Graph Neural Networks for News Domain Classification: Detecting Misinformation in Telegram Chat Groups

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Introduction

In my thesis, I want to apply GNNs to classify news domains shared in Telegram chat groups as misinformation. My hypothesis is that GNNs outperform state of the art methods for classifying domains into misinformation. By modeling Telegram groups and their associated URLs as a graph, where nodes represent grouped URLs as domains and edges represent the sharing patterns of chat groups, GNNs can learn the hidden patterns that distinguish legitimate content from misinformation.

The spread of misinformation on online platforms poses a significant threat to public discourse, trust in society and individual decision-making. Messaging platforms such as Telegram are growing in popularity as they allow users to create large chat groups and remain semi-anonymous. Unfortunately, these features make Telegram a fertile ground for the spread of misinformation, often through shared URLs that lead to external content. Identifying and classifying such URLs to detect misinformation in Telegram groups can be an important step in drawing attention to this threat and addressing this global challenge.

Traditional approaches classifying URLs and detecting misinformation often rely on natural language processing or metadata analysis. While these methods are effective to a certain extent, they struggle with the nuanced relationships and complex structures that underlie misinformation networks, such as repeated sharing patterns, interaction-based dissemination, and the networked nature of content in groups. Graph Neural Networks (GNN) provide a powerful solution by leveraging the graph structure of data to uncover and analyze these relationships. In order to test the hypothesis of the thesis, different approaches will be experimented, combined and compared.

Misinformation on Telegram

Misinformation have played a significant role throughout history, shaping public perception and even leading to catastrophic events. A prominent example is the spread of misinformation about the Jewish population by the Nazis in Germany in the twentieth century, which contributed to the Holocaust. [Bytwerk and College, 2010].

Since the US elections in 2016 at the latest, the massive spread of misinformation has become a public issue. In 2017, "fake news" was voted word of the year by the Collin Dictionary [Dictionary, 2017]. Fake news, distinct from misinformation, consists of intentionally fabricated or manipulated content with the aim of deception, often amplified by echo chambers and malicious accounts [Phan et al., 2023]. According to Khan et al. and Shu et al., fake news is characterized by its fabrication of information with the intent to mislead, while misinformation lacks a clearly defined intent but still distorts facts [Khan et al., 2021, Shu et al., 2017] .

The rise of social media has further complicated this issue, as platforms increasingly serve as primary news sources, making it easier for both misinformation and fake news to circulate widely. The Digital News Report 2024 of Reuter showed that more than a third of the world's population consume news through social media and more than half are concerned about what is real and what is fake [Newman et al., 2024]. Consuming news through online social networks is convenient, cheap and fast but also decentralized and unsupervised [Ksiazek et al., 2016, Khan et al., 2021].

Telegram, a messaging platform founded by a Russian entrepreneur, has become a particularly fertile ground for misinformation. With its emphasis on privacy and encrypted communication, the platform fosters a sense of security that appeals to users who distrust mainstream authorities. Public chat groups, despite being open to large audiences, maintain a perception of exclusivity, making them ideal spaces for misinformation to spread. Telegram is the third most downloaded messenger worldwide and should therefore be placed more in the focus of science [Varela, 2023, Ceci, 2025].

GNN for Classifying Misinformation

Graph Neural Networks (GNNs) offer a promising framework for the classification of misinformation in social media by utilizing the relational structure of online interactions. Unlike traditional machine learning models that often assume data points are independent, misinformation spreads within interconnected networks, making graph-based approaches particularly effective. Social media generates vast amounts of user interactions, content, and chat data, which form complex, non-Euclidean structures that GNNs are well-equipped to handle [Phan et al., 2023, Zhang et al., 2020]. Moreover, misinformation exhibits a "monological belief system," where individuals who believe in one conspiracy theory or fake fact are likely to believe in others [Goertzel, 1994]. This phenomenon creates a web of misinformation, where fake articles cite one another and reinforce a false framework of evidence. Therefore misinformation objects do not exist in isolation; they are interconnected, often forming clusters that are distinguishable from legitimate news sources. By detecting fake content, GNNs can utilize network structures to identify additional misinformation, as nodes within a misinformation network share attributes and exhibit relational inductive bias [Luan et al., 2024]. Furthermore, a content-agnostic approach to misinformation detection allows GNNs to classify fake news based on its network structure rather than relying just on textual analysis [Carragher et al., 2024]. This is crucial as misinformation frequently mimics the language of legitimate news, making content-based classification challenging [Zhang and Ghorbani, 2020].

The Data

The data used for this study was obtained from the Priesemann Research Group of Max-Plank Institute in Göttingen and consists of Telegram chat data collected between 2020 and 2023. The data includes structured information about chats, such as names and descriptions, as well as URLs shared within these chats, each with corresponding timestamps. A key component of the dataset is the Chat $\times$ URL share matrix, which captures the interaction between chats and shared links. An additional dataset from Lin et al. with 11,520 domain ratings that provide credibility ratings for various news sources serves as ground truth [Lin et al., 2023]. The authors made a principal component analysis of 6 fact-checker databases, in order to harmonize the misinformation measurements from different sources based on different dimensions and scales.

In order to focus only on actual news domains, social media platforms such as Facebook, Instagram and Snapchat, as well as video platforms such as YouTube and Rumble were excluded from the data. The shape of the content and the content itself are considered too diverse and decentralized on these platforms to be classified consistently. In addition, we only kept the 100 most frequently forwarded URLs per domain and scraped their text articles with the selenium package. This data was then merged with the ground truth data and divided into a train and test set. For content representation, article embeddings of the articles and the messages in the telegram chat groups were generated using the SBERT multilingual model (paraphrase-multilingual-MiniLM-L12-v2). The final data consisted of 388 chats, 4,753 training domains, and 1,189 test domains, with an initial 1,519,640 edges representing connections between chats and shared news domains. To validate the network structure, a Bipartite Configuration Model was applied, utilizing a Poisson distribution to statistically validate node similarities (p-value = 0.05). This filtering process significantly reduced the number of edges of the bipartite network to 154,254, ensuring a more robust and meaningful network representation.

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