Fake News Detection in Today's World

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Abstract

Online media aims to reach a larger audience and hold their interest for a longer period of time. This rivalry fosters an atmosphere that encourages sensational, false, and harmful news. This study aims to develop a Machine Learning model that detects Fake News articles. Well-known models and algorithms have been used and modified to produce better accuracy results, and different datasets have been scanned. The data has been visualized in order to demonstrate interesting aspects of both fake and real articles. The main findings include that when using the Multinomial Naïve Bayes classifier with TF-IDF Vectorizer and Count Vectorizer, the accuracy results are higher. Demonstrations of Cross-validation score, Passive Aggressive Classifier, TF-IDF Vectorizer, and Count Vectorizer are shown. A prototype for a web page was created to demonstrate how a simple and useful page would look for a Fake News Detection program. A survey was released to examine the way of thinking of different age groups regarding fake news, social media, and traditional news outlets. It was filled by 477 participants from 23 countries. The survey results were compared with other surveys on the same topic.

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1. Introduction

Fake news is deceptive information presented as news. Most of the time, its aim is to mislead and manipulate the readers in order to damage the reputation of a person, company, organization or even a whole country. Despite being a relatively new term, fake news has existed long before the internet – it has been around since the invention of the first writing systems (Tandoc, et al., 2017).

In today's fast-paced world, every member of society strives to get information about the world around him as quickly as possible. This thirst for information can very easily be used for manipulation, distortion of public opinion through so-called "fake" news. False information comes in various forms: video, audio, photos, or text.

There are multiple methods of finding fake news such as knowledge-based, style-based, propagation-based, and source-based fake news detection. All the mentioned methods can be processed manually and automatically (Zhou & Zafarani, 2020).

Detecting fake news with a program is one of the easiest ways – the program automatically does all the work for the user such as checking if a similar article has been posted somewhere else, reverse searching the image in the article (if there is one), checking the sources of the article, etc. Doing this process manually would take a significant amount of time, compared to using a program for it.

The purpose of a fake news detection system is to help users detect and remove varieties of potentially fraudulent and misleading news. The prediction of the probability that a particular news article is deceptive on purpose is based on the analysis of previously seen truthful and deceptive news (Rubin, et al., 2015).

2. Literature review

2.1. What is Fake News?

Fake news is false information posing as news. It often aims to misinform the reader in order to manipulate them. Its existence has been around as the same extent of time as there has been news. With the rise of social media, its prevalence has been increasing drastically.

In an article published by the American Association for the Advancement of Science (Lazer, et al., 2018), fake news outlets are represented as news sources which lack the news media's editorial processes and norms that ensure the truthfulness and integrity of information. The paper also points that the term "false news" is favored in some places (i.e., Facebook and First Draft) because of the use of fake news as a political weapon (Wardle & Derakhshan, 2017). Since the term draws attention to a crucial topic because of its political importance and it is useful as a science construct, the term is being retained by numerous articles.

A classic example of fake news is dated back in 1938, when a group of actors, disguised as news reporters, narrate a story of a Martian invasion on Earth (Cantril, 2017). The intention of the drama director Orson Welles was to entertain listeners for Halloween, people interpreted it as factual news, since radio was the main source of information in the United States (Tandoc, et al., 2017). There were listeners who realized that the report must be false and did not panic, but many others became hysterical, praying for their lives, telephoning relatives and trying to run away (Cantril, 2017). If the story was narrated nowadays, most of the listeners will not believe it due to the enormous access to information we have now. However, quite a big number of people tend to share news articles without checking if they are true or not, despite the access to all the information on the internet.

The fake story, directed by Orson Welles, was created with the intention to entertain listeners, not to damage or convince someone to take matters in their own hands. However, majority of fake news articles aim to change the reader's point of view, fill them with doubt against something or someone or scam them. A conspiracy theory was spread in 2016 that claimed Hillary Clinton was involved in child trafficking in the basement of a pizzeria in Washington DC. This led to numerous death threats and abuse on social media towards the owner of the place and its staff. One man even took it further, going into the pizzeria with an assault rifle, firing one or more shots. Luckily, no one was injured (Kang & Goldman, 2016). The story about Hillary was completely fabricated, the pizzeria did not even have a basement. Often people believe in what they read without checking if the information is true just because they dislike the person, organization, etc. the article was written about. This can often lead to readers sending death threats, acting in an abusive way and even seriously injuring someone.

2.2. Fake News Characterization

The characteristics of fake news articles can be easily determined by looking at the writing style and quality of the text, quantity such as word count and points of view (Zhou & Zafarani, 2020). These theories target deceptive information, which is similar to fake news, but not the same. Therefore, these characteristics should be statistically detectable in order to separate fake news from disinformation and reliable news.

In an article from the journal "Information Processing & Management" (Zhang & Ali, 2020) fake news is split in four groups, which have their own two sub-groups, described by elements.

The first group is the Creator/Spreader. They can be either real human or non-human. Both harmless writers and users who accidentally publish fake news and malicious users who deliberately produce false information are examples of actual human fake news producers. The non-human fake news spreaders can be either social bots or cyborgs (Ferrara, et al., 2016).

The second group is News Content, which refers to the body of the news. It includes Physical and Non-physical Content. The physical content consists of the headlines and body text (linguistic & syntactic features) and image/video (visual features). The Non-physical content contains the main purpose (rumors, satire, fake reviews, etc.), sentiment (positive or negative) and news topics.

The third group is Social Context, which includes Platform and Distribution. The platform involves Social media and Main Streaming, and the distribution is about the Broadcast Pattern and Community of users. The way news is disseminated on the Internet is referred to as social content. User network analysis (how Internet users are interested in the news) and broadcast pattern analysis (temporal pattern of dissemination) are two forms of social context analysis.

The last group is the Target Victims. Based on the purposes of the news, the targets can be students, seniors, voters, parents, etc. The potential risk analysis for target victims is divided in two sections – role-based (determined by the age of the target) and temporal-based (time series analysis for potential risk prediction).

Another way to characterize fake news articles is by investigating the users involved in an article. Unlike fake reviews, fake news can “attract” both normal users and social bots (malicious users) (Shao, et al., 2018). Social bots are created to provide a useful service. However, their first idea has been tampered in order to use them as malicious users who spread, comment and share fake news (Ferrara, et al., 2016). In order to detect bots in social media, the reader must understand what modern social bots can do. Early bots are the easiest to spot – they post content automatically, which is usually unlikely for a human to do in such a fast way. In some social media such as Facebook, Instagram and Twitter, the user may see a post with numerous comments that are similar. This is often because the poster has used a program or paid to have their content boosted with likes and comments. It can be used on content which is considered harmless, such as someone posing, with bots commenting positive things. However, it can also be used on a post which has false information. By boosting a post with likes and comments from a bot, it becomes more relevant and is more likely to appear on more users' social media. These types of bots are also easy to detect, since their comments are very similar if not the same, and most of the times their profiles seem like brand new, with close to zero followers and zero posts.

2.3. Fake News Detection

In order to detect whether a piece of information is true or not, there are multiple detection schemes to do this task. This can be done both manually and by using a program.

Detecting fake news is a multidimensional task due to the traits of fake news. The detection schemes exploit multiple news-related (e.g., headline, publisher, body text) and social-related (e.g., feedback, spreaders) types of information (Zhou & Zafarani, 2020). Style-based fake news detection aims to capture and evaluate the differences between writing styles of true and fake news. Propagation-based fake news detection works with information provided in news distribution. Credibility-based fake news detection determines the credibility of headlines (e.g., using clickbait detection (Shu, et al., 2017)), comments, authors and readers to indirectly detect fake news. Each perspective has its own set of datasets and tools with various strategies to detect fake news in machine learning, data mining, information retrieval, natural language processing and social research (Zhou & Zafarani, 2020).

Fake news detection on traditional news media (broadcast television, radio, newspapers, etc.) leans mostly on news content. However, in social media there is more helpful information which can be used to help with the detection of fake news (Shu, et al., 2017). ACM (Association for Computing Machinery) used news content features such as source, headline, body text, image and video in order to extract discriminative characteristics of fake news. Their studies show that typically the news content which is looked at is mostly linguistic-based and visual-based.

Linguistic-based content is related to "clickbait" (i.e., when the reader clicks on an article with a title that they find interesting to read, but the information inside has little or nothing to do with the title). In order to capture such deceptive cues in writing styles in linguistic-based content, existing work has made use of both common linguistic features (lexical features, syntactic features) and domain-specific linguistic features (quoted words, external links, number of graphs, average length of graphs, etc.).

A content is visual based when there are included videos and images in an article. In fake news articles, visual cues are an important manipulator. Their aim is to provoke an emotional response from the reader with sensational or even fake visual content.

2.4. Machine Learning

Machine learning is a method of data analysis which automates diagnostic model building. It is based on the idea of programs learning from data, identify patterns and make decisions with minimal human intervention (Anon., n.d.). There are two main types of machine learning – supervised and unsupervised.

Supervised machine learning is the search for algorithms that depend on externally supplied instances to develop general hypothesis, which afterwards can predict future instances (Kotsiantis, 2007). In supervised machine learning, one can create a model by using labeled training data which contains input and wanted output data. It is often used in bioinformatics, database marketing, information retrieval, spam detection, pattern and speech recognition, etc.

Unsupervised machine learning is an algorithm that learns patterns from untagged data. The machine's task is to build a compact internal representation of its world by mimicking it.

Unsupervised learning performs self-organization that captures patterns as probability densities (Hinton & Sejnowski, 1999). Unsupervised machine learning is often used in clustering (i.e., customer segmentation, genetics, recommender systems, etc.).

In a journal from Cornell University (Khan, et al., 2021) there are pointed out various traditional machine learning-based methods. The author of one of the mentioned articles (Fürnkranz, 1998) proposed that for fake news identification, linguistic-based features such as total words, characters per word, frequencies of phrases, i.e., "n-grams" (contiguous sentences of *n* items from a given sample of text) & bag-of-words strategies be used, as well as parts-of-speech tagging.

Deep learning models were used in many studies to detect false news. William Wang developed a hybrid convolutional neural network model that outperformed other machine learning models (Wang, 2017). Shu et al. argued in a recent paper that the complexity of fake news identification is a crucial feature of such detection in (Shu, et al., 2017). To take advantage of both news content and user feedback, the authors created a sentence-comment co-attention sub-network. In this process, they were able to capture both explainable check-worthy sentences and user feedback for the purpose of detecting false news. A hybrid method has been suggested by Hamdi et al. to detect misinformation in social media such as Twitter (Hamdi, et al., 2019).

In the papers of Khan et. al. there are a few questions answered regarding traditional machine learning compared with deep learning models to detect fake news. They discovered that deep learning models outperform traditional machine learning models in general. Among traditional learning models, Naive Bayes reaches 93 percent accuracy on combined corpus. Bi-LSTM and C-LSTM show great promise among deep learning models, with 95 percent accuracy on combined corpus (Khan, et al., 2021).

2.5. Conclusion

Fake news is a major problem that often leads to manipulation, fraud, and, in extreme cases, life-threatening situations. There are many types of fake news – satire, misleading content, fabricated content, gossip, etc. Detecting fake news is crucial in order to prevent the harm it may cause.

The writing style, as well as the consistency and quantity of text, are easily noticeable characteristics of fake news posts. Investigating the users involved in the article is another way to characterize fake news stories. In fake news posts, social bots are very popular. Despite their original intent to provide a valuable service, they have been tainted and are now used as malicious users who distribute, comment on, and post fake news. Early bots are easy to spot since they post content automatically, which is an unusual activity for a human. In social media posts, social bots can be spotted by the similarity in their comments.

Fake news detection systems are a significant support these days, allowing readers to verify if the article they are reading is true or fake. Fake news detection can have many types – style-based, propagation-based, and credibility-based. The most common techniques for fake news detection are based on linguistics and visualization.

When it comes to deep learning models and identifying fake news, machine learning plays a vital role. Linguistic-based features such as total words, characters per words, bag-of-words strategies, parts-of-speech tagging are essential in these detection systems. Neural network models have shown great performance for such systems. Complexity of fake news identification plays a key role. It was discovered that deep learning models outperform traditional machine learning models. Hybrid methods have also been suggested to detect false information on social media.

3. Related Work

Most of the existing research have been aimed at classifying social media news. A variety of methods have been presented by different researchers for fake news detection.

Fake news can be classified in various categories. For example, in the research Fake News *Detection on Social Media: A Data Mining Perspective* (Shu, et al., 2017), they have proposed to use linguistic-based features as total words, frequency of large words and phrases, characters per word, parts-of-speech tagging. They have also stated that a news article has two main components – Content and Publisher. The Content includes a set of attributes that represent the News Article and includes a headline, image, text, etc. The Publisher has a set of profile features which describe the author, such as name, age, domain. By looking into the relevance of the main components, it is often effortless and uncomplicated to determine whether a news article is fake or real.

Deception Detection for News: Three Types of Fakes (Rubin, et al., 2015) there are three types of fake news: Serious Fabrications (Type A), Large-Scale Hoaxes (Type B) and Humorous Fakes (Type C). Serious fabrications are most often found in Yellow press and Tabloids, which present a wide spectrum of unverified news and use eye-catching headlines and images, known as "clickbaits", in order to increase profits. Large-scale hoaxes attempt to deceive the reader by fabricating a whole story, which can sometimes be mistakenly validated and published by traditional news outlets. The Invasion from Mars (Cantril, 2017) is an example of a harmless large-scale hoax. The Humorous Fakes are intended to catch the reader's eye by making them aware of the humorous intent. Their aim is not to deceive the reader, but to heavily include irony and humor to mimic a genuine news source.

Rubin, Chen, and Conroy have also noted that simple content-related n-grams and part-of-speech tagging have been found unsatisfactory for the classification task. Instead, they suggest Deep Syntax Analysis using Probabilistic Context-Free Grammars, which method was used by *Syntactic stylometry* *for deception detection* (Feng, et al., 2012) to distinguish rule categories (parent nodes, lexicalized, non-lexicalized, etc.) for fake news detection with accuracy of 85-91%.

Contrary to Rubin, Chen, and Conroy, in *Evaluating machine learning algorithms for fake news detection* (Gilda, 2017) it is mentioned that the Probabilistic Context-Free Grammar features do not do enough to add to the models' efficacy. However, Gilda also mentioned that bi-gram TF-IDF yields highly effective models for detecting deceptive news.

Several researches show encouraging results in detecting fake news through tracing user propagation and neural networks. In *"Liar, liar pants on fire": A new benchmark dataset for fake news detection* (Wang, 2017) is seen a hybrid convolutional neural network model that can outperform other traditional machine learning models. Demonstrated in *CSI: A hybrid deep model for fake news detection* (Ruchansky, et al., 2017) , a CSI model is created where they capture text, article response and source characteristics based on user behavior. A three-level hierarchical attention network has been proposed in *3Han: A deep neural network for fake news detection* (Singhania, et al., 2017) where each level is for fords, sentences and the headline of a news article.

4. Survey

4.1. Survey Background and Goals

The idea of this survey was to collect data from various groups of people, in order to examine how nowadays' society deals with fake news, what their main news source is and questions that examine the participants' way of thinking regarding this topic. The survey was open for a total of two weeks (16th March – 31st March 2021) and 477 participants of six different age groups took part. The questions were written both in English and Bulgarian to ensure that each participant understood the question and provided an appropriate response.

The survey relates to the main topic and literature review by investigating how participants recognize fake news on a daily basis. Each question is carefully chosen to ensure useful results that can be used in future research.

4.2. Survey Limitations

Because of the survey's non-probability sample, the findings are not indicative of the populations of the surveyed countries.

4.3. Survey Content

The survey's main goal was to establish key research questions for fake news detection, with a total of 11 questions, two about age group and country and nine about the real issue. The age group and country sections are used to categorize the data and study how different age groups and nationalities respond to fake news.

The nine questions regarding fake news are as follows:

- *How often do you read news from online sources?* – This question had multiple choice answers from *daily* to *twice a month or less often*. This question had multiple choice responses ranging from *daily* to *twice a month or less frequently*. This is a preliminary question that will help us understand how focused the participants on news are in general.

- *When you think of social media brands (e.g., Facebook, Instagram, Twitter, etc.) do you consider them as news sources?* – This was a simple *Yes* or *No* question that assisted us determine whether the participant considers social media to be a news source or not. Since there are numerous social media brands available today, the majority of the most popular ones strive to do their best to remove deceptive news articles in order to maintain their good reputation.
- *What is your primary news source?* – The answers here were *Traditional News Sources, Digital Versions of Traditional News Sources on the Web* and *Social Media*. Another option allowed the participant to write their own response. With regard to age and country, the goal of this question is to estimate which group of people uses which news source the most.
- *Do you know what Fake News is?* – Another simple *Yes* or *No* question, followed by a definition of the term "Fake News" for those who are unfamiliar. The objective here is to find what amount of respondents are aware of fake news and which age group has the highest number of negative responses.
- *Do you know when you are reading fake news?* – This question has three available answers – Yes, No or Not Sure. The purpose of this question is straightforward: divide the participants into three groups and study how each group responds to the other questions. However, this question may be problematic because someone who believes they know when they are reading fake news may not always be aware of it.
- *In your opinion, why is fake news published online?* – Because some people may have more than one opinion on the subject, the answers to this question were provided in

the form of checkboxes. There was also an option for the participant to write their own opinion.

- *Do you think traditional news outlets report fake news?* – Another simple *Yes* or *No* question, which actually complicates the concept of a program for Fake News Detection. With the current technology and research regarding Fake News Detection, fraudulent articles cannot be detected from traditional news outlets. Many times, the news in traditional media comes from a person, group or organization with big influence (such as politicians, actors, music artists, businessmen, etc.) and their word is not allowed to be questioned because of their position.
- *If you read from media that is not well-known, do you check the sources of the information provided?* – The answers provided were *Yes*, *Sometimes*, *No* and *I do not read news from random websites*. The purpose of this question is to see if the participant makes any effort to verify whether or not what they are reading is correct. A major issue with reading fake news is that people tend to share whatever information appeals to their understandings, regardless of whether the information is true or not.
- *Have you or anyone you know spread information from a news article that you/they have not checked their authenticity?* – The aim of this question is to see whether the participant has received and/or shared any unchecked information. This is a complicated question because the majority of participants believe that traditional news sources share fake news, so sharing and receiving fake news is unavoidable. However, if we imagine that we live in a world where traditional news outlets only report the truth, the question is straightforward.

4.4. Survey Results

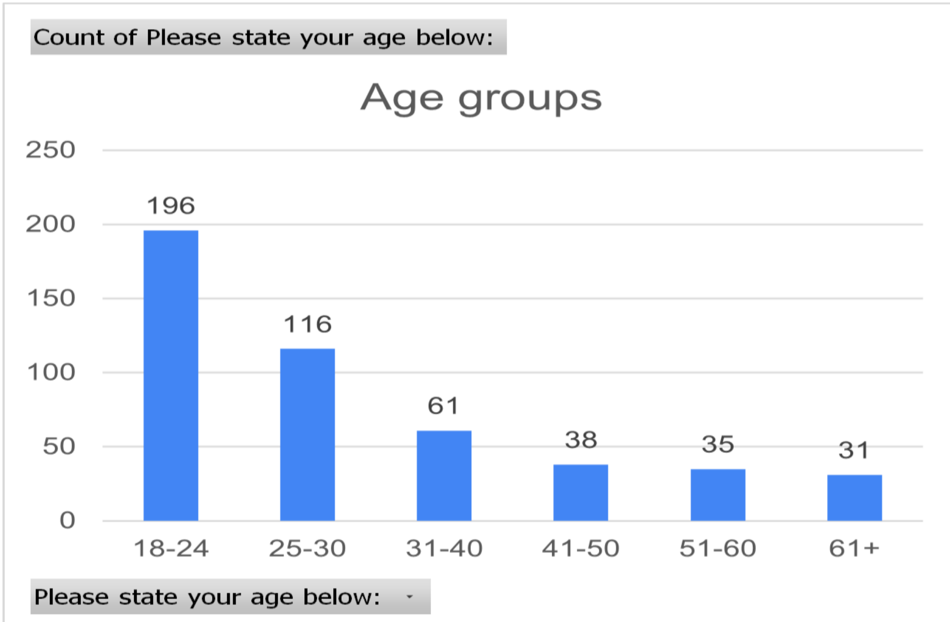

Figure 1 - Age groups

The survey was filled by 477 participants. Most of the participants are between the age 18-30 (65.41%) so comparing directly age groups would be insufficient. The age group is crucial for the survey because different generations have different opinions, particularly when it comes to news, social media, traditional news sources, and detecting fake news.

Some survey questions, separated by age group, provide intriguing responses that reveal the ways of thinking among different generations.

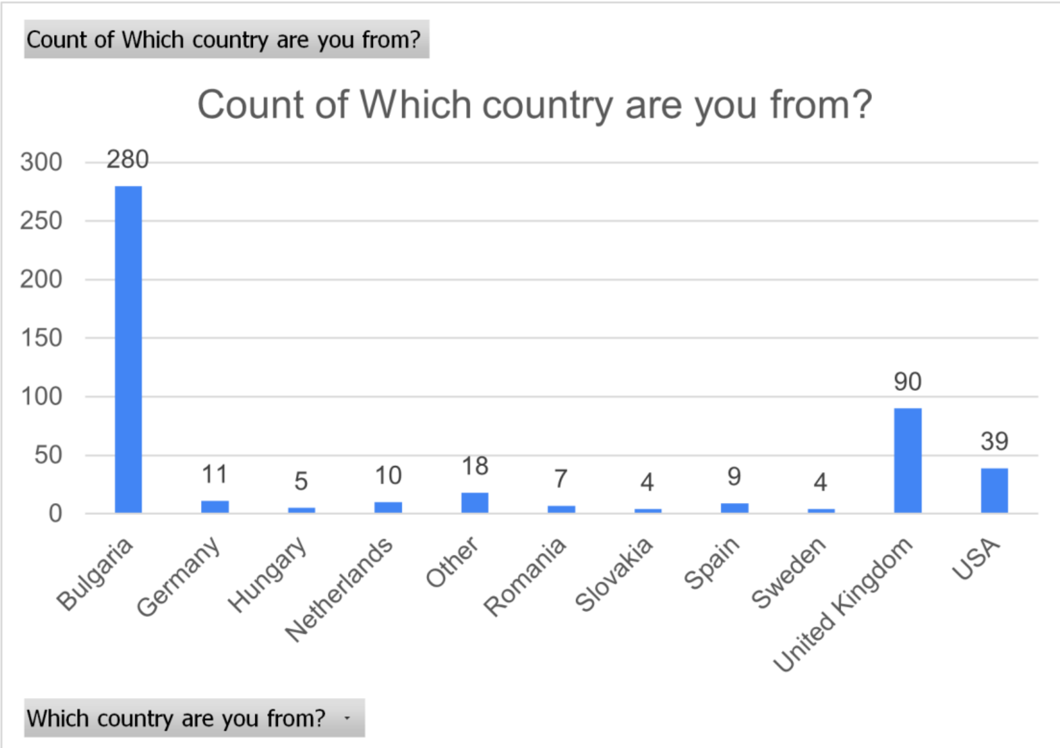

Figure 2 - Countries

The survey results show that 58.7% of the participants are from Bulgaria, 18.87% from the United Kingdom, 8.18% from the United States. In the *Other* section, there are 13 countries from around the world that I decided to combine into one because the number of participants from said countries was less than four. The table depicts the majority of countries, but statistics will be drawn from the top three.

The countries which were combined in the section *Other* with the count of participants respectively are Austria(1), Canada(1), Croatia(1), Finland(1), France(1), Greece(2), Israel(2), Italy(1), Poland(2), Portugal(1), Serbia(3), United Arab Emirates(1) and Venezuela(1).

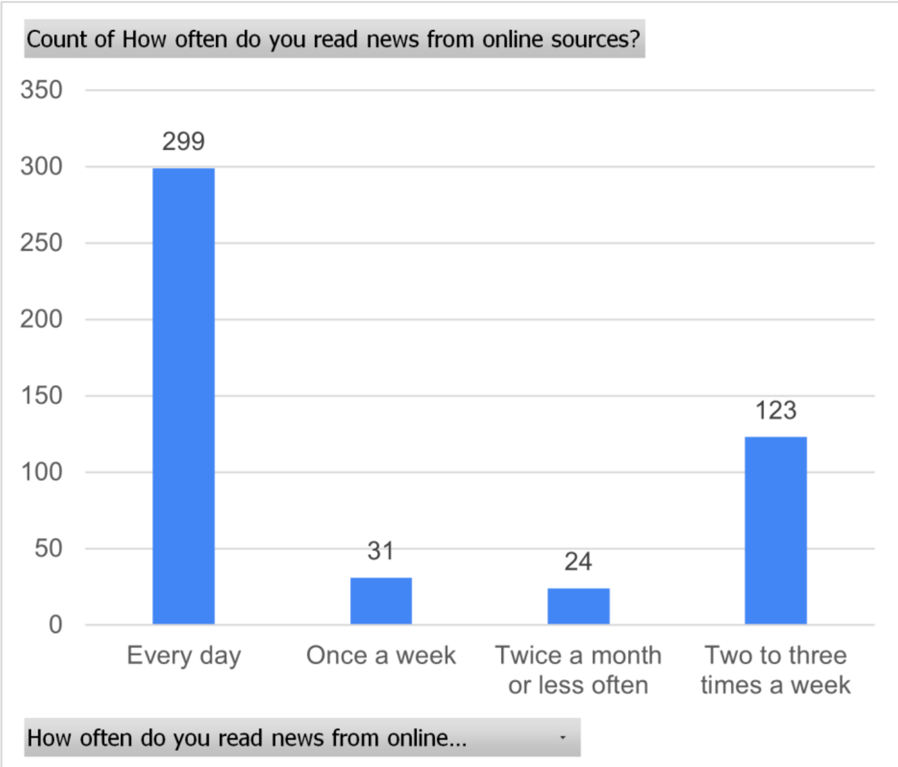

Figure 3 - Survey Question 1

The statistics from the first question show that 62.68% of the participants read news from online sources daily, 25.79% read two to three times a week, and 11.53% read news online less often. The statistics show that most participants use internet to get their news quite often, which can sometimes lead them to deceptive news articles if they are not careful. Some links to news articles can even lead to viruses as well. However, most social media websites do their best to prevent the spread of malicious websites that can harm the user in any manner. Here are some examples of news articles that report on this type of activity and how the social media company handles it:

Facebook Removes Accounts Used to Infect Thousands With Malware

Coronavirus: Twitter will label Covid-19 fake news

Instagram Launched an Algorithm to Fight Fake News

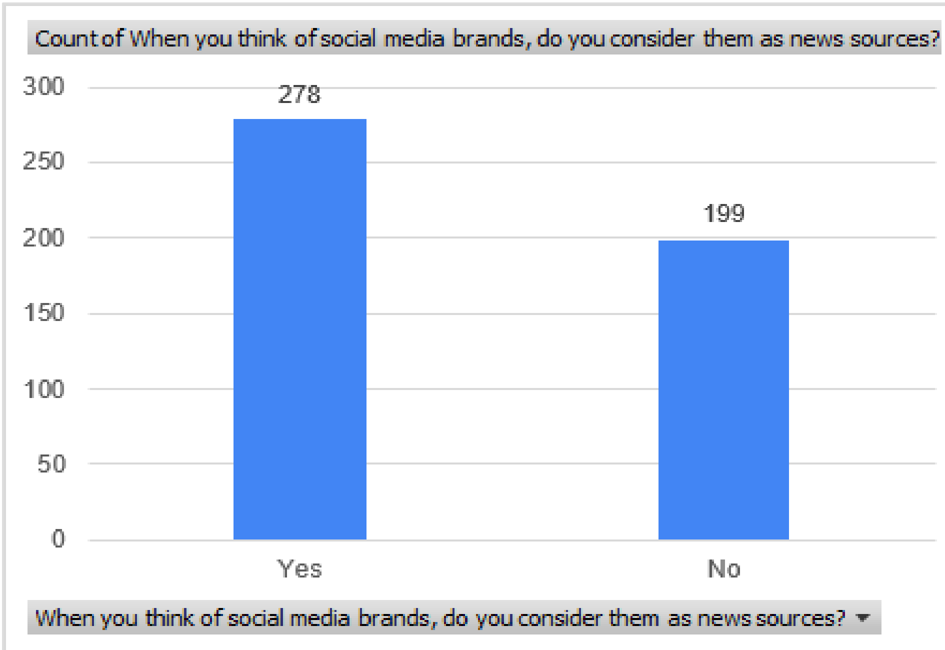

Figure 4 - Survey Question 2

The second question results show that 41.72% of the participants think that Social media brands cannot be considered as news sources, and 58.28% have the opposite opinion.

Looking into the detailed statistics, we can see that the younger the age group is, the more it trusts social media as reliable news sources. The results show the ones who view on social media as a reliable news source are 67.3% of the age group between 18-24, 60.3% of the next group (25-30), 52.5% of the ones between 31 and 40, 50% of the participants from 41-50, 48.6% from the 51-60 age group, and only 22.6% in the oldest age group, which is 61 and above. Charts with the detailed results can be seen in Appendix Heading 5.

The younger and older generations differ in their ability to adapt to newer technology and their trust in it. Jung et.al. studied how people above the age of 65 react to social media by interviewing 46 participants. Those who responded positively stated that they only use social media as a form of communication to stay in touch with their family and friends. Those who responded negatively stated that they cannot trust social media because they believe it violates their privacy, referring to it as a "dispenser of information" and claiming it is a dangerous form of communication media (Jung, et al., 2017).

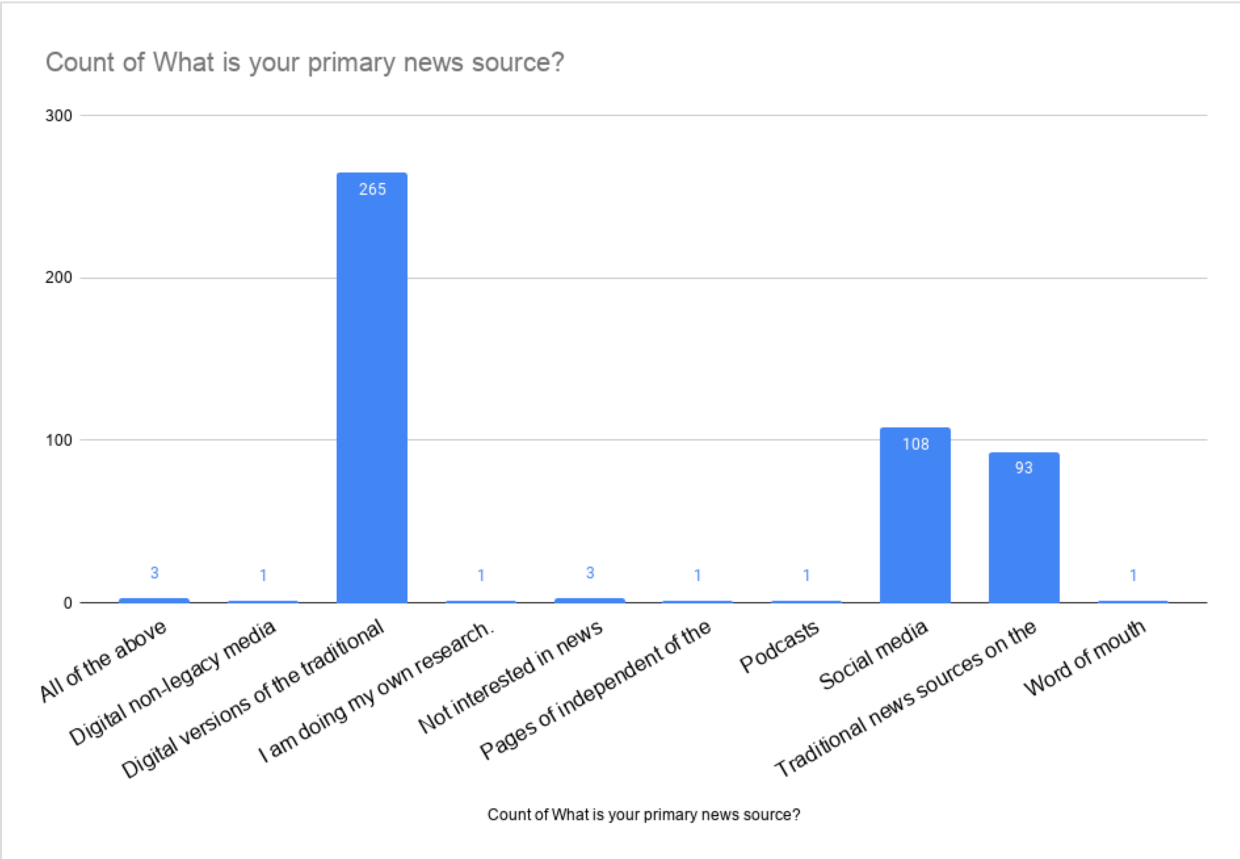

Figure 5 - Survey Question 3

The statistics from this question show that 55.56% of the participants read their news from digital versions of the traditional news media, 22.64% use social media for this purpose and 19.5% rely mainly on traditional news sources, such as TV, newspapers and radio. There are other answers given as well, as shown on the graph. The answer *Digital Non-Legacy Media* can be considered a part of the *Social Media* answer, since Legacy media is the mass media. Another interesting answer is given by another participant, stating that their primary news source is "*Pages of independent of the government news agencies, that have pages in social medias or their own websites*". There are three participants, saying that they are not interested in news, one who does their own research, one from podcasts and one from word of mouth.

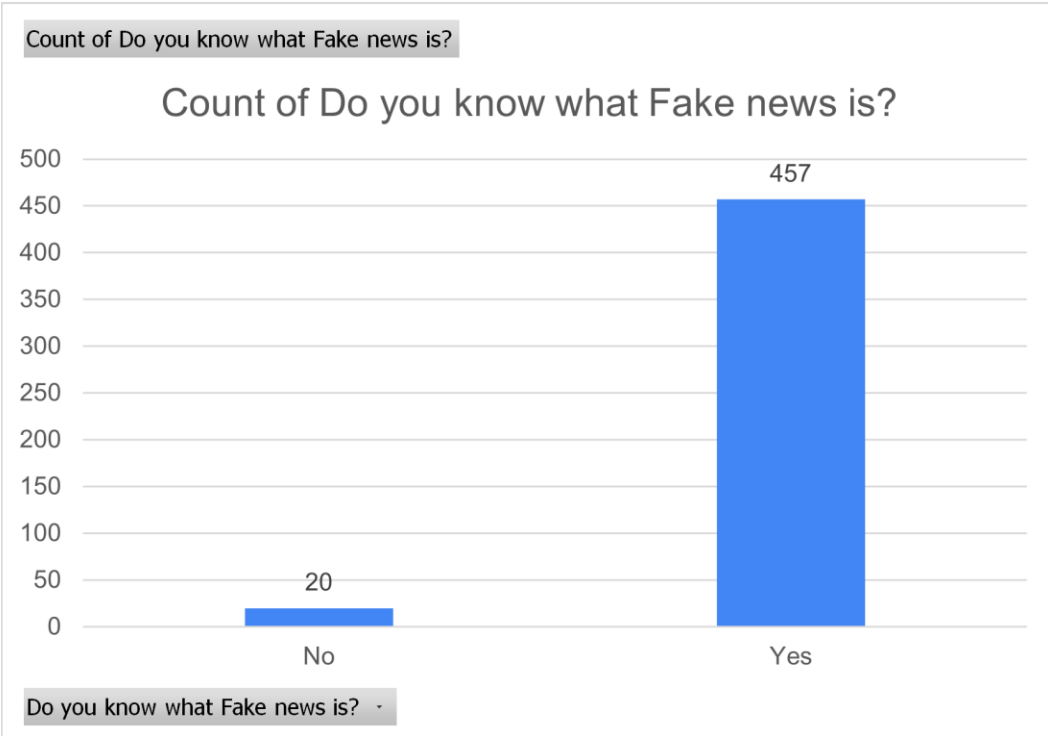

Figure 6 - Survey Question 4

The results of this question show that 95.81% of people taking part understand what Fake News is, while only 4.19% do not. Because fake news has existed for as long as news as whole, the results are not unexpected. However, there will always be people thinking that "If it's on the internet/TV, it must be true". Fortunately, as time has passed and the majority of internet users have fallen for traps such as fake news or malicious websites that lead to viruses, leading to most people learning not to trust every link or news on the internet.

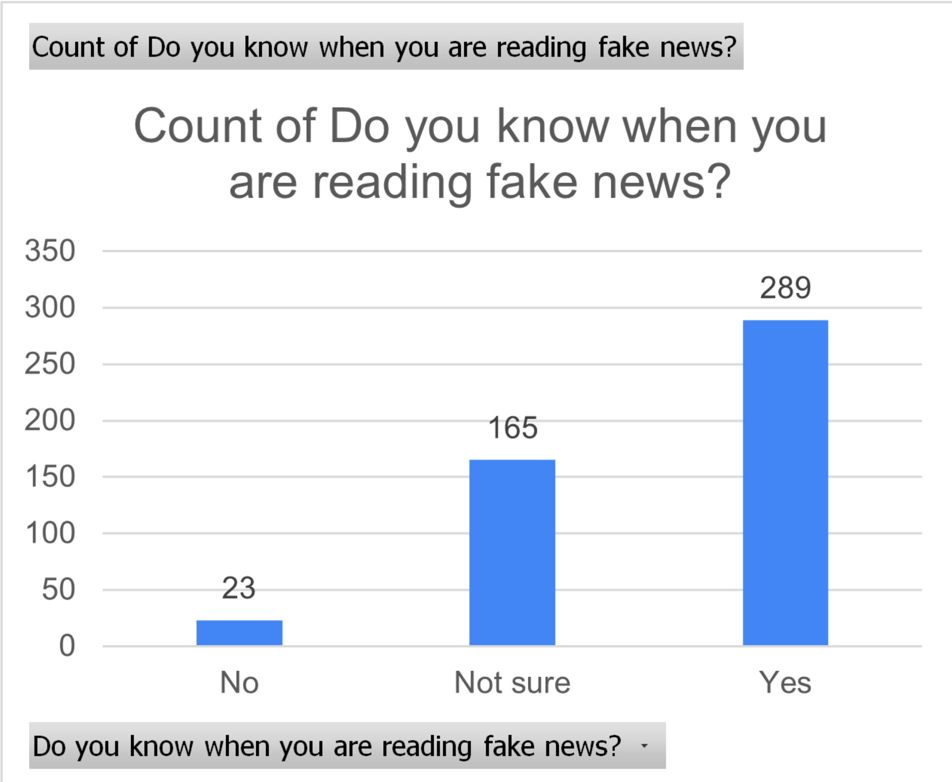

Figure 7 - Survey Question 5

The results from the fifth question returned with 60.59% of participants saying they know when they are reading fake news, 34.59% responding with *Not sure*, and only 4.82% answering with *No*. When comparing the results of the previous question results, the difference between the number of participants who do not know what fake news is and those who do not know when they are reading fake news is almost unnoticeable. Given that deceptive news can be difficult to distinguish, especially when it comes from a source that does not typically post such material, it is not surprising that so many respondents voted *Not sure*.

Looking more into detail, nearly 42% of participants from age group 61+ have voted *Yes*, 19.4% have voted *No*, and 38.7% have voted *Not sure*. From the 35 participants of age group 51-60, almost 43% voted *Yes*, 51.4% said that they are unsure, and only 5.7% (two participants) voted *No*. The next age group (41-50) have 57.9% of participants voting *Yes*, 39.5% voting *Not sure* and a single person (2.6%) voting *No*. Getting closer to the generations which grew up with technology, 62.3% of the participants from age group 31-40 voted with *Yes*, 27.9% were unsure, and 9.8% (6 participants) voted with *No*. The data collected from 116 respondents aged between 25-30, we can see that 64.7% voted *Yes*, 31% voted *Not sure* and 4.3% voted *No*. The last and biggest in means of participants group, people aged between 18-24, 64.3% voted with *Yes*, 34.2% were unsure and only 1.5% voted with *No*. The detailed results can be seen in **Error! Reference source not found.**.

There is a connection between the oldest age groups (51-60 and 61+) – both have a sizable percentage of people who are unsure when they are reading fake news. Barnard et.al. stated in their article that when it comes to the older generations, there is found to be more fear and stress associated with operating computers, as well as a lower appraisal of their own skills and abilities, both in accessing and learning to handle them, than in other age groups (Barnard, et al., 2013). Thus, older generations are less confident in their ability to discern fake news, as the majority of such articles are on the internet.

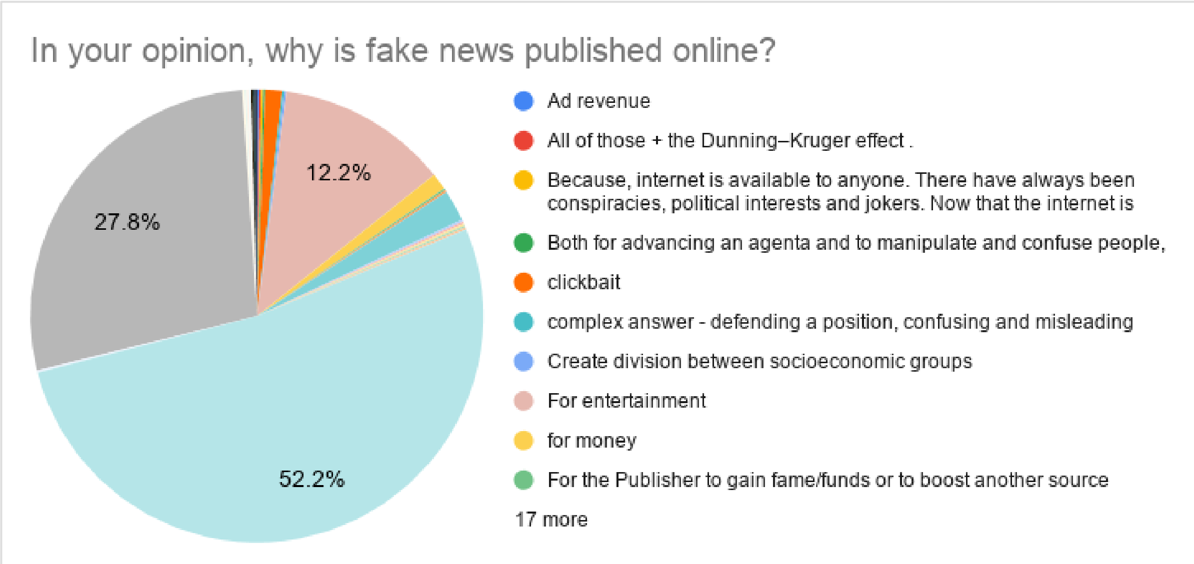

Figure 8 - Survey Question 6

The 6th Question *In your opinion, why is fake news published online?* participants had the option of selecting more than one answer or writing their own. A total of 673 answers were given from 477 respondents. The top answers are the three provided beforehand, with *To advance a specific position or agenda* having 52.2%, *To confuse people* following with 27.8%, and *For entertainment* with 12.2%. Only 2.2% answered with *I don't know*, which was the last option, excluding the open answer.

Several intriguing answers were given by participants, either on their own or with other options included. It is seen in the statistics that there are 8 people each who have written *Clickbait* and *For Money* in the open answer, as well as similar responses, such as *To gain popularity on the respective site / magazine / TV channel*; *To shock people and get clicks that translate to revenue*; *to clickbait / scam / get personal data / create a hoax / sell products*; *For website interactions and attention leading to better monetization outcome* and so on. This leads us to the conclusion that many fake news articles are published solely for the purpose of profiting from clicks and viewers, with no further plans. A news article written by Joshua Gillin explains how clickbait works and includes interviews with authors of news websites that write faux news.

One of the participants has answered with *The Dunning-Kruger Effect*, which states that incompetent people with high self-esteem are more likely to read fake news articles and share information without fact-checking, simply because they believe they are superior and know better. In 2016, Khalid Mahmood conducted a meta-analysis of 53 English language studies that provided observational evidence for the existence or non-existence of the Dunning-Kruger Effect in evaluating people's information literacy abilities (Mahmood, 2016). Out of 53 studies, evidence of inconsistency between the self-reported and actual skills was found in 49 of them. In 34 studies (64%) the evidence strongly demonstrated that participants overestimated their self-reported information literacy skills in comparison to their real skills.

Another answer states that the aim of fake news is to manipulate and confuse people, referring to the approach used by Julius Cesar – *Divide and Conquer*. Other answers stated that the aim can be also to fulfill an order of someone; to create division between socioeconomic groups; for political benefits; for manipulation. These responses reveal another aspect of fake news that is still undetected by fake news detection systems, that is related to issues with media corruption. Post-communist countries are shown to have higher rates of media corruption than progressive democratic countries with advanced journalism traditions (Yang, 2012). Bulgaria is a strong example of such a country, with a lack of transparency along with media politicization (Dobek-Ostrowska & Głowacki, 2015). Media corruption can take the form of concealing information from the general public, staging events with the sole purpose of portraying someone in a negative or positive light, depending on who owns the media, disseminating false information in order to conceal reality from the general public, and so on. On a daily basis, such behavior can be seen in traditional Bulgarian news outlets. Although there are no accurate research papers on media corruption in Bulgaria, scholars have highlighted examples of both independent corruption among journalists and governmental rent-seeking practice (Blagov, et al., 2014). This reinforces the justification for the next question's results.

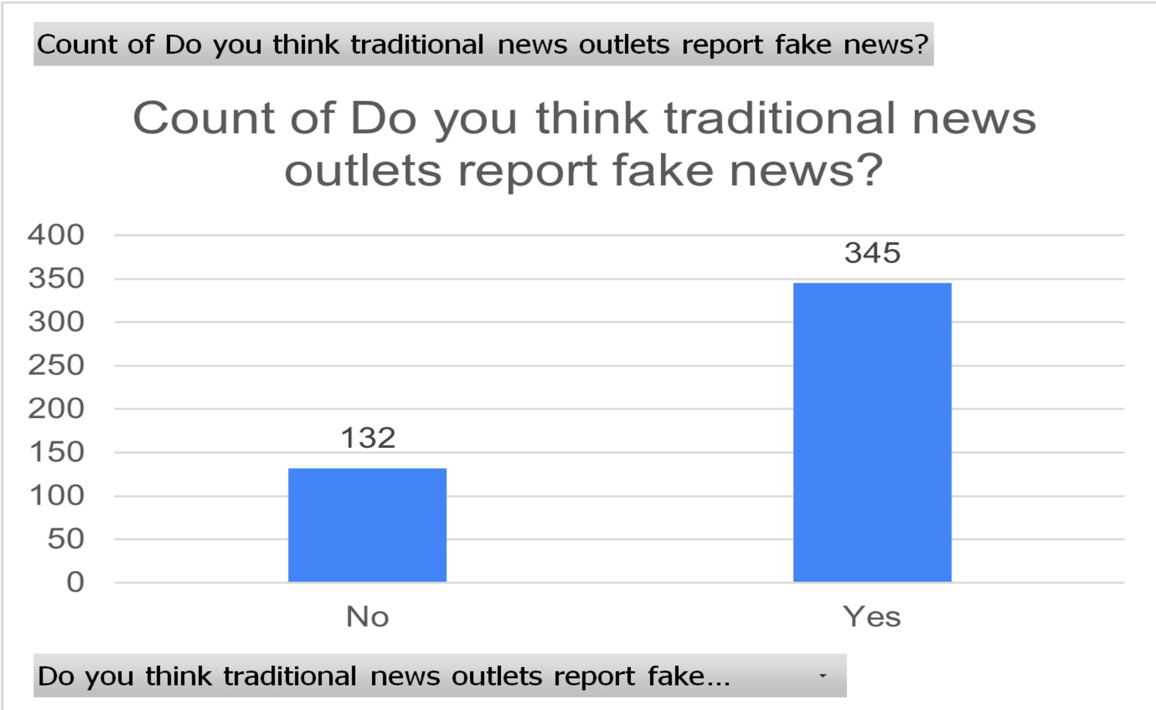

Figure 9 - Survey Question 7

According to the seventh question, 72.3% of the participants believe traditional news outlets report fake news, while 27.7% have the opposite opinion. Having in mind the answers from the previous question, the results are not unexpected.

When the answers are separated by age group, it is seen that participants from 18 to 50 have answered in a rather similar manner, with the 25-30 age group having the lowest percentage (19%) with the answer No, and the 18-24 age group having the highest percentage (27.6%) of the four groups. However, the statistics from the two oldest age groups show a significant difference in response percentages: those aged 51-60 have 15 out of 30 participants (42.9%) with a negative answer, while those over 65 have 41.9%. Charts with the separated answers by age groups can be found in Appendix Heading 6.

The large disparity in responses between younger and older generations is due, once again, to technological adaptation. As stated in Survey Question 2, older people do not trust social media and are less likely to accept it as a source of news. The results of this question are also related to Survey Question

6 – traditional news sources are frequently owned by or influenced by a political member. People whose primary news source is traditional news media or digital forms of it, on the other hand, can be easily brainwashed if they do not conduct their own research. People have been brainwashed for centuries and it keeps going. The purpose of this is to get viewers, readers, and listeners to think the same way as the person or group behind the scenes, because it is much easier to control. The Dunning-Kruger Effect is another good example here as well, with many people believing they are "very well informed" simply because they read newspapers and/or watch the news on a daily basis (Wolfe, 1998).

If there had been an equal number of participants from each age group, the overall results would have been very different. However, this would have had no effect on the detailed statistics. According to studies, the older generations (*Baby Boomers*) believe they are entitled and know best, thus invalidating the opinions of the younger generations (Airey, et al., 2020). Despite Baby Boomers being born when the telephone and television were by far the most significant technological contributions, some find it difficult to adjust to their new surroundings and maintain their title as “Digital immigrants” (Venter, 2017). As a result, they prefer to stick to what they are familiar with. In this case, newspapers and television.

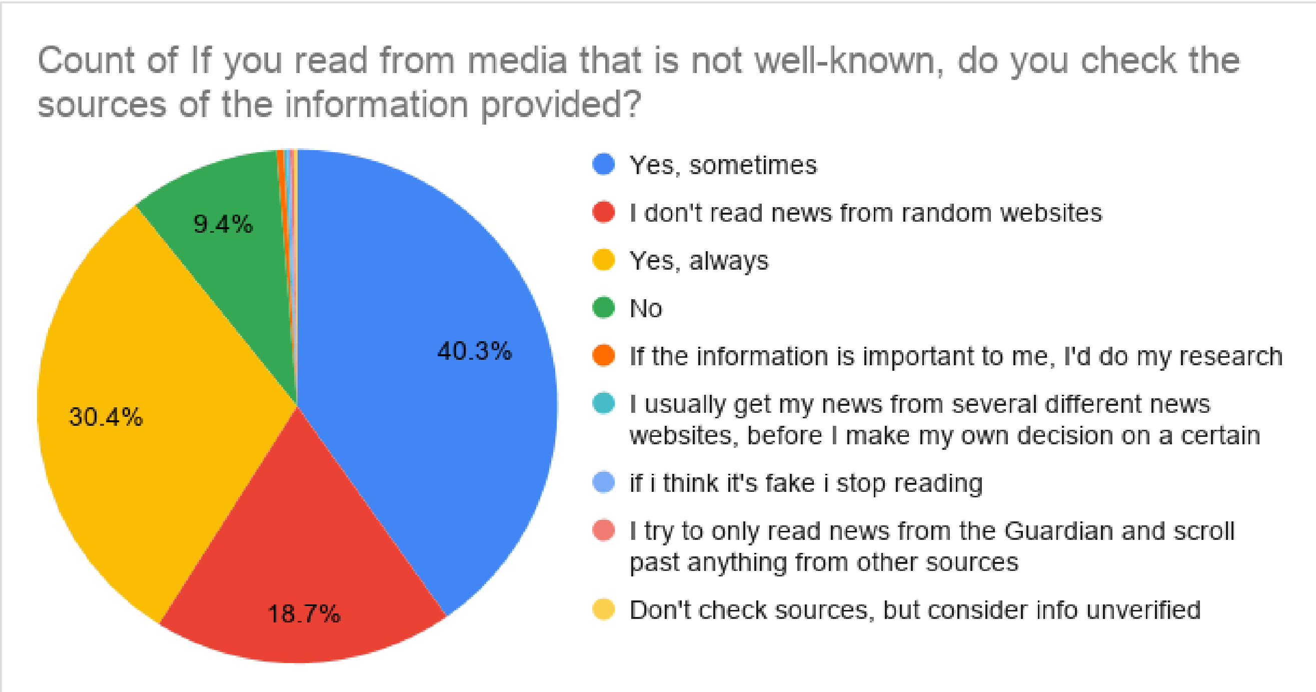

Figure 10 - Survey Question 8

According to the results of the eighth question, 40.3% of participants check their news source occasionally, 30.4% always check it, 18.7% do not read news from random websites, and 9.4% do not check the source they are reading from. Since there was an option for an open answer, a handful of responses can be seen. They are, however, similar to the top choices in some ways.

The voting patterns of different age groups and participants from different countries are generally similar. This finding implies that most people either inspect the source of information while reading an article from a non-famous media or avoid reading from such websites.

From a personal point of view, most participants who answered with *Yes, sometimes*, look up if the article is valid only if the information is significant to them, as one participant specified in their response.

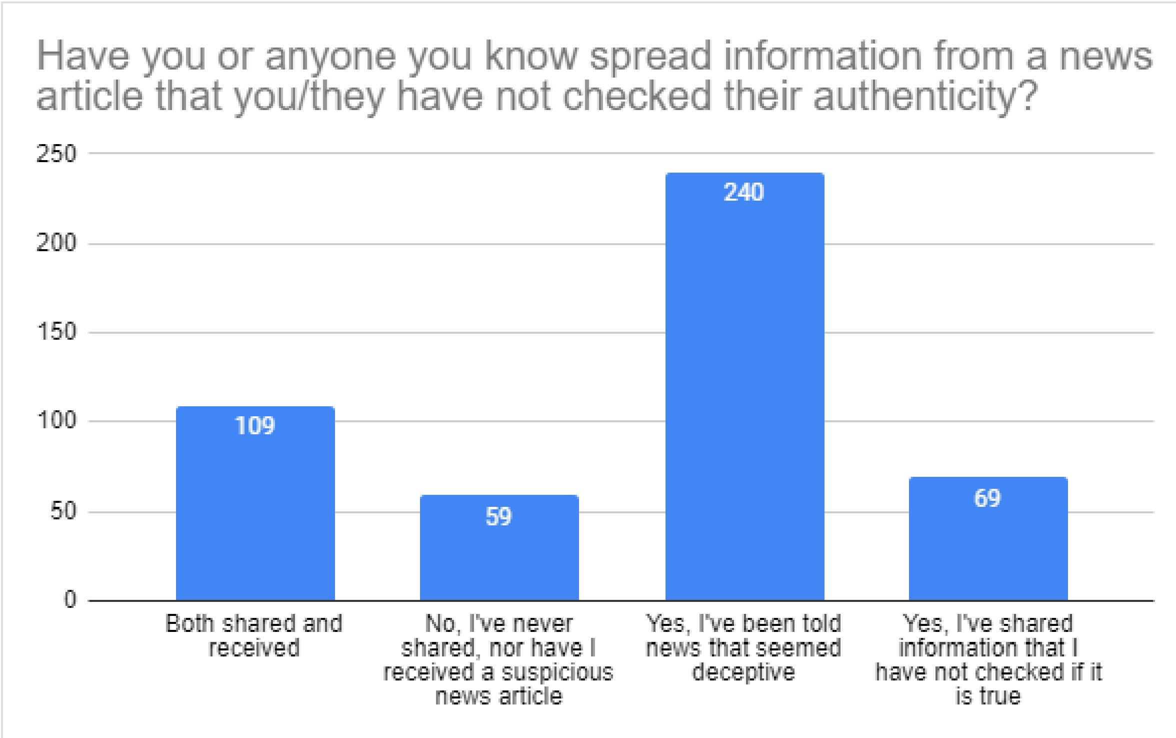

Figure 11 - Survey Question 9

According to the survey's final question, 87.6% of all participants have exchanged and/or received unchecked information.

People spread false news for a variety of reasons. Gossiping is a type of social bonding and status enhancement (Lyons & Hughes, 2015). The desire for recognition has also been described as a motivator for online self-disclosure (Christofides, et al., 2009). Additionally, it is to be expected that, in order to gain exposure or the interest of others, social media users will post content that is intriguing and sensational, with little regard about whether it is false or real (Talwar, et al., 2019). As a result, the survey findings are expected, given that many people post deceptive news in order to gain publicity.

4.5. Conclusions

The survey uncovered rather interesting findings, separating generations based on their way of thinking. The older age groups were skeptical of social media and did not consider it as a reliable source of news. Those aged 51 and up had a high level of confidence in traditional social media, not questioning it as strongly as those in younger age groups. The participants who were most certain that they could tell when they were reading fake news were the youngest, aged 18 to 24, and the most uncertain ones were the oldest, aged 61 and above. This demonstrates their discomfort and distrust towards social media and technologies that they did not grow up with (Venter, 2017) (Barnard, et al., 2013).

Surprisingly, there was no eye-catching gap in the responses of participants from different countries. Post-communist countries such as Bulgaria has lower level of democratic standards compared to Western mature democracies, and the traditional media still acts under pressure from external factors, such as politics (Dobek-Ostrowska & Głowacki, 2015). As a result, it is believed that the nations' thinking would vary from that of Western European countries. However, the internet can aid in these situations by offering information that is not available via traditional media. People who travel to other countries to study or live notice the difference and realize where the reality lies. As a result, no matter where they come from, the way of thinking of the younger generations differs very little, at least in terms of fake news and social media.

Given that older people do not trust the internet, fake news detection systems may help them avoid being deceived, scammed, manipulated, or worried. It has yet to be researched how to spot fraudulent news in traditional media, although this is nearly impossible given that politics are involved.

4.6. Comparison with Other Surveys

To display the efficiency of the performed survey and its findings, it should be compared to the research of others. In this case, to the surveys conducted by SMARTeD and EBU, since certain survey questions were influenced by their surveys.

Smart eDemocracy Against Fake News (SMARTeD) is a project that focuses on promoting European citizenship and strengthen conditions for civic and democratic engagement at European Union level by increasing public awareness of national and EU-level programs to combat deceptive news and online propaganda. They conducted a survey on disinformation and fake news (SMARTeD, 2019) with 48 participants from six different countries.

The survey questions were quite close to those in this paper, as well as their results. Most participants are confident that they know when they are reading fake news in both surveys. Both surveys have a generous amount of participants believing that traditional media reports fake news articles. The SMARTeD survey has more political-oriented questions, receiving opinions of their participants that certain events, social processes, social issues and milestones are politicized in order to produce a significant change in how the public understands certain events in their respective countries. Some participants from the survey conducted for this project also recognized this as a problem, noting that some fake news is produced to promote political propaganda, and often times this disinformation comes from the traditional news sources.

A suggestion is made by the majority of the SMARTeD survey participants (88%) that the EU should be given the authority to take a more active role in fighting false news/politization/misinformation of information. 50% of respondents considered that in order to tackle fake news, there should be developed more tools for empowering users and journalists, and 47% of respondents believe that critical thinking about where information on the internet comes from is important.

The European Broadcasting Union (EBU), the world's leading alliance of public service media, conducted a survey on fake news with 22 EBU Member organizations participating (The European Broadcasting Union, 2017). Their survey results showed that all respondents ranked combating fake news as a high or medium priority, with 50% of them already taking part in a fact-checking initiative partnership or are considering joining one.

In conclusion, both the SMARTeD survey results and the survey results for this project revealed that people believe traditional news outlets report false news, and that politics is often involved. All three surveys recognize fake news as a serious issue, with some participants stating that the key motives are rarely positive and often seek to misinform the reader/viewer. Both SMARTeD and EBU participants state that more tools should be developed for fact-checking and fake news detection.

5. Technologies, tests and design

5.1. Used technologies, platforms and libraries

The chosen programming language for this project is Python, using PyCharm IDE and Jupyter Notebook. There are plenty of libraries which are useful for Fake news detection. Here is a list of the ones I chose with a brief description:

- Pandas (Python Data Analysis Library) is a library for data analysis and manipulation. The name is derived from the term "panel data", which is an econometrics term for multidimensional structured datasets. It works by taking data (SQL database, CSV or TSV file) and creates a Python data frame.
- NumPy (Numerical Python) is a Python library used to add support for large, multi-dimensional arrays and matrices, including a large collection of high-level mathematical functions. The library is written partially in Python, but most of the parts that require fast computation are written in C and C++.
- SciPy is a library used to solve scientific and mathematical problems. The library is built on the NumPy extension and it gives the user a wide range of high-level commands to visualize data. It contains modules for linear algebra, optimization, integration, image processing, etc.
- Scklearn (Scikit-learn) is a library for machine learning in Python. It includes a number of useful machine learning and statistical modeling methods, such as classification, regression, clustering, and dimensionality reduction, among others.
- Itertools is a Python module, used to iterate over data structures which can be stepped over in order to produce efficient looping. This package supports functions that make effective use of computational resources.

- NLTK (Natural Language Toolkit) is a Python-based collection of libraries and programs for symbolic and computational natural language processing. It includes graphical demonstrations and sample data.
- Matplotlib is a plotting library for Python and its computational mathematics extension Numpy which offers an object-oriented API for inserting plots into apps that use general purpose GUI development tools.
- Seaborn is a Python data visualization library, based on Matplotlib that offers a high-quality interface for designing appealing and insightful data visualization.
- WordCloud is a data visualization library which is used to represent text data where the size of each word or phrase represents its frequency or significance.
- BeautifulSoup is a Python library for parsing HTML & XML documents. It provides Pythonic idioms for searching, modifying, and iterating the parse tree.

5.2. Data preprocessing

Before conducting any research, the representation and quality of data must be prioritized. One of the most important phases of a machine learning project is data preprocessing.

To accomplish proper results with good accuracy scores and avoid incorrect assumptions, the data that was used had to be ‘cleaned’ from stop words, dates, links, brackets, and anything that might negatively affect the result.

In order to avoid reduced performance in the model, the dataset was split into training and testing. The performance on the testing dataset should be roughly equivalent to the performance on the training dataset, indicating that the model correctly learned the associations between the data as a whole, rather than only for those particular rows. This enables the model to predict accurate findings on new information that it has never seen before.

5.3. Methods & Algorithms

Some of the most important algorithms for this project are imported from the Scklearn library.

- TF-IDF Vectorizer - Tf-idf is a short term for Term Frequency-Inverse Document Frequency. It presents a numerical statistic which intends to reflect the importance of a word to a document in a collection or corpus (Dua, et al., 2017). The frequency at which a given word appears in a text is summarized by Term Frequency. Inverse Document Frequency reduces the frequency at which terms appear through documents. TfidfVectorizer transforms text to feature vectors that can be used as an input to estimator. It is very efficient for such programs and testing since all of the information in the datasets is in text, which needs to be vectorized into information that can be used by machine learning standpoint.
- Passive Aggressive Classifier (PAC) - Passive Aggressive Classification is a simple to implement incremental learning algorithm. Its core concept is to adjust the weight vector for each misclassified training sample it receives, aiming to correct it (Arduino, 2020) (Wu, et al., 2017). PAC algorithms are generally used for large-scale learning. They do not require a learning rate. They do, however, include a regularization parameter. They are called so because they are *Passive* if the prediction is correct, they keep the model and do not make any changes, or they are *Aggressive* if the prediction is incorrect, they make changes to the model to correct it.
- Count Vectorizer (CV) – It tokenizes the text (divides sentences into words) and performs very simple preprocessing. It eliminates all punctuation marks and lowercases all of the words. An encoded vector with the entire vocabulary's length and an integer count for the number of times each word appeared in the document is returned.

5.4. Conducting tests and experiments

5.4.1. First test (using PAC & TfidfVectorizer)

The first test done was using TfidfVectorizer with PAC. The test was made by using NumPy, Pandas, Itertools and Scklearn models, and it was written and executed in Google Colab. The dataset used for the test has a shape of 7796x4. The first column identifies the news, the second column contains the article title, the third column is the text, and the fourth column includes labels which indicate if the article is real or fake. The dataset used for the first project is acquired from Data Flair, which can be found here: Detecting Fake News with Python and Machine Learning.

The dataset was added into the data frame by using Pydrive, read by Pandas and got the shape and head of the first 5 records in order to see if it is working properly (Appendix Heading 7). Afterwards, the labels (true/false) had been fetched from the data frame and the data was then split into training and testing sets. A TfidfVectorizer was initialized with stop words from the English language with a maximum document frequency of 0.7 where terms with a higher document frequency had been discarded. A PassiveAggressiveClassifier was then initialized to predict the test set and calculated the accuracy of the fake news detector.

The test was run 5 consecutive times and the mean accuracy score was 92.85% (Appendix Heading 8). By using a confusion matrix, an insight into the number of false and true negatives and positives was gained. The confusion matrix returned a mean of 590 true positives and 587 true negatives (Appendix Heading 9).

5.4.2. Second test (using PAC & TfidfVectorizer)

The second test was conducted by using TfidfVectorizer with PAC again, however, the test had different datasets and was executed in Jupyter Notebook. Pandas and Scklearn were used for this test as well, since Pandas is needed to read the data, and Scklearn includes important methods, including *TfidfVectorizer*, *PAC*, *train test split*, *confusion matrix*, *accuracy score* and *cross validation score*.

The datasets used are acquired from Kaggle (1)(2). The training dataset has a shape of 20800x5. The first column shows the ID of the news article, the second one is the title, the third one includes the author, the fourth one is the text, and the fifth one is the label, where 0 stands for *Real* and 1 stands for *Fake*.

In order to have the label show directly if it is real or fake instead of numbers, the label list was converted into a dictionary (Appendix Heading 10). Afterwards, the labels were divided to see if they were balanced enough to produce proper results (Appendix Heading 11). This dataset has 10413 fake reviews and 10387 real reviews.

For the first test of this dataset, only 25% of the data was used. The data was shuffled in order to get a good mix of the sample articles. Afterwards, the text was vectorized using the TfidfVectorizer, The train and test sets were fitted and transformed, but beforehand they had to be decoded. The PAC was then used in order to fit the vectorized *x* models and used against the *y* training data, which in this case is whether it is real or fake. The PAC then predicts whether the article is real or fake, then comparing the results to the actual *y* test values that we had, and then printing out the PAC accuracy. The test was executed 5 times in order to get a mean value of the accuracy (Appendix Heading 13). The mean accuracy result of this test is 96.25% which is better by nearly 3.5% than the previous test. The confusion matrix was run on the last execution of this test, resulting in 2485 true positives and 2518 true negatives (Appendix Heading 14).

To test the dataset even further, the test size has been increased to 50%. The test was executed three times, ending with 95.69% mean accuracy result (Appendix Heading 15). With the test size being 75%, the results show a mean of 95.13% accuracy (Appendix Heading 17). A tendency is seen that the larger percentage of dataset is used, the less accurate is the algorithm. However, despite having three times more dataset used in the third run, the accuracy result went down with only 1.12%. Also, this is not the K Fold accuracy, which will be used to calculate the accuracy of the whole database. K-folds cross validation is a method for training and testing models that tries to make the best use of the available data.

The next step was to vectorize the text from the entire data frame (100%). In order to calculate the K means score, which is in Machine Learning is considered a Gold standard, the PAC was used again, with the vectorized text, labels (*Real* or *Fake*), and five folds. The results show 96.2% K Fold accuracy, which is just 0.05% less than the mean accuracy of the 25% of data (Appendix Heading 16).

To stress test this further, the other mentioned datasets were used (True.csv & Fake.csv). The difference between these two datasets and the previous one is that these two have been reviewed and determined to be authentic or fakes. In Appendix Heading 18 can be seen how the True dataset looks like, and in Appendix Heading 19 is shown the Fake dataset. An adjustment was made by taking out the publisher out of the datasets, so that the program does not use it as a representation to determine whether an article is true or fake.

Since the previous dataset is created specifically to train such algorithms, the accuracy score will always come up as trustworthy. However, by using unknown text, the prediction would not be as accurate. This is why the next step was to create a function that helps with the prediction of the authenticity of news articles. This is done by passing a new text, that has not been seen and is not a part of the model (Appendix Heading 20). Afterwards, the program goes through the data frame that is presented. Any time that the program predicts that an article is actually real or fake, corresponding to the labels given, it allocates a 1, and whenever it predicts wrongly, it allocates a 0. In theory, the results should give back 100% accuracy, since the articles were reviewed and are supposed to correspond to their labels. However, this data is not created to train such algorithms, and the text has not been seen by the program. The results come up with 72% accuracy for true positives and 69.6% true negatives (Appendix Heading 21).

The main difference between the accuracy percentage of the training dataset and the other two datasets is that the training dataset is designed specifically to train such algorithms, and the second model which tested the two datasets has no tweaking in the hyperparameters, has excluded the publishers, and is checking never seen before text. Therefore, the 70% accuracy for this simple model is a very good score, since it can predict 70% of the time whether an article is real or fake, without having any training data or change in hyperparameters.

5.4.3. Test 3 NLP & Data Visualization

This test was done by using the same databases from the previous test (Fake.csv & True.csv). The idea of this test is to see what subjects are most commonly found in fake news articles, how Natural Language Processing (NLP) can be used to detect fake news, and when is it useful.

The first step was to visualize the two datasets and see how many there from each are (Appendix Heading 22). The results showed 21 417 articles that were marked as real and 23 481 articles that were marked as fake. The two datasets are relatively the same size, therefore they are balanced and will conduct relevant results. Another point worth mentioning is that by visualizing the two datasets, it is clear that the real news articles have actual news sources cited in their text, while the fake articles do not. In addition, some of the fake articles in the dataset have the entire title capitalized, which is not seen in any of the authentic articles.

Since there were no true and fake labels, they have been added so that the dataset can be compared properly after being merged (Appendix Heading 23). Afterwards, the combined dataset was checked to see if there are any null values, and then separated into different subjects, visualizing the information into a chart, using Matplotlib and Seaborn libraries (Appendix Heading 25). A very intriguing aspect came when the breakdown of categories from fake to real news was visualized. This was accomplished by categorizing the dataset by hue. The results showed that there are no fake news articles with a subject *politicsNews* or *worldNews* (Appendix Heading 24). However, this cannot be included in the model, since it would pick up the information and decide that everything that is different from the authentic articles in terms of subject is fake news and will be flagged out.

To have a clean text for the NLP process to work on, some details from the database had to be removed. A single column with the relevant text was created, after which the title, subject and date were removed. Square brackets, URLs and stop words were also removed, after which the text was denoised (Appendix Heading 26). The WordCloud library was then used to produce an image including the most common words and phrases found in the authentic articles (Appendix Heading 27) and the fake articles (Appendix Heading 28). When comparing the two produced images, it is clear that there are numerous phrases and terms that appear in both locations. Some phrases are larger (used more often) in the true articles, and vice versa. A trend is seen, especially in politics, where certain names appear more often in fake articles, meaning that there is more false news about these individuals. In Appendix Heading 29 can be seen a chart showing the characters per article in the two separate categories of data. In the real news category, 2500 characters or less in text is the most common pattern, while in the fake news category was seen to have most commonly around 5000 characters or less. A similar result was seen in the word count in the two categories (Appendix Heading 30).

The next step was to do a data Train-Test Split, then create a Count Vectorizer object, a Tfidf Vectorizer object and transform the train and test data (Appendix Heading 31). The MultinomialNB was used in order to get the naive Bayes algorithm for multinomially distributed data. Naive Bayes is a simple learning algorithm that employs the Bayes rule (the probability of an event, based on prior knowledge of conditions) along with a serious assumption that the attributes are conditionally independent, considering the class. By using the Multinomial Naïve Bayes model, it was fit to the Count Vectorizer and Tfidf Vectorizer's train words, after which it predicted the accuracy score for the two separate vectorizers (Appendix Heading 32), resulting in 94.3% accuracy for the Count Vectorizer and 92% accuracy for the Tfidf Vectorizer.

5.5. Webpage design prototype

According to the survey results and several articles (Venter, 2017) (Glass, 2007), older people find it challenging and confusing to use computers and social media. Thus, the produced webpage prototype is designed to be simple to use, easy to understand, and to display only the information needed by the user.

The page should function by inserting a link from a news article and clicking on the button *"Go!"*. This should pass the information to the algorithms, which should inspect the author, photo/video, text and sources (if available) and compare them to the ones which are already saved in the database. Then, it should decide whether the news article is fake or true and show the outcome to the user.

In Appendix Heading 33 is demonstrated how the result should show if the news article is true. Since it is comparing the information in the article to other news sources which can be trusted, the result prints out web page(s) of articles which have similar information.

In Appendix Heading 34 is demonstrated the result when the news article is fake and cannot be trusted. In this case, an image of the inspected article was discovered in a different location that had nothing to do with the fake story. A website containing the original picture is printed out for the user to view.

6. Results & Discussion

6.1. Survey Results

A table will represent the number of answers for each question, separated by different target groups, such as age groups and country. Some questions are not included since they have multiple answers which cannot be displayed properly in a table.

How often do you read news from online sources?	Every Day	Two to three times a week	Once a week	Twice a month or less often
18-24	60.7%	27%	7.7%	4.6%
25-30	62.1%	26.7%	6%	5.2%
31-40	54.1%	29.5%	9.8%	6.6%
41-50	84.2%	13.2%	2.6%	0%
51-60	71.4%	22.9%	2.9%	2.9%
61+	58.1%	25.8%	6.5%	9.7%

Table 1 - Survey Question 1 by Age group

How often do you read news from online sources?	Every Day	Two to three times a week	Once a week	Twice a month or less often
Bulgaria	65%	25.7%	5.7%	3.6%
United Kingdom	52.2%	32.2%	7.8%	7.8%
USA	79.5%	12.8%	2.6%	5.1%

Table 2 - Survey Question 1 by Country

When you think of social media brands do you consider them as news sources?	Yes	No
18-24	67.2%	32.8%
25-30	60.7%	39.3%
31-40	52.5%	47.5%
41-50	50%	50%
51-60	51.4%	48.6%
61+	22.6%	77.4%

Table 4 – Survey Question 2 by Age group

When you think of social media brands do you consider them as news sources?	Yes	No
Bulgaria	66.8%	33.2%
United Kingdom	53.3%	46.7%
USA	28.2%	71.8%

Table 3 - Survey Question 2 by Country

What is your primary news source?	Traditional news sources on the TV, radio or in the newspaper	Digital versions of the traditional news sources on the web	Social media	Other
18-24	9.7%	57.7%	31.1%	1.5%
25-30	14.7%	58.6%	22.4%	4.3%
31-40	24.6%	52.5%	18%	4.8%
41-50	31.6%	60.5%	7.9%	0%
51-60	40%	48.6%	8.6%	2.9%
61+	51.5%	38.7%	9.7%	0%

Table 5 - Survey Question 3 by Age group

What is your primary news source?	Traditional news sources on the TV, radio or in the newspaper	Digital versions of the traditional news sources on the web	Social media	Other
Bulgaria	19.4%	51.6%	26.9%	2.4%
United Kingdom	19.1%	61.8%	16.9%	2.2%
USA	21.1%	68.4%	2.6%	7.8%

Table 6 - Survey Question 3 by Country

Do you know what Fake news is?	Yes	No
18-24	97.4%	2.6%
25-30	98.3%	1.7%
31-40	91.7%	8.3%
41-50	97.3%	2.7%
51-60	94.1%	5.9%
61+	86.7%	13.3%

Table 8 - Survey Question 4 by Age group

Do you know what Fake news is?	Yes	No
Bulgaria	95.7%	4.3%
United Kingdom	96.7%	3.3%
USA	97.4%	2.6%

Table 7 - Survey Question 4 by Country

Do you know when you are reading fake news?	Yes	Not sure	No
18-24	64.3%	34.2%	1.5%
25-30	64.7%	31%	4.3%
31-40	62.3%	27.9%	9.8%
41-50	57.9%	39.5%	2.6%
51-60	42.9%	51.4%	5.7%
61+	41.9%	38.7%	19.4%

Table 9 - Survey Question 5 by Age group

Do you know when you are reading fake news?	Yes	Not sure	No
Bulgaria	65.4%	31.1%	3.6%
United Kingdom	56.7%	40%	3.3%
USA	64.1%	33.3%	2.6%

Table 10 - Survey Question 5 by Country

Do you think traditional news outlets report fake news?	Yes	No
18-24	72.4%	27.6%
25-30	81%	19%
31-40	75.4%	24.6%
41-50	78.9%	21.1%
51-60	57.1%	42.9%
61+	41.9%	58.1%

Table 12 - Survey Question 7 by Age group

Do you think traditional news outlets report fake news?	Yes	No
Bulgaria	73.2%	26.8%
United Kingdom	80%	20%
USA	61.5%	38.5%

Table 11 - Survey Question 7 by Country

If you read from media that is not well-known, do you check the sources of the information provided?	Yes, always	Yes, sometimes	No	I don’t read news from random websites	Other
18-24	31.1%	40.3%	9.7%	17.9%	1%
25-30	30.2%	44%	4.3%	20.7%	0.9%
31-40	34.4%	37.7%	13.1%	11.5%	3.2%
41-50	36.8%	31.6%	10.5%	18.4%	2.6%
51-60	25.7%	45.7%	8.6%	20%	0%
61+	16.1%	35.5%	19.4%	29%	0%

Table 13 - Survey Question 8 by Age group

If you read from media that is not well-known, do you check the sources of the information provided?	Yes, always	Yes, sometimes	No	I don't read news from random websites	Other
Bulgaria	32.9%	40.4%	9.1%	16.8%	0.8%
United Kingdom	28.9%	38.9%	10%	20%	2.2%
USA	33.3%	33.3%	5.1%	28.2%	0%

Table 14 - Survey Question 8 by Country

It is seen that the participants from the USA have quite different answers from the other two main countries. However, they were the smallest group from the three, having only 39 participants, 14 of which from the oldest age group (61+), 10 from 51-60 and 7 from 41-50. This suggests that 79.4% of the American participants were in the three oldest age groups and looking at all of the responses sorted by age group reveals that the older participants had different responses than the rest.

6.2. Tests and Experiments results

The first test was conducted as a simple experimentation over a quite small dataset to demonstrate how TF-IDF Vectorizer and PAC work. The accuracy results (92.85%) were good but considering the small dataset which is designed specifically for training and testing such algorithms, it cannot be taken as a final decision. The second test was using the same algorithms with some modifications, such as cross-validation score, and using a bigger dataset. The results from the second test showed a better score (96.2%). However, when testing a dataset which was never seen before by the algorithm, it returned a lower accuracy (70%). A model with such a low accuracy cannot be implemented in a real program since 30% of the time it will not produce proper results, therefore it cannot be trusted. The third test used the same dataset as the second one, but it was based on NLP and produced 94% accuracy with the Count Vectorizer and 92% with the TF-IDF Vectorizer. The difference between the second and third tests is that the Multinomial Naïve Bayes model was used in the last test, fitting the model to the two vectorizers, predicting it for them and checking the accuracy score.

	Models used	Dataset shape	Accuracy Score
Test 1	Tfidf Vectorizer PAC	7796x4 (training data)	92.85%
Test 2	Tfidf Vectorizer PAC Cross-Validation Score	20800x5 (training data) 44898x5 (real & fake)	96.2% ~70%
Test 3	MultinomialNB TfidfVectorizer Count Vectorizer	44898x5 (real & fake)	92% (Tfidf) 94% (CV)

Table 15 - Test Comparisons

6.3. Discussion

6.3.1. Survey Discussion

The survey findings demonstrate a difference of the mindset of different age groups. Older people believe traditional news sources much more than the younger ones, have little trust in social media, and are not confident when they are reading news from sources that are not known to them. They prefer sticking to their beliefs, since the internet and social media is something relatively new for them and if it is not in the newspapers or TV, it cannot be trusted. The younger generations, however, rely more on the internet, since they grew up with it and are more competent in doing their own research when it comes to fake news on social media and unpopular websites. According to the survey results, a fake news detection program will be beneficial to the older generations, so that they can have more trust in their online news sources and not rely only on traditional media, which according to the survey and several cited papers, cannot be completely trusted due to politicization.

6.3.2. Testing Discussion

The first test had the least complex model with smallest dataset. Because of the size and nature of the data – it was very small, and it is specifically built for such models – the results that it revealed cannot be taken into account. However, it provides a clear example on how TF-IDF vectorizer and PAC function.

The second test used a bigger dataset and due to its structure, it produced even better results than the first one when being run on data specifically designed for such models. However, the results it generated for the previously unseen dataset were too inefficient to be used in an actual program. For such a simple model, the results were not terrible, but a program with 70% overall accuracy would not be something a user would rely on, especially for checking if the news article they are reading is real or fake. The test provides a clear example of how cross-validation score performs.

The third test was based on Natural Language Processing and Data Visualization. It also included a Count Vectorizer and Multinominal Naïve Bayes. This resulted in really good accuracy scores with using a dataset that had all titles, subjects, dates, stop words, brackets and links removed. The visualization libraries also helped by showing how the data is actually structured, comparing word and character count of the real and fake news articles, visualizing the amount of subjects and articles in these subjects, and showing which words appear the most in the real news and which in the fake news.

7. Evaluation

7.1. Survey Evaluation

The survey was beneficial to this project, and the results were essential, especially for developing the web page prototype. It definitely could have been much better, including more detailed questions and actually testing the participants if they could really tell whether a news article is real or fake, and including a section where people can tell their opinion on how to tackle fake news. However, I limited the open answer options on purpose, since in the very beginning (the first 20 respondents) there were people either trolling or not understanding the questions at all, answering with whatever they have in mind. Then I removed most open answer options and deleted the responses which would not provide any relevant data.

There is most likely a way to perform such a survey with more specific questions, resulting in better findings that can be included in this project. However, for the first survey I have ever done, I think the work and effort I put in it is quite good.

While describing the survey results, I found it very challenging to include my personal opinion and back it up with information from articles. This definitely took much longer than I expected, but it made me realize how difficult it is to write actual articles without giving opinion with no backup. It also helped me find some really interesting articles regarding fake news and politicization of traditional media, which I am planning to research deeper in the future.

I have learned a little bit more about Microsoft Excel and Google Spreadsheets as a result of the survey, how to use them more efficiently and how to produce relevant information out of the data I had. I definitely have much more learning to do there.

7.2. Tests and Experiments Evaluation

Overall, I am pleased with the test results and experiments that I was able to complete. There is much more work that could have been done, such as training a Latent Semantic Analysis (LSA) model in order to analyze relationships between articles and produce a collection of concepts relevant to the articles and design a web page for the program.

The main struggles of the concluded tests came with understanding how exactly each library and each algorithm work so that I can include them in the models properly. I had almost no knowledge on how to work with Python, so I had to spend much more time on learning how to do basic tasks than on the actual project. If I had this knowledge beforehand, I would have probably achieved better results.

7.3. Overall Project Evaluation

In my honest opinion, I am incredibly proud of this project. Many additional things could have been done, but due to scope and time constraints, only a few were implemented. In perspective, I would had spent less time trying to get the algorithms to function efficiently and pre-processing data and more time implementing multiple ML algorithms and simply improving the ones that showed the best overall performance.

This project provided the motivation I needed to finally dive deep into Fake News Detection, a topic in which I had always been interested but had never attempted on my own. It also greatly enhanced my Python expertise, problem-solving skills, and understanding of ML in a less mathematical and more programming-oriented manner.

To obtain a greater understanding of the algorithms I was using for my project, I had to read the Scklearn documentation several times and specifically go through multiple explanations of how TF-

IDF and Passive Aggressive Classifier work. Because of the interest I have in this topic, I did my best to absorb all the information and use it in the most beneficial way for the project.

This project made me want to contribute more to Fake News Detection, learn ways how to tackle politicized media, help anyone who is easily manipulated to see the truth. Finally, I believe I performed well in this Honours project. I created a model that predicts correctly 92-94% of the time whether a news article is real or fake, made a survey and got nearly 500 participants to fill it in and conducted some really interesting findings out of it, and overcame fears, such as working with a language and libraries that I have never used before, of which I am proud of.

8. Future Work

Several changes could be made to improve this project:

- Creating a web page in which the user pastes a link to a news article, and the program predicts whether it is true or fake, including information like websites with similar news if the article is true, or the website from which the image was taken if the article is fake (as shown in the web page prototypes).
- Using BERT: Bidirectional Encoder Representations from Transformers (Delvin, et al., 2019), a language representation model that is intended to pre-train deep bidirectional representations from unlabeled data by conditioning on both left and right context simultaneously in all layers. As a result, the pre-trained BERT model can be fine-tuned with only one additional output layer to build cutting-edge models for a broad variety of tasks like query responding and language inference, without requiring significant task-specific design changes.
- Testing the models on a dataset with Bulgarian articles in order to create a program specifically designed for Bulgaria. A good example of such program is created by three Bulgarians – Yoan Dinkov, Ivan Koychev & Preslav Nakov (Dinkov, et al., 2019).
- Categorizing the news articles in different toxicity groups, not only fake and real, such as *Conspiracy Theories*, *Hate Speech*, *Satire*, *Gossip*, etc.
- Executing another survey, which aim is to actually see whether the participants are able to detect fake news or not. This could be done by including a group of titles and short text and a task to determine whether each title with text is fake or real. This would show a more accurate result for the participants' ability to spot fake news.

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10. Appendix A – IPO & Interim Report

Initial Project Overview

SOC10101 Honours Project (40 credits)

Title of Project:

Fake News Detection

Overview of Project Content and Milestones:

Fake news is all around social media. Although sometimes it's easy to notice if something on the internet is true or not, there are numerous news blogs, websites and pages which spread fake news to their many followers. Quite often people read something from the web and without checking if it is true or not, they spread it around.

The idea of this project is to create a program which detects fake news articles around the internet by scanning through the information (text), inspect the author, if there are any sources and if they are trustworthy and check if the used image(s) have been used anywhere else.

To do this, a database must be created in which the program can store information and learn from it in order to become more efficient. The database would include reliable and unreliable sources which can be used as comparison models. The program would be able to extract keywords from the scanned article in order to scan for similar articles around the reliable and unreliable sources.

The milestones of the project for now are deciding what technology, platform and library to use and choosing which programming language will be the most efficient to implement the program.

1. The Main Deliverable(s):

A system that detects whether a news article is trustworthy or not by providing it a link to an article in the user interface. The system should be able to learn from all the previous inputs in order to become more efficient and give more precise answers.

2. The Target Audience for the Deliverable(s):

Other researchers working in the field, students, elderly people (since the web is quite new concept to them, they tend to read false information and spread it immediately because they think it is true)

3. The Work to be Undertaken:

- Research fake news detection methods that could be applied to the problem.
- Research technology needed to analyze and process the data.
- Create database(s) in which the program can store data, learn from it and use it in the future.
- Create and design a user interface.

4. Additional Information / Knowledge Required:

Machine learning knowledge: data extraction, data processing, classification of data.

5. Information Sources that provide a context for the Project:

- "Fake News Detection on Social Media: A Data Mining Perspective" – A research article that covers the issues with fake news on social media.
- "Automatic deception detection: Methods for finding fake news" – A research article that demonstrates methods for spotting fake news.

- https://en.wikipedia.org/wiki/Detecting_fake_news_online - A website including types of fake news, features and methods in fake news detection.
- “Nikhil Sharma "Fake News Detection using Machine Learning" Published in International Journal of Trend in Scientific Research and Development (ijtsrd), ISSN: 2456-6470, Volume-4 | Issue-4, June 2020, pp.1317-1320”, URL: https://www.ijtsrd.com/papers/ijtsrd31148.pdf - A journal paper that includes analysis of fake news, a literature survey and a way to create a fake news detector using machine learning .

The importance of the Project:

False information is spread with the idea to manipulate a group of people’s perspectives. By falling into that trap, people are often prone to get scammed, get their personal information stolen, or even believe in that false information, which would lead to endanger their and their family and friends’ safety and wellbeing. Fake news detection can assist with preventing lies to be spread and avoid future damage done by false information.

6. The key challenge(s) to overcome:

Machine learning knowledge limitations – need to spend time understanding how it works in order to create a model which is efficient, trustworthy and usable by everyone.

Web development knowledge limitations – may take up a considerable amount of time to learn how to implement the program as I have done a small amount of backend development and no frontend.

Appendix Heading 1 - IPO

SOC10101 Honours Project (40 Credits)

Week 9 Report

Student Name: Bogoslava Dyankova

Supervisor: Christos Chrysoulas

Second Marker: Brian Davison

Date of Meeting: 1 Dec 2020

Can the student provide evidence of attending supervision meetings by means of project diary sheets or other equivalent mechanism? **yes**

If not, please comment on any reasons presented

Please comment on the progress made so far

There is some technical progress which is good to see; however, the report is under-developed at this stage compared to where it should be. The risk is that important background information will be missed if the literature review is not completed promptly. This could lead to the eventual results being of lower quality than they could be.

Is the progress satisfactory? **yes**

Can the student articulate their aims and objectives? **yes**

If yes then please comment on them, otherwise write down your suggestions.

The aim of the project is critical for the structure of the practical work and for the evaluation. Currently, there is not clear statement of the aim in the introduction chapter. This should be done as soon as possible.

* Please circle one answer; if **no** is circled then this **must** be amplified in the space provided

Appendix Heading 2 - Interim Report 1

Does the student have a plan of work? **no**

If yes then please comment on that plan otherwise write down your suggestions.

There is a rough notional plan, but again it needs to be written down.

Does the student know how they are going to evaluate their work? **no**

If yes then please comment otherwise write down your suggestions.

Some options were discussed in the meeting, but this needs to be finalised

Any other recommendations as to the future direction of the project

The written work is currently not where it should be. This should be a priority.

While it is entirely possible to pass the Honour module without detailed planning and analysis, the result will be much better if these things are done.

Signatures: Supervisor Second Marker: BD

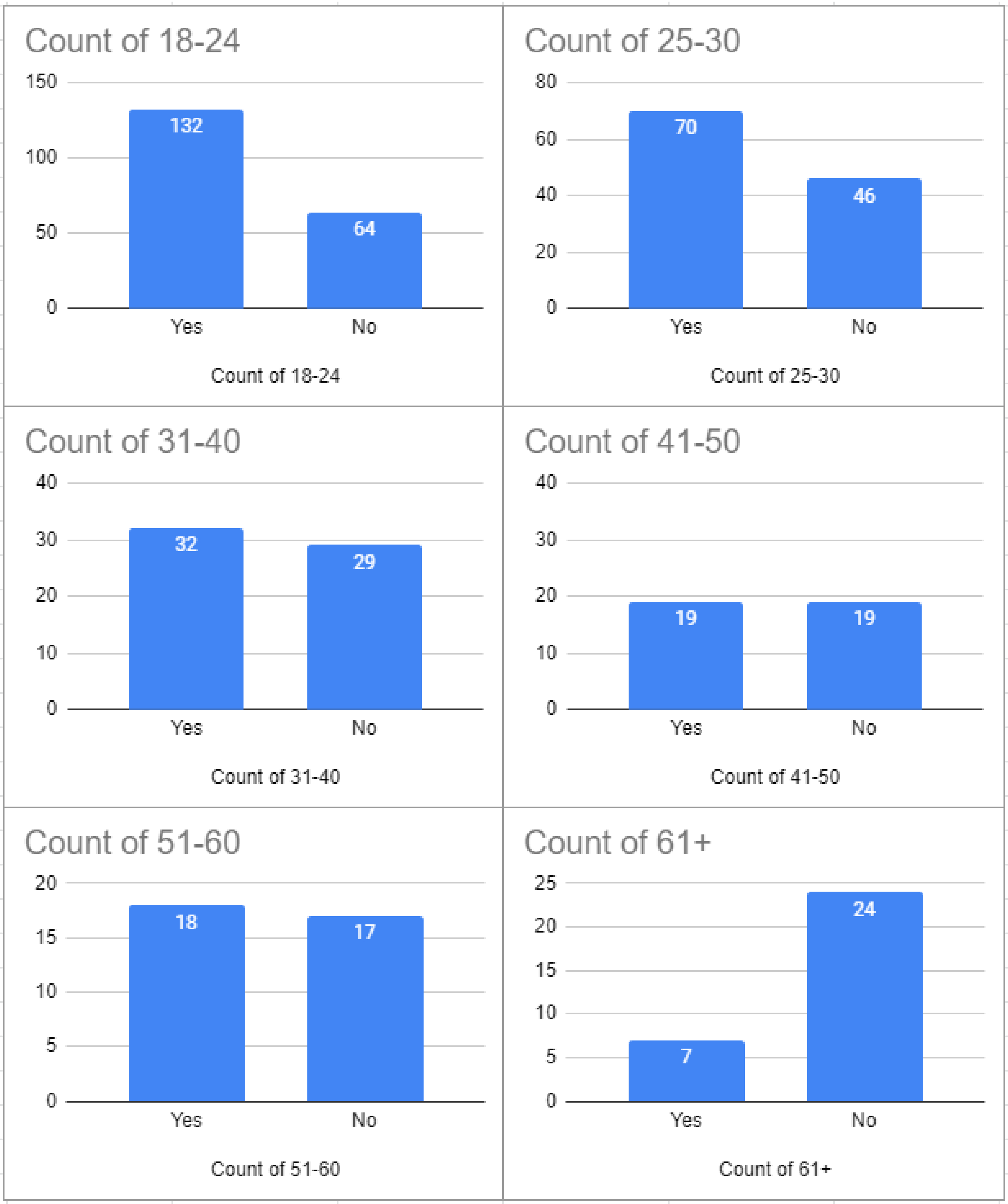
Student

The student should submit a copy of this form to Moodle immediately after the review meeting; A copy should also appear as an appendix in the final dissertation.

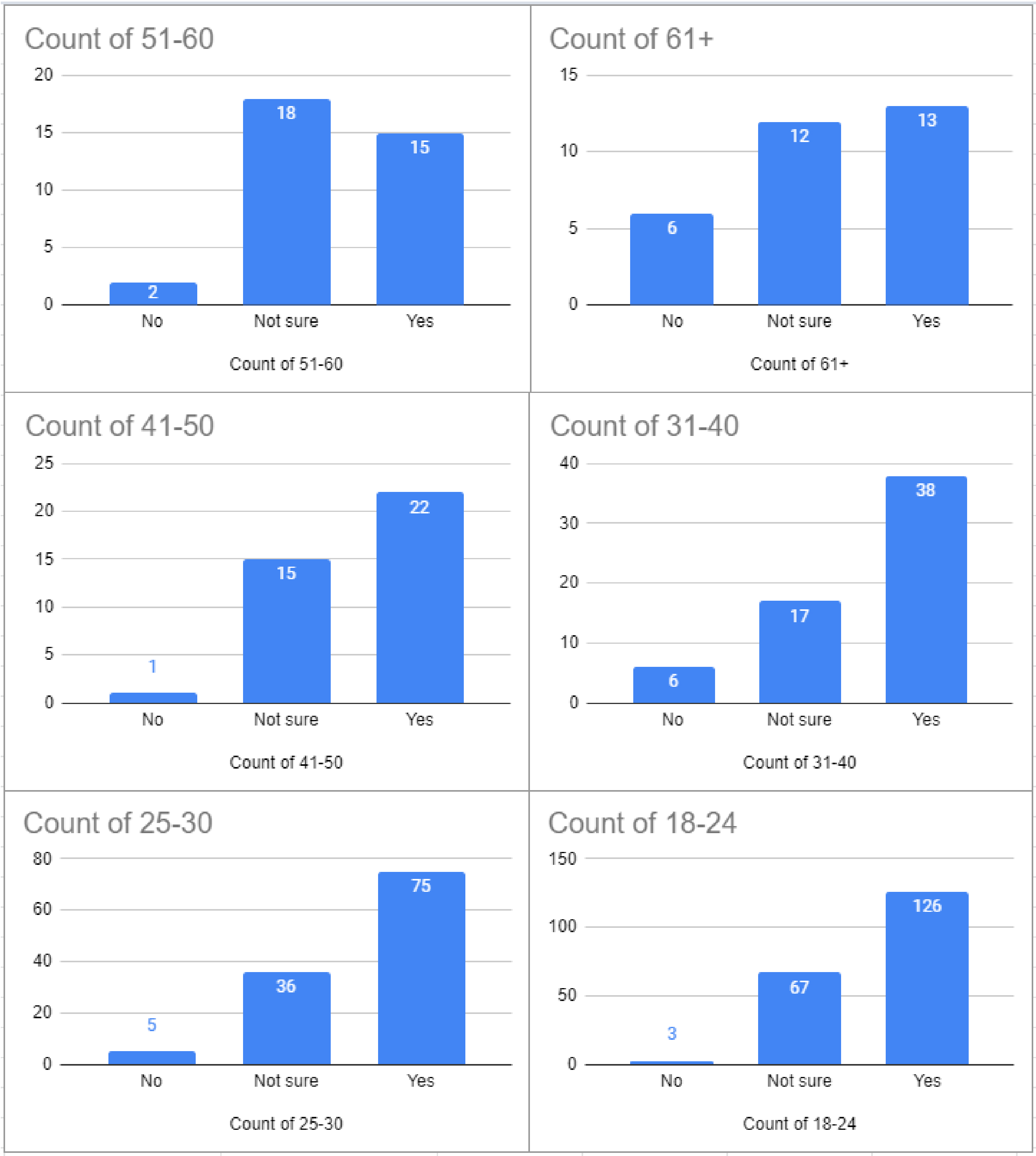
* Please circle one answer; if **no** is circled then this **must** be amplified in the space provided

Appendix Heading 3 - Interim Report 2

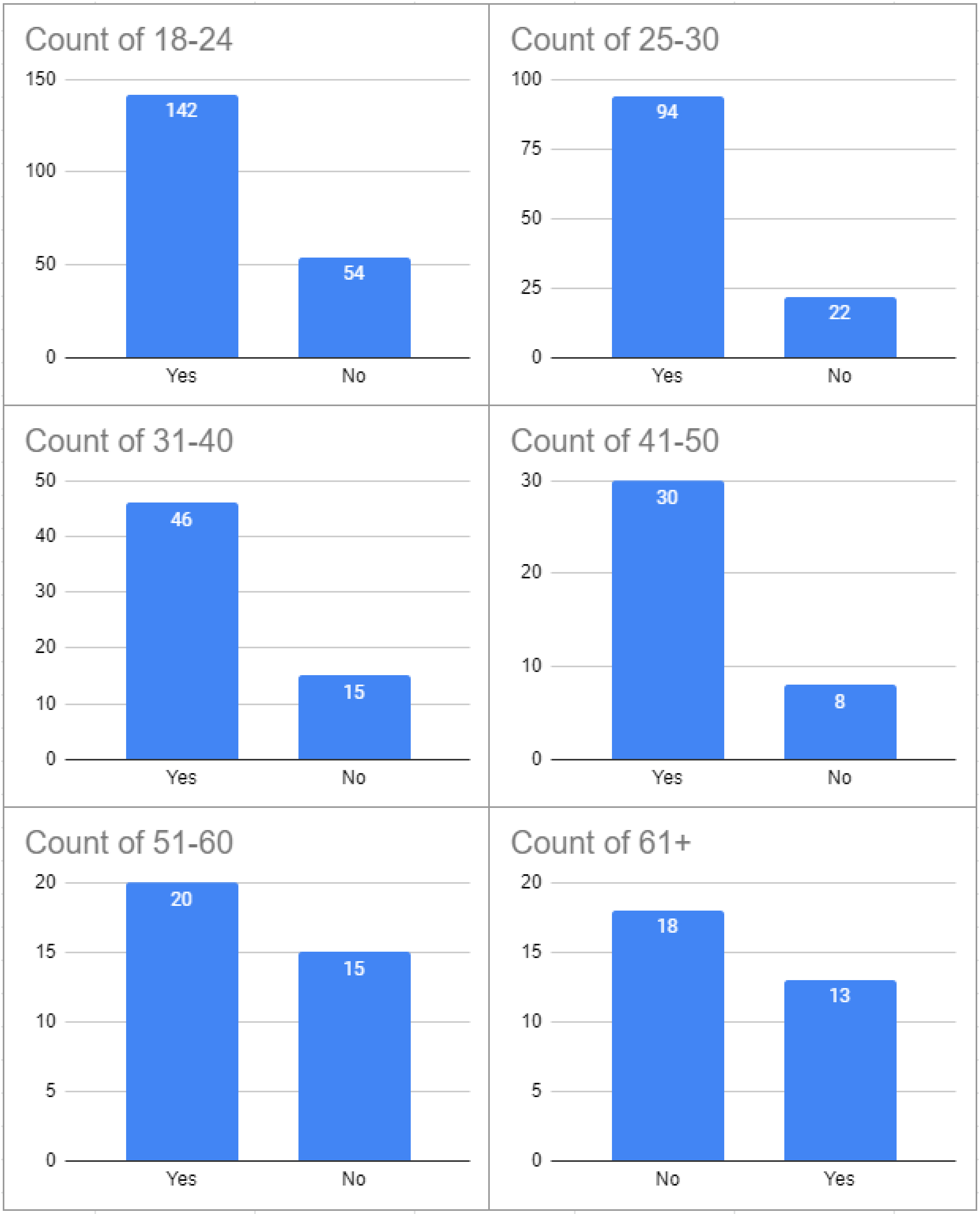
11. Appendix B – Detailed Survey Results, Tests & Web page



Appendix Heading 4 - Survey Question 2 Detailed Results



Appendix Heading 5 - Survey Question 5 Detailed Results



Appendix Heading 6 - Survey Question 7 Detailed Results

	Unnamed: 0	title	text	label
0	8476	You Can Smell Hillary's Fear	Daniel Greenfield, a Shillman Journalism Fello...	FAKE
1	10294	Watch The Exact Moment Paul Ryan Committed Pol...	Google Pinterest Digg Linkedin Reddit Stumbleu...	FAKE
2	3608	Kerry to go to Paris in gesture of sympathy	U.S. Secretary of State John F. Kerry said Mon...	REAL
3	10142	Bernie supporters on Twitter erupt in anger ag...	— Kaydee King (@KaydeeKing) November 9, 2016 T...	FAKE
4	875	The Battle of New York: Why This Primary Matters	It's primary day in New York and front-runners...	REAL

Appendix Heading 7 - Test 1 Demo of dataset

```
[19] #DataFlair - Initialize a PassiveAggressiveClassifier
     pac=PassiveAggressiveClassifier(max_iter=50)
     pac.fit(tfidf_train,y_train)
     #DataFlair - Predict on the test set and calculate accuracy
     y_pred=pac.predict(tfidf_test)
     score=accuracy_score(y_test,y_pred)
     print(f'Accuracy: {round(score*100,2)}%')

     Accuracy: 92.9%

     Accuracy: 93.13%

     Accuracy: 92.42%

     Accuracy: 92.74%

     Accuracy: 93.05%
```

Appendix Heading 8 – Test 1 Accuracy results

```
#DataFlair - Build confusion matrix
confusion_matrix(y_test,y_pred, labels=['FAKE','REAL'])

array([[590,  48],
       [ 42, 587]])

array([[592,  46],
       [ 41, 588]])

array([[586,  52],
       [ 44, 585]])

array([[588,  50],
       [ 42, 587]])

array([[593,  45],
       [ 43, 586]])
```

Appendix Heading 9 - Test 1 True & False Positives and Negatives

In [5]:
```
df=pd.read_csv('train.csv')
#change 0 to real and 1 to fake
conversion_dict = {0: 'Real', 1: 'Fake'}
df['label'] = df['label'].replace(conversion_dict)
df
```

Out[5]:

	id	title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucus	House Dem Aide: We Didn't Even See Comey's Let...	Fake
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	Real
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	Fake
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Airstr...	Fake
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to...	Fake
...	...	...	...	...	...
20795	20795	Rapper T.I.: Trump a 'Poster Child For White S...	Jerome Hudson	Rapper T. I. unloaded on black celebrities who...	Real
20796	20796	N.F.L. Playoffs: Schedule, Matchups and Odds -...	Benjamin Hoffman	When the Green Bay Packers lost to the Washing...	Real
20797	20797	Macy's Is Said to Receive Takeover Approach by...	Michael J. de la Merced and Rachel Abrams	The Macy's of today grew from the union of sev...	Real
20798	20798	NATO, Russia To Hold Parallel Exercises In Bal...	Alex Ansary	NATO, Russia To Hold Parallel Exercises In Bal...	Fake
20799	20799	What Keeps the F-35 Alive	David Swanson	David Swanson is an author, activist, journa...	Fake

20800 rows × 5 columns

Appendix Heading 10 – Test 2 Conversion Dictionary

```
df=pd.read_csv('train.csv')
#change 0 to real and 1 to fake
conversion_dict = {0: 'Real', 1: 'Fake'}
df['label'] = df['label'].replace(conversion_dict)
df.label.value_counts()
```

```
Fake    10413
Real    10387
Name: label, dtype: int64
```

Appendix Heading 11 - Test 2 Split labels results

```
x_train,x_test,y_train,y_test=train_test_split(df['text'], df['label'], test_size=0.25, random_state=7, shuffle=True)
tfidf_vectorizer=TfidfVectorizer(stop_words='english', max_df=0.75)
```

```
vec_train=tfidf_vectorizer.fit_transform(x_train.values.astype('U'))
vec_test=tfidf_vectorizer.transform(x_test.values.astype('U'))
```

```
pac=PassiveAggressiveClassifier(max_iter=50)
pac.fit(vec_train,y_train)
```

```
PassiveAggressiveClassifier(max_iter=50)
```

Appendix Heading 12 - Test 2 TfidfVectorizer & PAC

```
y_pred=pac.predict(vec_test)
score=accuracy_score(y_test,y_pred)
print(f'PAC Accuracy: {round(score*100,2)}%')
```

```
PAC Accuracy: 96.15%

PAC Accuracy: 96.23%

PAC Accuracy: 96.13%

PAC Accuracy: 96.19%

PAC Accuracy: 96.21%
```

Appendix Heading 13 - Test 2 PAC prediction results

```
confusion_matrix(y_test,y_pred, labels=['Real','Fake'])
```

```
array([[2485,  101],
       [  96, 2518]], dtype=int64)
```

Appendix Heading 14 - Test 2 True and False Positives and Negatives

```
PAC Accuracy: 95.73%
array([[4970,  236],
       [ 208, 4986]], dtype=int64)
PAC Accuracy: 95.64%
array([[4965,  241],
       [ 212, 4982]], dtype=int64)
PAC Accuracy: 95.71%
array([[4978,  228],
       [ 218, 4976]], dtype=int64)
```

Appendix Heading 15 - Test 2 50% Dataset Results

```
PAC Accuracy: 95.1%
array([[7425,  365],
       [ 399, 7411]], dtype=int64)
PAC Accuracy: 95.26%
array([[7434,  356],
       [ 384, 7426]], dtype=int64)
PAC Accuracy: 95.02%
array([[7422,  368],
       [ 409, 7401]], dtype=int64)
```

Appendix Heading 17 - Test 2 75% Dataset Results

```
#vectorize the whole text
X=tfidf_vectorizer.transform(df['text'].values.astype('U'))

scores = cross_val_score(pac, X, df['label'].values, cv=5)
print(f'K fold accuracy: {round(scores.mean()*100,2)}%')

K fold accuracy: 96.2%
```

Appendix Heading 16 - Test 2 K fold accuracy of the whole dataset

```
df_true=pd.read_csv('True.csv')
df_true['label']='Real'
df_true_rep=[df_true['text'][i].replace('WASHINGTON (Reuters) - ','').replace('LONDON (Reuters) - ','').replace('(Reuters) -
df_true['text']=df_true_rep
df_fake=pd.read_csv('Fake.csv')
df_fake['label']='Fake'
df_final=pd.concat([df_true,df_fake])
df_final=df_final.drop(['subject','date'], axis=1)
df_true
```

	title	text	subject	date	label
0	As U.S. budget fight looms, Republicans flip t...	The head of a conservative Republican faction ...	politicsNews	December 31, 2017	Real
1	U.S. military to accept transgender recruits o...	Transgender people will be allowed for the fir...	politicsNews	December 29, 2017	Real
2	Senior U.S. Republican senator: 'Let Mr. Muell...	The special counsel investigation of links bet...	politicsNews	December 31, 2017	Real
3	FBI Russia probe helped by Australian diplomat...	Trump campaign adviser George Papadopoulos tol...	politicsNews	December 30, 2017	Real
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/President Donald Trump called on the U...	politicsNews	December 29, 2017	Real
...	...	...	...	...	...
21412	'Fully committed' NATO backs new U.S. approach...	BRUSSELS NATO allies on Tuesday welcomed Presi...	worldnews	August 22, 2017	Real
21413	LexisNexis withdrew two products from Chinese ...	LexisNexis, a provider of legal, regulatory an...	worldnews	August 22, 2017	Real
21414	Minsk cultural hub becomes haven from authorities	MINSK In the shadow of disused Soviet-era fact...	worldnews	August 22, 2017	Real
21415	Vatican upbeat on possibility of Pope Francis ...	MOSCOW Vatican Secretary of State Cardinal Pie...	worldnews	August 22, 2017	Real
21416	Indonesia to buy $1.14 billion worth of Russia...	JAKARTA Indonesia will buy 11 Sukhoi fighter j...	worldnews	August 22, 2017	Real

21417 rows × 5 columns

Appendix Heading 18 - Test 2 True.csv Dataset

```
df_true=pd.read_csv('True.csv')
df_true['label']='Real'
df_true_rep=[df_true['text'][i].replace('WASHINGTON (Reuters) - ','').replace('LONDON (Reuters) - ','').replace('(R
df_true['text']=df_true_rep
df_fake=pd.read_csv('Fake.csv')
df_fake['label']='Fake'
df_final=pd.concat([df_true,df_fake])
df_final=df_final.drop(['subject','date'], axis=1)
df_fake
```

	title	text	subject	date	label
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017	Fake
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017	Fake
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017	Fake
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017	Fake
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017	Fake
...	...	...	...	...	...
23476	McPain: John McCain Furious That Iran Treated ...	21st Century Wire says As 21WIRE reported earl...	Middle-east	January 16, 2016	Fake
23477	JUSTICE? Yahoo Settles E-mail Privacy Class-ac...	21st Century Wire says It s a familiar theme. ...	Middle-east	January 16, 2016	Fake
23478	Sunnistan: US and Allied 'Safe Zone' Plan to T...	Patrick Henningsen 21st Century WireRemember ...	Middle-east	January 15, 2016	Fake
23479	How to Blow $700 Million: Al Jazeera America F...	21st Century Wire says Al Jazeera America will...	Middle-east	January 14, 2016	Fake
23480	10 U.S. Navy Sailors Held by Iranian Military ...	21st Century Wire says As 21WIRE predicted in ...	Middle-east	January 12, 2016	Fake

23481 rows × 5 columns

Appendix Heading 19 - Test 2 Fake.csv Dataset

```
def findlabel(newtext):
    vec_newtest=tfidf_vectorizer.transform([newtext])
    y_predl=pac.predict(vec_newtest)
    return y_predl[0]
```

Appendix Heading 20 - Test 2 Prediction function

```
sum([1 if findlabel((df_true['text'][i]))=='Real' else 0 for i in range(len(df_true['text']))])/df_true['text'].size
0.7201288695895783

sum([1 if findlabel((df_fake['text'][i]))=='Fake' else 0 for i in range(len(df_fake['text']))])/df_fake['text'].size
0.6957540138835654
```

Appendix Heading 21 - Test 2 New Text Accuracy Result

```
true.head()
```

	title	text	subject	date
0	As U.S. budget fight looms, Republicans flip t...	WASHINGTON (Reuters) - The head of a conservat...	politicsNews	December 31, 2017
1	U.S. military to accept transgender recruits o...	WASHINGTON (Reuters) - Transgender people will...	politicsNews	December 29, 2017
2	Senior U.S. Republican senator: 'Let Mr. Muell...	WASHINGTON (Reuters) - The special counsel inv...	politicsNews	December 31, 2017
3	FBI Russia probe helped by Australian diplomat...	WASHINGTON (Reuters) - Trump campaign adviser ...	politicsNews	December 30, 2017
4	Trump wants Postal Service to charge 'much mor...	SEATTLE/WASHINGTON (Reuters) - President Donal...	politicsNews	December 29, 2017

```
fake.head()
```

	title	text	subject	date
0	Donald Trump Sends Out Embarrassing New Year'...	Donald Trump just couldn t wish all Americans ...	News	December 31, 2017
1	Drunk Bragging Trump Staffer Started Russian ...	House Intelligence Committee Chairman Devin Nu...	News	December 31, 2017
2	Sheriff David Clarke Becomes An Internet Joke...	On Friday, it was revealed that former Milwauk...	News	December 30, 2017
3	Trump Is So Obsessed He Even Has Obama's Name...	On Christmas day, Donald Trump announced that ...	News	December 29, 2017
4	Pope Francis Just Called Out Donald Trump Dur...	Pope Francis used his annual Christmas Day mes...	News	December 25, 2017

```
true.shape, fake.shape
((21417, 4), (23481, 4))
```

Appendix Heading 22 - Test 3 Startup

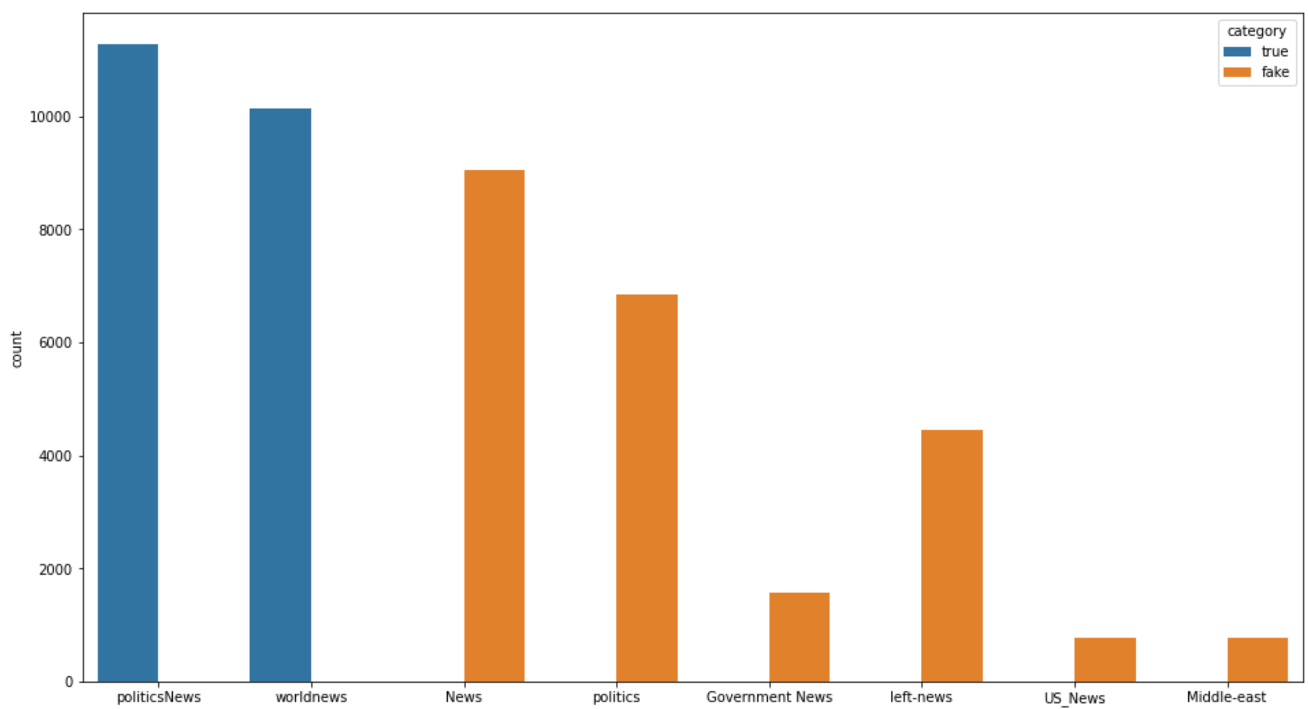
```
#putting labels on the data
true['category'] = 'true'
fake['category'] = 'fake'
#merge datasets
df = pd.concat([true,fake])
df.sample(10)
```

	title	text	subject	date	category
6021	Black Family BLASTS Trump For Using Photo As ...	The black family whose family reunion photo wa...	News	June 4, 2016	fake
9734	Biden visits Iraq in show of support amid mult...	ERBIL, Iraq/BAGHDAD (Reuters) - U.S. Vice Pres...	politicsNews	April 28, 2016	true
18436	Islamic State releases video it says shows two...	CAIRO (Reuters) - Islamic State released a vid...	worldnews	October 3, 2017	true
15822	Spanish judge orders Catalan leaders to be hel...	MADRID (Reuters) - A Spanish judge on Thursday...	worldnews	November 2, 2017	true
7665	Bernie Sanders Compares Republicans To Childr...	He s not wrong.Demonstrating that he is the on...	News	March 6, 2016	fake
9837	U.S. Capitol replacing flag display over Confe...	WASHINGTON (Reuters) - A display of U.S. state...	politicsNews	April 21, 2016	true
7532	Ben Cohen's Response To Fox News' Bernie Sand...	Fox News and other conservative outlets are do...	News	March 12, 2016	fake
4177	Defense, finance, telecoms donated heavily to ...	WASHINGTON (Reuters) - Large U.S. companies an...	politicsNews	April 20, 2017	true
7568	Insight: Emails show how Republicans lobbied t...	(This version of the November 3 story officia...	politicsNews	November 3, 2016	true
3794	Former Candidate Ben Carson Declines Trump Ca...	Retired neurosurgeon Ben Carson, who is an adv...	News	November 15, 2016	fake

Appendix Heading 23 – Test 3 Add labels and Merge datasets

```
plt.figure(figsize=(16,9))
sns.countplot(x='subject', hue='category', data=df)
```

<AxesSubplot:xlabel='subject', ylabel='count'>



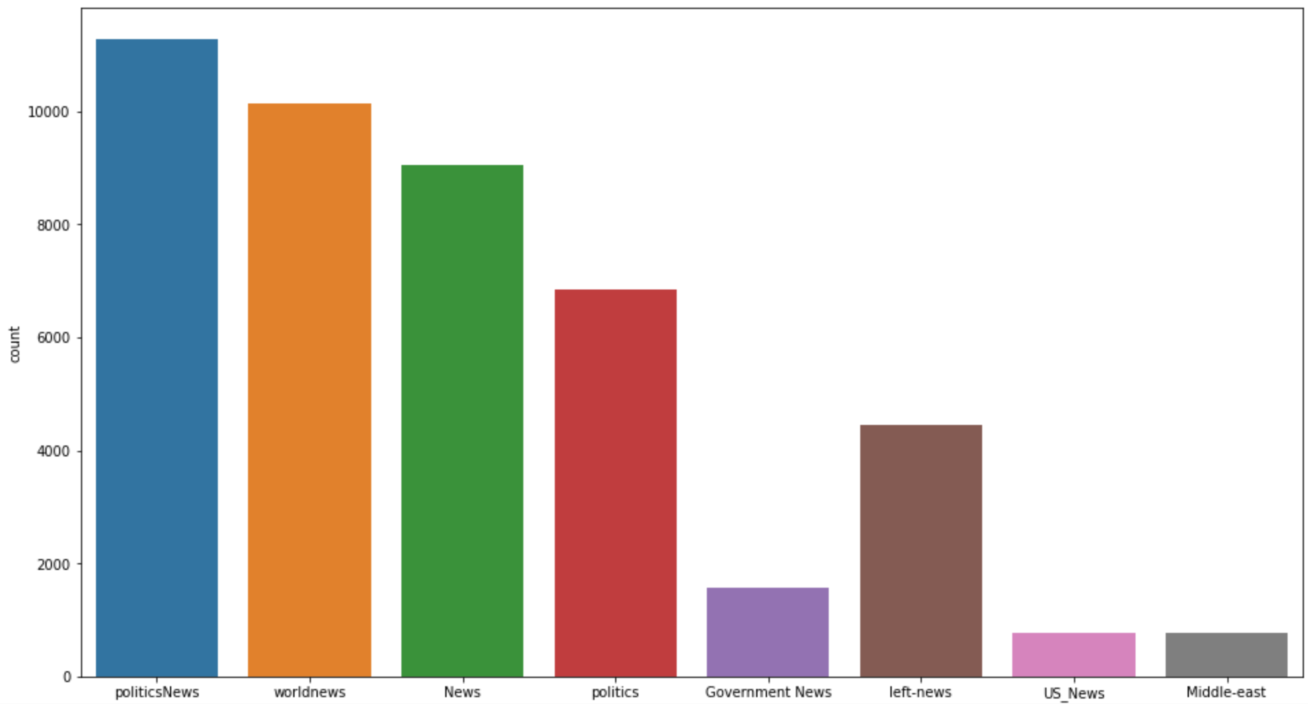
Appendix Heading 24 - Test 3 News subjects separated by Label

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 44898 entries, 0 to 23480
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   title     44898 non-null  object
 1   text      44898 non-null  object
 2   subject   44898 non-null  object
 3   date      44898 non-null  object
 4   category  44898 non-null  object
dtypes: object(5)
memory usage: 3.1+ MB
```

```
plt.figure(figsize=(16,9))
sns.countplot(x='subject', data=df)
```

```
<AxesSubplot:xlabel='subject', ylabel='count'>
```



Appendix Heading 25 - Test 3 Dataset info & Subject chart

```
#make a single column with all relevant text
df['text'] = df['title'] + " " + df['text']
#delete all other columns which aren't needed for the rest of the work
del df['title']
del df['subject']
del df['date']
```

```
stop = set(stopwords.words('english'))
punctuation = list(string.punctuation)
stop.update(punctuation)
```

```
def strip_html(text):
    soup = BeautifulSoup(text, "html.parser")
    return soup.get_text()

#remove square brackets
def remove_between_square_brackets(text):
    return re.sub('\[[^]]*\]', '', text)

#remove url
def remove_between_square_brackets(text):
    return re.sub(r'http\S+', '', text)

#remove stopwords
def remove_stopwords(text):
    final_text = []
    for i in text.split():
        if i.strip().lower not in stop:
            final_text.append(i.strip())
    return " ".join(final_text)

#remove noisy text
def denoise_text(text):
    text = strip_html(text)
    text = remove_between_square_brackets(text)
    text = remove_stopwords(text)
    return text

#apply function on review column
df['text'] = df['text'].apply(denoise_text)
```

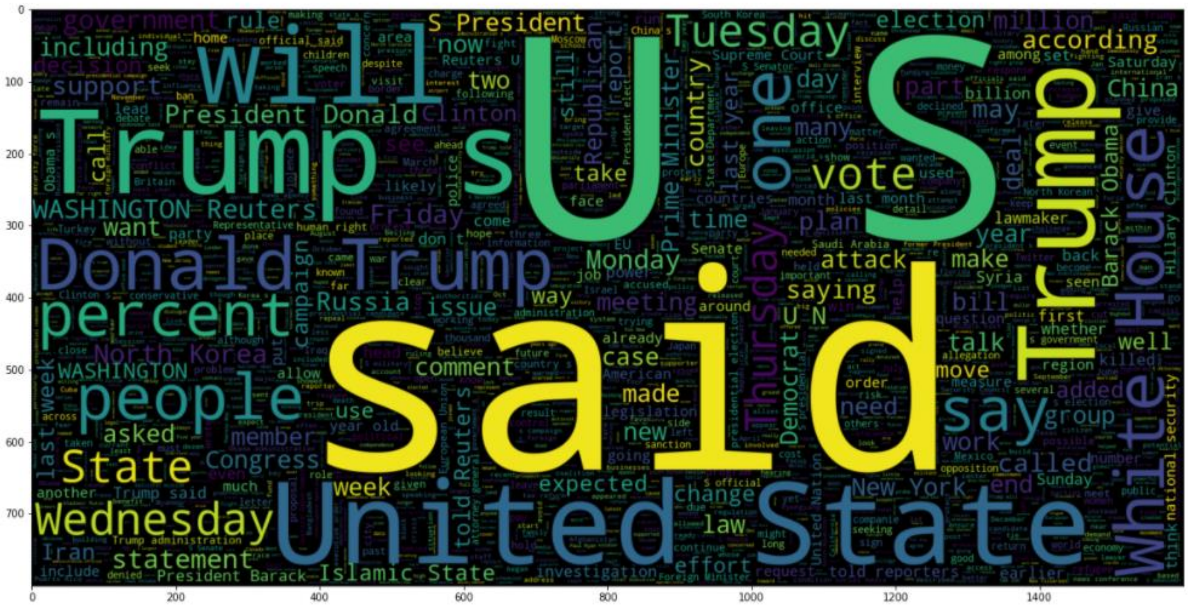
```
df.head()
```

	text	category
0	As U.S. budget fight looms, Republicans flip t...	true
1	U.S. military to accept transgender recruits o...	true
2	Senior U.S. Republican senator: 'Let Mr. Muell...	true
3	FBI Russia probe helped by Australian diplomat...	true
4	Trump wants Postal Service to charge 'much mor...	true

Appendix Heading 26 - Test 3 Data Preparation for NLP

```
plt.figure(figsize = (20,20))
wc = WordCloud(max_words = 2000, width = 1600, height = 800, stopwords = STOPWORDS).generate(" ".join(df[df.category == 'true'].t
plt.imshow(wc, interpolation='bilinear')
```

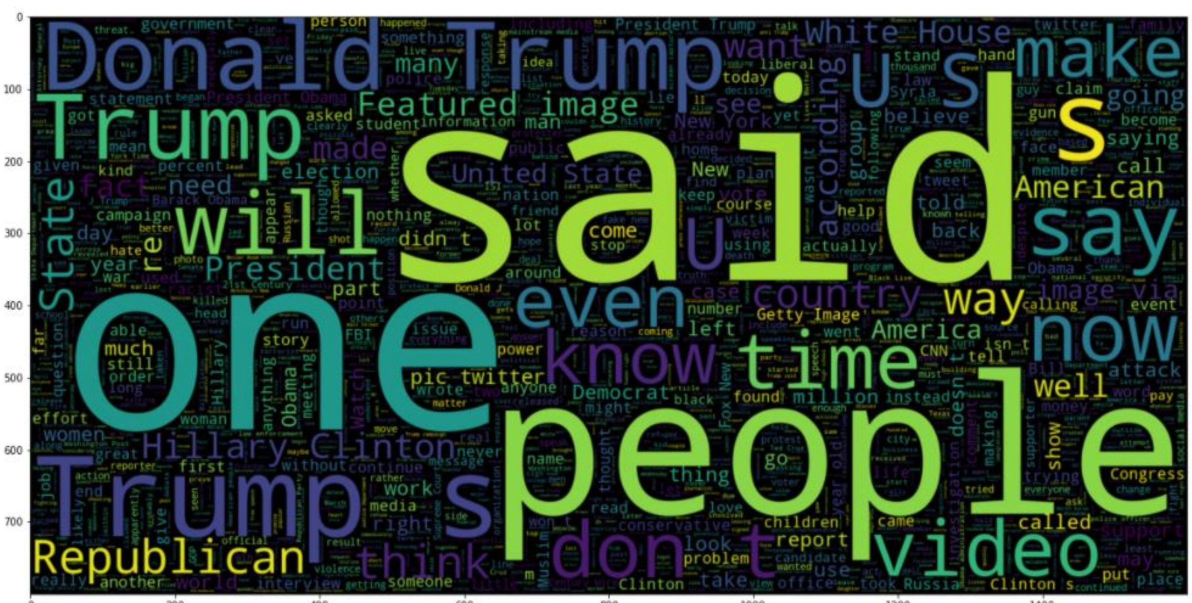
```
<matplotlib.image.AxesImage at 0x2be115798b0>
```



Appendix Heading 27 – Test 3 WordCloud Authentic Articles

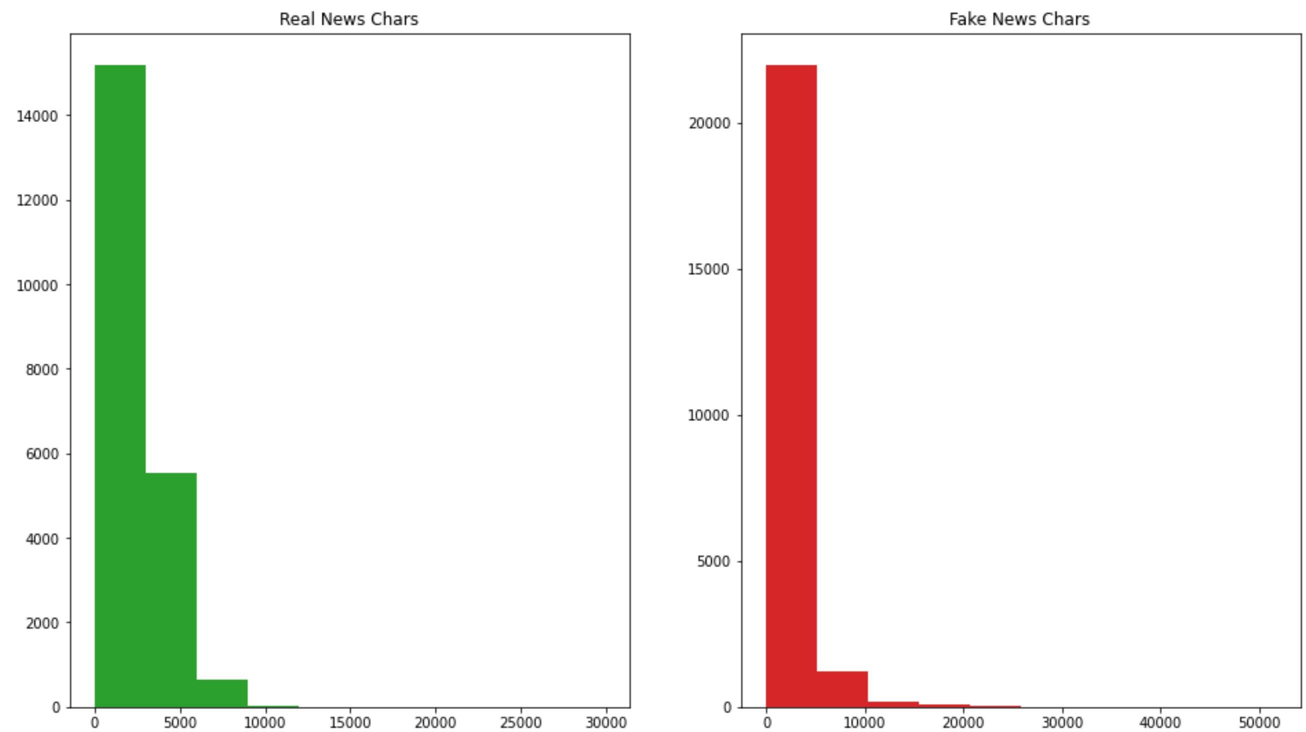
```
plt.figure(figsize = (20,20))
wc = WordCloud(max_words = 2000, width = 1600, height = 800, stopwords = STOPWORDS).generate(" ".join(df[df.category=='fake'].te
plt.imshow(wc, interpolation='bilinear')
```

```
<matplotlib.image.AxesImage at 0x2be0d829340>
```



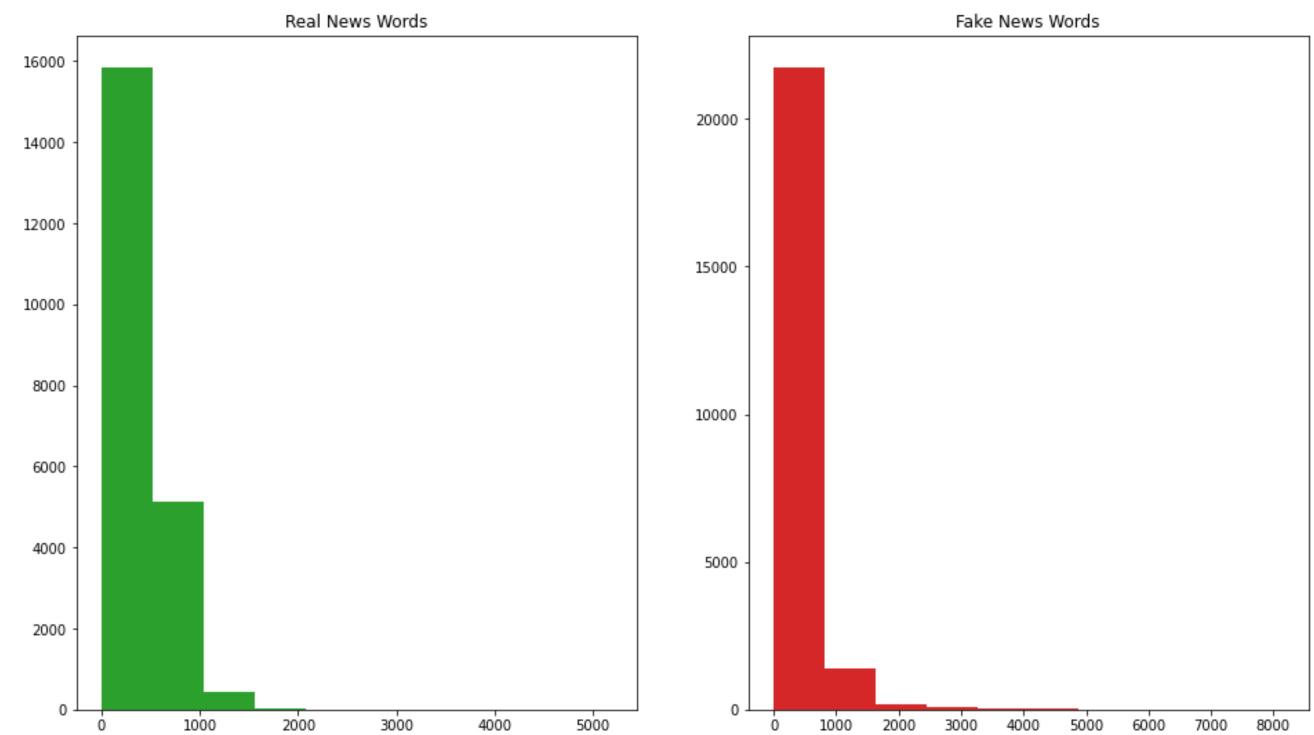
Appendix Heading 28 - Test 3 WordCloud Fake Articles

```
#check characters per article
fig, (ax1,ax2) = plt.subplots(1,2,figsize = (16,9))
text_len = df[df['category'] == 'true']['text'].str.len()
ax1.hist(text_len, color = 'tab:green')
ax1.set_title('Real News Chars')
text_len = df[df['category'] == 'fake']['text'].str.len()
ax2.hist(text_len, color = 'tab:red')
ax2.set_title('Fake News Chars')
plt.show()
```



Appendix Heading 29 - Test 3 Characters per Article

```
fig, (ax1, ax2) = plt.subplots(1,2,figsize = (16,9))
text_len = df[df['category'] == 'true']['text'].str.split().map(lambda x: len(x))
ax1.hist(text_len, color = 'tab:green')
ax1.set_title('Real News Words')
text_len = df[df['category'] == 'fake']['text'].str.split().map(lambda x: len(x))
ax2.hist(text_len, color = 'tab:red')
ax2.set_title('Fake News Words')
plt.show()
```



Appendix Heading 30 - Test 3 Words per Article

```
#split data into train test
X = df.text
Y = df.category
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, train_size = 0.8, stratify = Y, random_state = 19)

cv = CountVectorizer(min_df = 0, max_df = 1, binary = False, ngram_range = (1,3)) #CV object
cv_train = cv.fit_transform(X_train) # transform train data
cv_test = cv.transform(X_test) #transform test data

print('Words Train:', cv_train.shape)
print('Words Test:', cv_test.shape)
```

```
Words Train: (35918, 6600698)
Words Test: (8980, 6600698)
```

```
#Tfidf object
tf = TfidfVectorizer(min_df = 0, max_df = 1, use_idf = True, ngram_range = (1,3))
tf_train = tf.fit_transform(X_train) #transform train data
tf_test = tf.transform(X_test) #transform test data

print('Tfidf Train:', tf_train.shape)
print('Tfidf Test:', tf_test.shape)
```

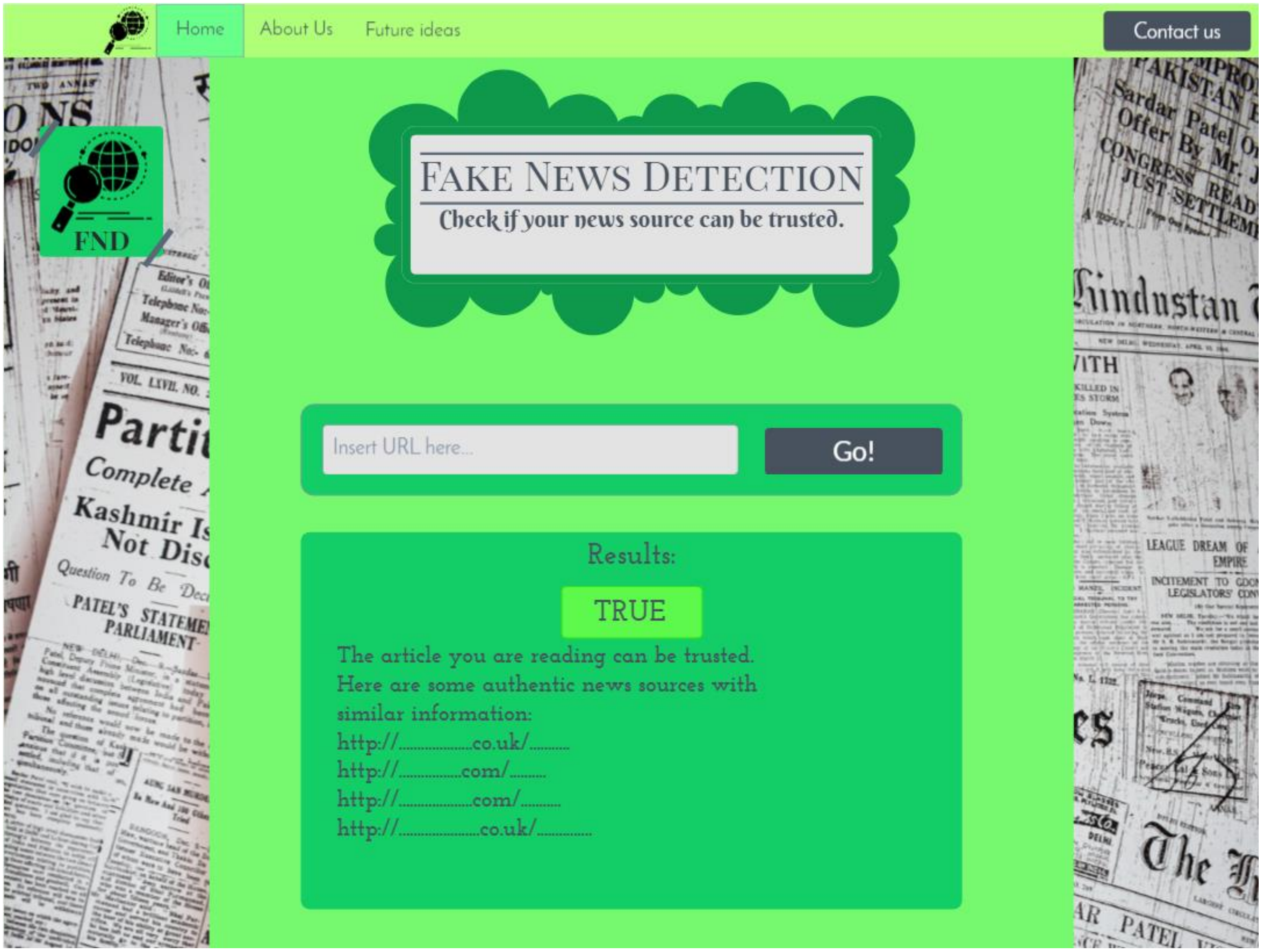
```
Tfidf Train: (35918, 6600698)
Tfidf Test: (8980, 6600698)
```

Appendix Heading 31 - Test 3 Train test split, Count Vectorizer, Tfidf Vectorizer

```
#create model object
mnb = MultinomialNB()
#fit model to CV words
mnb_cv = mnb.fit(cv_train, Y_train)
#fit model to Tfidf
mnb_tf = mnb.fit(tf_train, Y_train)
#predict model for CV
mnb_cv_predict = mnb.predict(cv_test)
#predict model for Tfidf
mnb_tf_predict = mnb.predict(tf_test)
#check accuracy score of CV
mnb_cv_score = accuracy_score(Y_test, mnb_cv_predict)
print("Accuracy score of CV:", mnb_cv_score)
#check accuracy score of Tfidf
mnb_tf_score = accuracy_score(Y_test, mnb_tf_predict)
print("Accuracy score of Tfidf:", mnb_tf_score)
```

```
Accuracy score of CV: 0.9435412026726058
Accuracy score of Tfidf: 0.9200445434298441
```

Appendix Heading 32 – Test 3 CV & Tfidf Accuracy Score



Appendix Heading 33 - Webpage Prototype - 1

Appendix Heading 34 - Webpage Prototype 2

12. Appendix C - Project To-do list & Diary

Honours Project To-Do list

- Literature review
  - !!!! Don't forget to add enough recourses that back up your information !!!
  - Give examples for related work
  - Brief explanation for machine learning, then how it is useful for Fake news detection
  - Give characteristics that will make the reader understand properly fake news
  - Give examples for fake news detection (manual and with a program?)
  - Explain what fake news is
- Testing and experimenting
  - give a conclusion on how the process was executed (maybe with a flowchart or something)
  - search for different datasets to test the models to see proper results
  - see if there is anything that can be edited to improve the performance of the chosen models
  - check for related work and see what models were used
  - research which libraries will be the most useful for this project
- Survey
  - don't get too political, please
  - !!! if you have a personal opinion on some survey results, research if anything similar was mentioned elsewhere and back it up with a reference !!!
  - also may add detailed charts with separated age groups/ countries if any interesting findings show
  - while writing about it in the report, include charts to shows info
  - include survey limitations, there will definitely be some
  - describe in report each question, why I chose it and what information would it provide
  - share it with as many people as possible, need around 500 participants
  - include age groups and countries, may find interesting relations
  - make the survey quick so that people actually participate and not quit half way because it's too long
  - research questions that can produce useful results for the project

Appendix Heading 35 - To-do list 1

- Web page
  - include details in the results, like showing related articles for real news or real source of pics from fake articles
  - make it seem easy to use and not confusing (for older people)
  - make logo related to news in a way (not sure if it's possible)
  - make sure it's not too extra, more simple but not boring
  - learn how to do a web page?
- Results
  - Include any information that would describe the results better
  - Provide tables with the test results comparing them
  - Provide tables with the survey results separated by age groups and countries
- Evaluation
  - Give personal evaluation on the tests and experiments
  - Compare tests with different models as well
  - Compare my test results with other tests with same models
  - Give my personal evaluation on the survey
  - Compare my survey results with other surveys I found on fake news
- Discussion
- Conclusions & Future work
- !!! Do Not Forget !!!
  - Submit everything in Moodle !!!
  - Add the to-do list and project diaries !!!
  - Make sure that all appendices are linked properly !!!
  - Update the bibliography !!!
  - Update the table of contents, figures, tables and appendices !!!

Appendix Heading 36 - To-do list 2

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 22/09/2020 **Last diary date:**

Objectives:

Discuss the project idea with my new supervisor
Set up goals to achieve
Read lots of literature on the topic

Progress:

Read some literature on the topic
Checked similar projects

Supervisor's Comments:

Appendix Heading 37 - Project Diary 22nd Sept

Appendix Heading 38 - Project Diary 30th Sept

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 30/09/2020 **Last diary date: 22/09/2020**

Objectives:

Choose the proper programming language and libraries for the project Create a skeleton for the report

Progress:

Installed PyCharm with some libraries which I found suitable for the project Read more literature on Fake News and Fake News Detection

Supervisor's Comments:

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 20/10/2020 **Last diary date: 30/09/2020**

Objectives:

Finish the Initial Project Overview
Learn how to use the imported libraries

Progress:

Created a skeleton for the project report

*The past month hasn't been very productive as some awful things happened and I haven't been able to concentrate at all

Supervisor's Comments:

Appendix Heading 39 - Project Diary 20th Oct

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 4/11/2020 **Last diary date: 20/10/2020**

Objectives:

Continue writing the literature review for the project
Create a skeleton for the program (and add it to the report if there is anything to add)

Progress:

Started writing the literature review
Practiced with the installed libraries
Checked out interesting ideas which would help the creation of the project making it more efficient

Supervisor's Comments:

Appendix Heading 40 - Project Diary 4th Nov

Appendix Heading 41 - Project Diary 24th Nov

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 24/11/2020 **Last diary date: 4/11/2020**

Objectives:

Continue the literature review
Continue doing tests and document them

Progress:

Wrote more of the literature review
Started doing tests and documenting their results

Supervisor's Comments:

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 20/12/2020 **Last diary date: 4/11/2020**

Objectives:

Maybe do a survey?
Research more on NLP

Progress:

Finished the literature review
Found some interesting surveys on fake news

Supervisor's Comments:

Appendix Heading 42 - Project Diary 20th Dec

Appendix Heading 43 - Project Diary 16th Jan

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 16/01/2021 **Last diary date: 20/12/2020**

Objectives:

Research how to make a NLP model for the data to give better results

Progress:

Researched on NLP
Conducted another test by fixing the model and using it on bigger dataset, did not work so well on data that is not for training

Supervisor's Comments:

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 30/01/2021 **Last diary date: 16/01/2021**

Objectives:

Still need to figure out how to include NLP in the tests
Maybe fix the logo of the web page, looks too boring

Progress:

Created a prototype for the web page, how it would look like
Researched which libraries would be good for NLP

Supervisor's Comments:

Appendix Heading 44 - Project Diary 30th Jan

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor:** Christos Chrysoulas

Date: 15/02/2021 **Last diary date:** 30/01/2021

Objectives:

Create the survey and send it to enough people
Finish with the tests part in the report and make a table comparing the tests

Progress:

Tested the NLP model, described what I have done so far with the tests in the report
Researched what questions to include in the survey to have useful results for the project

Supervisor's Comments:

Appendix Heading 45 - Project Diary 15th Feb

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor:** Christos Chrysoulas

Date: 4/03/2021 **Last diary date:** 15/02/2021

Objectives:

Still need to complete the survey

Progress:

Fixed the web page logo to be more eye-catching Included more information in the lit review

Supervisor's Comments:

Appendix Heading 46 - Project Diary 4th Mar

EDINBURGH NAPIER UNIVERSITY

SCHOOL OF COMPUTING

PROJECT DIARY

Student: Bogoslava Dyankova **Supervisor: Christos Chrysoulas**

Date: 16/03/2021 **Last diary date: 4/03/2021**

Objectives:

Make conclusions from the survey results Include charts and tables for the survey

Progress:

Survey was completed, opened, and sent to fill Each question was added in the report and described why it was chosen

Supervisor's Comments:

Appendix Heading 47 - Project Diary 16th Mar