more worrisome that people easily read and click on fake news links because they want to be up to date with the current happenings around them, have a sense of urgency, have sociopolitical polarization and due to curiosity or fear [2]. It is shocking to note that cyber criminals can use fake news as a bait to get their victims to perform their fraudulent activities. For example, clicking on a fake news link could lead to giving hackers access to your digital devices (e.g. computers and phones). This could lead to the cyber criminals accessing victims password, personal information, financial information capable of defrauding the victim of their funds. Once a victim clicks on such fake news, it could an infected news, it could infect not only their system but also the entire company's network [2].

In Nigeria, fake news is a great challenge. This has created much fear and warnings from Nigerian scholars, information experts and Nigerian government. A case in hand is the warning from Nobel Laureate, Prof. Wole Soyinka, who stated that 'Nigeria may start a World War III through fake news [3]'. If care is not taken fake news will lead to a cyber war within a country or even one country fighting with another country. Joseph Carson, an experienced enterprise security expert stated that: 'Only one fake news story from a trustworthy source can devalue an entire news feed [4]'.

A. Iorliam, *Cybersecurity in Nigeria*, SpringerBriefs in Cybersecurity,
https://doi.org/10.1007/978-3-030-15210-9_3

Fake news has been rampant on social media, and news outlet. The news (later confirmed fake news) that made Nigerians worrisome was the fact that some news outlets stated that they were very sure the Nigerian President (President Mohammadu Buhari) was confirmed dead in London. After some time, the president returned to Nigeria [5]. To emphasize how scary fake news is in Nigeria, even the INEC are worried about the negative effects fake news could have in the 2019 elections and the Nigerian democracy. As such, their staff were recently trained to detect and uncover fake news [6].

This means there is every need to detect and classify fake news from real/authentic news. One of the most suitable techniques in differentiating fake news from authentic news should have been supervised learning. Unfortunately, using supervised learning means that there should be clear labels showing what is fake news and what is real/authentic news. For the fact that the above task seems difficult currently, then supervised learning cannot effectively detect/classify fake news. Again, there are no publicly available labelled fake news databases for experiments. The most closely related tool that has been able to generate pseudo fake reviews is the Amazon Mechanical Turk (ATM) crowd sourcing tool. But it should be noted that ATM generates reviews that cannot be totally considered as fake. It is in a way unnatural, as such this kind of data is not suitable for experiments that relate to detecting/classifying fake news from authentic news especially with Natural laws (such as Benford's law and Zipf's law).

In Nigeria, fake news and hate speech are classified to be similar to each other. Nigerians are warned that before sharing information on Facebook, Twitter, Instagram or WhatsApp, two things should be considered such as 'how credible is the source' and 'share what you can only vouch for'. Nigeria is doing its best to curb fake news. Recently, CrossCheck Nigeria was launched to check and detect potential fake news. This is launched in Nigeria by a UK-based investigative journalism outfit, International Centre for Investigative Reporting (ICIR) and First Draft News [7]. Even though such platforms have started coming up in Nigeria to curb fake news, the rate of fake news on social media and other news outlets is increasing tremendously. As such, there is every need to develop more effective tools/techniques to curb this serious challenge.

3.1 Combination of Benford's Law and Zipf's Law for Fake News Detection

In most cases what appears to be fake news may just use exaggeration and introduce some non-factual elements, and is intended to amuse or make a point, rather than to deceive. Therefore, it is very tricky for detecting fake news. However, we propose a novel method designed to analyse different news sources and detect fake news. The aim of this study is to analyse and differentiate between real news and fake news data set using the hybrid of Benford's and Zipf's law. Benford's law and Zipf's law are carefully explained in Sect. 3.2. Briefly, a review of the most relevant research on Benford's law and Zipf's law is presented. Tirunagari et al. [8], presented a method for differentiating Alzheimer's disease (AD) patients from healthy ones based on their electroencephalograms (EEG) signals using Benford's law and support vector machines (SVMs) with a radial basis function (RBF) kernel. They divided EEG signals from 11 AD and 11 age-matched controls into artefact-free 5-sec epochs and trained the SVM. They performed tenfold cross-validation at both the epoch- and subject-level to evaluate the importance of each electrode in discriminating between AD and healthy subjects. In their research, they found that performance across the electrodes was reduced when subject-level cross-validation was performed, but relative performance across the electrodes was found to be consistent using epoch-level cross validation. Iorliam et al. [9] used the divergence values of Benford's law as input features for a Neural Network for the classification and source identification of biometric images. Their experimental analysis shows that the classification and identification of the source of the biometric images can achieve good accuracies between the range of 90.02 and 100%. Iorliam et al. [10] in their investigation to examine whether biometric images will follow Benford's law and whether or not they can be used to detect potential malicious tampering of biometric images discovered that, the biometric samples do indeed follow Benford's law; and the method can detect tampering effectively, with Equal Error Rate (EER) of 0.55% for single-compressed face images, 2.7% for single-compressed fingerprint images, 4.3% for double-compressed face images and 3.7% for double-compressed fingerprint images. Iorliam et al. [11] in their paper, investigated the use of keystroke data to distinguish between humans using keystroke biometric systems and non-humans for auditing application. The authors noted that Benford's Law and Zipf's Law, which are both discrete Power law probability distributions, have been effectively used to detect fraud and discriminate between genuine data and fake/tampered data. As such, their motivation was to apply Benford's Law and Zipf's Law on keystroke data and to determine whether they follow these laws and discriminate between humans using keystroke biometric systems from non-humans. From their results, it is observed that, the latency values of the keystroke data from humans actually follow Benford's law and Zipf's law, but not the duration values. There are a number of unsolved issues concerning the analysis of the fake news and propaganda especially in Nigeria. In this research, we will analyse news sources as a dataset using Benford's and Zipf's law. Iorliam [12] stated that combining Benford's law and Zipf's should improve the performance of differentiating authentic data from fake data. Hence, we are motivated from [12] to combine these two laws for fake news detection.

The main steps to combine Benford's law and Zipf's law for fake news detection are as follows:

1. Load the news to be investigated into the developed system.
2. Analyse the data using Benford's law and Zipf's law.
3. Combine the results for Benford's law and Zipf's law.
   Note: The data analysed by Benford's law are fused to be classified as Ranks and Frequencies. As such, both the values for Benford's law and Zipf's law are

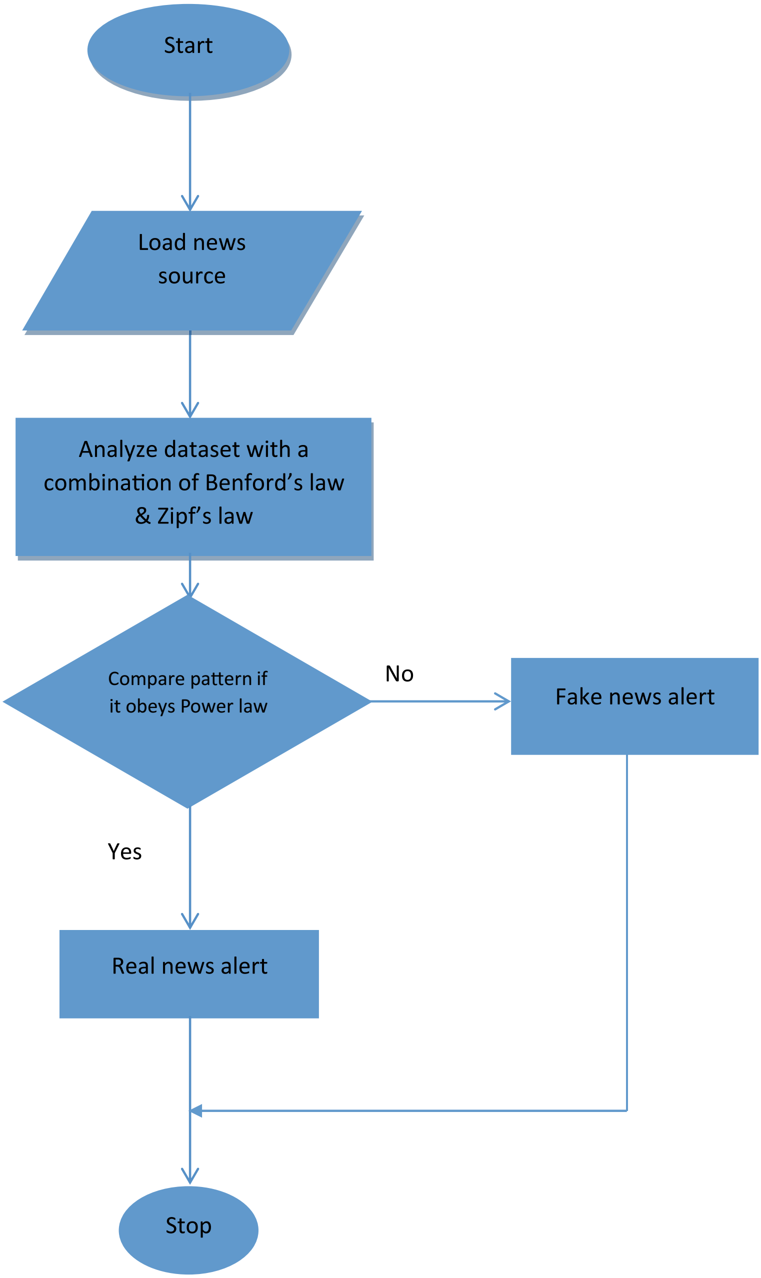

Fig. 3.1 A Combined Benford's and Zipf's law for fake news detection flowchart

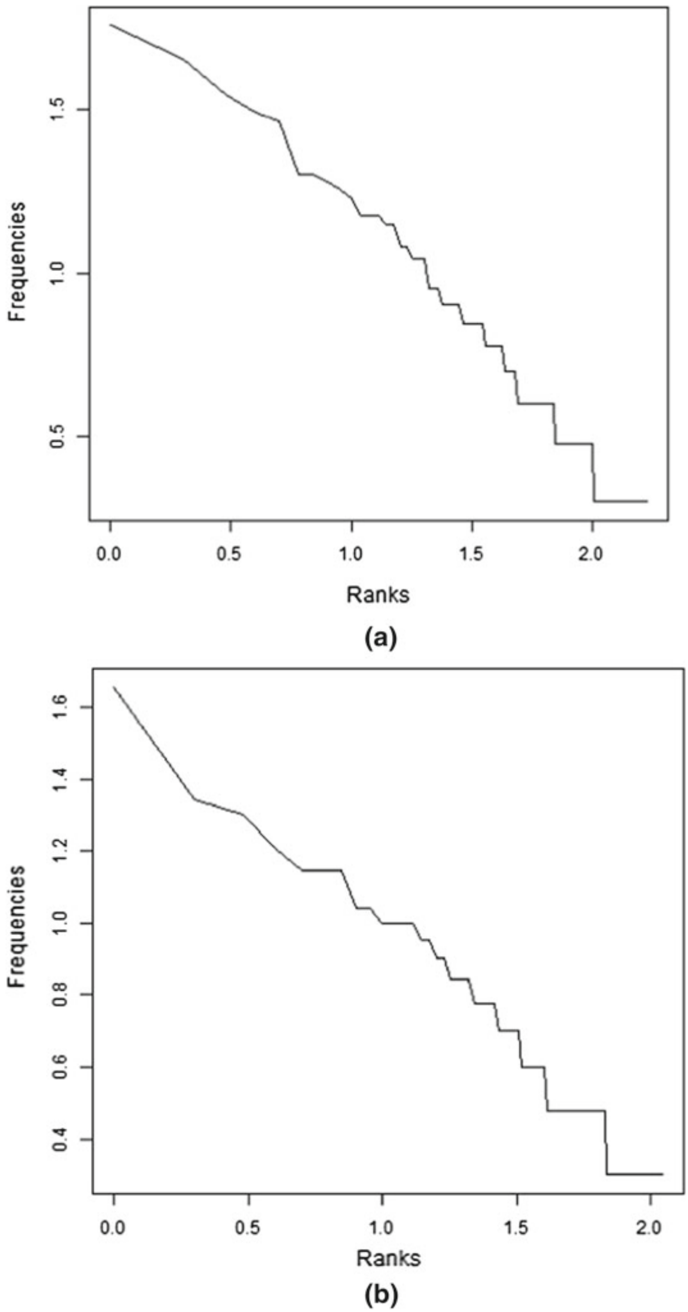

Fig. 3.2 Combination of Benford's law and Zipf's law results for: **a** First real news dataset; **b** Second real news datasets

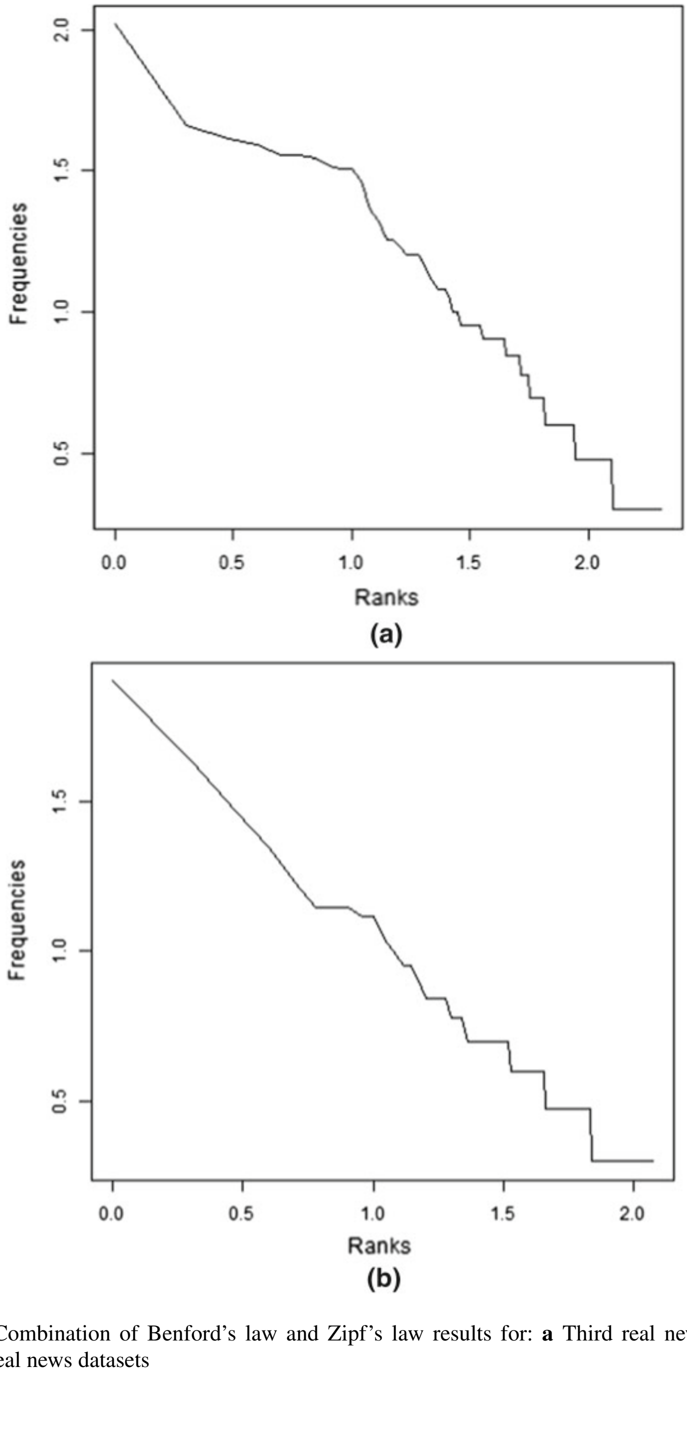

Fig. 3.3 Combination of Benford's law and Zipf's law results for: **a** Third real news dataset; **b** Fourth real news datasets

now in Ranks and Frequencies. In this way, alphanumeric dataset could also be analysed.
4. Plot the $log_{10}(R)$ against $log_{10}(F)$ for values obtained in (3).
5. Analyse the patterns and identify irregularities.
6. Patterns that follow Power laws should be real/authentic news whereas patterns that deviate from Power law should be fake/fabricated news.

Figure 3.1 shows the flowchart of the proposed system. The proposed system is designed to analyse news with the combination of Benford's law and Zipf's law. Furthermore, compare its patterns against the Power law. All patterns that deviate from the Power law are supposed to be fake news.

3.2 Results and Discussions

Based on the proposed method in Sect. 3.1, four news datasets believed to be real/authentic are plotted to observe their patterns as shown in shown in Figs. 3.2 and 3.3. It should be noted that these datasets are randomly picked. This means that properly labeled dataset should be investigated for this proposed method. This labeled dataset should be for real/authentic news and fake/fabricated news and should be publicly available so that other scientists could repeat these experiments and achieve similar results. From Figs. 3.2 and 3.3, it is observed the resultant plots produces a pattern that obeys the Power law. This shows that real news follows the Power law. However, more analysis should be done and the patterns observed for the cases of real/authentic dataset compared against fake/fabricated dataset. Furthermore, the P-Values for each of the cases should be calculated and compared under the hypothesis that P-values for the real news datasets should be greater than 0.1 and those for the fake news/fabricated news should to be lower than 0.1.

3.3 Conclusion

In this chapter, we combined Benford's law and Zipf's law to perform analysis such that the hybrid of the two laws will obey a Power law for real news dataset and a deviation for fake news dataset. The prevalent rate of fake news and propaganda is on the rise and there are really not much research work going on to combat fake news in Nigeria. The use of a combination of Benford's law and Zipf's law in news analysis has proven that all real news sources obeys the Power law. We, however, proposed that fake news sources will behave differently, i.e. not obeying the Power law. During this research work, we were able to get verified real news sources for analysis but we could not get verified or certified fake news sources, hence we are proposing that the analysis of fake news sources will behave differently.

In our future work, we plan to do the following:

i. Perform experiments on realistic fake news
ii. Compare the experiments in (i) with that of the realistic real news.

More results from other real news and fake news datasets would be needed before this assumption could be generalized.

Acknowledgements The author would like to specially thank Mr. William Waakaa and Mr. Myom Atu for their assistance. Furthermore, the author expresses huge thanks to Prof. Anthony T. S. Ho for his support.

References

1. Shu K, Sliva A, Wang S, Tang T, Liu H (2017) Fake news detection on social media: a data mining perspective. ACM SIGKDD Explor Newsl 19(1):22–36
2. New England College. How fake news leads to cyber attacks. https://www.newenglandcollegeonline.com/resources/communications/how-fake-news-leads-to-cyber-attacks/2019. Accessed 19 Jan 2019
3. New England College (2019) #BeyondFakeNews: Nigerian may start World War III through fake news Soyinka. https://www.vanguardngr.com/2019/01/beyondfakenews-nigerian-may-start-world-war-iii-through-fake-news/. Accessed 19 Jan 2019
4. Carson J (2019) Will fake news lead to the next cyber war? https://thycotic.com/company/blog/2018/03/16/fake-news-disruption-and-cyber-war/. Accessed 19 Jan 2019
5. techcabal.com (2018) Nigeria has a fake news problem its not paying attention to. https://techcabal.com/2018/08/03/nigeria-has-a-fake-news-problem-its-not-paying-attention-to/. Accessed 19 Jan 2019
6. guardian.ng (2019) Election: INEC trains staff to detect, counter fake news. https://guardian.ng/news/election-inec-trains-staff-to-detect-counter-fake-news/. Accessed 19 Jan 2019
7. premiumtimesng.com (2019) Platform to check fake news launched in Nigeria. https://www.premiumtimesng.com/news/top-news/298087-platform-to-check-fake-news-launched-in-nigeria.html. Accessed 19 Jan 2019
8. Tirunagari S, Abasolo DE, Iorliam A, Ho AT, Poh N (2017) Using benfords law to detect anomalies in electroencephalogram: an application to detecting alzheimers disease. In: 2017 proceedings on IEEE CIBCB, 21 Dec 2017
9. Iorliam A, Ho ATS, Waller A, Zhao X (2016) Divergence using benfords law, networks neural, for classification and source identification of biometric images. In: Shi Y, Kim H, Perez-Gonzalez F, Liu F (eds) Digital forensics and watermarking, IWDW (2016), Lecture Notes in Computer Science, vol 10082. Springer, Cham
10. Iorliam A, Ho ATS, Poh N, Shi YQ (2014) Do biometric images follow Benford's law? In: 2014 international workshop on biometrics and forensics (IWBF)
11. Iorliam A, Ho ATS, Poh N, Tirunari S, Bours P (2015) Data forensic techniques using Benfords law and Zipfs law for keystroke dynamics. In: Conference on international workshop on biometrics and forensics (IWBF 2015), Gjøvik, Norway
12. Iorliam A (2016) Application of power laws to biometrics, forensics and network traffic analysis. Doctoral dissertation, University of Surrey