**SENTIMENT ANALYSIS OF GHANAIANS' PUBLIC OPINIONS OF E-LEVY: USING TWITTER DATA**

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**Introduction**

The 2022 Budget and Economic Policy Statement presentation by the Ghanaian government included an announcement of a 1.75% tax on electronic transactions. Following a review, this amount was changed to 1% on all transactions in the most recent budget reading on November 24, 2022. Mobile money transfers, mobile money merchant payments, in-store payments utilizing POS or QR, e-commerce/online payments, and bank-to-mobile money transfers are among the transactions that will be subject to the charge, according to the Electronic Transfer Levy Bill, 2021 (J Djokoto, 2022). Transfers between one's accounts, bank transfers, cheques, and a daily tax-free transaction maximum of GHS 100 are all examples of transactions that are exempt from tax.

There are issues whenever a proposed or implemented government policy is made. The common Ghanaian is continually experiencing the significant consequences of government policy. Using the concept of sentiment analysis and data from Twitter, we have carefully studied this government policy from the perspective of the common citizen. Many well-known people and regular people around the nation have responded to the E-Levy concerns. The ease with which people may now convey their opinions owing to social media has led to statistics on sentiments. Popular social media sites, like Twitter, have a ton of information regarding expressed sentiments. This study's objective is to gather user comments about the e-levy policy utilizing data from Twitter, and then examine these various points of view.

Sentiment analysis has recently been successful with the use of deep learning, which has been effective in several application sectors (Lei Zhang, 2018). Sentiment analysis, commonly referred to as opinion mining, is the computer-based examination of people's views and attitudes regarding various things, such as products, services, businesses, individuals, events, topics, themes, and their characteristics. The field's emergence and rapid growth coincide with those of the social media on the Web, such as forum discussions, blogs, Twitter, and social networks, because we have a vast amount of opinionated data recorded in digital forms for the first time in human history (Qurat Tul Ain, 2017). In addition to analyzing various tweets and reviews, sentiment analysis also gives an understanding of information on public viewpoints.

The need to analyze and organize unstructured data that comes through social media in the form of hidden information has increased, which has increased the need for sentiment analysis. The mining of sentiments has made blogs and social networks useful resources. To express their opinions on various subjects or products, they are handled by a variety of people. As a result, gathering statistics about their goods and enhancing results is a resource that is advantageous for businesses and organizations. In addition, academics are now interested in this vast amount of information to learn what individuals think. Researchers mostly employ machine learning to categorize consumer opinions of items or businesses (Yaser Maher Wazery, 2018).

The machine learning algorithm may be seen as a computer model that manages input data to complete a job and provide a certain outcome. Additionally, machine learning is employed to create an algorithm that enhances a system's performance in response to knowledge or experience. The three categories that make-up machine learning is discussed as follows:

* The model is trained using supervised learning with labelled training data (method).
* Unsupervised learning: Unlabeled data are used to train the model.
* Reinforcement learning: At every level, the system engages with a changing environment.

The proposed system in this paper includes five main phases which are: Loading data from a CSV file, Pre-processing, Polarity Scoring, Sentiment Analysis and, Model Evaluation.

**Related Works**

Twitter has become a popular tool for monitoring consumer trends or opinions on particular goods or issues. Many researchers have concentrated their effort on sentiment classification subjects utilizing the Twitter dataset to apply classifiers and assess findings, creating a sizable corpus of past research on sentiment analysis. It is possible to efficiently execute sentiment analysis tasks by utilizing a variety of models, including recently developed deep learning models. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Neural Networks (DNN), and Deep Belief Networks (DBN) are some of the models in this category.

There are primarily three approaches to sentiment analysis: (i) lexicon-based technique (unsupervised approach), (ii) hybrid method, and (iii) machine learning-based method (supervised approach) (G Paltoglou, 2014). In the lexicon-based method, one or more effective dictionaries are used to assess the emotional content of text segments. In these word lists, each lemma is assigned an emotional value, such as how much positivity or negativity it often conveys. Lexicon-based and machine-learning approaches are combined in the hybrid approach. The text is initially analyzed using a lexicon, and the findings are utilized as training data for a machine-learning system. The size of the relevant dictionary is then expanded using the results from the second step. The method is repeated until a termination requirement is reached (ASM Alharbi, 2019).

According to a survey paper by (Lei Zhang, 2018), more exciting deep learning for sentiment analysis research will likely be published soon. Their article begins with a brief introduction to deep learning before offering a thorough analysis of the technology's most recent sentiment analysis applications. Three granularity levels have mostly been the focus of research on sentiment analysis. The document level, the sentence level, and the aspect are all included in this. A document that contains opinions is classified as conveying a generally positive or negative view using document-level sentiment classification. It presupposes that the entire text serves as the primary source of information and that it is understood to be opinionated and to include views on a particular subject. A document's sentences are categorized at the sentence level using sentiment classification. Aspect-level sentiment analysis, often known as "targets," focuses primarily on gathering and analysing views that have been expressed about entities and the features and/or aspects of those entities.

(Prabhsimran Singh, 2018) considers one such government initiative, the demonetization of high-denomination money by the Indian government, which went into effect at midnight on November 8, 2016. They analyzed this government policy from the common person’s perspective by using the concept of sentiment analysis and taking Twitter as a tool. In addition to performing a nationwide analysis, they also performed a state-wide analysis using geolocation to further elucidate the reasons for displeasure among people of respective states. Based on the Twitter dataset, RNN-LSTM was used to classify people's opinions into positive and negative ones. The accuracy of this method was compared to that of other machine learning techniques such as the Support Vector Machine, K-Nearest Neighbor, Nave Bayes, and Decision Tree (Yaser Maher Wazery, 2018).

**Methodology**

**Data Collection**

For data collection, the Twitter API was used through Tweepy and snscrape. Twitter API enables programmatic access to core elements of Twitter such as Tweets, Direct Messages, Spaces, Lists, users, and more in unique and advanced ways, (Twitter, 2022). The researchers had Essential level assess on the Twitter Developer platform which afforded them retrieve up to 500,000 tweets per month for free. This access was however limited in functionality and seeing as the researchers needed a tool with advanced functionalities, the researchers used snscrape alongside tweepy. snscrape is a scraper for social networking services (SNS). It is a tool written in Python for scraping data from social networking sites such as Twitter, Reddit, Instagram, Facebook, Telegram, Weibo, Mastodon, and VKontakte, (JustAnotherArchivist, 2022).

The tweets were collecting in two phases, representing two equally important stages in the implementation of E-Levy. The first stage was the announcement of the e-levy during the budget reading. This stage also marked the initial reaction of the Ghanaian public in the subject. Thus, tweets in the first phase were collected from 17th November, 2021 (day of announcement) to 30th April, 2022 (a month after implementation). For this phase, a total of 15,000 tweets were collected. The second phase captured tweets from the rest of the year regarding e-levy from 1st May, 2022 to 1st December, 2022. At this stage, Ghanaians had already become conversant with the e-levy and its full implications on their lives and daily activities were more visible. A total of 10,000 tweets were collected in the second phase. Together, a total of 25,000 tweets that contained e-levy hashtags and variations like “#elevy”, “#ELEVY”, “#ELevy”, “#Elevy”, “#e-levy”, “#E-LEVY”, “#E-Levy” and “#E-levy” were collected between 17th November, 2021 and 1st December, 2022.

**Data Preprocessing**

A tweet contains a lot of opinions about the data which are expressed in different ways by different users. Thus, the raw data is highly susceptible to inconsistency and redundancy, hence the need to clean the data before use. Therefore, after collecting the tweets and saving them to a CSV file, text pre-processing was conducted to clean the data. Because only English tweets were being examined, all non-English tweets were removed. In addition, links like <https://t.co/RQ0HHVAxCE>, hashtags such as #ghana or #election2024, and targets or usernames such as @NAkufoAddo from the dataset. Ppunctuations, emojis, emoticons, special characters, repeated characters and stop words were also removed from the tweets. Although sometimes needed for better context, numbers were also removed from the data set. In addition, all the text were converted to lowercase to make them easier to work with.

To further clean the dataset, lemmatization was applied. This technique is important because it reduces inflectional forms and sometimes derivationally related forms of a word to a common base form, (Khyani, Siddhartha, Niveditha, & Divya, 2020). An inflexion expresses one or more grammatical categories with a prefix, suffix or infix, or another internal modification such as a vowel change. For instance, inflectional forms of the root word “play” is “playing”, “played”, and “plays”. Finally, a word cloud representing the frequency distribution of the most occurring words and hashtags was created.

**Sentiment Analysis**

To conduct the sentiment analysis, extensive use of already available Data Science, Machine Learning and Python packages was used. Some of the packages used are pandas, nltk, textblob matplotlib, and wordcloud. Pandas is a fast, powerful, flexible and easy-to-use open-source data analysis and manipulation tool, built on top of the Python programming language. It is built on top of another package named NumPy, which provides support for multi-dimensional arrays. NLTK (Natural Language Toolkit) is of great importance to the project because it is the go-to package for Natural Language Processing with Python. It is a powerful tool to preprocess text data for further analysis and features functionalities such as text classification, tokenization, stemming, tagging, parsing, semantic reasoning, and wrapping, (NLTK, 2022).

To begin the sentiment analysis process, the polarity scores of the tweets was calculated. Polarity refers to the overall sentiment conveyed by a particular text, phrase or word which can be expressed as a numerical rating known as a “sentiment score”, (Calefato, Lanubile, Maiorano, & Novielli, 2018). This score can be a number between -100 and 100 with 0 representing neutral sentiment but is often represented by a float within the range -1.0 and 1.0, where -1 indicates the sentiments of the speaker toward the subject is highly negative, to +1, which indicates the sentiments of the speaker toward the subject are highly positive. The subjectivity and objectivity of the text was also considered. Subjective sentences generally refer to personal opinion, emotion or judgment whereas objective refers to factual information, (Luan & Lin, 2019). Like the polarity score, the subjectivity is a float within the range [0.0, 1.0] where 0.0 is very objective and 1.0 is very subjective.

Scores were calculated for the positivity, negativity and neutrality of the tweets. These scores were assigned columns in the dataset with their respective headings. Afterwards, the sum of all the polarity was calculated and compared to see which sentiment dominated in the dataset.

**Results and Analysis**

After applying the sentimental analyzer to the dataset, various analysis and observations were made.

**Announcement and Before Implementation**

As stated earlier, 15,000 tweets were collected from the period of announcement to the period of implementation (17th November, 2021 to 30th April, 2022). Out of these tweets, 1,762 were removed during the data cleaning stage because these tweets did not originate from Ghanaian locations. Thus, tweets from this phase that were used for the sentiment analysis was 13,238. Below is a graph showing the proportional distributions of the tweets based on the various sentiments.

**Figure 1**

Pie chart showing proportional distribution of tweets based on sentiment before E-Levy implementation

As can be seen from the chart, Ghanaians’ sentiment towards the introduction of the E-Levy was neutral. Out of the 13,238 used, 11,020 representing 83% of the whole was considered to contain neutral sentiments while 1113 tweets were considered to contain positive sentiments. Surprisingly, tweets that contained negative sentiments were 1104. Looking at the findings, it is safe to say that Ghanaians were generally undecisive because although they know the implications of the tax imposition, they could not conclude because it was the first time something like that had been proposed, thus they had not experienced it.

**Post Implementation**

Tweets collected after the implementation of the E-Levy totalled 10,000. Similar to the tweets from the first phase, only 5,616 tweets were used for the sentimental analysis because dropped 4,384 tweets did not originate from Ghana. Below is a graph showing the proportional distributions of the tweets based on the various sentiments.

**Figure 2**

Pie chart showing proportional distribution of tweets based on sentiment after E-Levy implementation

As can be seen from the chart, Ghanaians’ sentiment towards the imposition of the E-Levy was still neutral for rest of the year. Out of the 5,616 used, 4,722 representing 84% of the whole was considered to contain neutral sentiments while 391 tweets were considered to contain positive sentiments. Again, it is surprisingly to note that this time around that with a tweet count of 1104, negative sentiments were higher that positive one. This shows that even though Ghanaians are largely neutral in terms of sentiments towards the imposition of the E-Levy, there is some level of negative reaction.

The researcher attribute the large numbers of neutrality to the fact that the imposition of the E-Levy is relatively new, compared to other taxes and levies. As such, Ghanaians are yet to acclimatize to the effects of the E-Levy. At that point, the researchers project that there will be larger varied scores between the sentiments. Until then, the findings show that Ghanaians are still evaluating the advantages, disadvantages and effects of the E-Levy on the nation’s economy and their lives.

**Future Works**

The researchers intend to collect more data on disclosures and opinions of the E-Levy. Seeing as Ghanaians are more conversant with Facebook than Twitter, the researchers intend to expand the data collection range to include Facebook. Additionally, the researchers intend to further examine Ghanaians’ sentiments towards the E-Levy relative to other taxes the government has imposed. Most importantly, the researchers intend to endeavour to use Deep Neural Networks in the next sentiment analysis project.

GitHub Link:

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