

DEPARTMENT OF INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Master's Thesis

**Explainability of Fake News Detection  
Models for Social Media**

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# **Explainability of Fake News Detection Models for Social Media**

## **Erklärbarkeit von Modellen zur Fake-News-Erkennung in Sozialen Medien**

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I confirm that this master's thesis is my own work and I have documented all sources and material used.

Munich, Submission date

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## Acknowledgments

# Abstract

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# 1 Introduction

With the rapid development of communication technologies, social media has become one of the most frequently used news sources. It is easier, faster, and offers interaction with people. For example, a study from Pew Research Center (Walker & Matsu, 2021) reports that in 2021, 48% of U.S. adults got their news from social media "often" or "sometimes". Furthermore, global data from 2022 (Watson, 2022) shows that over 70% of adults from Kenya, Malaysia, Philippines, Bulgaria, and Greece use social media as one of their news sources, while this share is lower than 40% for the adults in the United Kingdom, The Netherlands, Germany, and Japan. These examples show that a considerable percentage of the population uses social media as a news source.

In contrast to its convenience, interactivity, and speed, social media can spread any kind of information since no regulatory authority checks the posts. As a result, a flood of false and misleading information is observed on social media (Allcott & Gentzkow, 2017).

The research community introduced numerous approaches to counteract the uncontrolled dissemination of fake news. For instance, some studies focused on building datasets (Dou et al., 2021; Nakamura et al., 2020; Santia & Williams, 2018; Shu et al., 2017; Tacchini et al., 2017; Wang, 2017), and some studies leveraged the power of *Machine Learning* (ML) to automatically detect fake news (Bian et al., 2020; Han et al., 2020; Monti et al., 2019; X. Zhou et al., 2020) by learning features from the data. Due to the number of posts and the limitation of staff to check the posts, ML-based techniques can reduce manual labor when used with human supervision to counter the spreading of fake news. However, ML-based techniques with high complexity, such as *Deep Neural Networks* (DNNs), are harder to understand and interpret since they act like black-boxes (Castelvecchi, 2016).

The integration of ML-based methods into human society impacts more people every day. While incredibly helpful in some aspects, ML-based techniques do not offer a reason for a particular prediction. Furthermore, we can not simply accept classification accuracy as a metric to evaluate real-world problems (Doshi-Velez & Kim, 2017). Integrating ML-based methods into human society makes interpretability a requirement to increase social acceptance (Molnar, 2022).

Consequently, a new research field called *eXplainable Artificial Intelligence* (XAI) surfaced to fill this missing link between humans and *Artificial Intelligence* (AI). XAI proposes



creating a set of ML techniques that deliver more explainable models while preserving learning performance, and help humans to understand, properly trust, and effectively handle the emerging generation of artificially intelligent partners (Gunning & Aha, 2019). While incorporating XAI increases social acceptance, it also aims to create more privacy-aware (Edwards & Veale, 2017), fairer, and trustworthy systems (Z. C. Lipton, 2016).

Like all ML techniques, *Fake News Detection* (FND) models need interpretability, particularly when implementing countermeasures for fake news. However, the interpretability of a model is not often considered despite the large amount of research produced in the last decade. Incorporating social context (Shu et al., 2018), representing the propagation networks as graphs (Dou et al., 2021), and using *Graph Neural Networks* (GNNs) to produce *State Of The Art* (SOTA) models (Monti et al., 2019) have increased the complexity, but also the performance of FND models. For instance, using social context data alone has proved to be more effective than textual data alone in recent studies (Dou et al., 2021). However, it is not clear which social features impact the decision process of these models.

This thesis focuses on the explainability of FND models using tools from the XAI suite. Specifically, we focus on content-based models and social context-based models to elaborate on their interpretability. Thus, we define three research objectives:

**RO1** Determine the interpretation tools for explaining FND models.

**RO2** Show that interpretations of FND models play an essential role in understanding the shortcomings of the FND models.

**RO3** Determine which features impact the outcome the most.

In the next section, we elaborate on fake news, FND methods and xAI. We give foundations of fake news and define its characteristics. Then we categorize FND models and give important examples from literature. After examining fake news and detection methods for it, we focus on characterization of xAI, give definitions that will be used throughout this thesis.

In the third section, we examine FND models that were used in this thesis, and characterize them as defined in 2.1.3. Furthermore, we deliver information about the model architecture, technologies and datasets used, and a detailed mathematical background on DNNs and GNNs. We also draw attention to some crucial matters such as model aging.

In the fourth section, we focus on xAI techniques that are used in this thesis. We give a comprehensive explanations and show their importance when dealing with complex models. We illustrate results from our experiments, draw attention to shortcomings of models, and show a model is fair or not. We also discuss the plausability of the

produced explanantions in this section.

In the last section, we talk about our overall findings. We show that research objectives are satisfied. Additionally, we discuss the limitations that we have encountered, and possible future works.

## 2 Background and Related Work

We explain two research fields that create the bedrock of this thesis, namely, fake news detection and explainable artificial intelligence. Both areas provide the foundation of tools used in this work. The first provides the mechanisms and approaches to detect fake news, and the second offers a suite of techniques to interpret these mechanisms and strategies.

Initially, in 2.1, we discuss societal challenges, the characteristics, and the history of fake news. Then we talk about the detection methods that were developed over the years. After showing the challenges of creating FND models, we conclude the first section with SOTA FND models.

After fake news detection, in 2.2, we first examine when XAI is necessary and its importance. Then, we define the suite of explainable artificial intelligence and the goals of XAI, and finally, we determine the suite that aims to satisfy these goals.

### 2.1 Fake News Detection

In the past decade, social media has become a place where anyone can share information. Although fast, free, and easy to access, obtaining real news from social media can be difficult, and one should do so at their own risk and always check the facts (Allcott & Gentzkow, 2017; Lazer et al., 2018). Nevertheless, the news stream never ends; thus, the need to verify the credibility of news using automated systems arises. To address this necessity, the number of studies involving *Fake News* or *Fake News Detection* has dramatically increased in the last decade (Fig. 2.1).

In 2.1.1, we briefly present the history of fake news and look at studies that display the impact of fake news on society. In this section, we also define the terms fake news, disinformation, and misinformation.

In 2.1.2, we make an excursion into social sciences and human psychology, delivering insights into why humans fall for or tend to believe fake news. Furthermore, we draw some insights from the social, technical, and data-oriented foundations of fake news.

We then list the available datasets used in FND and deliberate their advantages and disadvantages in 2.1.3. Finally, in 2.1.3, we summarize the evolution of detection

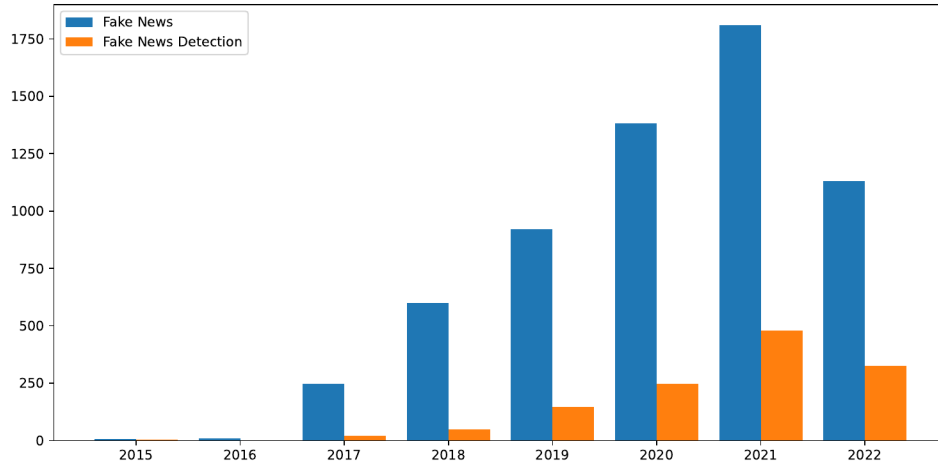


Figure 2.1: Total number of publications that include (1) *Fake News* (blue) and (2) *Fake News Detection* (orange) publications by year. Source: Scopus; Search Arguments: (1) TITLE-ABS-KEY("fake news\*") PUBYEAR AFT 2014 (2) TITLE-ABS-KEY("fake news detection")

algorithms, then we classify FND algorithms with respect to their input data type and what they focus on that data.

### 2.1.1 Fake News

Throughout history, various forms of widespread fake news have been recorded. For instance, in the thirteenth century BC, Rameses the Great decorated his temples with paintings that tell stories of victory in the Battle of Kadesh. However, the treaty between the two sides reveals that the battle's outcome was a stalemate (Weir, 2009). Just after the printing press was invented in 1439, the circulation of fake news began. One of history's most famous examples of fake news is the "Great Moon Hoax" (Foster, 2016). In 1835, The Sun newspaper of New York published articles about a real-life astronomer and a made-up colleague who had observed life on the moon. It turns out that these fictionalized articles brought them new customers and almost no backlash after the newspaper admitted that the articles mentioned earlier were a hoax<sup>1</sup>.

In order to highlight the difference, using the definitions from (Pennycook & Rand, 2021), we formally introduce the terms disinformation and misinformation as follows.

**Definition 2.1.1 (Disinformation).** "Information that is false or inaccurate and was created with a deliberate intention to mislead people." (Pennycook & Rand, 2021)

<sup>1</sup><https://www.politico.com/magazine/story/2016/12/fake-news-history-long-violent-214535/>

**Definition 2.1.2** (*Misinformation*). "Information that is false, inaccurate, or misleading. Unlike disinformation, misinformation does not necessarily need to be created deliberately to mislead." (Pennycook & Rand, 2021)

There is no fixed definition for fake news. Thus, we elaborate on the definitions of fake news. A limited definition is news articles that are intentionally or verifiably false (Allcott & Gentzkow, 2017). This definition stresses authenticity and intent. The inclusion of false information that can be confirmed refers to authenticity. On the other hand, intent refers to the deceitful intention to delude news consumers (Shu et al., 2017). This definition is widely used in other studies (Conroy et al., 2015; Mustafaraj & Metaxas, 2017; Shu et al., 2017).

Furthermore, recent social sciences studies (Lazer et al., 2018; Pennycook & Rand, 2021) define fake news as fabricated information that mimics news media content in form but not in organizational process or intent. Similarly, this definition covers authenticity and intent; additionally, it includes the organizational process. More general definitions for fake news consider satire news as fake news due to the inclusion of false information even though satire news aim to entertain and inherently reveals its deception to the consumer (Balmas, 2014; Brewer et al., 2013; Jin et al., 2016; V. Rubin et al., 2016). Further definitions include hoaxes, satires, and obvious fabrications (V. L. Rubin et al., 2015). In this thesis, we are not interested in the organizational process and do not consider conspiracy theories (Sunstein & Vermeule, 2009), superstitions (Lindeman & Aarnio, 2007), rumors (Berinsky, 2017), misinformation, satire, or hoaxes. Therefore, we use the limited definition from (Allcott & Gentzkow, 2017) and formally introduce it.

**Definition 2.1.3** (*Fake News*). "News articles that are intentionally or verifiably false." (Allcott & Gentzkow, 2017)

Fake news can lead to disastrous situations, such as crashes in stock markets, resulting in millions of dollars. For example, Dow Jones industrial average went down like a bullet (see Fig. 2.2) after a tweet about an explosion injuring President Obama went out due to a hack (ElBoghdady, 2013).

The detrimental impacts of fake news further extend to societal issues. When fake news rose to prominence with the 2016 U.S. Presidential Election (Beckwith, 2021), a man, convinced by what he read on social media about a pizzeria trafficking humans, went on a shooting spree in that pizzeria. Later named Pizzagate (Fisher et al., 2016), this incident illustrates the deadly impact of fake news. In fact, fake news can even affect presidential elections (Allcott & Gentzkow, 2017; Read, 2016).

Recent history exhibits that some fake news spreads like wildfires through social media. Evidence shows that the most popular fake news stories were more widely shared than the most popular mainstream news stories (Silverman, 2016).

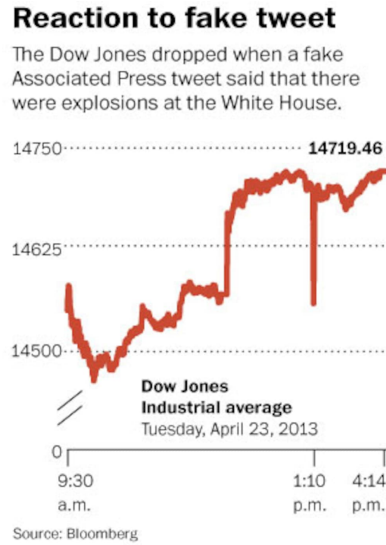


Figure 2.2: The market's reaction to the fake tweet. The sharp decline caused by a single tweet. Image obtained from (ElBoghdady, 2013)

Digital News Report 2022 (N. Newman et al., 2022) reports in its key findings that trust in the news is 42% globally, the highest (69%) in Finland, and the lowest (26%) in the U.S.A. Additionally, the same study shows that in early 2022, in the week of the survey, between 45% and 55% of the surveyed social media consumers worldwide witnessed false or misleading information about COVID-19. The same study also reports the appearance of fake news in politics was between 34% and 51%, and between 9% and 48% for fake news about celebrities, global warming, and immigration (Watson, 2022).

### 2.1.2 Foundations of Fake News

The environment for fake news has been the traditional news media for a long time. First started with newsprint, then continued with radio and television, and now with social media and the web, the dissemination of fake news reached its peak. Next, we discuss the psychological and social foundations of fake news to stress the importance of human psychology, especially when accepting fake news as genuine and sharing it with others. Then we focus on the technical foundations where we discuss how social media and technology have accelerated the diffusion of fake news.

**Psychological Foundations.** Understanding the difference between real and fake news is not an easy task for a human. Two psychological theories, namely, *naïve realism* and *confirmation bias*, examine why humans fall for fake news. The first refers to a person's

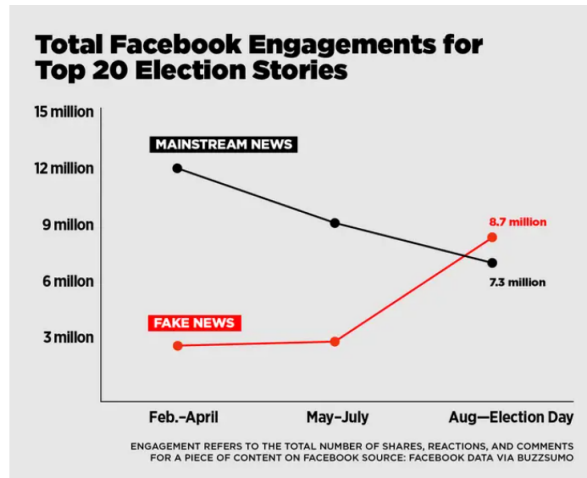


Figure 2.3: The rising engagement for fake news stories observed after May-July, just before Presidential Elections. Image obtained from (Silverman, 2016)

disposition to believe that their point of view is the mere accurate one, while people who believe otherwise are uninformed or biased (Reed et al., 2013). The second, often called selective exposure, is the proclivity to prefer information that confirms existing views (Nickerson, 1998).

Another reason for human fallacy in fake news is that once a misperception is formed, it becomes difficult to correct. In fact, it turns out that correcting people leads them to believe false information more, especially when given factual information that refutes their beliefs (Nyhan & Reifler, 2010).

**Social Foundations.** The prospect theory explains the human decision-making process as a mechanism based on maximizing relative gains and minimizing losses with respect to the current state (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992). This inherent inclination to get the highest reward also applies to social cases in which a person will seek social networks that provide them with social acceptance. Consequently, people with different views tend to form separate groups, which makes them feel safer, leading to the consumption and dissemination of information that agrees with their opinions. These behaviors are explained by social identity theory (Ashforth & Mael, 1989) and normative social influence (Asch & Guetzkow, 1951).

Two psychological factors play a crucial role here (Paul & Matthews, 2016). The first, social credibility, is explained by a person's tendency to recognize a source as credible when that source is deemed credible by other people. The second, called the frequency heuristic, is the acceptance of a news piece by repetitively being exposed to it. Collectively, these psychological phenomena are closely related to the well-known filter

bubble (Pariser, 2011), also called echo chamber, which is the formation of homogenous bubbles in which the users are people of similar ideologies and share similar ideas. Being isolated from different views, these users usually are inclined to have highly polarized opinions (Sunstein, 2001). As a result, the main reason for misinformation dispersal turned out to be the echo chambers (Vicario et al., 2016).

**Technical Foundations.** Social media’s easy-to-use and connected nature give rise to more people selecting or even creating their own news source. Naturally, this gives way to more junk information echoing in a group of people on social media. As algorithms evolve to understand user preferences, social media platforms recommend similar people or groups to those in echo chambers. A recent study (Cinus et al., 2022) shows that these recommenders can strengthen these echo chambers. They discuss that some of these recommenders contribute to the polarization on social media. In other words, people can convince themselves that any fake news is real by staying in their echo chambers. One main reason that some fake news spreads so rapidly on social media is the existence of malicious accounts. The account user can be an actual human or a social bot since creating accounts on social media is no cost and almost no effort. While many social bots provide valuable services, some were designed to harm, mislead, exploit, and manipulate social media discourse. Formally, a social bot is a social media account governed by an algorithm to fabricate content and interact with other users (Ferrara et al., 2016). A more recent study from the same author shows that malicious social bots were heavily used in the 2016 U.S. Presidential Elections (Bessi & Ferrara, 2016). On the other hand, malicious accounts that are not bots, such as online trolls who aim to trigger negative emotions and humans that provoke people on social media to get an emotional response, contribute to the proliferation of fake news (Cheng et al., 2017). Building upon three foundations, we draw some results for fake news to be considered when building a fake news detection model:

1. *Invasive*: Fake news can appear on anyone’s feed if it spreads for a sufficient amount of time.
2. *Hard to discern*: Fake news is fabricated in such a way that it resembles the authenticity of a real news source. This indistinguishability leads to issues when working with news-content-based FND models.
3. *The source is crucial*: The credibility of a news source is essential. We can use news from credible sources to teach the model to distinguish genuine from fabricated.
4. *Fake news has hot spots*: The echo chambers are invaluable examples when trying to understand the behaviors of fake news. We can leverage this attribute and use social models, such as graphs, to successfully detect fake news.



5. *Early detection is essential*: As discussed in psychological foundations, the volume of exposure to a piece of fake news can significantly affect one's opinions, thus leading to more misinformed individuals.

**Data-Oriented Foundations.** We define features for news content and social context to represent the news pieces in a structured manner. First, we introduce attributes for news content (Shu et al., 2017):

- *Source*: Publisher of the news piece.
- *Headline*: Short title text that aims to catch the readers' attention and describes the article's main topic.
- *Body Text*: The main text piece that details the news story.
- *Image/Video*: Part of the body content supplies visual input to articulate the story.

Using these attributes, we extract two types of features for news content:

*Linguistic-based features*: The news content is heavily based on textual content. Thus, the first feature that belongs to this class is lexical features which make use of character and word level frequency information which can be obtained by the utilization of *term frequency-inverse term frequency* (TF-IDF) (Jones, 1972; Luhn, 1957) or bag-of-words (BoW). The second feature is based on syntactic features which include sentence-level features that can be obtained via *n-grams* and punctuation and *parts-of-speech* (POS) (Daelemans, 2010) tagging. We can extend these features to domain-specific ones, such as external links and the number of graphs (Potthast et al., 2017).

*Visual-based features*: Particularly for fake news, the visual content is a strong tool for establishing belief (Dan et al., 2021). Hence, the features that reside in images and videos become significant. Fake images and videos which brings the fake story together are commonly used (e.g. Harding, 2012; Sawyer, 2020). To counteract the effects of misleading visual input, recent studies (Qi et al., 2019) examined visual and statistical information for fake news detection. Visual features consist of clarity score, similarity distribution histogram, diversity score, and clustering score. Statistical features are listed as count, image ratio, multi-image ratio etc. (Shu et al., 2017).

Now, we define features for social context, which has recently drawn much attention from the research community (Shu et al., 2020; Shu et al., 2019). Overall, we will concern three aspects of social context data: user-based, post-based, and network-based features.

*User-based:* As mentioned in the Technical Foundations part of this subsection, fake news has various ways of disseminating, such as via echo chambers, malicious accounts, or bots. Therefore, analyzing user-based information can prove useful. We distinguish user-based features at the group and individual levels (Shu et al., 2017). Individual levels are extracted to deduce the credibility of each user by utilizing, for example, the number of followers and followees, the number of tweets authored by a user, etc (Castillo et al., 2011). On the other hand, group-level user-based features are the general characteristics of groups of users related to the news (Yang et al., 2012). Parallel to the social identity theory and normative social influence idea, the assumption is the consumers of real and fake news tend to form different groups, which may lead to unique characteristics. Typical group-level features stem from individual-level features by obtaining the share of verified users, and the average number of followers and followees (Ma et al., 2015).

*Post-based:* Analysis of reactions by users can prove helpful when determining whether a news piece is real or not. For example, if a news piece is getting doubtful comments, this can help determine the news piece’s credibility. As such, post-based features are based on inferring the integrity of a news piece from three levels. Namely, post-level, group-level, and temporal-level (Shu et al., 2017). Post-level features can be embedding values for each post or take forms as mentioned in linguistic-based features, e.g., n-grams, BoW, etc. For post-level features, we can also consider general approaches such as topic extraction (e.g., using latent Dirichlet allocation (LDA) (Blei et al., 2003)), stance extraction, which provides information about users’ opinions (e.g., supports, opposes (Jin et al., 2016)), and finally credibility extraction, which deals with estimating the degree of trust for each post (Castillo et al., 2011). Group-level post-based features collect feature values for all relevant posts and apply an operation to extract pooled information. When determining the credibility of news, group-level features proved to be helpful (Jin et al., 2016). Temporal-level features deal with changes in post-level features over time. Typically, unsupervised learning methods such as Recurrent Neural Networks (RNN) are employed to capture the changes over time (Ma et al., 2016).

*Network-based:* As discussed in the Technical Foundations part, fake news is likely to give rise to echo chambers, which leads to the idea of a network-based approach. When represented as networks, the propagation behavior of fake news can be analyzed further, and patterns can be discovered (Shu et al., 2017). In literature, various types of networks exist, the most common ones are stance networks, occurrence networks, and friendship networks. Stance networks are constructed

upon stance detections which is a part of sentiment analysis and deal with determining a user's viewpoint using text and social data (Du et al., 2017). Using all users' stances, a network is built in which the nodes are the tweets relevant to the news piece and the edges represent the similarity of stances between nodes (Jin et al., 2016; Tacchini et al., 2017). On the other hand, occurrence networks leverage the frequency of mentions or replies about the same news piece (Kwon et al., 2013). Friendship networks are based on the follower/followee relationship of users who share posts connected to the news piece. Derived from friendship networks, in the form of one of the datasets we use in our experiments (Dou et al., 2021), diffusion networks are designed to track the course of the dissemination of news (Kwon et al., 2013). Briefly, a diffusion network consists of nodes representing users and diffusion paths representing the relationship and interaction between users. In detail, a diffusion path between two users  $u_i$  and  $u_j$  exists if and only if  $u_j$  follows  $u_i$ , and  $u_j$  shares a post about a news piece that  $u_i$  has already shared a post about (Shu et al., 2017). It has been shown that characterizing these networks is possible (Kwon et al., 2013). Approaches for these networks have gained traction recently, especially with some SOTA GNNs, e.g., (Monti et al., 2019).

To conclude this subsection, we have covered psychological, social, technical, and data-oriented foundations in this section. We established that, from different aspects, there are various reasons for the dissemination of fake news. Accordingly, we consider these reasons when building FND systems. In the next section, we discuss FND approaches and how they have evolved. Moreover, we characterize FND models and talk about each type of approach.

### 2.1.3 Evolution of Fake News Detection

Fake news detection is as old as fake news itself. Before social media became a hub for news consumers, fact-checkers, i.e., fake news detectors, were only journalists and literate people. Following the source shift of the news from printed paper to online, then social media, detection of fabricated news have become costly, cumbersome, and not as rewarding due to the endless stream of information and decreasing trust in journalism. Automatic detection for news thus became a necessity in our world (Chen et al., 2015).

Similar to what we did in the Data-Oriented Foundations part of the previous subsection, we classify fake news detection models as *News Content Models* and *Social Context Models* (see 2.4) and start with News Content Models by following the classification principles in (Shu et al., 2017).

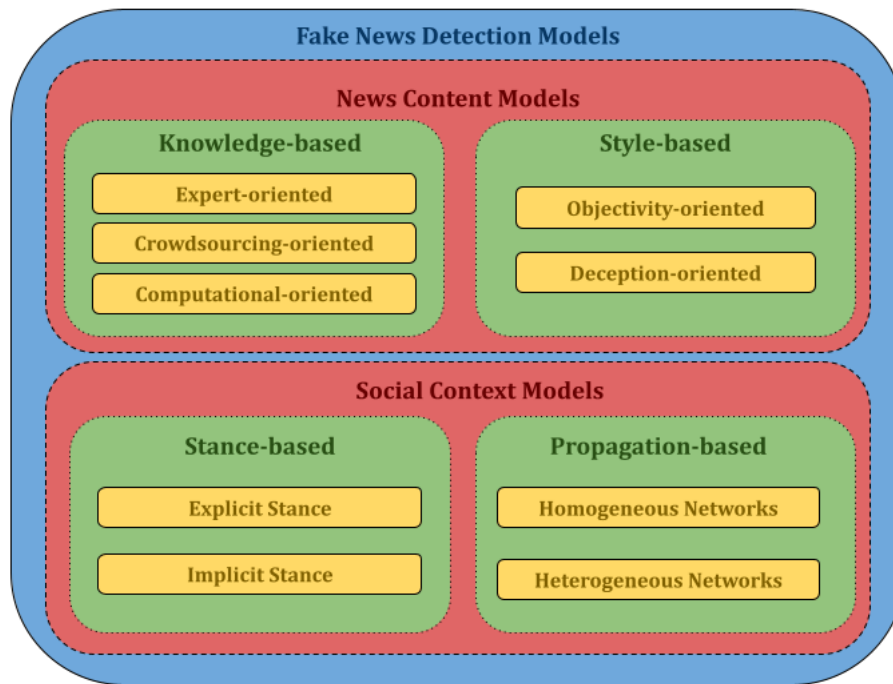


Figure 2.4: Characterization of Fake News Detection Models, Figure inspired by Figure 1 in Shu et al., 2017.

**News Content Models.** Based on news content and fact-checking methodologies, these models are the starting point of fake news detection. News content models are classified as Knowledge-based and Style-based. We first introduce style-based models as they are the initial approaches for FND.

*Style-based:* Previous research in psychology has mainly focused on style-based approaches to detect *manipulators* in the text. Particularly deception detection techniques were popular and commonly developed in early works in criminology and psychology. We describe two different ways to approach style-based news content models, namely, *Deception-oriented* and *Objectivity-oriented* (Shu et al., 2017).

- *Deception-oriented:* The initial approaches for automated fake news detection focus on news context and stem from deception detection in language. The first study that focuses deception detection in language (Undeutsch, 1954) hypothesized that the truthfulness of the statement is more important than the integrity of the reporting person, and there exist definable and descriptive criteria that form a crucial mechanism for the determination of the truthfulness of statements. Even though this study is from experimental psychology, it stresses the feasibility of defining a set of rules that determine the truthfulness of a statement.

An early study from criminology, Scientific Content Analysis (SCAN) (Sapir, 1987), analyzes freely written statements. In this process, SCAN claims to detect potential instances of deception in the text but cannot label a statement as a lie or truth. The next study for SCAN (Smith, 2001) is the first known study that correlates linguistic features with deceptive behavior using high-stakes data. Similar to SCAN, the subsequent studies (Adams, 2002; M. L. Newman et al., 2003) that link linguistic features to deception classify the owner of the statement as truth-teller or liar according to the frequency of deception indicators in the statement.

Although for automated deception detection, defining a methodology is more challenging (DePaulo et al., 1997), early studies have shown that this task is achievable. A detailed study (L. Zhou et al., 2004) makes a structured approach using linguistic-based cues and draws attention to further studies for automating deception detection. In this study, the authors extend linguistic-based cues with complexity, expressivity, informality, and content diversity. Instead of using humans as cue identifiers, authors use *Natural Language Processing* (NLP) techniques, namely an NLP tool called iSkim (L. Zhou et al., 2002), to extract cues automatically. Another study also focuses on linguistic cue analysis. With a small dataset and employing

the C4.5 (Salzberg, 1994) algorithm, the authors reach 60.72% accuracy using 15-fold cross-validation.

Similarly, in (Bachenko et al., 2008), the authors developed a system for automatically identifying 275 truthful or deceitful statements with the use of verbal cues using Classification and Regression Tree (CART) (Breiman et al., 1984). Additionally, the studies (Hancock et al., 2007; V. L. Rubin, 2010) make use of a relatively small dataset and analyze linguistic-based cues. Rubin’s series of studies (V. Rubin et al., 2015; V. L. Rubin, 2010; V. L. Rubin & Lukoianova, 2015; V. L. Rubin & Vashchilko, 2012) makes use of Rhetorical Structure Theory (RST) and Vector Space Modeling (VSM). The first captures the coherence of a story using functional relations among meaningful text units and delivers a hierarchical structure for each news story (Mann & Thompson, 1988). The second is the way to represent rhetorical relations in high-dimensional space. The authors utilized logistic regression as their classifier and reached 63% accuracy.

Furthermore, a study from Afroz and colleagues (Afroz et al., 2012) investigates stylistic deception and uses lexical, syntactic, and content-specific features. Lexical features include both character- and word-based features. Syntactic features represent sentence-level style and include frequency of function words from LIWC (Pennebaker et al., 2007), punctuation, and POS tagging in which a text is assigned its morphosyntactic category (Daelemans, 2010). Finally, content-specific features are keywords for a specific topic. For classification, the authors then leveraged Support Vector Machines (SVM) (Hearst et al., 1998). More comprehensive and modern approaches such as (Wang, 2017) also leveraged the power of *Convolutional Neural Networks* (CNNs) to determine the veracity of news.

- *Objectivity-oriented*: Objectivity-oriented news content models aim to detect indicators of the lessening of objectivity in news content (Shu et al., 2017). These indicators are observed in the news from misleading sources, such as hyperpartisan sources which display highly polarized opinions in favor of or against a particular political party. Consequently, this polarized behavior motivates the fabrication of news that supports the sources’ political views or undermines the opposing political party. *Hyperpartisan news* are a subtle form of fake news and defined as misleading coverage of events that did actually occur with a strong partisan bias (Pennycook & Rand, 2019). Since the spread of hyperpartisan news can be detrimental, many approaches to detect hyperpartisanship in news articles have been developed. For instance, in (Potthast et al., 2017), the authors take a stylometric methodology to

detect hyperpartisan news. In this study, the authors employ 10 readability scores, and dictionary features where each feature represent the frequency of words from a carefully crafted dictionary in a given document with the help of General Inquirer Dictionaries (Stone et al., 1966). A competition for detecting hyperpartisan news (Kiesel et al., 2019) hosted several teams with a variety of ideas which include the utilization of n-grams, word embeddings, stylometry, sentiment analysis etc. The most popular method was the usage of embeddings, particularly the models that leveraged BERT (Devlin et al., 2018).

Also used for dissemination of hyperpartisan news (Kiesel et al., 2019), another form of fake news that is evaluated under this focus is *Yellow-journalism*, which utilizes clickbaits such as catchy headlines, images etc. that invokes strong emotions, and it aims to generate revenue (Agrawal, 2016; Palau-Sampio, 2016). Studies that aim to detect clickbaits mainly focus on headlines. For example, in (Rony et al., 2017), the authors construct a DNN in which they use distributed subword embeddings (Bojanowski et al., 2016; Joulin et al., 2016) as features with an extension of skip-gram model (Mikolov, Sutskever, et al., 2013).

*Knowledge-based:* Being the most direct way of detecting fake news, these approaches make use of external fact-checkers to verify the claims in news content (Shu et al., 2017). Fact-checkers are either sophisticated algorithms, domain experts or crowdsourced to assess the truthfulness of a claim in a specific context (Vlachos & Riedel, 2014). With growing attention on fake news detection, automated fact-checking has drawn much attention, and considerable efforts have been made in this area (Barrón-Cedeño et al., 2020; Thorne & Vlachos, 2018). We categorize knowledge-based news content models as *Expert-oriented*, *Crowdsourcing-oriented*, and *Computational-oriented*.

- *Expert-oriented:* These approaches are essentially dependent on human domain experts who investigate the integrity of a news piece collecting relevant information and documents to come up with a decision about the truthfulness of a claim <sup>1</sup>. Platforms like Politifact <sup>2</sup> and EUfactcheck <sup>3</sup> are examples for expert-oriented fact-checking for all news from a variety of sources. These platforms label news in a range such that the label reflects the veracity of the news. A different approach for labeling is exercised by Snopes <sup>4</sup>, which

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<sup>1</sup><https://www.politifact.com/article/2018/feb/12/principles-truth-o-meter-politifacts-methodology-i/>

<sup>2</sup><https://www.politifact.com/>

<sup>3</sup><https://eufactcheck.eu/>

<sup>4</sup><https://www.snopes.com/>

extends the same logic of Politifact by including different aspects of fact-checking such as Scam, Miscaptioned, Outdated, etc <sup>1</sup>. Recently replaced by an irrelevant magazine website, another instance was Gossipcop <sup>2</sup>, which dealt with celebrity fact-checking and contributed to the creation of fake news dataset (Shu et al., 2018). Even though expert-based fact-checking is reliable, with the increasing magnitude of news stream and speed of spread, it is not scalable to fact-check every news piece by hand; thus, manual validation alone becomes insufficient (Guo et al., 2022).

- *Crowdsourcing-oriented*: Powered by the wisdom of crowds (Galton, 1907), crowdsourcing-oriented fact-checking is a collection of annotations that are afterward aggregated to obtain an overall result indicating the veracity of the news. Unlike professional fact-checkers, who are in short supply, this approach is scalable given that the crowd contains enough literate people (Allen et al., 2021). For instance, Twitter launched a program called Birdwatch <sup>3</sup>, in which the users are able to leave notes for tweets that they think contain misinformation. Furthermore, this tool allows users to rate each other's notes, leading to the diversity of perspectives <sup>4</sup>. Another example is from Facebook <sup>5</sup>, which uses a third party of crowdsourced fact-checkers called International Fact-Checking Network <sup>6</sup> (IFCN).
- *Computational-oriented*: Heavily dependent on external sources, computational-oriented models are scalable, automated systems that are designed to predict whether a claim is truthful or not. The studies that focus on this type of approach mainly try to solve two issues: (i) identifying check-worthy claims and (ii) estimating the integrity of claims (Shu et al., 2017). The first issue requires the extraction of factual claims from news content or other related textual content. For example, in (Hassan et al., 2015), the authors collect presidential debate transcripts, then label them into three classes with the help of crowdsourcing. Using annotated data and supervised learning techniques, the authors uncover some interesting patterns in these transcripts. Another study that covers both issues uses Wikipedia information to generate factual claims and then check whether a given claim is truthful or not (Thorne et al., 2018). The second issue, compared to the first one, requires the utilization of structured external sources. *Open web* and *structured knowledge graphs* are the

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<sup>1</sup><https://www.snopes.com/fact-check-ratings/>

<sup>2</sup><https://web.archive.org/web/20190807002653/https://www.gossipcop.com/about/>

<sup>3</sup><https://twitter.github.io/birdwatch/overview/>

<sup>4</sup><https://twitter.github.io/birdwatch/diversity-of-perspectives/>

<sup>5</sup><https://www.facebook.com/formedia/blog/third-party-fact-checking-how-it-works>

<sup>6</sup><https://www.poynter.org/ifcn/>



two most prominent tools when tackling this issue. Open web tools analyze features like mutual information statistics (Etzioni et al., 2005), frequency, and web-based statistics (Magdy & Wanas, 2010). On the other hand, knowledge graphs are interconnected. One noteworthy example is ontologies such as DBPedia (Auer et al., 2007), using which one can define semantic relations and rules in order to infer whether a claim is correct (Braşoveanu & Andonie, 2019).

**Social Context Models.** The interconnected design of social media can be leveraged by extracting user-based, post-based, and network-based features and utilizing these features to supplement news content models. Social context models exploit related user engagements for a news piece by capturing this external information from multiple angles. Two types of social context models are prominent: *Stance-based* and *Propagation-based* (Shu et al., 2017).

- *Stance-based:* Given a news piece, these approaches estimate the user’s stance toward a specific news topic. More formally, stance detection in social media deals with users’ viewpoints toward particular topics by means of various aspects related to users’ posts and characteristic traits (ALDayel & Magdy, 2021). The user’s stance information can be extracted either implicitly or explicitly. Implicit stance can be automatically obtained from social media posts with the help of NLP tools such as sentiment analysis (Mohammad et al., 2016). Explicit stances are rather easier to obtain since they are direct expressions of opinions or emotions. For example, “like” on Twitter or Facebook, “upvote” and “downvote” ratings on Reddit, and “like” and “dislike” on Youtube are explicit stances of users. A study that utilizes explicit stances called *Some Like it Hoax*, uses logistic regression and harmonic boolean label crowdsourcing for classification on a dataset they curated from Facebook. In the stance classification process, they consider the likes and the issuer of likes for each post. They state that logistic regression comes short in this task since it cannot learn anything about posts without likes (Tacchini et al., 2017). An early example of implicit stance detection leverages the dialogic relations between authors by constructing graphs that represent the interaction between authors. They show that this information can improve the performance of stance-detection models (Walker et al., 2012). A more detailed study (Adda-wood et al., 2017) investigates stance classification considering lexical, syntactic, twitter-specific and argumentation feature types. Although some twitter-specific features can be considered as explicit stances, such as if the tweet is a retweet, if a tweet contains the title to an article, if a tweet contains a hashtag, etc., those features are later aggregated before it is fed to the classifier. The authors reach the highest F1 score using lexical and argumentation features. In literature, there

are also implicit stance-based approaches that aim to detect the veracity of a news piece by exploring the relationship between a headline and the article (Ghanem et al., 2018; Hanselowski et al., 2018).

Another variation of stance-based detection is rumor detection. One example of a rumor detection model is a Bayes classifier that utilizes content-based, network-based, and twitter-specific meme features through *Information Retrieval* (IR) techniques (Qazvinian et al., 2011). In this study, the authors propose a general framework that leverages statistical models and maximizes a linear function of log-likelihood ratios to retrieve rumor tweets. They show that the features they used contribute to their model’s overall performance.

- *Propagation-based*: Inspired by the assumption that the veracity of a news event is highly correlated with the credibilities of related social media posts, propagation-based models employ the interrelations of related social media posts to classify a news piece as truthful or not (Shu et al., 2017). These models can be based on either *homogeneous networks* or *heterogeneous networks*. Homogeneous networks are built upon a single type of entity, such as a post or event (Jin et al., 2016). A study by Jin et al., 2016 created homogeneous credibility networks for each topic which is extracted using an unbalanced version of the Joint Topic Viewpoint Model (Trabelsi & Zaiane, 2014). These credibility networks consist of nodes as tweets and edges as links, defined by either supporting or opposing. On the other hand, heterogeneous networks can contain multiple types of entities such as events, sub-events, posts, comments, etc. For example, in (Jin et al., 2014), the authors build a hierarchical propagation graph that contains events, sub-events, and messages from parent to child, respectively. Using an iterative method, they provide a globally optimal solution for the graph optimization problem in the study.

Furthermore, an interesting study from a decade ago based its credibility estimation algorithm on PageRank and similarity scores. Their propagation network consists of graphs in which possible nodes are events, tweets that were posted about that event, and users who posted those tweets.

**Mixed Approaches.** We examined two types of FND models, namely, news content models and social context approaches. It is crucial to note that approaches are not necessarily purely news content or social context-based; they can be based on both. The models that use news content and social context are referred to as mixed approaches (Han et al., 2020). *User Preference-Aware Fake News Dataset* (UPFD) (Dou et al., 2021) is a dataset that houses two of these types. The authors use news content and social engagement information to construct a hierarchical tree. The node features are textual representations of variety of sources which will be discussed in 4.1. The

best-performing model uses GraphSAGE (Hamilton et al., 2017) as graph encoder and BERT (Devlin et al., 2018) as the text encoder and reaches 84.62% and 97.23% accuracy on Politifact and Gossipcop, respectively.

To summarize this section, we have introduced the history and definitions of fake news in subsection 2.1.1. Then, we investigated the foundations of fake news and gave motivations for developing automated FND systems in subsection 2.1.2. Following that, we examined the evolution and characterized FND models in section 2.1.3. We have included at least two examples for each type of model and briefly summarized their approaches. We also briefly examined one of the datasets (Dou et al., 2021) and models (Hamilton et al., 2017) used in this thesis; however, in-depth information will be provided in the next chapter.

In 2.2, we elaborate on the techniques available in explainable artificial intelligence. We discuss the qualities of a reasonable explanation, and we highlight the importance of the interpretability of a model. We give essential definitions that will be used throughout this thesis.

## 2.2 Explainable Artificial Intelligence

Understanding and interpreting a model’s prediction is very important nowadays since this understanding allows to validate the reasoning of the model and extract rich information for a human expert, and can lead to increased trust in the model (Ribeiro et al., 2016). Furthermore, explanation of a model can help to improve the model (Lundberg & Lee, 2017) and alleviate concerns raised by Ethical AI (Angwin et al., 2016; Goodman & Flaxman, 2017). In this section, we introduce the background for XAI techniques that were used in this thesis. First, in 2.2.1 we characterize XAI by following works from Z. C. Lipton, 2016 and Barredo Arrieta et al., 2020 and give definitions to clarify the taxonomy. Then, in 2.2.2, we discuss the properties of good explanations, the goals of XAI and the evaluation techniques for explanation methods. Finally, in 2.2.3 we briefly lay out the most frequently mentioned explanation methods in the literature, along with the ones we use in this thesis. We summarize each of them and cover explanation techniques offered to any kind of neural network.

### 2.2.1 Foundations of Explainable Artificial Intelligence

Initial AI methods were not sophisticated enough to require additional explanation schemes. In the last years, expanding applications of DNNs have led to the adoption of these opaque systems even more. Although empirically successful thanks to enormous parameter spaces and numerous layers, DNNs are complex *black-box* models in terms of interpretability (Castelvecchi, 2016).

In the XAI context, *black-box* or *opaque* models are considered to be the opposite of *transparent* because they require a further search to understand their inner workings (Z. C. Lipton, 2016). Accordingly, humans hesitate to use systems that are not directly interpretable and reliable (J. Zhu et al., 2018), making *interpretability* essential. Moreover, from a legal perspective, the notion *right to explanation* brings more attention to interpretability (Z. C. Lipton, 2016). Particularly in situations such as when:

- The prediction of AI directly affects human life, e.g., fully autonomous cars in traffic, medical AI assistants etc.
- The reasons behind an AI system’s decision can not be clearly determined.

With the additional demand from the Ethical AI field (Goodman & Flaxman, 2017), the research community has put in a great amount of effort to gap the bridge between a black-box model and its interpretability. However, the lack of consensus on taxonomy has led to synonymous usages of interpretability. The early definitions for interpretability were too broad, describing it as essentially an additional design driver when building a model (Kim, Rudin, et al., 2015) or a requirement for *trust* (Kim, 2015). But can trust be defined in an objective way? Is the accuracy or F1 score of the model is enough to trust a model? To answer the first question, Z. C. Lipton, 2016 argues that trust is subjective and it is not technically defined. To answer the second question, taking only the performance metrics as a baseline for trust in the model is shown to be an incorrect approach, particularly studies that analyze models with *adversarial examples* (Liang et al., 2021; Yuan et al., 2017). Moreover, Doshi-Velez and Kim, 2017 argues that the need for interpretability comes from the *incompleteness* of the problem formalization.

Instead of trying to find a technical definition for interpretability, we can categorize existing systems in terms of their transparency. Z. C. Lipton, 2016 states two properties for interpretable models: *transparency* and *post-hoc interpretability*. The definition for the first and its related terms are given as in the following,

**Definition 2.2.1 (Understandability).** “Denotes the characteristic of a model to make a human understand its function - how the model works - without any need for explaining its internal structure or the algorithmic means by which the model processes data internally” (Barredo Arrieta et al., 2020; Montavon et al., 2018).

**Definition 2.2.2 (Transparency).** “A model is considered to be transparent if by itself it is understandable” (Barredo Arrieta et al., 2020).

To elaborate further, we discuss degrees of transparent models as not all models provide the same extent of understandability (Barredo Arrieta et al., 2020). Both in Z. C.

Lipton, 2016 and Barredo Arrieta et al., 2020 the categorization is made as: *simulability*, *decomposability*, and *algorithmic transparency*. We discuss each of them briefly.

- *Simulability*: Denotes the model’s characteristic to be simulated or thought only by a human. Thus, the complexity of a model plays an important role here. Models that can be presented to a human in terms of text and visualizations are considered interpretable (Ribeiro et al., 2016), and in this case, models this elementary fall into simulatable models category (Barredo Arrieta et al., 2020; Tibshirani, 1996).
- *Decomposability*: Represents the model’s characteristic to explain each part of the model. Basically, when all components of a model are simulable, then that model is decomposable (Z. C. Lipton, 2016) given that the inputs are already interpretable (Barredo Arrieta et al., 2020).
- *Algorithmic Transparency*: Deals with the user’s comprehension of the input’s journey from entering the model to becoming a prediction (Barredo Arrieta et al., 2020; Z. C. Lipton, 2016). For example, linear models can be considered algorithmically transparent since the user can understand how the model can act in a given situation (James et al., 2013).

The second property of interpretable models, *post-hoc explainability*, aims to improve the interpretability of not readily interpretable models. It does so by means of *text explanations*, *visual explanations*, *local explanations*, *explanations by example*, *explanations by simplification*, and *feature relevance explanations* techniques (Barredo Arrieta et al., 2020; Z. C. Lipton, 2016). In a more general sense, post-hoc explainability methods can be grouped into three categories in terms of the knowledge of the target model, granularity of focus, and form: *model-specific or model-agnostic*, *local or global* and *form*. The first category refers to the explainability method’s assumption on the model’s structure. *Model-specific* techniques can be utilized with a limited set of models since these techniques make an assumption on the model to be explained. On the other hand, *model-agnostic* techniques are designed in such a way that does not require knowledge about model’s inner workings (Barredo Arrieta et al., 2020; Guidotti et al., 2018). The second category denotes the explanation’s domain. *Local* explanations reason about a particular prediction of a model at feature level (Doshi-Velez & Kim, 2017) (e.g. compute a saliency map by taking the gradient of the output with respect to a given input vector (Z. C. Lipton, 2016)), whereas global explanations aim to outline the model’s general behavior on the dataset (Barredo Arrieta et al., 2020; Doshi-Velez & Kim, 2017; Guidotti et al., 2018). Global explanations are usually presented in the structure of a series of rules (Lakkaraju et al., 2016). The third and last category, form of the explanation is the manner that is conveyed to the user. We will discuss specific

forms of explanation in detail after we give a definition of *explainability*, since from now on we talk about the explainability of a model rather than its interpretability.

**Definition 2.2.3** (Explainability). “*Explainability is associated with the notion of explanation as an interface between humans and a decision maker that is, at the same time, both an accurate proxy of the decision maker and comprehensible to humans.*” (Barredo Arrieta et al., 2020; Guidotti et al., 2018)

- *Text explanations* are techniques that learn to produce textual expressions that assist user to understand the outcomes of the model (Bennetot et al., 2019).
- *Visual explanations* are techniques that supplement a model’s explainability by visualizing the model’s behavior. Due to the mismatch between high-dimensional nature of complex ML systems and the capacity of human reasoning (Burrell, 2016), visual explanations often employ dimensionality reduction practices (Barredo Arrieta et al., 2020).

From the perspective of explainability, one would intuitively prefer transparency since transparent models can be explained with ease. However, some works argue that as transparency of a model increases their performance usually tends to decrease (Dosilovic et al., 2018), although other works argue that this is not necessarily true, particularly in cases where the data is well structured and the quality and value of available features is outstanding (Rudin, 2018). Furthermore, considering FND models, the need for big and complex models can not be avoided since news pieces tend to be long texts, or social networks are represented as graphs, thus forcing SOTA FND models to utilize complex approaches that decreases transparency such as word embeddings, data fusion, graph data structure (Dou et al., 2021).

On the other hand, although global explanations can be helpful to domain experts by providing information about what model has learnt on a global level, it might be difficult to obtain (Z. C. Lipton, 2016). Instead, local explanation methods are more easier to obtain and more practical for real-world applications. For example, if a user requests an explanation for a prediction, local explanations can provide it, which also complies with “right to explanation” (Goodman & Flaxman, 2017).

Depending on the model adopted for FND, we might be required to use model-specific or model-agnostic approaches. For instance, when dealing with a GNN, model-agnostic approaches do not provide easily interpretable explanations, thus requiring a model-specific explanation method. On the other hand, when dealing with a DNN model-agnostic post-hoc approaches are usually the choice (Barredo Arrieta et al., 2020). Therefore, for FND models used in this thesis, we are required to adopt both model-agnostic and model-specific post-hoc approaches. Below we list types of post-hoc approach as listed in (Barredo Arrieta et al., 2020).

- *Explanations by example*, a method suggested by Caruana et al., 1999, focus on obtaining representative information from a model by providing explanations for an example that sufficiently illustrates the inner workings of the model (Baehrens et al., 2010; Barredo Arrieta et al., 2020).
- *Explanations by simplification* techniques construct a new and simplified system to provide explanations for a model. These simplified systems keep the performance of the original model while displaying less complexity (Barredo Arrieta et al., 2020).
- *Feature relevance explanations* compute feature relevance scores for a model's variables in order to determine the effect of a feature has upon a model (Barredo Arrieta et al., 2020).

We discussed what kind of explanation methods we can adopt and how these methods can shape the design of a model and the forms of explanations that aims to convey information about the model's behavior. It is possible to see a combination of the previously mentioned explanation forms. In order to present the user with an comprehensible explanation, we characterize a good explanation and define its important properties in the next subsection.

### 2.2.2 What Makes A Good Explanation

In literature, the requirements for a *good explanation* are rigorously researched. However, there is not a clear definition of how an explanation should look like or convey to the user. It is challenging to objectively define what makes a good explanation (Barredo Arrieta et al., 2020). In order to tackle the issue of subjectivity of explanations, XAI draws wisdom from social and cognitive sciences. A comprehensive study on social sciences and XAI by Miller, 2017, analyzes explanations in terms of the content, the explainer and the explainee. The author argues that the research in AI is lacking knowledge about the properties and structure of an explanation. The major findings on how a good explanation should be are outlined below.

- Explanations are *contrastive* (P. Lipton, 1990; Miller et al., 2017). When presented with counterfactual explanations, users can understand the decision made by the model easier (Byrne, 2019; Escalante et al., 2018; Lopez-Paz et al., 2016). For example, rather than asking why event *A* occurred, we ask why event *A* occurred instead of an event *B* (Barredo Arrieta et al., 2020; Miller, 2017).
- Explanations are *selective*. Presenting all the causes for an event to a human is pointless, since humans are inclined to select a couple main causes out of

numerous, sometimes countless, causes as shown in (Herlocker et al., 2000). Accordingly, Miller, 2017 argues that this selection process is shaped by specific cognitive biases.

- Explanations are *social*. They are conveyed from explainer to explainee via a social interaction. Hence, explanations are transferred through the frame of explainer's beliefs about the explainee's beliefs (Miller, 2017).
- Probabilities probably don't matter. Even though probabilities matter when creating the explanations, the usage of these statistical relations in explanations is not as effective as that of causes. If the underlying causal explanation is not included, then the utilization of statistical generalisations is not sufficient (Miller, 2017).

It should be noted that the characteristics of a good explanation is not limited to the ones mentioned above. These are the most prominent characteristics of numerous which is discussed in (Miller, 2017) detail. An important aspect here is that the explanations are provided to an *explainee* who is the *audience* in (Barredo Arrieta et al., 2020), which refers to the person receiving the explanation. It is further noted in (Barredo Arrieta et al., 2020) that explanations are dependent on the audience, i.e., an explanation meant for an end-user will not be enough for a domain expert or an explanation for a domain expert might be too complicated for an end-user. Also, we will refer to the explainee as *audience* from now on.

Main target audience is the main driver when considering the needed outcomes for an explanation. Barredo Arrieta et al., 2020 summarizes the pursued goals when trying to attain explainability. These are listed below.

- *Trustworthiness* deals with the assurance of a model's intended behavior when the model is presented with real-world scenarios (Antunes et al., 2008; Z. C. Lipton, 2016). Some studies highlight the importance of *trustworthiness* as a requirement for explainability (Kim, Glassman, et al., 2015; Ribeiro et al., 2016). The main target audience for this goal is domain experts, and users affected by the model decisions (Barredo Arrieta et al., 2020).
- *Confidence* refers to the robustness and stability of a model (Barredo Arrieta et al., 2020). Yu, 2013 argues that stability is a prerequisite when obtaining explanations from a model. Moreover, (Barredo Arrieta et al., 2020) argues that trustworthy explanations should not be obtained from unstable models. The audience relevant for this goal are domain experts, developers, managers, and regulatory entities.
- *Fairness* refers to a model's potential to ensure a fair prediction for a user affected by the model's prediction on the basis of characteristics such as age, race, gender,



etc (Barredo Arrieta et al., 2020; Oneto & Chiappa, 2020). The audience for this goal consists of users affected by model decisions and regulatory entities.

- *Transferability* refers to the model's capability to perform on unseen data. It is a desired goal to have not just for explainability but also for obtaining a good performance from the model (Kuhn & Johnson, 2013). The audience for this goal is domain experts and data scientists.
- *Causality* denotes the causal relationships between variables of a model (Pearl, 2009). It aims to provide causal information among the data variables. Its main audience is domain experts, managers, and regulatory entities (Barredo Arrieta et al., 2020).
- *Informativeness* is a goal meant for all users and it deals with the information provided by the model. In order to fill the gap between user's decision and the prediction of a model, a massive amount of information about the problem at hand needs to be conveyed to the end user (Barredo Arrieta et al., 2020).
- *Accessibility* refers to the possibility of end users getting more involved in a model's development or improvement (Miller et al., 2017). The audience for this goal includes product owners, managers, and user affected by model decisions.
- *Interactivity* denotes a model's capability to interact with the user (Kim, 2015). The main audience consists of domain experts and users affected model decisions.
- *Privacy awareness* is a goal not frequently seen in the literature. It deals with the learnings of a model's internal representation such that these learnings might pose a privacy breach. From the opposite perspective, it is a differential privacy breach when an unauthorized third party can explain the inner workings if a trained model (Barredo Arrieta et al., 2020).

On the other hand, for a given explanation and its preferred characteristics, how do we objectively evaluate an explanation? For example, considering a model, the evaluation metrics obtained from the test set reflect the model's overall performance on unseen data and allow to compare different models that use the same dataset (Olson et al., 2017). For example, metrics like accuracy, F1 score, recall, and precision are often used in the evaluation of models. Given that there are numerous metrics, it should be noted that different domains and models may require different evaluation metrics (Handelman et al., 2019; Hossin & Sulaiman, 2015; McNee et al., 2006). For a comprehensive study on the evaluation metrics of ML models, please refer to (Japkowicz & Shah, 2011). Similar to models, explanations require evaluation methods that can quantify their performance. So far, we have seen that explanations might have different audiences,

they can take several forms, and they have desired properties. Therefore, like models, there should be a set of explanation evaluation methods which focus on different categories of explanation approaches. In fact, a rigorous study by Doshi-Velez and Kim, 2017 lays out the categorization of explanation evaluation approaches. The authors split the evaluation methodologies into three:

1. *Application-grounded evaluations* involve conducting experiments on real humans who are domain experts interacting with explanations in a real-world application. This kind of evaluation directly tests the objective of the system, thus, attaining high performance with respect to application-grounded evaluation suggests good evidence of the explanation's success. The fact that we need humans interacting with a real-world application in an environment which can be observed for experimentation makes this type of evaluation more specific and thus the most costly of all three types of evaluation (Doshi-Velez & Kim, 2017).
2. *Human-grounded evaluations* are constructed by simpler experiments conducted on real humans who are not necessarily domain experts. Although this type of evaluation is less specific compared to the application-grounded evaluations, it offers more flexibility and less costly. It is a good choice when the task is to test the quality of an explanation in a general sense (Doshi-Velez & Kim, 2017). For example, a recent study (Mohseni et al., 2018) used human attention maps that overlay on images as explanations and asked users to rate the decision made by the model. The study further argues that the evaluation on these attention maps can be utilized to understand the *trustworthiness* of a model.
3. *Functional-grounded evaluations* do not include real humans, instead this kind of evaluations use a formal definition of interpretability as a proxy to assess the explanation's quality. The lack of human dependency makes them favorable due to the low cost. Typically, these evaluations are preferred when conducting experiments with humans in the loop might be unethical. The challenge with these evaluations is to select the right proxy models. Accordingly, when possible, it is considered good practice to first obtain proxies that were verified, for instance, by human-grounded evaluations (Doshi-Velez & Kim, 2017).

From high cost to low cost, and more specific to more broad, one can opt for an evaluation technique to obtain a performance indicator of an explanation. As discussed above, each approach requires a completely different setting, which brings their shortcomings with it. For instance, depending on the availability of resources such as time, finances, expertise of the user or sufficiency of human subjects one might have to opt for a different evaluation technique.

Having highlighted important characteristics of a good explanation, we now move

forward to the frequently mentioned techniques used in XAI. We mostly focus on post-hoc local explanation techniques and outline their contribution to this thesis.

### 2.2.3 Overview of Techniques in Explainable Artificial Intelligence

As discussed in the last section, when constructing an explanation method, one has to consider the audience, opt between model-specific or model-agnostic, local or global explanations, and also, utilize various forms of explanation. In literature, there exist various combinations of previously mentioned options. For transparent models, no further explanation method needed, one can obtain relevant information in the forms of weights or attention scores, given that the features are simple enough (Barredo Arrieta et al., 2020). In particular, we talk about explanation methods that were frequently mentioned in studies and relevant for this thesis.

First, we discuss the initial methodologies aimed to gain insight from a black-box model. The one of the initial approaches was to ask the question: *What happens if we remove this part of the input?* *Sensitivity Analysis* (SA) deals with analytical assessment of the effect of an omitted input variable on the uncertainty of a model (Novak et al., 2018). SA can be done on two levels, local and global. *Local Sensitivity Analysis* (LSA) assesses the impact of the changes in the input on the output whereas *Global Sensitivity Analysis* (GSA) examines the effect of each variable (feature) with respect to the variations of all parameters (Rao et al., 2019). In literature, there are a variety of approaches for both GSA and LSA. For instance, Novak et al., 2018 constructs a GSA that employs the partial derivative of each parameter in the back-propagation algorithm to explore the change rule, which admits the *Input-Perturbation-Sensitivity* (IPS) that allows to obtain global sensitivity. An interesting example of a GSA and LSA fusion approach, Kowalski and Kusy, 2018, utilizes LSA to reduce the number of input features and GSA to reduce the number of patterns learned by a model.

Another approach was to calculate relevance scores for each feature using saliency maps. The usage of saliency maps first appeared in CNNs for images (Simonyan et al., 2014), then extended to NLP in Bansal et al., 2016; Denil et al., 2014. Typically, saliency maps compute a gradient to get a relevance score to an input feature. In other words, they convey information about the model’s sensitivity with respect to the input.

A popular method used in XAI is *Layer-wise Relevance Propagation* (LRP) which was first introduced for *Fully Connected Networks* (FCNs) and CNNs in Lapuschkin et al., 2015, then extended to *Recurrent Neural Networks* (RNNs) in Arras et al., 2017. LRP assumes that a model can be *decomposed* into several layers which can contain feature relevant information. From the last layer to the input layer, LRP computes a relevance score for each dimension of the vector at a layer, and as LRP moves backwards in the layers, the sum of relevance scores do not change, staying always equal to the prediction

probability (Lapuschkin et al., 2015).

Similar to LRP, a study for explaining DNNs offers another solution named *Deep Learning Important FeaTures* (DeepLIFT) (Shrikumar et al., 2017). This approach addresses two shortcomings of LRP, namely, the failure to model saturation caused by activation functions, and the possibility of getting misleading importance scores due to discontinuous gradients. Combining techniques from LRP and integrated gradients (Sundararajan et al., 2016), DeepLIFT computes importance scores based on the *difference-from-reference* approach which allows propagation of information even if the gradient is zero. Difference-from-reference is a method which involves determining a reference then getting the difference between the reference and the output. This method is also later adopted by to create DeepSHAP (Lundberg & Lee, 2017).

In contrast to model-specific approaches like LRP and DeepLIFT, *Locally Interpretable Model-agnostic Explanations* (LIME), as the name suggests, is a model-agnostic method. LIME interprets the predictions of any black-box model by approximating the model around a prediction. This approximation allows to obtain a locally faithful and interpretable version of the model (Ribeiro et al., 2016).

So far, there is no study that unifies all the works to create one explainability framework. To address this lack of unification, Lundberg and Lee, 2017 offers *SHapley Additive exPlanation* (SHAP) framework, in which the authors utilize recent studies from game theory based on (Shapley, 2016). These studies are *Shapley regression values* (Lipovetsky & Conklin, 2001), *Shapley sampling values* (Štrumbelj & Kononenko, 2014) *Quantitative input influence* (Datta et al., 2016), and recent approaches like LIME, DeepLIFT are utilized to create a model-agnostic and model-specific explainers. SHAP values measure the feature importance and obtained via Shapley values of conditional expectation function of a model (Lundberg & Lee, 2017). Model-agnostic SHAP values are computed using Shapley sampling values method which uses an approximation of a permutation adaption of of classic Shapley value estimation. For example, *KernelSHAP* employs LIME with linear explanations and Shapley values to find a weighting kernel that enables regression based estimation of SHAP values. On the other hand, the authors propose *LinearSHAP* which can approximate Shapley values using weights for linear models, and *DeepSHAP* which connects DeepLIFT with Shapley values, *Low-order SHAP*, and *Max SHAP* for model-specific explainers. We will discuss SHAP values further in Section 3.2.1.

In literature, there is a lack of explanation tools for GNNs. GNNs require graphs as input and an output for either graph or node depending on the focus of the task (Zhang et al., 2018). Graphs are capable of representing rich relational information between nodes and the node feature information (Zhang et al., 2018; J. Zhou et al., 2018). GNNs are powerful tools that are able to learn relational information between nodes as well as node features, making them a perfect candidate for analyzing social media net-

works (Zang et al., 2016). In our case, we want to understand how a GNN behaves when classifying fake and real news pieces and their propagation networks. A study by Ying et al., 2019 proposes a model-agnostic approach called *GNNExplainer* to explain predictions made by GNNs. *GNNExplainer* takes a trained GNN, input graph(s) and its prediction(s) and it returns explanations in the form of subgraph(s) of input graph(s) along with the most influential node features for the prediction. These subgraphs are constructed by maximizing the mutual information between the subgraph and the input graph with respect to the prediction (Ying et al., 2019).

Bearing in mind the FND models and explanation methods discussed one can use LIME, DeepLIFT, or SHAP for news content models which are essentially DNNs with textual data as inputs. Especially for understanding which words or word groups are of the most importance, SHAP provides text plots and easily interpretable importance scores. Therefore, when assessing our choice of news content model, we employ SHAP framework, in particular, DeepSHAP. On the other hand, for GNNs the choice is straightforward as there is only one choice. Although, *GNNExplainer* can be helpful to identify the most important spreaders of a news piece which will be discussed in Chapter 4.2.

To conclude this chapter, it should be noted that due to the numerous studies in the literature, we did not cover all explanation methods, but an extensive study can be found in (Molnar, 2022). Moreover, we were not able to fully cover the psychological and social background of explanations as we did for fake news, however Miller, 2017 provides a rigorous research in that field. In the next chapter, we elaborate on FND models that were used in this thesis. We show how a neural network produces a prediction for a given input. We share our analysis on both textual and graph datasets. After talking about model parameters and hyperparameters, we evaluate our models and talk about the evaluation process. Also, we examine issues like early fake news detection and model aging, particularly for our SOTA FND models.

## 3 News Content Models for Fake News Detection

The automated detection of fake news on social media comes with its characteristic challenges. The fact that fake news are constructed to misguide its consumers makes them hard to distinguish by only using news content. In this chapter, we examine how these challenges effect the model and dataset’s design. We initially take a look at news content models in Section 3.1. In first section, we lay out the definitions for the materials used. After we give a detailed analysis of the dataset, we talk about the tokenizer and model itself, discuss its performance on the dataset. Then we apply model-agnostic explanation methods to understand the model’s behavior in Section 3.2.

### 3.1 News Content Models

The majority of approaches for FND models utilizes news content. Models that base their predictions only on news content focus on the patterns in the text, especially words or word groups that appear frequently in other instances of the same class. As discussed in Section 2.1, there exist a variety of approaches available for news content models, however, due to unavailable or outdated datasets, we were unable to work with most news content models.

#### 3.1.1 Notation and Definitions

Here we introduce the notation utilized in this section. Note that these notations will appear in its context, which will provide concrete examples for each symbol defined in Table 3.1.

Using this notation we now define some relevant concepts. First, we talk about terms and definitions for *tokenization*, illustrate the mathematical insight in the tokenization process. First, to build upon a concrete foundation, let us consider a news article  $x^{raw}$  fed to the tokenizer.

**Definition 3.1.1 (Tokenizer).** A tokenizer  $T : X^{raw} \mapsto X^{tok}$  is a function that maps raw textual data to smaller units called tokens.

$x^{raw} \in X^{raw}$	A news article.
$y^{raw} \in Y^{raw}$	A label of news article.
$T$	Tokenizer function
$\psi$	Label mapping function
$x^{tok} \in X^{tok}$	Tokenized news article
$y \in Y$	Vectorized class value.
$ x^{tok} $	The number of tokens in $x^{tok}$ .
$\hat{y}$	Prediction of model.
$x \in X$	Numeric vector of $x^{tok}$
$ x $	The length of input vector
$l$	Index of a layer
$l_{embedding}$	Embedding layer
$a_i^{(l)}$	The value of unit $i$ in layer $l$
$w_{ij}^{(l)}$	Weight between units $i$ in layer $l$ and $j$ in layer $l + 1$
$\sigma$	Activation function

Table 3.1: Notation used in this section.

A token can be a word, character or a subword. Therefore, we define three types of tokenization techniques:

- *Word tokenization* splits the given text into individual words based on a delimiter such as whitespace, comma, etc. This approach creates a vocabulary from the inputs it was trained on. All words do not appear in the vocabulary are replaced with unknown token ([UNK]), and this concept is called being *Out Of Vocabulary*(OOV). Depending on the task, the size of the vocabulary can grow quite large. The solution for exploding vocabulary sizes was introduced in subword tokenization. The commonly used examples for word tokenizers are Word2Vec (Mikolov, Chen, et al., 2013) and GloVe (Pennington et al., 2014).
- *Character tokenization* splits the text into single characters. Since the size of available characters is limited and known, the OOV problem is solved by encoding the unknown word by means of its characters. Although looks like a good solution, the length of tokens can be massive for long texts.
- *Subword tokenization* splits the given text into subwords, also called *n-gram characters*. For instance, comparative words like harder is segmented into hard-er, or superlative words like hardest is segmented into hard-est. The most common method for subword tokenization is *Byte Pair Encoding* (BPE). BPE was introduced by Gage, 1994 but adapted to word segmentation by Sennrich et al., 2015. BPE

iteratively merges the most frequently appearing character or character sequences. This approach allows for an efficient space usage thus smaller vocabularies (Sennrich et al., 2015).

We say that an input is *tokenized* after it is fed to the tokenizer. A tokenized news article  $x^{tok}$  is a vector of tokens in which the order of the words and characters in  $x^{raw} \in X^{raw}$  are kept. Furthermore, to get a fixed length output, we pad the tokenized sequence  $x^{tok}$  with padding tokens ([PAD]) where the news article is not long enough. In case it is longer than the fixed length, then it is truncated. In case the sequence is padded, some tokenizer implementations in Huggingface use masks to mask out the pads so that they are not included in the computation. These are called masked transformers (Wolf et al., 2020). In fact, our news content classifier has the same behavior which can be observed in 3.1.

$$T(x^{raw}) = x^{tok} = [x_1^{tok}, \dots, x_n^{tok}], \text{ where } n = |x^{tok}|.$$

Furthermore, we denote the space of raw label  $Y^{raw} = \{"fake", "real"\}$ , with  $y^{raw} \in Y^{raw}$ . We use a label mapping function  $\psi : Y^{raw} \mapsto Y$  that maps raw labels to classes, where  $Y \in \mathbb{R}^2$  with,

$$\psi(y^{raw}) = y = \begin{cases} 0, & y^{raw} = "fake" \\ 1, & y^{raw} = "real" \end{cases}$$

In order to feed the input to the model, we need numeric data which can be obtained by numerous techniques. One widely used approach is BoW representation which produces features based on the number of occurrences of a word or token. An alternative BoW representation uses the presence/absence of word instead of frequencies. A more sophisticated approach is *Word2Vec*, which encodes words into numeric values by learning word associations. From the perspective of representation of a word, *Word2Vec* can capture different degrees of similarity between words which allows for preservation of semantic and syntactic relationships (Mikolov, Chen, et al., 2013). It is clear that the transformation of words into numeric vectors is a very crucial stage for FND since we need to maintain as much contextual information as possible. Yet, the SOTA is an even more sophisticated approach called *Transformer* which is utilized by many language models such as BERT. We will discuss Transformer architecture in 3.1.2. For ease of the notation, we refer to this stage as *Embedding Layer* and denote it with  $l_{embedding}$ .

The input transformation pipeline is illustrated in 3.1.

**Definition 3.1.2 (Classifier).** A classifier  $f : X \mapsto Y$  is a function that outputs a predicted scores  $f(x)_y$  for each class  $y$  for a given input  $x$ .



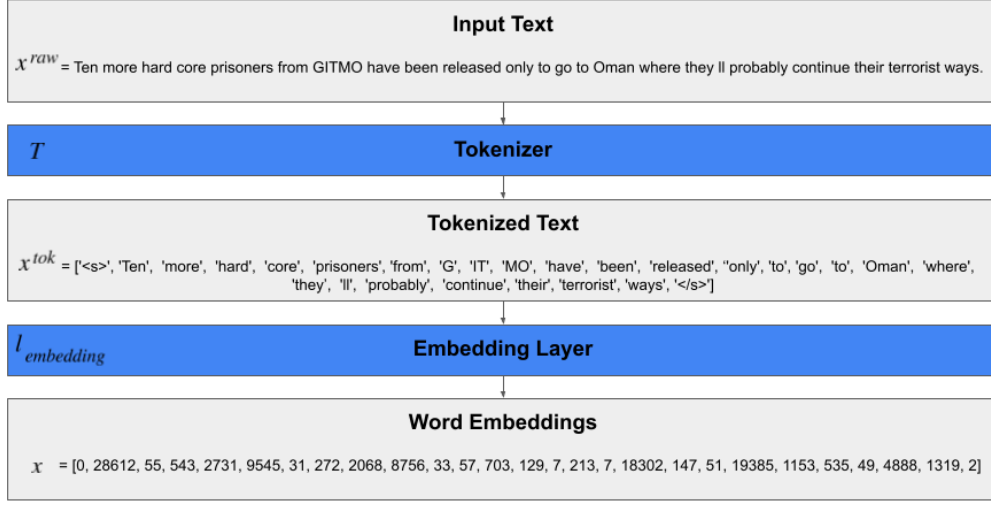


Figure 3.1: The preprocessing pipeline for a textual input.

Our news content model is our classifier. It will predict whether a news piece is real or fake via assigning each label a probability.

**Definition 3.1.3 (Prediction).** A prediction  $\hat{y}$  is the maximum of predicted scores  $f(x)_y$  of a classifier.

$$\hat{y} = \operatorname{argmax}_{y \in Y} f(x)_y$$

We use a model that consists of several layers and a sophisticated architecture. Our model is able to work with big vocabularies and can classify news pieces based on various features.

**Definition 3.1.4 (Neural Network Classifier).** A neural network classifier is a *classifier*  $f$  that comprises of layers  $l$  with  $1 \leq l \leq L$ , where  $L$  denotes the number of layers. Each layer has a set of units  $a_i^{(l)}$  with  $i$  denoting the position of the unit in a layer  $l$ . We say that between two units  $a_i^{(l)}$  belonging to layer  $l$  and  $a_j^{(l+1)}$  belonging to layer  $l+1$  have a weight value  $w_{ij}^{(l)}$  that connects them. Along with a non-linear activation function  $\sigma$ , we can define the value of the  $j$ -th unit  $a_j^{(l+1)}$  in terms of weights and unit values from previous layer for an FCN, with  $N$  is the number of units in layer  $l$ .

$$a_j^{(l+1)} = \sigma\left(\sum_{i=1}^N a_i^{(l)} w_{ij}^{(l)}\right)$$

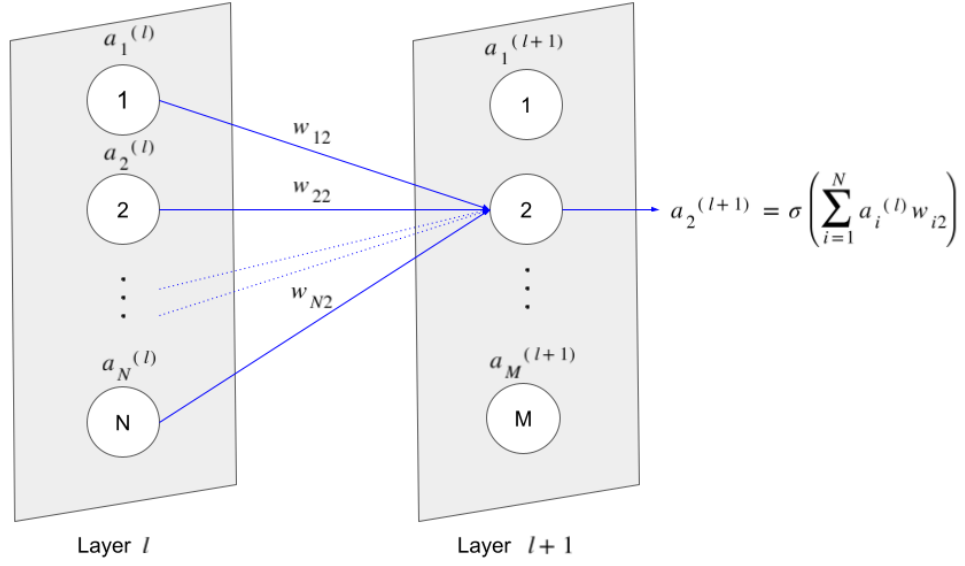


Figure 3.2: Units and layers of an FCN. For brevity, arrows and weights are only drawn for  $a_2^{(l+1)}$

Neural networks are very powerful models. They can train millions of parameters using matrix multiplications, gradient-based optimization methods and a fruitful set of other techniques, some of which will be discussed later. Neural networks iteratively optimize the weights between layers such that the produced output is as close as to the expected output. This is done so using optimization methods such as *Gradient Descent* (GD) (Cauchy, 1847), *Stochastic Gradient Descent* (SGD) (Robbins & Monro, 1951), *Adaptive Moment Estimation* (Adam) (Kingma & Ba, 2014) to minimize the loss function. While there exist many optimization methods available for neural networks, we do not examine any of them.

For classification problems, we adopt a layer called *Softmax* (Bridle, 1989) outputs the predicted scores  $f(x)_y$  for each class  $y$  by normalizing outputs  $Z_y(x)$  from the previous layer.

$$f(x)_y = \frac{\exp(Z_y(x))}{\sum_{y' \in Y} \exp(Z_{y'}(x))}$$

The FCNs are the simplest architectures for neural networks. In an FCN, all units are connected which means there is a weight between each unit in layer  $l$  and  $l + 1$ . While

very simple to construct, usage of these architectures when modeling sequences is not preferred due to the number of trained parameters such as weights and biases. Instead, when modeling sequences like sentences and documents, a common approach is RNNs which allow previous outputs to be used while having hidden states. However, RNNs are not powerful enough to represent long-term dependencies (Bengio et al., 1994) and suffer from vanishing/exploding gradients (Pascanu et al., 2012). Utilizing RNNs, an idea was proposed in which these shortcomings were addressed. Called *Long Short-Term Memory* (LSTM) (Hochreiter & Schmidhuber, 1997), the idea is to keep a cell state which is updated with previous cell's state. This cell state is conveyed to the consequent cells to form a chain that represents the document. More precisely, each cell corresponds to a token whose information will be shared with consequent tokens by the propagation of previously mentioned cell states. This approach is indeed very useful for long documents since news articles tend to be long and their sentences contextually relevant. LSTM is usually used in different variations based on the same idea. For instance, a consequent study has extended LSTMs with *peephole connections* in (Gers & Schmidhuber, 2000). LSTMs have been proven to deliver a good performance in NLP tasks such as *speech recognitions* (Xiong et al., 2016). LSTMs perform well however due to long training times and large memory requirements during training, they are being replaced with attention-based models.

One last thing to discuss is how the models are trained in terms of supervision. *Supervised* models are trained with label data. *Unsupervised* models work with unlabeled data and aims to find patterns in the data. A different setting is *semi-supervised* models. These models are often provided with small amounts of labeled data and large amounts of unlabeled data for training. There are two settings for semi-supervised learning. *Transductive* learning aims to predict unlabeled data whereas *inductive* learning samples unlabeled data from the same distribution to infer (Gammerman et al., 1998). Having introduced all necessary notation and definitions, in 3.1.2, we discuss the SOTA approach the Transformer models which are based on attention mechanism.

### 3.1.2 Transformer Architecture

Transductive learning has been successfully utilized along with encoder-decoder structure in many language tasks (Cho et al., 2014; Sutskever et al., 2014; Vaswani et al., 2017). Transduction is first proposed in Gammerman et al., 1998 to counteract with unlabeled data problem. In contrast to supervised learning, transductive learning does not require all data to be labeled, instead it utilizes the clustered behavior of data. Using the gaps between different clusters and a small set of labeled data, transductive learning assigns labels to unlabeled data. Accordingly, Transformer models are transductive models and use encoder-decoder structure to achieve that.

Encoder-decoder structure that takes into account the order of words was proposed in (Cho et al., 2014). This encoder-decoder structure consists of one RNN as encoder and one RNN as decoder. The encoder maps an input sequence to fixed-length vector, and the decoder maps this fixed-length vector to a target sequence. Transformer architecture adopts a similar approach which employs feed-forward and Multi-Head Attention layers in both encoder and decoder which is illustrated in Fig. 3.3 with  $N=6$  stacks of encoders and decoders.

In order to reduce sequential computation, CNNs have been adopted as building blocks that parallelly compute hidden representations for all input and output positions (Vaswani et al., 2017). Although aimed to reduce computation, the number of operations to convey information from one random input or output to another increases linealy in ByteNet (Kalchbrenner et al., 2016) and logarithmically in ConvS2S (Gehring et al., 2017). Contrary to CNNs, Transformers are able to fix the number of operations by averaging attention-weighted positions which decreases the effective resolution. However, this decrease in resolution is neutralized by the utilization of Multi-Head Attention (Vaswani et al., 2017). Initially suggested in the decoder of the model proposed in (Bahdanau et al., 2014), an attention mechanism works similar to human attention; it learns to put more importance on some words that convey the relevant information about the sentence. It does so by means of a context vector that depends on a sequence of *annotations*. An annotation  $h_i$  for a word (or embedding)  $x_i$  contains information about the complete input sentence but with a focus on the words that are closer to the word  $x_i$ . The context vector  $c_i$  for word  $x_i$  is obtained as a weighted sum of all these annotations  $h_i$  (Bahdanau et al., 2014):

$$c_i = \sum_{j=1}^{|x|} \alpha_{ij} h_j.$$

The weight  $\alpha_{ij}$  is obtained by applying softmax to associated energy  $e_{ij}$  which is an output of the alignment model  $a$ . The alignment model  $a$  is a feed forward neural network that jointly learns with the rest of the system. More precisely, we compute these values as follows (Bahdanau et al., 2014):

$$\alpha_{ij} = \frac{e_{ij}}{\sum_{k=1}^{|x|} \exp(e_{ik})}$$

where

$$e_{ij} = a(s_{i-1}, h_j)$$

with  $s_i$  representing the current and  $s_{i-1}$  the previous state of the model (Bahdanau et al., 2014). This is called *additive attention*.

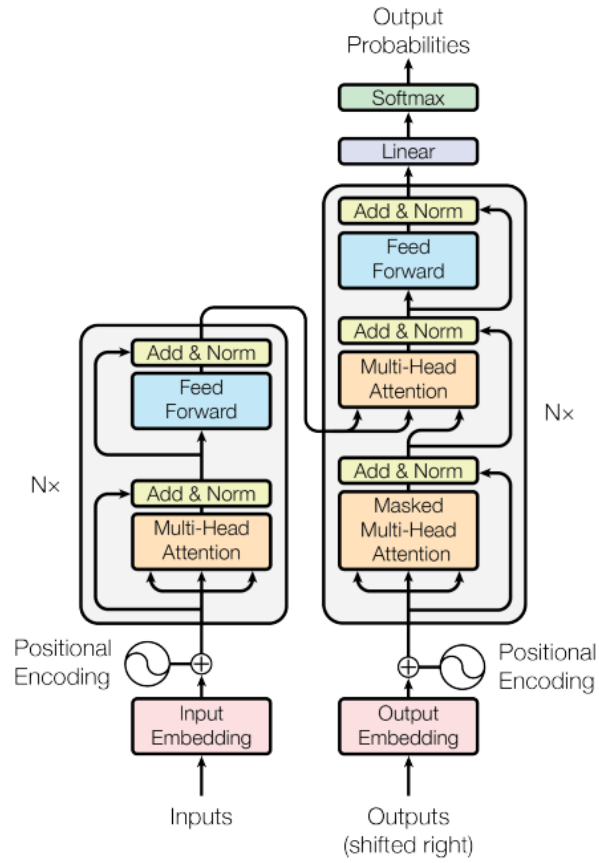


Figure 3.3: The Transformer Model Architecture ( $N=6$ ). Figure obtained from (Vaswani et al., 2017)

For Transformer models, the authors define an attention function as *mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a compability function of the query with the corresponding key.* (Vaswani et al., 2017). The Transformer model employs two different attention mechanisms, namely, *Scaled Dot-Product Attention* and *Multi-Head Attention*. Following (Vaswani et al., 2017), we denote that the input for the attention layers are matrices called queries  $Q \in \mathbb{R}^{d_{model} \times d_k}$ , keys  $K \in \mathbb{R}^{d_{model} \times d_k}$ , and values  $V \in \mathbb{R}^{d_{model} \times d_v}$ , with  $d_k$  as the number of keys or values and  $d_{model}$  being the model dimension. Scaled Dot-Product Attention computes the dot product of all queries  $q_i \in Q$  with all keys  $K$  and scale the resulting weights with  $\frac{1}{\sqrt{d_k}}$ . After obtaining the softmax of the scaled weights, each weight is multiplied with the corresponding value to obtain attention values.

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

The second attention mechanism, Multi-Head Attention, uses multiple attentions each of which uses a different learned linear projection of  $Q, K, V$ . Output of each of these attentions are then concatenated to obtain the final result. More precisely, it is computed as follows,

$$MultiHead(Q, K, V) = Concat(head_1, head_2, \dots, head_h)W^O$$

where each  $head_i$  is calculated as,

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$$

with projection for  $Q$  as  $W_i^Q \in \mathbb{R}^{d_{model} \times d_k}$ ,  $K$  as  $W_i^K \in \mathbb{R}^{d_{model} \times d_k}$ ,  $V$  as  $W_i^V \in \mathbb{R}^{d_{model} \times d_v}$ , and lastly,  $W^O \in \mathbb{R}^{hd_v \times d_{model}}$  (Vaswani et al., 2017).

We now discuss each part of the Transformer model briefly.

- *Encoder*: Consists of  $N=6$  identical layers. Each of these layers have two sub-layers the first of which uses a Multi-Head Attention and layer normalization (Ba et al., 2016) along with a residual connection (He et al., 2015) around. The second sub-layer consists of a feed-forward layer and layer normalization as well as a residual connection around the feed-forward layer (Vaswani et al., 2017)
- *Decoder*: Same as the encoder, this part is also composed of  $N=6$  layers. Additional to the previously discussed two sub-layers in encoder, decoder adopts a third sub-layer which computes the attention values over the output of encoder. As it was done for encoder, decoder also utilizes layer normalization at the end of each sub-layer as well as the residual connection (Vaswani et al., 2017).

Each of the feed forward networks in the sub-layers are position-wise, meaning that they are applied to each position separately and identically. These feed-forward networks use different parameters for each layer. The embeddings are obtained through transductive learning. Lastly, the positional encodings for input embeddings are calculated using sine and cosine functions of different frequencies (Vaswani et al., 2017). We have summarized the Transformers architecture in order to lay foundations for the model we use, DistilRoBERTa (Liu et al., 2019; Sanh et al., 2019). Next, we initially introduce details of BERT, then RoBERTa, and lastly DistilRoBERTa which is our news content model.

### 3.1.3 Dataset and Model

We employ a fine-tuned version of case-sensitive Transformer model DistilRoBERTa<sup>1</sup> for our task of FND with news content. DistilRoBERTa is a distilled version of *A Robustly Optimized BERT Pretraining Approach* (RoBERTa) (Liu et al., 2019). It uses the same distillation procedure adopted for DistilBERT (Sanh et al., 2019) to *Bidirectional Encoder Representations from Transformers* (BERT) (Devlin et al., 2018). This distillation procedure is referred to as *Knowledge Distillation* and it compresses a model (Buciluă et al., 2006) - the teacher - by means of training a smaller model - the student - to reproduce the same behaviour (Hinton et al., 2015). In our case, the teacher is RoBERTa and the student is DistilRoBERTa. First, in order to examine properties of RoBERTa, we discuss BERT in detail.

As the name suggests, the model architecture of BERT is a multi-layer bidirectional Transformer based on the Transformer model. BERT uses BookCorpus (Y. Zhu et al., 2015) and English Wikipedia as training dataset, with two training objectives, *Masked Language Modeling* (MLM) and *Next Sentence Prediction* (NSP). MLM procedure applies the following for each sentence sampled from a document in the cumulative dataset.

- Mask 15% of the tokens.
- In 80% of the cases, replace the masked tokens with [MASK].
- In 10% of the cases, replace the masked tokens with a different random vocabulary token.
- In the remaining 10% of the cases, the masked tokens are left unchanged.

NSP procedure is a binary classification loss that predicts whether two segments (sequences of tokens) are consecutive in the original text. *Positive* and *negative* examples are sampled with equal probability in this process. Positive examples are created with

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<sup>1</sup><https://huggingface.co/GonzaloA/distilroberta-base-finetuned-fakeNews>

taking the consecutive sentences from the text corpus, whereas negative examples are generated by pairing segments from different documents (Liu et al., 2019).

RoBERTa is an optimized, longer pretrained with longer sequences version of a BERT implementation that uses only MLM as training objective. Contrary to BERT, RoBERTa keeps a dynamic masking pattern that changes in training. It is pretrained on reunion of five datasets (three more datasets than BERT) that size up to 160 gigabytes (GB): BookCorpus (Y. Zhu et al., 2015), English Wikipedia ("English Wikipedia," 2022), CC-News (Nagel, 2016), OpenWebText (Radford et al., 2019), Stories (Trinh & Le, 2018).

RoBERTa tokenizes texts using BPE with a vocabulary size of 50,000 and maximum sequence length (maximum number of tokens) as 512. The beginning and end of each document (news article) is marked with <s> and </s> respectively. With MLM as training objective and Adam (2014) as the optimizer, the model reaches better results than BERT. Additionally, it should be noted that since these models are further trained for downstream tasks, thus we refer to training stage as pretraining to avoid any confusion.

DistilRoBERTa has the same general architecture as RoBERTa but the number of layers are reduced by a factor of two, the *token-type embeddings* and the pooler are removed. Then DistilRoBERTa is initialized with layers from the teacher. The distillation is done with very large batches (Sanh et al., 2019). Using RoBERTa as a teacher, the student DistilRoBERTa is pretrained on OpenWebTextCorpus (Gokaslan & Cohen, 2019) a reproduction of OpenWebText (Radford et al., 2019).

Our fine-tuned DistilRoBERTa was trained on a dataset<sup>1</sup> curated from different sources. Although there exist better datasets and news content models, we opted for this particular model for two reasons. First, most SOTA news content models do not provide their code and dataset to reproduce results. Second, since Transformers are SOTA and this particular trained model provides us with not only the dataset but also with the train/test/validation splits which allows us to analyze its explanation. Now, we analyze the dataset, convey the distribution of labels and discuss potential peculiarities. Then we talk about the performance of the model, and reason about it.

**Dataset.** The news content dataset comprises of 40587 samples whose distribution of labels and train/validation/test splits are provided in Fig 3.4. The proportion of fake news is 46%, which is a fair distribution between real and fake news instances. The train/validation/test split is 60%/20%/20% which is common practice. We analyze 500 most frequently occurring tokens in the dataset using a WordCloud (Oesper et al., 2011) visualization for all samples of real and fake news separately in Fig 3.5. From the visualization, we can observe that samples from both datasets contain the words *new*, *state*, *President*, *Republican*. In fact, 500 most frequent tokens from fake news samples

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<sup>1</sup>[https://huggingface.co/datasets/GonzaloA/fake\\_news](https://huggingface.co/datasets/GonzaloA/fake_news)



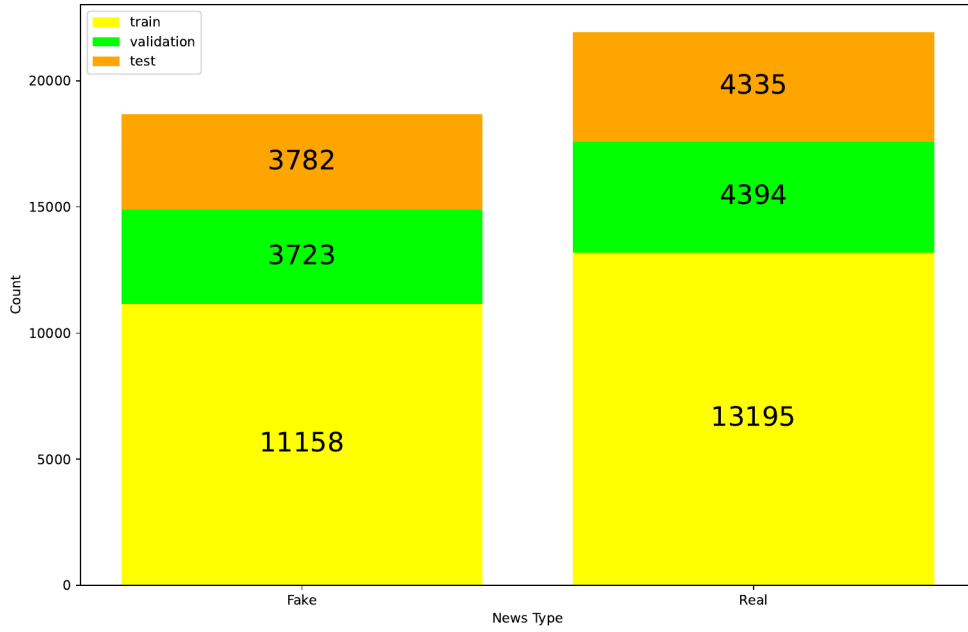


Figure 3.4: News content dataset distribution by label and train/validation/test split

and real news samples share 63% of tokens. Furthermore, we observe that one of the most frequent token is *Reuters* in real news instances. In fact, 95.93% of real news samples contain the keyword (*Reuters*). This might give rise to a problem where the model learns the real news instances based on a couple tokens like (*,* *Reuters,* *,*). This will be analyzed in detail in the next section.

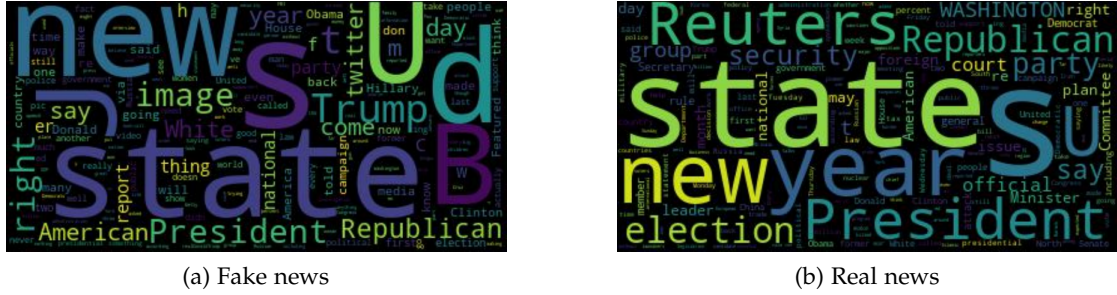


Figure 3.5: WordCloud visualizations for most frequently occurring 500 tokens in samples of both classes

Attention dropout probability	0.1
Batch size	16
Classifier dropout	None
Epochs	3
Hidden layer activation function	GELU (Hendrycks & Gimpel, 2016)
Hidden size	768
Intermediate size	3072
Layer normalization factor ( $\epsilon$ )	1e-05
Maximum position embeddings	514
Number of attention heads	12
Number of layers	6
Vocabulary size	50265

Table 3.2: Hyperparameters of news content model

**Training.** Huggingface provides us with a *TextClassificationPipeline* which allows to feed the dataset from Huggingface directly (Wolf et al., 2020). This pipeline includes the tokenization process and the embedding layer before feeding it to our classifier. Our news content classifier has 6 layers, 12 attention heads and hidden size of 768 that totals up to 82M parameters (RoBERTa has 125M parameters). The vocabulary size is 50265 including special tokens. The model also uses a technique called *dropout* which is a regularization technique that drops some connections between layers based on a probability value (Srivastava et al., 2014). All model hyperparameters are defined in 3.2. Note that maximum position embeddings parameter also considers document start and end tokens when reporting its length. When feeding tokens  $x^{tok}$  to the model, the start ( $\langle s \rangle$ ) and end ( $\langle /s \rangle$ ) tokens are added by the model pipeline, so this leaves us with

Accuracy	Precision	Recall	F1 score
98.85%	98.82%	99.03%	98.92%

Table 3.3: The performance metrics for news content model.

maximum sequence length of 512, i.e.,  $|x| = 512$ . Note that in Figure 3.1 the length of  $x$  is not 512 since the paddings are masked out before feeding the input  $x$  to the model. Model is trained for 3 epochs with a batch size of 16, Adam ( $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ,  $\epsilon = 1e - 08$ ) as the optimizer and a linear learning rate scheduler. The performance metrics for the model is provided in Table 3.3.

The model performs very well on the dataset. Only 4 samples out of 8117 are classified incorrectly in the test split of the dataset. We will closely work with those 4 samples when explaining our model and inspect the reasons behind this performance in the next section.

We have laid out the foundations for the model we used, reported the characteristics, training details, and performance of the news content model in this section. Although seems powerful in this case, usually news content models are easily outdated as the structure of news changes rapidly and fake news fabricators can replicate the properties that can be seen in real news content (Shu et al., 2020). Thus, we consider a different approach which primarily considers social context features for FND.

## 3.2 Explaining News Content Models

Although there exist models that can detect fake news with high accuracy such as our model, the reasons behind this performance is seldom investigated. There could be a number of reasons from dataset characteristics to wrong model architecture. Just by looking at our model’s performance on a single dataset, one should not trust the model’s spectacular performance, instead look at the reasons behind this to understand why this is happening. Is model actually learning to distinguish between classes or is it learning some other thing that we do not want? In order to answer questions like these and more, Lundberg and Lee, 2017 proposes a unified framework in which any model (except GNNs) can be explained.

We start this section by describing how Shapley Additive exPlanation (SHAP) framework helps explain a model. After examining SHAP framework, we utilize it for our model and examine the reasons behind this performance by conducting several experiments.

### 3.2.1 SHAP Framework

SHAP aims to explain a prediction of a single input instance  $x$  by computing Shapley values from coalitional game theory. These values correspond to the contribution of each input feature to the prediction made for  $x$  (Molnar, 2022). Specifically, we are interested in SHAP’s ability to capture local explanations for our news content model. Fortunately, SHAP provides explanation frameworks for a variety of models including DNNs. In order to handle DNNs, SHAP improves methods from DeepLIFT to produce DeepSHAP, however, DeepSHAP is not compatible with Transformers models. Thus, we use a model-agnostic explanation model provided in SHAP framework, namely the partition explainer. We begin with introducing Shapley values which are then converted to Owen values via feature coalitions. We will examine how Owen values and Shapley values are connected.

As before, let us denote our news content classifier to be explained as  $f$ , and its input as  $x$ . We focus on local explanations built for a single prediction  $\hat{y} = f(x)$  based on one input  $x$ . An explanation model  $g$  employs simplified inputs  $x'$  which are output of a mapping function  $h_x(x') = x$  that maps  $x$  to  $x'$ . Each  $h_x(x')$  is defined individually for each  $x$ . If two simplified inputs are similar  $x' \sim z'$  then local methods aim to guarantee the approximation  $g(z') \approx f(h_x(z'))$  (Lundberg & Lee, 2017).

The general framework is built upon *additive feature attribution methods*. These methods *have an explanation model that is linear of binary variables* (Lundberg & Lee, 2017).

$$g(z') = \phi_0 + \sum_{i=1}^M \phi_i z'_i$$

where  $z' \in \{0, 1\}^M$ ,  $M$  is the number of simplified input features, and  $\phi_i \in \mathbb{R}$  (Lundberg & Lee, 2017). Additive feature attribution methods have three desired properties. The first, local accuracy states that *the explanation model  $g(x')$  matches the original model  $f(x)$  when  $x = h_x(x')$*  (Lundberg & Lee, 2017). The second property is missingness and it states that the features not included in the input should have no impact (Lundberg & Lee, 2017). The last property, consistency describes that if a simplified feature  $x'_i \in x'$  have a greater impact in model  $f'$  than the model  $f$ , then the feature  $x_i$  should be assigned at least the same or a higher value for its contribution (Lundberg & Lee, 2017). The computation of each  $\phi_i$  involves a similar process to the calculation of classic Shapley regression values (Lipovetsky & Conklin, 2001):

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!} [f_x(z') - f_x(z' \setminus i)]$$

where  $z' \setminus i$  implies  $z'_i = 0$ ,  $|z'|$  is the number of non-zero elements in  $z'$ , and  $z' \subseteq x'$  denotes the set of vectors  $z'$  whose non-zero elements are a subset of non-zero elements

in  $x'$  (Lundberg & Lee, 2017).

In the supplementary material of Lundberg and Lee, 2017, the authors define four axioms all of which Shapley values satisfy.

1. *Efficiency forces the model to correctly capture the original predicted value* (Lundberg & Lee, 2017)
2. *Symmetry states that if two features contribute equally to the model then their effects must be the same* (Lundberg & Lee, 2017).
3. *Null effects* denotes that if a feature is missing in all subsets and this feature does not affect the outcome of the model, then this feature is ignored and its effect must be 0 (Lundberg & Lee, 2017).
4. *Linearity* states that if two models are written as a linear combination, then the sum of the effect of a feature in both models represent the effect of feature in the linear combination (Lundberg & Lee, 2017).

Given a hierarchy of features that define feature coalitions, the partition explainer recursively computes Shapley values through them and these Shapley values result in Owen values (Owen, 1977). Owen values do not satisfy symmetry axiom at all times, but it is satisfied for tokens in the same coalition. Owen values are not the same as Shapley values, but if the coalition consists of the whole sentence or individual tokens, then they are the same as Shapley values. A study (Casajus, 2009) also shows that Shapley values are the expected Owen values for all symmetric distributions on all partitions. Owen values will help us detect token groups (if any exist) that play a significant role in the prediction of a model. Moreover, Owen values are computationally very cheap which makes them more attractive.

We have summarized the foundations of SHAP framework. As recommended in the source code documentation of SHAP<sup>1</sup>, we use the partition explainer for our language model. Next, we will examine Owen values in action with our news content classifier.

### 3.2.2 Explaining News Content Classifier

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<sup>1</sup><https://github.com/slundberg/shap/>

## 4 Mixed Approaches for Fake News Detection

### 4.1 Mixed Approaches

As discussed in Section 2.1, social media’s interconnected nature leads to fast dissemination of fake news. When a news piece is shared, it cascades through social media by means of friendship networks. These networks can be exploited to gather information about how fake news spread. Moreover, a user’s historical information can prove effective when trying to analyze whether a news piece is real or not. This assumption stems from the psychological facts we discussed in Section 2.1. To recap, if a user is sharing fake news most of the time, i.e., the user’s tweets are marked as fake, then it is likely that the next news piece they share would be fake as well. Usually, fake news are shared most within echo chambers, which gives rise to quick spread of fake news.

There exist many different approaches for social context models, however, it is a long and challenging task to create a dataset for social context models as the amount of data to be collected can grow dramatically. Thus, we selected a dataset that provides us with the social context information as well as the news content. Being a graph dataset, *User Preference-aware Fake Detection* (UPFD) (Dou et al., 2021) builds a propagation tree for the news. But in order to build a model that takes graphs as input we can no longer rely on standard deep learning approaches as the graph data has a different structure than news content data. It holds node information as well as edge information between nodes, allowing to store rich relational data (Dou et al., 2021).

In this section, we lay out foundations for the dataset and GNNs we used. Then we talk about the social context models along with their dataset UPFD that we used in this thesis. We also give some insights from (Shu et al., 2020) in which the authors of UPFD dataset analyze the data they later utilized to create the graph dataset UPFD.

#### 4.1.1 Overview of Graphs

In this section, we introduce definitions to cover graphs and different types of GNNs. But we do not discuss each model type in detail due to GNNs’ extensive background.

Thus, we do not provide a notation for this section but we give mathematical definitions when required.

Graphs are an example of *non-euclidean* data, meaning that in contrast to *euclidean* data, they can represent complex relations and entities more accurate than one or two dimensional representations. Non-euclidean data used in GDL can be grouped into grids, graphs, groups, geosedics, and gauges, which are also called the 5G's of *Geometric Deep Learning* (GDL) (Bronstein et al., 2021). We are interested in one G only, graphs.

**Definition 4.1.1** (*Geometric Deep Learning (GDL)*). A class of deep learning that aims to build models that can learn to predict on the non-euclidean domain.

GDL is an extensive field covering various techniques that can be applied to non-euclidean domain. Due to its complex nature, we do not provide a rigorous background on GDL. For a detailed background on GDL, we refer the reader to an extensive study on GDL (Bronstein et al., 2021). We only discuss parts related to GNNs that we utilized. First we define a graph.

**Definition 4.1.2** (*Graph*). A graph is a non-euclidean type of data that represents the relations between entities.

From the perspective of individual node connections, graphs can be categorized into two classes, *directed* and *undirected* graphs. Directed graphs have direction information in their edges, i.e., the information flows strictly from one node to another. On the other hand, undirected graphs do not have this limitation, the information flow is bidirectional. Since we are only interested in undirected graphs like our dataset, we give preliminaries for an undirected graph.

Following common notation on graphs, we define an undirected graph as  $\mathcal{G} = (\mathcal{V}, \mathcal{E})$  with  $\mathcal{V}$  as the set of nodes and  $\mathcal{E}$  as the set of edges in a graph  $\mathcal{G}$ . We say that an edge  $(v_i, v_j)$  exists between two nodes  $v_i$  and  $v_j$ . Moreover, from the perspective of a graph's connectedness, there exist two types of graphs, *cyclic* or *acyclic*. Simply put, cyclic graphs have cycles in them, i.e., the graphs allows for at least one node  $v_i$  to have a series of different edges that creates a cycle back to the node  $v_i$ . In contrast, acyclic graphs do not contain cycles. A concrete example for undirected acyclic graphs are trees. Also the structure of our dataset, trees have strictly one edge between two nodes. When we look at graphs from node and edge type, we classify graphs as *homogeneous* and *heterogeneous* graphs. Homogeneous graphs have nodes and edges of the same type, whereas heterogeneous graphs have different types of nodes and edges. One example for homogeneous graphs are social networks in which the nodes are users and the edges represent the friendship between two users. If we modify this social network into a more detailed version in which we choose to represent another relationship between users, such as colleagueship, then we would have a heterogeneous graph, because there

would be two types of edges in the graph.

Finally, if we consider graphs from a temporal aspect, we observe two kinds of graphs, *static* and *dynamic*. Static graphs stay the same over time, their topology or features do not change. In contrast, dynamic graphs' features and topology vary over time, thus making time an important factor when working with dynamic graphs.

#### 4.1.2 Graph Neural Networks

GNNs are neural networks that can take graphs as an input and produce predictions at three different levels: *node-level*, *edge-level*, and *graph-level*. Node-level tasks include node classification, node regression, node clustering. Node classification aims to categorize nodes into classes. Node regression deals with predicting continuous value for each node. Lastly, node clustering aims to group nodes into several clusters. Edge-level tasks consist of edge classification and link prediction. Edge classification tries to categorize an edge. Link prediction aims to find whether there is an edge between two nodes. Graph-level predictions are graph classification, graph regression, and graph matching. In all these settings, the model needs to learn representations of graph (J. Zhou et al., 2018).

In our experiments, we used two different models one of which uses a convolutional layer called GraphSAGE (Hamilton et al., 2017) and the other uses a convolutional attention layer called *Graph Attention* (GAT) (Veličković et al., 2017). Here we give background for both but we do not dive into details. We first give information about general framework.

J. Zhou et al., 2018 defines three modules that are involved in a generic GNN model: *propagation module*, *sampling module*, *pooling module*. Propagation module deals with information propagation between nodes so that the aggregated information can represent features and topology of the graph. Propagation modules usually employ a *convolution operator* or *recurrent operator* to aggregate information from neighbors of nodes. These aggregated values are then used to update the representation of the nodes, edges, and graph. Additionally these modules employ a skip connection that helps collect previous representations of nodes to alleviate the over-smoothing problem. Sampling module is used when the input graph is large to handle propagation. It is used before propagation module. Lastly, pooling modules are employed when we need to extract information to represent high-level graphs.

We will mostly deal with propagation module and the operations within. We do not dive into mathematical background of convolutions in detail but we introduce mathematical formulations in order to illustrate the operations our models are using. Also, we do not discuss recurrent operations on graphs as their background is extensive and out of scope of this thesis. We refer the reader to J. Zhou et al., 2018 for an extensive



mathematical background on convolutions and other operations on spectral domain. However, we will summarize the behavior of convolutions on graphs in order to give the sufficient knowledge for the models we used.

**Convolutions on graphs.** The idea of convolution operators is to generalize convolutions from another domain to spectral domain. In general there are two types of convolutional operations.

The first, *spectral approaches*, are based on graph signal processing and defines its convolutional operators in the spectral domain (Shuman et al., 2013). Spectral methods initially transform a graph signal  $x$  to the spectral domain by the graph Fourier transform  $\mathcal{F}$ , then the convolution operation is applied. The output from convolution is transformed back with the inverse Fourier transform  $\mathcal{F}^{-1}$ . Now we summarize the mathematics behind this approach in order to convey our models' characteristics. Graph Fourier and inverse graph Fourier transform are defined as,

$$\mathcal{F}(x) = U^T x$$

$$\mathcal{F}^{-1}(x) = Ux$$

where  $U$  is the eigenvalue matrix of normalized graph Laplacian  $L = I_N - D^{-\frac{1}{2}} A D^{-\frac{1}{2}}$  with  $I_N$  the identity matrix of dimension  $N$ ,  $D$  as the degree matrix and  $A$  as the adjacency matrix of the graph.  $L$  is a real symmetric positive semi-definite matrix which helps us with factorization  $L = U\Lambda U^T$  where  $\Lambda$  denotes the diagonal eigenvalue matrix (J. Zhou et al., 2018). Now that we can convert our graph signal  $x$  to spectral domain and back, following Mallat, 1999 and J. Zhou et al., 2018, we can define the convolution operation on  $x$ .

$$\begin{aligned} g \star x &= \mathcal{F}^{-1}(\mathcal{F}(g) \odot \mathcal{F}(x)) \\ &= U(U^T g \odot U^T x) \end{aligned}$$

where  $\odot$  stands for element-wise multiplication and  $U^T g$  is the convolution filter in the spectral domain. This can be further simplified into the basis function of spectral methods:

$$g_w \star x = U g_w U^T x$$

where  $g_w$  is a diagonal learnable matrix. Essentially, all spectral methods use a convolutional filter  $g_w$  but their choice of design creates a variety of approaches that are built upon each other. We only discuss the ones necessary for our models. The main idea of modern convolutional operators come from approximating  $g_w$  with  $k$ -th order Chebyshev polynomials. GCN adopts  $k = 1$  to avoid overfitting. Moreover, it introduces a renormalization trick to solve the exploding/vanishing gradient problem (Kipf

& Welling, 2016). Further works like AGCN (Li et al., 2018) have employed a similar approach. Additionally, GCN is employed to an extent in spatial approaches.

The second, *spatial approaches* focus on the graph structure. They define convolutions directly on graph topology. Spatial approaches can be grouped into *basic*, *attention-based*, and *framework*. Basic spatial approaches define convolution operations on the neighborhoods of different sizes. Neighborhoods are defined based on nodes as follows  $\mathcal{N}_v$  for a node  $v$ . There exist several basic spatial approaches such as the diffusion CNN (DCNN) (Atwood & Towsley, 2016) which describes the neighborhood for nodes using transition matrices, the learnable GCN (LGCN) (Gao et al., 2018) which utilizes CNNs as aggregators by applying max pooling on neighborhood matrices.

Another example, GraphSAGE uses an inductive learning approach to sample then aggregate features from a node’s local neighborhood. GraphSAGE uniformly samples a fixed-size collection of neighbors then aggregates this collection to produce embeddings for the graph (Hamilton et al., 2017). More precisely, let us assume that we have learned the parameters of  $K$  aggregator functions denoted as  $\text{AGG}_k$ , and a set of weight matrices  $W^k$  where  $\forall k \in \{1, \dots, K\}$ .  $k$  can be referred to as layer or search depth. Then for each  $k$  we go through all nodes  $v \in \mathcal{V}$  and apply an aggregation then an update. Concretely, at each  $k$  and at each  $v$ , let  $h_v^{k-1}$  denote the hidden state of a node  $v$  at layer  $k - 1$ . Following the same notation, we refer to the hidden state of a node’s neighborhood  $\mathcal{N}_v$  at layer  $k$  as  $h_{\mathcal{N}_v}^k$ . GraphSAGE formalizes its aggregation and update operation at layer  $k$  as:

$$h_{\mathcal{N}_v}^k = \text{AGG}_k(\{h_u^{k-1}, \forall u \in \mathcal{N}_v\})$$

$$h_v^k = \sigma(W^k[h_v^{k-1} || h_{\mathcal{N}_v}^k])$$

where  $||$  denotes concatenation of two vectors,  $[h_v^{k-1} || h_{\mathcal{N}_v}^k]$  concatenated vector and  $\sigma$  a non-linear activation function. GraphSAGE employs three different aggregators: *mean aggregator*, *LSTM aggregator*, and *pooling aggregator*. Mean aggregator collects sampled neighborhood information and takes the element-wise mean of the vector set  $\{h_u^{k-1}, \forall u \in \mathcal{N}_v\}$ . The inductive version also includes previous layer representation of node  $v$ ,  $h_v^{k-1}$ . LSTM aggregator uses an LSTM to collect neighborhood information. LSTMs are more expressive than mean aggregators. However, since LSTMs are not permutation invariant, i.e., they process their inputs sequentially, they need a modification to work with unordered sets. Finally, pooling aggregator first independently feeds each neighbor’s vector to a FCN, then apply a pooling operation on the output.

The third, *attention-based approaches*, utilizes the same attention logic introduced in 3.1.2 by following Bahdanau et al., 2014. A recent work Graph Attention Networks (GAT) (Veličković et al., 2017) proposes to integrate attention into the propagation step by computing the hidden state for node  $v$  at layer  $k$  as follows:

$$h_v^k = \sigma\left(\sum_{u \in \mathcal{N}_v} a_{vu} W h_u^k\right)$$

$$\alpha_{vu} = \frac{\exp(\text{LeakyReLU}(a^T [W h_v || W h_u]))}{\sum_{k \in \mathcal{N}_v} \exp(\text{LeakyReLU}(a^T [W h_v || W h_k]))}$$

with  $W$  as the weight matrix,  $a$  as the weight vector of feed forward network and the non-linear activation function LeakyReLU is defined as:

$$\text{LeakyReLU}(\gamma, x) = \begin{cases} x, & \text{if } x \geq 0 \\ \gamma x, & \text{otherwise} \end{cases}$$

The authors in Veličković et al., 2017 also utilize Multi-Head Attention in order to stabilize the learning process of attention(also called self-attention or intra-attention) (Vaswani et al., 2017). Concretely, same as GraphSAGE defined  $K$  aggregators, GAT defines  $T$  independent attention heads to compute hidden states and then features of these hidden states are either concatenated,

$$h_v^k = ||_{t=1}^T \sigma(\sum \alpha_{vu}^t W_t h_u^k)$$

or averaged,

$$h_v^k = \sigma\left(\frac{1}{T} \sum_{t=1}^T \sum_{u \in \mathcal{N}_v} \alpha_{vu}^t W_t h_u^k\right)$$

to obtain the output where  $\alpha_{vu}^t$  represents the normalized attention values of the attention head  $t$ .

The last convolutional spatial approaches cover general frameworks that aims to integrate multiple different models into one framework. A mixture model MoNet was proposed by Monti et al., 2016 which is a spatial framework for unifying models such as GCN Kipf and Welling, 2016, Masci et al., 2015, DCNN Atwood and Towsley, 2016 and many more in non-euclidean domain.

One more thing we need to investigate is graph sampling in order to cover everything that was utilized in this thesis. GNN models suffer from an issue called *neighbor explosion* which stems from having massive sizes of supporting neighbors from all previous layers as the number of layers increases J. Zhou et al., 2018. Likewise, as graph size increases, we will encounter the same problem. Sampling is used to solve this issue and it can be done on three levels: *node sampling*, *layer sampling*, and *subgraph sampling*. Node sampling creates a subset using the neighborhood set  $\mathcal{N}_v$  of the node's  $v$ . As discussed previously, GraphSAGE (Hamilton et al., 2017) employs node sampling. Layer

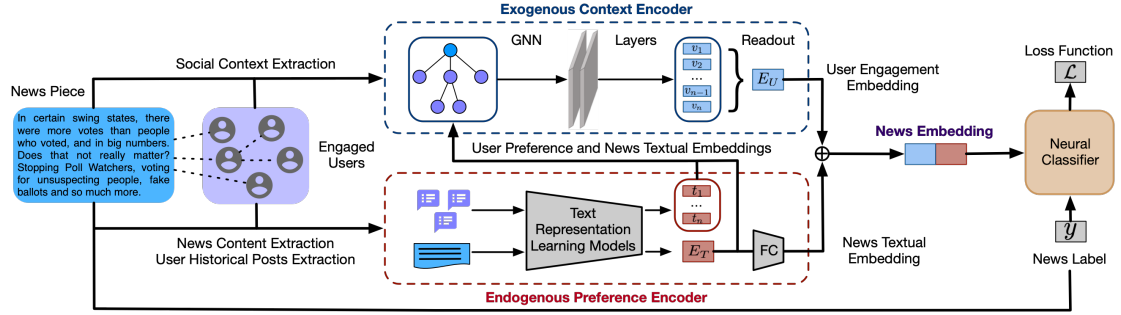


Figure 4.1: The framework of UPFD. Image obtained from (Dou et al., 2021)

sampling takes a different approach and it selects a subset of nodes for aggregation. Lastly, subgraph sampling deals with the graph as a whole. One approach is to use clustering algorithms to obtain these subgraphs (Chiang et al., 2019). Another is to sample nodes and edges from graph to create a subgraph (Zeng et al., 2019).

### 4.1.3 Dataset and Models

Our choice of dataset, UPFD (Dou et al., 2021) utilizes the dataset FakeNewsNet (Shu et al., 2018). From FakeNewsNet, the authors of UPFD build a graph dataset by collecting user preference information from historical posts and social context data with Twitter Developer API (Twitter, 2022). They further employ textual embedding techniques to encode historical posts and news content. We shall discuss how these operations are conducted in detail. UPFD has two three preparation levels which the authors coined as *endogeneous preference encoding*, *exogeneous context extraction*, and *information fusion*. The framework is shown in Fig 4.1

**Endogeneous preference encoding** deals with user historical posts and news content using the news content and social engagement data in FakeNewsNet. With social engagement data, the authors collect 200 historical tweets of each user who have retweeted the news in FakeNewsNet. Summing up to almost 20 million tweets, these collection procedure of historical tweets for each FakeNewsNet news instance is as follows (Dou et al., 2021):

- Collect user ids who have retweeted.
- For each user, collect 200 most recent tweets.
- For inaccessible (suspended or deleted) users, use randomly sampled tweets from accessible users who engage the same news piece. This step also increases the

effectiveness of the exogeneous encoder.

- Finally, remove special characters such as "@" and URLs before applying textual techniques.

Now that we have news content and user historical information, we encode these texts using text representation learning techniques. Still following Dou et al., 2021, the authors define two different settings for creating endogeneous preference encoding. The first setting, *spacy*, deals with obtaining the representation for user historical data and news content with spaCy (Honnibal & Montani, 2018) pretrained 300-dimensinal vectors for 680K words. For each user historical post (and similary for each news piece), if a word appears in the text, we include the vector for that word for final calculation in which all included vectors are averaged. As a result, we obtain a 300-dimensinal vector for each user historical information and news piece. The second setting, *bert*, uses BERT-Large model to encode news and historical user data. Using bert-as-a-service (Xiao, 2018), the authors encode the news content with maximum input sequence length as 768. To encode historical information, the authors opt for a different setting since 200 tweets cannot be processed as a single document due to BERT's maximum input sequence length limitation of 768. It is important to note that the paper of UPFD (Dou et al., 2021) states the maximum input sequence length as 512, however in the dataset itself, the maximum sequence length is 768 (Team, 2022). Keeping in mind that tweets are usually short texts compared to news pieces, the authors use maximum input sequence length of 16 for each historical tweet, then average all 200 tweets to obtain the final representation for user historical data. This representation is of the same dimension as the root news node. Note that these text representation vectors are node features of a hierarchical tree structured graph whose root node represents the news content and the children of root represent the users who have retweeted.

**Exogeneous context extraction** uses retweet information to build the previously mentioned hierarchical tree. The authors adopt a similar procedure used in Han et al., 2020; Monti et al., 2016; Shu et al., 2020. In detail, authors define a news piece as  $v_1$  and the set of users who retweeted  $v_1$  as  $\{v_2, \dots, v_n\}$  ordered by time. The rules are defined for this process to cover edge cases as well:

- Estimate that a news piece propagates to user  $v_i$  from user  $v_j$  with the latest timestamp, if any user from the set  $\{v_j | j \in \{2, \dots, n\} \setminus \{i\}\}$  retweeted the news piece before the user  $v_i$ . This conservative assumption is based on the fact that latest tweets are presented to the user first in the Twitter app (Dou et al., 2021).
- If user  $v_i$  does not follow any users in the set  $\{v_1, \dots, v_n\} \setminus i$ , i.e., all retweeters and news source except the user itself, the authors approximate the spreader of that news piece to user  $v_i$  as the user with most followers in the set. This

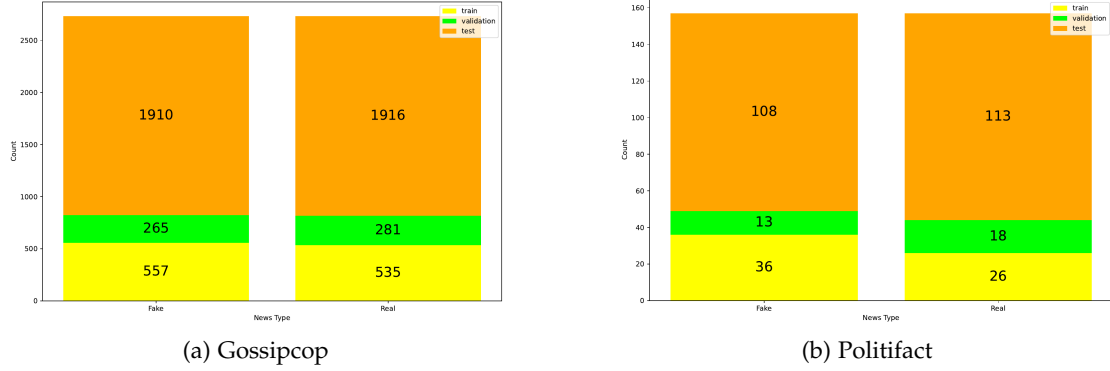


Figure 4.2: UPFD dataset distribution by label and split (train: 20%, val: 10%, test: 70%)

approximation is based on the phenomena that the tweets from accounts with more followers have a higher probability of being retweeted or viewed.

After this procedure, we have our hierarchical tree for each news obtained from FakeNewsNet which employs two sources: Politifact and Gossipcop. Thus, we evaluate these datasets separately within UPFD. The distribution of the instances with respect to train/val/test split and label is provided in Fig. 4.2.

**Information fusion** is achieved via GNNs. As discussed in 4.1.2, GNNs can encode graphs by maintaining the node features and structural information. From this point on, we need to utilize the models we introduced with a classification setting. Classification is done for each graph which represents the diffusion tree of the news piece (Dou et al., 2021). We adopted two models from this work’s ablation study, the first one is based on GraphSAGE (Hamilton et al., 2017), and classification is handled with an FCN. We use BERT as the encoder since the best performance is obtained via that according to the experiments in Dou et al., 2021 and the experiments we conducted. We call this model UPFD model as authors did in Dou et al., 2021. It is illustrated on Fig 4.3. After obtaining the graph encodings, the authors suggest to concatenate a representation of news content with graph embeddings. More precisely, the feature vector of root node is fed to an FCN to obtain a lower-dimensional representation which is then concatenated with graph embeddings. The concatenated vector is then fed to another FCN, and lastly the softmax layer for classification. With the setting illustrated in Fig 4.3, the optimizer as Adam with default  $\beta_1$  and  $\beta_2$ , and hyperparameters provided in Table 4.1, we obtain 95.49% and 83.16% accuracy from Gossipcop and Politifact averaged by 10 runs, respectively. All other statistics are provided in Table 4.2. Before we investigate what our classifier takes into account when classifying this news instance as fake news, we will summarize some of the features of our dataset which are proven to have significant

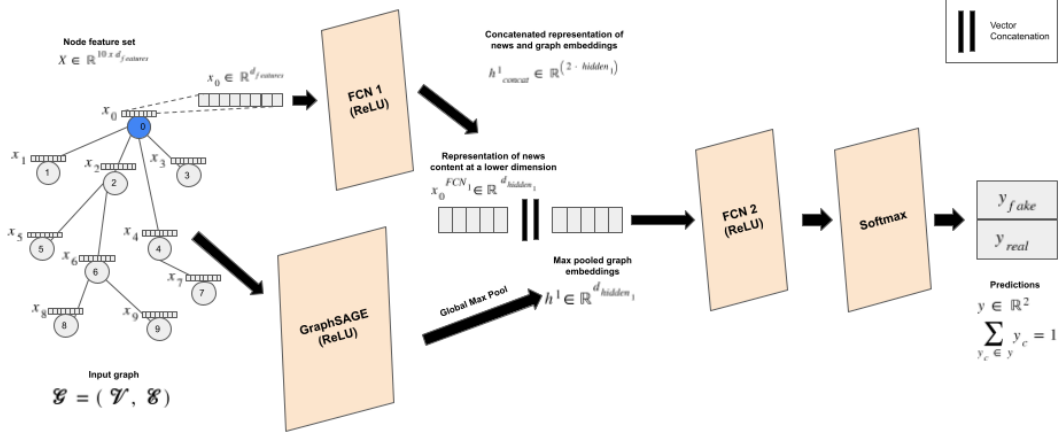


Figure 4.3: UPFD classifier model pipeline. We used an example input graph with 10 nodes.  $d_{hidden_1} = 128$  stands for hidden layer dimension of FCN 1, accordingly,  $d_{hidden_2} = 128$  for the hidden dimension of FCN 2, and  $d_{feature} = 768$  for feature dimension.

Activation function	ReLU (Nair & Hinton, 2010)
Batch size	128
Epochs	35
Learning rate	0.01
Hidden layer 1 size	128
Hidden layer 2 size	128
Weight decay	0.01

Table 4.1: Hyperparameters of UPFD classifier.

Dataset	Accuracy	Precision	Recall	F1 score
Gossipcop	95.49%	94.95%	96.17%	95.50%
Politifact	83.16%	84.05%	82.19%	83.25%

Table 4.2: UPFD classifier performance metrics averaged over 10 runs.

effect by statistical tests in Shu et al., 2020.

Shu et al., 2020 proposes to create two levels of propagation networks, *macro-level* and *micro-level*, using FakeNewsNet (Shu et al., 2018). For each level, the authors define and statistically test the significance of a set of features. We want to see if some of those features are adopted by our classifier. Briefly, macro-level networks are constructed to track the cascade of a news piece via retweets, whereas micro-level propagation networks are built using the replies to retweets. UPFD is the macro-level propagation network, thus our focus is on the features of macro-level propagation network.

The features of macro-level propagation networks are categorized into two: *structural* and *temporal*. Structural features capture the patterns in global dissemination of a news piece (Shu et al., 2020). These features include:

- ( $SF_1$ ) *Tree Depth*: Indicates how far the news piece has spread through the propagation network (Shu et al., 2020).
- ( $SF_2$ ) *Number of nodes in macro-network*: Indicates how many users have shared the news piece (Shu et al., 2020).
- ( $SF_3$ ) *Maximum outdegree*: Helps reveal the tweet/retweet with the most influence in the propagation network (Shu et al., 2020).
- ( $SF_4$ ) *Number of cascades*: The number of tweets that post the original news article (Shu et al., 2020).
- ( $SF_5$ ) *Depth of node with maximum outdegree*: Indicates steps of propagation required for a news piece to be retweeted by an influential user (node) whose post is retweeted by more users than any other users' retweet (Shu et al., 2020).
- ( $SF_6$ ) *Number of cascades with retweets*: Indicates the number of tweets shared the original news article and retweeted at least once (Shu et al., 2020).
- ( $SF_7$ ) *Fraction of cascades with retweets*: Corresponds to  $SF_6/SF_4$  (Shu et al., 2020).
- ( $SF_8$ ) *Number of bot users retweeting*: Captures the number of bot users that retweeted that news piece (Shu et al., 2020).
- ( $SF_9$ ) *Fraction of bot users retweeting*: Corresponds to  $SF_8/SF_2$  (Shu et al., 2020).

First of all, the feature set is not restricted to these features, one can derive more features for this dataset. We will investigate some of these features in order to understand whether we can capture similar features in our explanations. We do not have access to the information of bot users in our dataset, thus we drop the analysis of features  $SF_8$  and  $SF_9$ . Additionally, we did not analyze temporal features as obtaining them from



the explanation proved to be a long process. We now discuss which features' average values are found to be significant by statistical tests in (Shu et al., 2020). First structural feature  $SF_1$  is found to be consistently different for real and fake news instances in both datasets Gossipcop and Politifact under statistical t-test (Shu et al., 2020). Concretely, this finding indicates that tree depth of fake news are larger than that of real news. Next, another simple feature  $SF_2$  is also shown to be consistently different, particularly fake news instances have less nodes than real news instances. Although helpful, without additional information this feature is too broad. Thus, we look at the next structural feature  $SF_3$ . It is found in (Shu et al., 2020) that this feature consistently different for fake and real news in Gossipcop under t-test. More precisely, it is found that the maximum outdegree is bigger in fake news instances of Gossipcop. Considering this observation, we now proceed to more complex features.

When we look at features that analyze more subtle properties of the dataset such as  $SF_5$  and  $SF_7$ , it is reported that these features are also consistently different for fake and real news instances from both datasets Politifact and Gossipcop (Shu et al., 2020). According to the study,  $SF_5$  is discovered to be bigger in fake news, i.e., the finding suggests fake news reach the users from another user who retweeted the original fake news instance. The other feature  $SF_7$  investigates how many of the first retweeters of the original post were retweeted. The t-test tells us that this value is different in real and fake news instances in both datasets. Specifically, the value of  $SF_7$  is higher for fake news than for real news.

We have introduced the model we have employed for FND in mixed approaches. We will analyze the model's behavior on the graph data, and investigate its faithfulness, plausability and some other properties. We adopt GNNExplainer (Ying et al., 2019) as our explanation tool and try to uncover the patterns the model have learned. We shall also discuss some limitations we encountered while conducting these experiments.

## 4.2 Explaining Graph Neural Networks

Except GNNs, many neural networks can be explained using various tools such as SHAP, LIME, LRP etc. GNNs make their predictions by aggregating information from nodes, edges and graph topology. There can be cases where an edge is plays a significant role in the node prediction only if it is considered with another edge (Duvenaud et al., 2015). Therefore, we can not model separate contributions of node, edge, and graph features in a linear manner.

### 4.2.1 GNNExplainer

GNNExplainer is a post-hoc model-agnostic (works with any GNN) explainer tool that aims to provide information about the effects of node features, edges and graph structure on the prediction. More precisely, let us denote the node  $v$ 's computation graph as  $\mathcal{G}_c(v)$ , the binary adjacency matrix as  $\mathcal{A}_c(v) \in \{0, 1\}^{(n \times n)}$ , and the feature set as  $X_c(v) = \{x_j | v_j \in \mathcal{G}_c(v)\}$ . Then we say that a GNN model  $f$  learns a conditional distribution  $P_f(Y | \mathcal{G}_c, X_c)$  with  $Y \in \{1, \dots, C\}$  as a random variable that stands for class probabilities of nodes. Then in probabilistic terms, the prediction is denoted as  $\hat{y} = f(\mathcal{G}_c(v), X_c(v))$  which suggests that the prediction depends on three parts. Therefore, GNNExplainer takes into account the GNN model  $f$ , the graph information  $\mathcal{G}_c(v)$ , and the node features  $X_c(v)$  (Ying et al., 2019).

Simply put, GNNExplainer finds a subgraph  $\mathcal{G}_S(v) \in \mathcal{G}_c(v)$  and node feature subset  $X_S = \{x_j | v_j \text{ in } \mathcal{G}_S\}$  that are important for a given prediction  $\hat{y}$ . The subgraph that explains the prediction best is obtained by maximizing the *mutual information* MI between the prediction  $Y$  and the pair of subgraph and subset of node features  $(\mathcal{G}_S, X_S)$  (Ying et al., 2019).

$$\max_{\mathcal{G}_S} MI(Y, \mathcal{G}_S, X_S) = H(Y) - H(Y | G = \mathcal{G}_S, X = X_S)$$

where  $H(Y)$  is the marginal entropy of  $Y$  and fixed for a trained GNN, and  $H(Y | G = \mathcal{G}_S, X = X_S)$  stands for the conditional entropy. Since  $H(Y)$  is fixed, the authors reformulate their objective function as a minimization function that looks for a subgraph  $\mathcal{G}_S$  that minimizes the uncertainty of the GNN model  $f$  while using a subset of node features  $X_S$ , thus maximizing the probability of  $\hat{y}$ . However, this formulation brings computation issues as large dense graphs can have massive amounts of candidate explanation subgraphs for a prediction  $\hat{y}$ . Thus, the authors enforce a constraint on the fractional adjacency matrix  $A_S \in \{[0, 1]\}^{n \times n}$  ( $n$ : #nodes) of the subgraphs which are now treated as random variables  $\mathcal{G}_S \sim \mathcal{G}$ . With convexity assumption and upper-bound from Jensen's inequality, the minimization problem is rewritten as (Ying et al., 2019),

$$\min_{\mathcal{G}} = H(Y | G = \mathbb{E}_{\mathcal{G}}[\mathcal{G}_S, X = X_S]).$$

Finally, to estimate  $\mathbb{E}_{\mathcal{G}}$ , the authors employ mean-field variational approximation and decompose  $\mathcal{G}$  into a multivariate Bernoulli distribution. This allows to estimate the expectation in terms of mean-field approximation, thus obtaining  $A_S$  whose  $(i, j)$ -th element denotes the expectation of the existence of the edge  $(v_i, v_j)$ . The final objective is defined as (Ying et al., 2019),

$$\min_M - \sum_{c=1}^C \mathbb{1}[y = c] \log(P_f(Y = y | G = A_S \odot \sigma(M), X = X_S))$$

where  $M \in \mathbb{R}^{n \times n}$  is the mask to learn,  $\odot$  is element-wise multiplication, and  $\sigma$  is the mapping function of mask to values to interval  $[0, 1]^{n \times n}$ . For large graphs however, a threshold might be required to remove low values in the mask. We will propose two approaches to effectively handle this only for explanations of UPFD classifier (Ying et al., 2019).

Besides the edge mask  $M$ , as mentioned previously, GNNExplainer also learns a node mask  $F \in \{0, 1\}_{feature}^d$  through a binary feature selector that is learned by maximizing  $MI$  in the first equation. More formally, the explanation  $(\mathcal{G}_S, X_S)$  is optimized together to maximize  $MI$ :

$$\max_{\mathcal{G}_S, F} MI(Y, (\mathcal{G}_S, F)) = H(Y) - H(Y | \mathcal{G} = \mathcal{G}_S, X = X_S^F)$$

where  $X_S^F = \{x_j^F | v_j \in \mathcal{G}_S\}$  and  $x_j^F = [x_{j,t_1}, \dots, x_{j,t_k}]$  for  $F_{t_i} = 1$  denotes the node features that are not masked out by  $F$  (Ying et al., 2019). So far, the explanation method is defined for node classification setting. However, when the task is at graph-level, the method needs to be extended. Ying et al., 2019 suggest to unionize the adjacency matrices  $A_S$  for all nodes in the graph to be explained. The aggregation of node embeddings, however, restricts the explanation to a subset where the resulting subgraph must be connected. Thus, the threshold for the edge mask is set to a very low value or zero. This allows for a larger connected subgraph as an explanation (Ying et al., 2019).

### 4.2.2 Explaining UPFD Classifier

In Section 4.1, we have introduced our UPFD classifier, a GNN that uses GraphSAGE (Hamilton et al., 2017) as the graph encoder, two FCNs and softmax for classification of news propagation trees. We now investigate the reasons behind the model's performance on the UPFD-Politifact dataset by employing GNNExplainer as our explainer. Note that this model was trained only on the UPFD-Politifact dataset, thus data in UPFD-Gossipcop is unseen to this mode. The explanations we obtain for our classifier's performance on UPFD-Politifact dataset might provide us with useful information that enables us to improve the model.

First, to clarify how the explanations should be interpreted, let us consider an example where we obtain a single explanation  $(\mathcal{G}_S, X_S)$  for a graph (news propagation tree). We interpret the edge masks  $M$  of  $\mathcal{G}_S$  as the importance scores of edges between nodes. Therefore, an edge  $(v_i, v_j)$  with a mask value  $m_{ij}$  lower than a fixed *threshold* will be dropped, effectively dropping the connected nodes  $v_i$  and  $v_j$  as well.

We examine whether our classifier learnt a similar intuition that we discussed in 2.1.1. To recap, fake news tend to create an "echo chamber" effect.

In the echo chamber example in 4.4, it is trivial to observe some echo chambers created

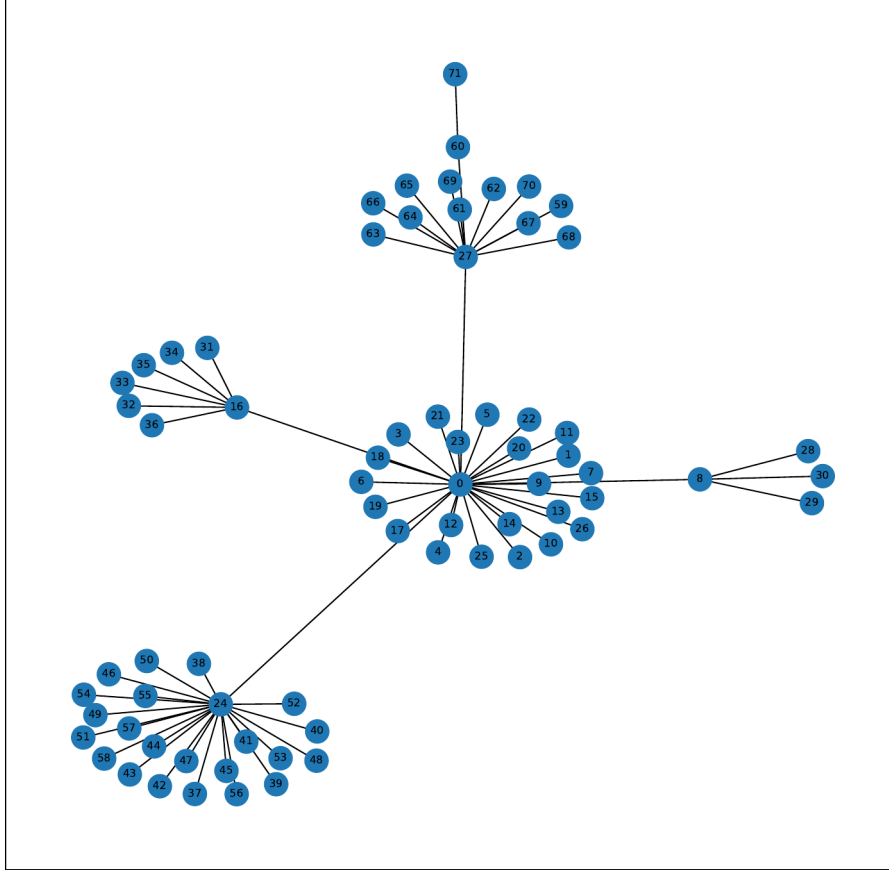


Figure 4.4: A randomly sampled fake news instance that exhibits echo chamber behavior. Random sampling is made from UPFD-Politifact fake news instances. 0-th node represents the root node with news embeddings. We will refer to this fake news example as the *echo chamber example*.

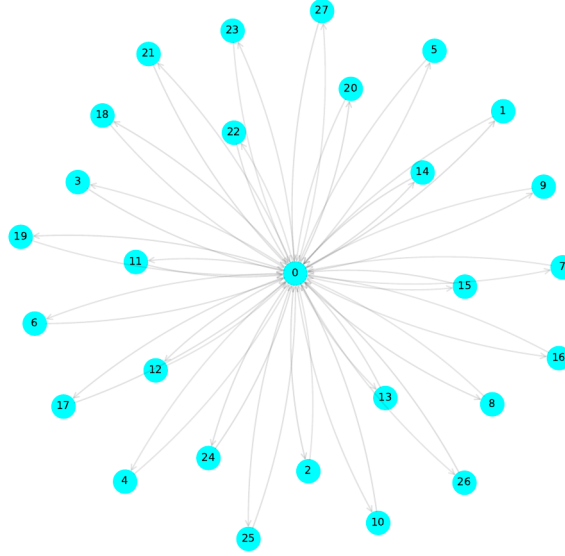


Figure 4.5: The explanation provided for our model and the echo chamber example for its root node. This instance was predicted as fake news with a probability of 0.9912. Contains 27 nodes.

by nodes 24, 27, 16, 8 from biggest to smallest respectively. Furthermore, the initial spreaders of this example are assumed to be followers of the publisher of root node. Similar to this, there exist many features for this dataset. Now that we have elaborated on the characteristics of our dataset, let us analyze whether these features were captured by our model. First, let us observe the explaining subgraph  $\mathcal{G}_S$  in Fig 4.5 for the echo chamber example. We first introduce how to interpret the explanation provided by GNNExplainer. Even though our dataset has undirected edges, we have obtained an explanation with bidirectional directed edges. To recap, undirected edges are interpreted as bidirectional edges, this is why GNNExplainer provided us with two edges per node pair. Additionally, there exist self-loops that simply is an edge from and to the same node  $(v_i, v_i)$ . The edge mask values for edges indicate the importance of the messages passed between two nodes. In order to understand the behavior of model in terms of the root node, we look at incoming edges to the root node in the explanation. Furthermore, the transparency of edges are an indicator for the magnitude of the edge mask value. However, this can not be clearly observed in this example. On the other hand, when we look at the node feature mask  $F$ , we can understand which features are deemed important by our model for a given node. We are particularly interested in the root node, and the explanation associated to it. Since the root

node consists of news content embeddings, intuitively, we can consider the root node explanation as the important subset of news content embeddings. However, we were not able to test this intuition due to (i) the size of data needed to be downloaded to construct FakeNewsNet (Shu et al., 2018) whose news content and social context data was utilized in our dataset, (ii) insufficient information on Dou et al., 2021 to reproduce the UPFD framework, (iii) large maximum input sequence (768) for BERT model to process the news content on a local computer. Thus, we continue our analysis without considering node feature mask from now on.

**Interpreting the Explanation.** As one would expect, the model thinks that the the cascaders (initial retweeters) are the most important users (nodes) for the prediction of fake for this instance. Although there should be a significant difference in the edge mask values, specifically, since the spreaders are the users  $v_8$ ,  $v_{16}$ ,  $v_{24}$ , and  $v_{27}$  we would expect larger importance scores on edges that connect these nodes to the root node. Interestingly, the edge  $(v_0, v_{13})$  was assigned the highest edge mask value with 0.1371. The edges  $(v_0, v_8)$ ,  $(v_0, v_{16})$ ,  $(v_0, v_{24})$ , and  $(v_0, v_{27})$  were assigned 0.1081, 0.0951, 0.1222, and 0.1181, respectively. While the reasons behind the maximal importance score assignment to edge  $(v_0, v_{13})$  remains unclear, we observe that the biggest echo chamber’s connection to the root node has a high edge mask value, which suggests that the model might be able to utilize the echo chambers with success for prediction. However, we need to observe similar behavior in other fake news instances that house echo chambers.

We also examined the highest edge mask valued five edges to understand which edges are important for our model. Before we proceed, it should be noted that the subgraph generation does not take into account where the maximal edge mask values reside, instead it tries to capture the biggest subgraph with the highest mutual information between the original graph and the subgraph with respect to the prediction.

**Edge Mask Analysis.** Proceeding our analysis for the five largest values in our edge mask provided by GNNExplainer, we observed that the second highest value belongs to the edge  $(v_{24}, v_{41})$ , i.e., an echo chamber connection. The third one belongs to a self-loop  $(v_{44}, v_{44})$  and the fourth one is for the edge  $(v_{44}, v_{24})$ . We can interpret the edge mask value for the self-loop as the significance that model puts on the node 44 ( $v_{44}$ ). The edge mask value for edge  $(v_{44}, v_{24})$  confirms our interpretation for node  $v_{44}$ , because this is the first instance for an important edge that is directed from a retweeter to its source. Thus, the user  $v_{44}$  and their historical data should be investigated. The fifth largest edge mask value is assigned to the edge  $(v_{27}, v_{62})$  which is another propagation edge in an echo chamber. The distribution of the edge mask values are given in Fig. 4.6 Visiting back the features we introduced, we observe that the feature  $SF_7$  is captured in this explanation. To elaborate, we see that the edges to the cascade node with the highest number of retweets were deemed important by the explainer. This implies

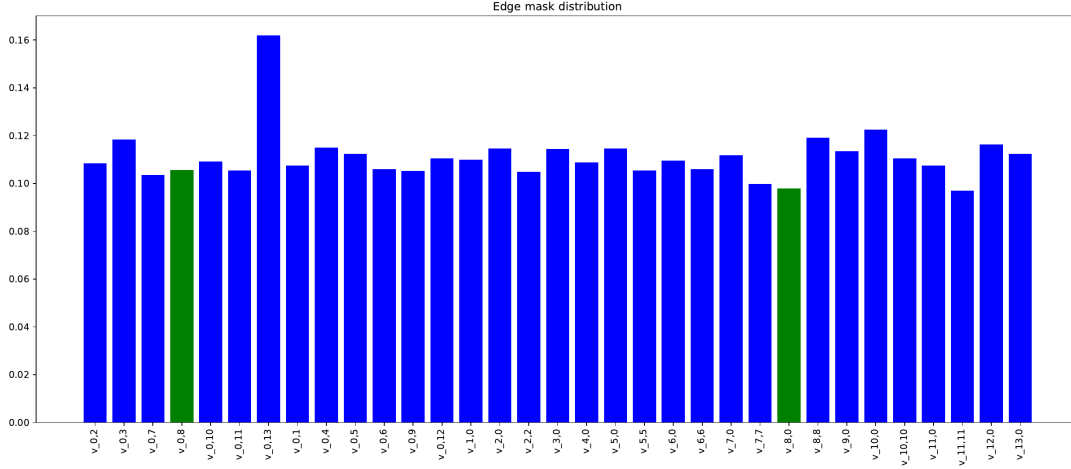


Figure 4.6: Edge mask distribution of the subgraph provided for echo chamber example explanation. The green bars represent the edge mask values of echo chamber connections.

that our model is able to capture important features. Although, in order to get this interpretation, one would require a data scientist. A domain expert or an end-user is likely to either misinterpret or not understand the explanation provided by GNNExplainer. Furthermore, some of the most important edges were not even included in the visualization. This certainly decreases the understandability of the explanations.

**Sensitivity Analysis.** We also analyzed the faithfulness of the explanations to the model. We took the explanation subgraph we provided in 4.5, restored its node features and fed it to model to see if the learned structure is still predicted as fake with high probability. In fact, the model predicted the subgraph as fake with 0.9915 which is higher than the prediction probability of our instance. Overall, we say that the model is faithful to this instance, and GNNExplainer can indeed reduce noise in a graph as the authors claimed in Ying et al., 2019.

We proceed our analysis of this instance an experiment in which we remove the news content and historical information of children nodes both in the input and the explanation to see their effect on the prediction. We provide the results in Table 4.3.

It is trivial to observe in Table 4.3 that the model’s confidence decreases as we remove news content for the echo chamber example. Interestingly, when we remove user historical information from all nodes except root node (root node contains the news content), the prediction probability does not drop too much. This suggests model takes into account the news content and structural information more than the historical information. This can also be observed from the model’s architecture in Fig. 4.3. The

Operation	$p_{original}$	$p_{subgraph}$
No change	0.9912	0.9915
Remove news content	0.8328	0.8018
Remove historical information	0.9812	0.9809
Remove all node information	0.4940	0.4940

Table 4.3: Model prediction probabilities for input perturbation experiment.  $p_{original}$  denotes prediction probability for the original input. Analogously,  $p_{subgraph}$  refers to the prediction probability for the explanation subgraph.

skip connection and concatenation of the news content in the root node appears to be doing what is expected of it. In fact, the authors of UPFD (Dou et al., 2021) showed that news content shows that with a vanilla version of UPFD classifier, i.e., without skip connection and concatenation, the performance drops. This finding of ours also goes in parallel with their finding. Furthermore, when we remove all node information, the model loses can no longer tell fake from real. Thus, without node information, just depending on the structure and diffusion of a news piece for prediction turns out to be a bad idea. We certainly need some node embeddings, at least the embeddings for the news.

We illustrate more examples in order to understand if the statistically significant features were captured. First, it is nontrivial to look for  $SF_1$  in the explanations as the tree depth will be decreased significantly. Most of the time the tree depth in the explanations we observed were 1. Thus, we skip this feature analysis. We look for the effect of feature  $SF_2$  in the explanations. We make a simple comparison with our echo chamber example in Fig. 4.4 with a real news example in Fig. 4.7. The echo chamber example has 72 nodes whereas the real news example has 59 nodes. Now let us observe the explanation provided for the real news instance in Fig. 4.8.

The explanation subgraph for the real news example contains more nodes than the explanation subgraph for the echo chamber example. This might imply the effect of  $SF_2$  on the explanations. In other words, explanations capture the importance of more nodes for the real news example. Although, this should be tested with other real and fake news instances to be verified. Furthermore, Although this instance has some nodes that create an echo chamber like effect, we can easily observe that some of these nodes were also retweeted, a behavior not observed in echo chamber example.

During our experiments, we realized that some explanations are hard to read, particularly the ones with too many nodes. Including the explanation provided in Fig. 4.8, it is hard to distinguish edges and nodes. In order to understand the importance of edges and simplify the explanation subgraph we employed three simple techniques in



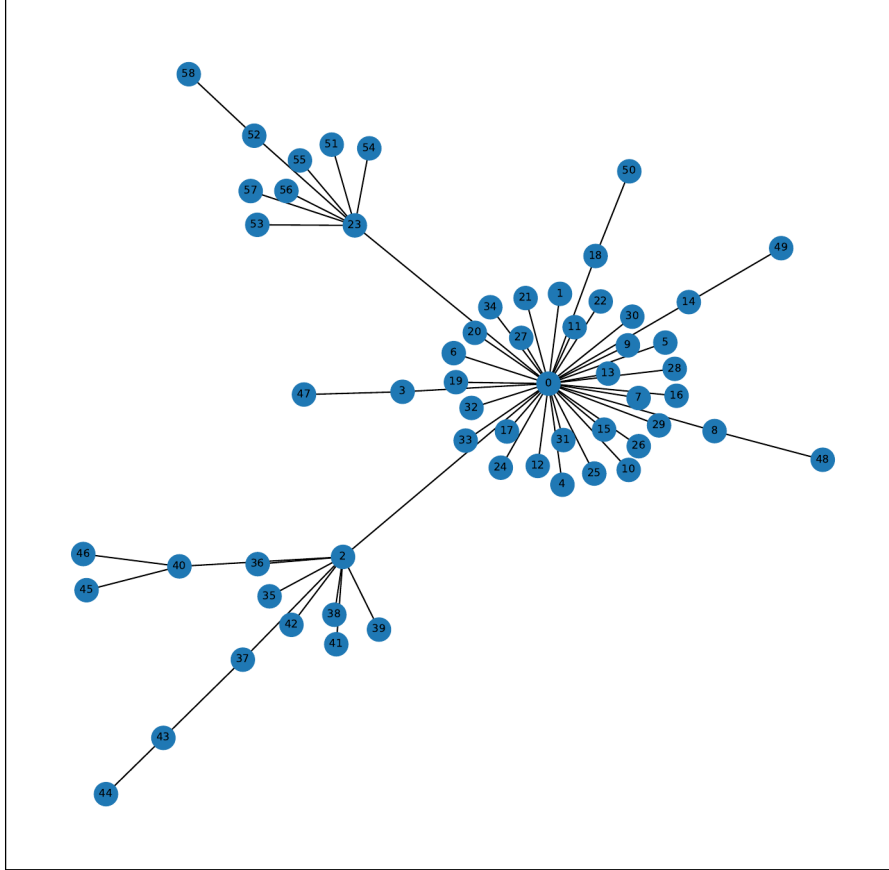


Figure 4.7: A real news instance from UPFD-Politifact. We shall refer to this example as the *real news example*. It was predicted as real news with probability 0.9956

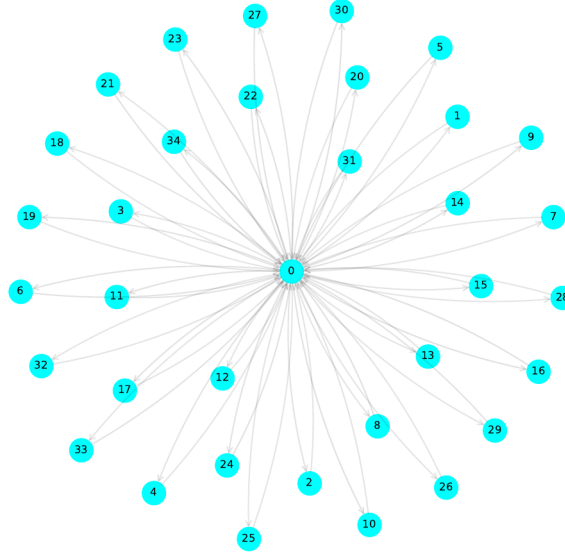


Figure 4.8: Explanation for the real news example from UPFD-Politifact. Contains 35 nodes.

which we used a threshold value. Then we apply this threshold to the edge mask in which the values less than or equal to the threshold are set to zero. The first approach was straightforward, take the maximum value and set the threshold to a value less than that, and observe the changes in the explanation subgraph as we change the threshold value. The second approach is to get the mean of all edge mask values to get a threshold value. This way we obtain less edges in our initial explanation, but keeping an important set of edges to understand their importance. Our third approach is to take the median of the edge mask set, and use it as a threshold that applies the same effect as the averaging approach. There were no big differences between mean and median method. However, we opted for median as it was able to capture more edges for small explanation subgraphs. We illustrate the explanations with threshold methods mean and median in Fig 4.9.

We can extend our method to an interactive plot in which we are able to change the threshold value dynamically. Furthermore, we can use the edge mask values provided for the edges in the subgraph to apply average and mean thresholding methods. We leave this for future work.

**Introducing Unseen Data.** We analyzed the predictions made for one real and one fake news instances that were in the test split. This time, we randomly sampled one fake news from the fake news set and one real news from the real news set in the test split



Figure 4.9: Threshold methods for subgraph explanations of the real news example. In this case median and mean provides the same output.

of our UPFD-Gossipcop dataset which is unseen data for our model which was trained on the UPFD-Politifact dataset. We did not generate a new graph instance as obtaining the news piece, creating embeddings for it, and collecting its social context information is a very long process without some of this data prepared beforehand.

Our fake news example from Gossipcop is illustrated in Fig. 4.10. It is obvious that this fake news piece does not display echo chamber patterns, in fact, structurally it looks more like a real news piece. This may be why our model mispredicted this instance. Let us further dive in to understand this. There can be a variety of reasons. It can be because of the difference in the news style in both datasets. Politifact houses a set of political news whereas Gossipcop houses a massive set of celebrity news. So the difference of textual structure could be a reason. Another reason can be the small number of training instances for the set. However, we were not able to gather suggestive information from the explanation thus we did not include the explanation. One way to understand whether the model responds to echo-chamber like structures is to create these echo chambers by adding children nodes to some of cascade nodes (initial retweeters) and feed this to the model. Thus, initially, we added 20 nodes with no information in them, and selected nodes  $v_{37}$  and  $v_{39}$  arbitrarily. The resulting graph is illustrated in Fig. 4.11. When the fed the perturbed sample to our model, the increase in prediction probability for fake news unnoticeably increased. So we also sampled some historical information from a randomly obtained fake news instance that is different

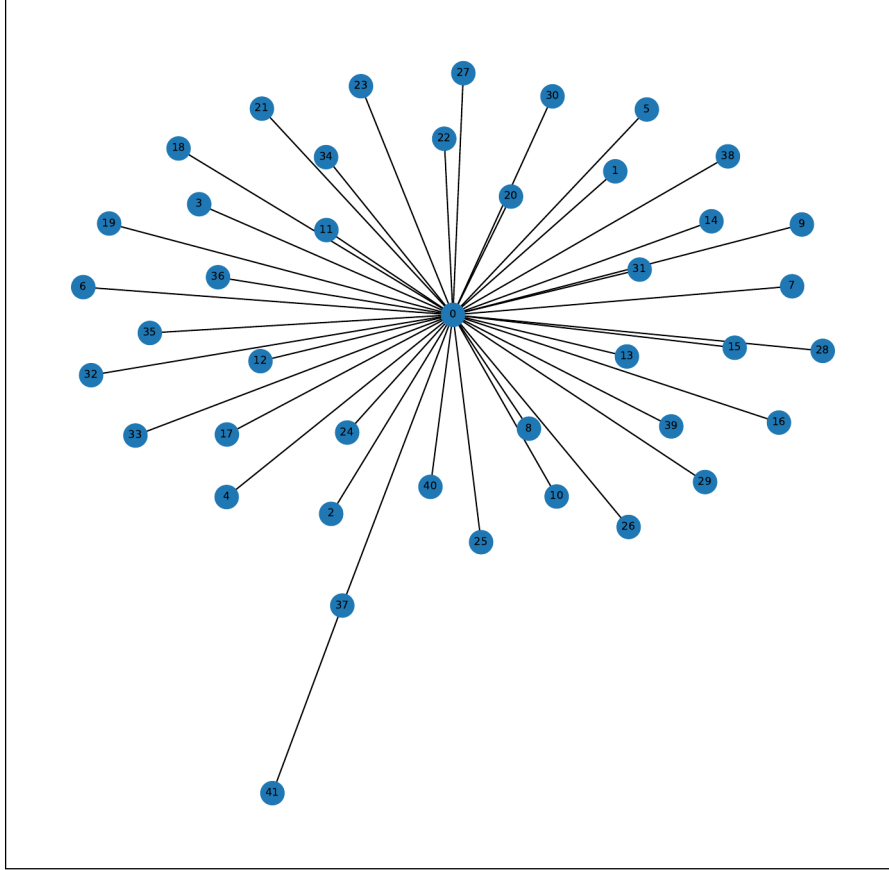


Figure 4.10: A fake news example from UPFD-Gossipcop. We introduced this instance as an unseen data to our model, and it predicted this fake news piece as real with a probability of 0.9984.

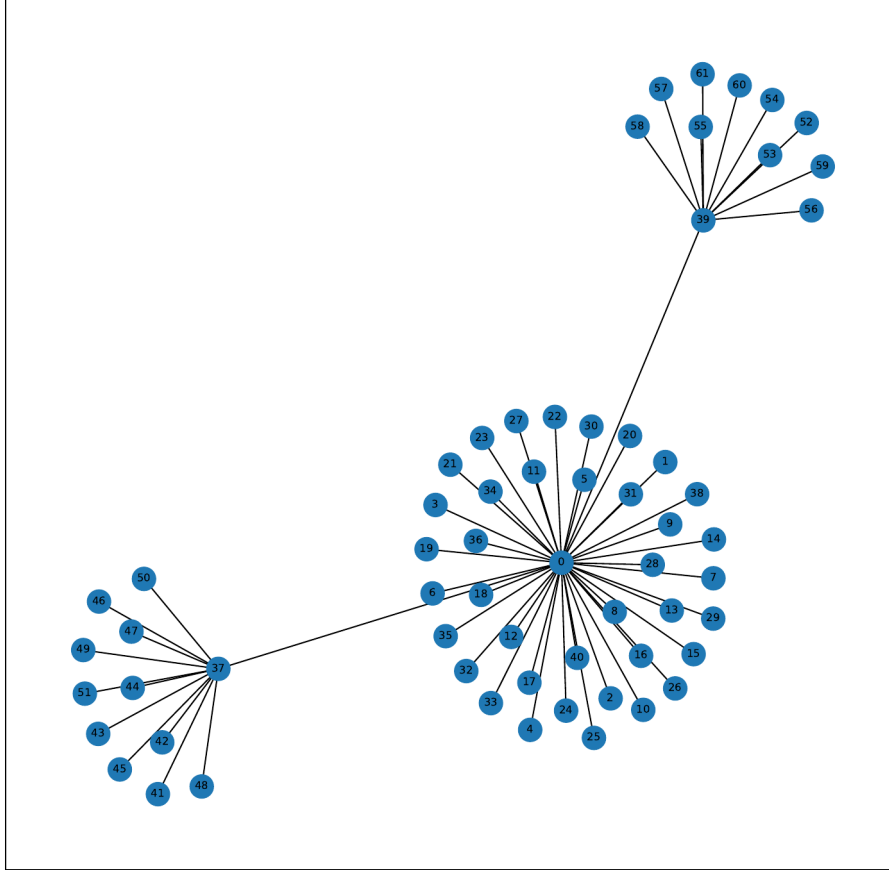


Figure 4.11: The perturbed version of the fake news example from UPFD-Gossipcop. We added echo-chamber like structures to nodes  $v_{37}$  and  $v_{39}$ .

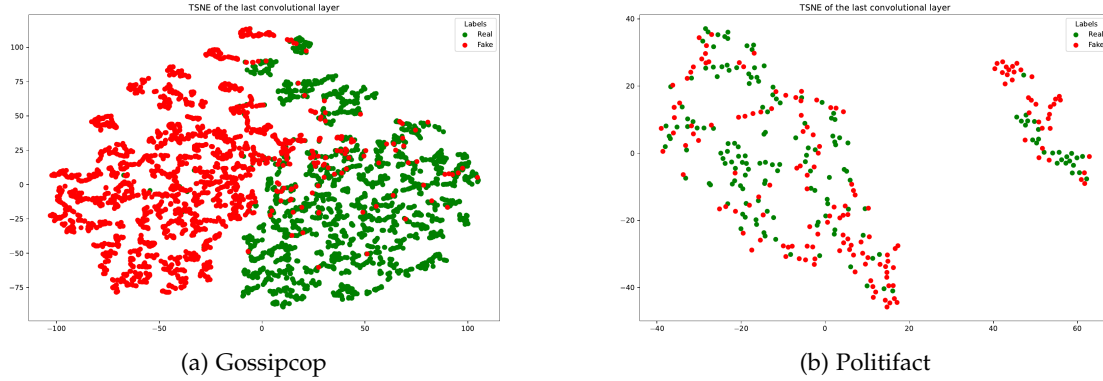


Figure 4.12: t-SNE visualizations for max pooled GraphSAGE on UPFD.

than the one we are analyzing. We embedded the new nodes with randomly obtained user historical information. Then we fed this instance to the model, but the change in probability was too small to omit. Thus, for this instance our experiment suggests that echo-chamber like structures does not necessarily increase the probability for fake news.

**Latent Space Analysis.** We apply t-SNE (van der Maaten & Hinton, 2008) using default settings provided by scikit-learn (Pedregosa et al., 2011) to see if GraphSAGE is able to distinguish fake and real news before its outputs are concatenated with news content in the root node and then fed to the FCN. The visualization for this procedure is provided in Fig 4.12. Clearly GraphSAGE is able to distinguish fake and real news instances better in Gossipcop dataset, but it fails to make this discrimination with Politifact dataset. This can be due to the low amounts of instances in the Politifact dataset.

**Target Audience and XAI Goals for GNNExplainer.** It is quite clear that understanding the model’s behavior locally with just a visualization is not sufficient for an end-user to understand why a particular news piece was predicted as real or fake. However, given enough resources, one can reverse engineer the process in the UPFD framework, which would allow for the analysis of node feature masks of news content and historical information embeddings. That would certainly increase the trustworthiness and informativeness of the model. We also suggest to employ interactive visualizations when working with GNNExplainer since the explanations can get very big. Explanations produced by GNNExplainer should be investigated by a data scientist who will simplify the explanation for a domain expert or an end-user. For our dataset, this simplification process can include aggregation of bidirectional edge mask values so that they can be represented as an undirected edge. Moreover, these undirected edges can be color-coded such that each color represents a value above a certain threshold

which can be obtained using the methods we suggested. Also for GNNs with language models, the node features should be easily mappable to the textual content in such a way that we can create a variation of force plots provided by SHAP framework.

To sum up, we have analyzed the explanations produced by GNNExplainer for our model which was trained on UPFD-Politifact dataset. We have observed some of the statistically significant features' existence in the explanations. We have also addressed shortcomings of GNNExplainer, suggested simple yet effective methods to reduce the complexity of an explanation. All experiments were conducted using Python 3.7 (van Rossum, 1995), PyTorch 1.11.0 (Paszke et al., 2019) and PyTorch Geometric 2.0.4 (Fey & Lenssen, 2019). All visualizations were obtained through the use of NetworkX 2.6.3 (Hagberg et al., 2008) and Matplotlib 3.5.1 (Hunter, 2007). The detailed library usage and the implementation of all models are provided in our github repository <sup>1</sup>.

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<sup>1</sup>[https://github.com/sersery35/Explainability\\_of\\_FND\\_Models/tree/main/GNNFakeNews](https://github.com/sersery35/Explainability_of_FND_Models/tree/main/GNNFakeNews)

## 5 Conclusion



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