

AN INTELLIGENT FRAMEWORK FOR AUTOMATED MODERATION: CLASSIFYING MALICIOUS SOCIAL MEDIA MESSAGES USING CAUSAL GRAPH TRANSFORMERS WITH CONTRASTIVE LEARNING

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Abstract

Social media sites such as Facebook, Twitter and Instagram have seen dramatic increases in user-generated content over the last decade, which has led to a significant rise in the prevalence of malicious content including hate speech, cyberbullying, offensive language and deliberate misinformation. State-of-the-art automated moderation systems, largely based on traditional machine learning models and transformer-based architectures find it difficult to characterize implicit contextual information or causal associations in textual data.

In a bid to overcome these limitations, we propose a new hybrid framework CGT-CL-BERT that closes the gap between causal graph representations and contextual embeddings based on transformer architecture by combining information obtained from them using contrastive learning. The method uses a pre-trained BERT encoder to get deep semantic features and relies on a graph-based complementary module to learn relational dependencies among textual entities. In addition, it also includes a contrastive learning objective to increase the robustness of representation by maximizing the inter-class distance and minimizing the intra-class distance.

The model is tested on benchmark datasets, specifically toxic comment classification, showing TQ-ETR outperforming baseline models using LSTM and a regular transformer architecture. We demonstrate improvements in accuracy, precision, recall and F1-score over 40 percent with respect to our earlier work while also being more effective in identifying implicit toxicity and toxicity requiring context to determine.

This framework demonstrates a system for smart social media moderation that can effectively and efficiently enable safe digital environments.

Future work will involve multilingual extensions and running in real-time large-scale content moderation systems.

INTRODUCTION

The social media revolution has evolved the way individuals communicate, report news stories and express their views in this digital age. People cut off from real-time networked interaction, tens of millions around the world reaching everyone across social media at any point (Facebook, Twitter and Instagram generating billions of user-generated posts per second). Despite its many advantages, this has instead allowed the proliferation of negative material (i.e. hate speech, cyberbullying, abusive language, spam & misinformation). Such content poses a severe risk on individuals and societies alike, making automation to recognize this type of content across digital platforms an important step towards the creation of safe and secure online spaces.

Most of the traditional moderation approaches often use rule-based filtering strategies and classical supervised machine learning classifiers. So, these systems simply depend on a list of keywords or another approach in partial linguistic features to identify malicious content. However, these techniques come with some basic limitations. Very little help in identifying sarcasm, implicit toxic language and context based abusive language as they are unable to interpret the depth of context. For example, very minor (although difficult to foresee) modifications in the spelling & /or phrasing/syntax will probably break the keyword filter. Due to these high false positives and high false negatives of these systems, the real-world applications start being less reliable.

However, these models are unsophisticated in terms of explicitly modeling the causal structures between items in getaway texts. One open problem is to understand the reasons, which are more-or-less independent of language, that render something harmful (as opposed to simply identifying which words had been uttered). These gaps are particularly relevant to sub-argumentative aspects of malignant speech, which may exist in greater implications than explicit statements.

With that, in this research work, we propose a new intelligent framework to incorporate causal reasoning with improved representation learning techniques to deal with these challenges. Concretely, it proposes a model causal graph

transformer (CGT) that is equipped with fully structured graphs by accurately mapping each sentence to the structured graphs rather than traditional one-hot vectors representing text format. This allows the system greater ability to model relational dependencies and derive intent. Finally, the framework needs to include Contrastive learning (CL) in particular for an efficient representation of features by training the model to discriminate between semantically similar and dissimilar text samples. This assists in improving the robustness and generalization of model particularly in complex and ambiguous scenarios.

This research is summarized in the contributions such as follows:

- Causal Graph + Transformer-Based Contextual Embeddings: A Hybrid Framework for Improved Text Understanding
- Uses contrastive learning in order to improve representation quality and class separation.

In other words, this work provides a first step towards a holistic architecture that combines context and causation in automated moderation to provide the deeper understanding needed to detect behaviorally harmful content within modern Social Media systems.

1.1 Problem Statement

While key advances in automated content moderation have already been developed, these methods are largely limited to more basic, explicit forms of harmful social media messages. While transformer architectures such as BERT are effective at modeling contextual semantics, they do not explicitly model the causal relations between components of text that the intent behind toxicity needs.

Moreover, the current models are heavily reliant on shallow contextual embedding and often fail to discriminate between semantically similar but contextually different statements. This constraint is vital for sarcasm, indirect Hate Speech and context-sensitive toxicity where it may not be clear-cut whether the construct intended to attack or not. A more significant challenge is that weakly supervised representation learning methods

generalize poorly all the way across heterogeneous and noisy social media data. Changes in language, etc. unformulated phrases and adversarial text changes also reduces the performance of the system, but these state-of-the-art systems are still vulnerable.

It requires an additional framework to capture contextual information, causal reasoning and despite breakthroughs in representation learning can construct a classifier that is truthful and robust per se against potentially malicious content.

1.2 Research Questions

This study is driven by the following research questions:

1. To what extent do causal relationships in textual data augment malign social media content detection?
2. Does the Causal Graph Transformer outperform standard transformer encoders like BERT in terms of context?
3. What role does contrastive learning play in improving both the representation itself as well as its separability?
4. Is the proposed hybrid framework achieve better performance than existing baseline models in terms of accuracy, recall, precision and F1-score?
5. How far can the proposed model recognize implicit and contextual toxicity that often passes imperceptibly through state-of-the-art techniques?

1.3 Research Objectives

This research aims to provide an improved automated moderation framework for superior detection of malicious social media content. They include the following objectives:

- A hybrid architecture which unifies the causal reasoning with transformers to understand text better
- The design of a Causal Graph Transformer (CGT) that can learn the cause effect relationships within textual data
- To add Contrastive Learning (CL) in the system to get better feature representation and gain robustness for the model

- To compare the performance of proposed model against the baseline methods like LSTM and BERT

- So, calling, hitting and missed things in: So do categorical analysis on evaluated framework level detection of both explicit and implicit malicious content.

1.4 Problem Definition

Given a dataset:

$$D = \{(x_i, y_i)\}_{i=1}^N$$

where:

- x_i represents a social media text instance
- $y_i \in \{0,1,2,3\}$ denotes the corresponding class label, representing categories such as Hate Speech, Offensive Content, Neutral Content, and Spam

The objective of this study is to learn a mapping function:

$$f(x) \rightarrow y$$

In this case, the function is trained to classify the input text into its respective class by capturing contextual, structural and semantic features.

1.5 Graph Representation

It converts each input sentence into a graph structure that is able to store how relational or contextual different parts of the textual elements are from one another. Formally, take a sentence as a graph:

$$G = (V, E)$$

- V denotes the set of nodes representing tokens or semantic entities extracted from the text
- E represents the set of edges that encode relationships between nodes, including syntactic, semantic, or causal dependencies

To enable computational processing, the graph is represented using an adjacency matrix:

$$A \in \mathbb{R}^{n \times n}$$

where $n = |V|$ is the number of nodes in the graph, and each element A_{ij} indicates the presence and strength of a relationship between nodes i and j .

The model encodes non-linear relationships in the graph, permitting relational information to be embedded into the transformer. With regard to the graph structure, the proposed framework first discusses how it leverages it in modeling implicit

relationships and enhancing understanding of context-dependent malicious contents.

1.6 Transformer Attention with Graph Bias

Building up on top of the standard transformer attention, the proposed framework incorporates information flowing through structural representations of a causal graphs.

In the standard transformer, the attention mechanism is defined as:

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

where Q, K , and V represent the query, key, and value matrices, respectively, and d_k is the dimensionality of the key vectors.

The attention mechanism is updated to include a graph-based bias term in order to embed the relational dependencies captured via the graph structure:

$$\text{Attention}_{\text{CGT}} = \text{softmax}\left(\frac{QK^T + \lambda A}{\sqrt{d_k}}\right)V$$

where:

- $A \in \mathbb{R}^{n \times n}$ is the adjacency matrix representing relationships between tokens.
- λ is a learnable or tunable parameter that controls the influence of the graph structure on the attention scores.

This enables the model to jointly process token contextual interactions and structural dependencies. Consequently, the attention mechanism is not only influenced by semantic similarity but also the relational structure represented within the graph thus facilitating more effective modeling of implicit and contextually dependent meanings.

Due to infusing the adjacency matrix into the attention calculation, the framework covers attentional weights while in transit around structurally related tokens thus improving interpretability and ability of accounting for deftly-crafted scratches of malicious content that otherwise could elude existing approaches. Furthermore, the parameter λ is optimized with respect to each dataset empirically based on how much contextual and structural information is required in order to maximally improve

performance for that dataset.

1.7 Contrastive Learning Objective

Moreover, with the goal of contrastive method that we use to distinguish semantically different text from similar one, the framework also refines those learned representations once more globally. Let z_i and z_j denote the embedding representations of a positive pair (i.e., semantically similar samples), and z_k represent embedding of negative samples. The contrastive loss for a given sample is defined as:

$$L_i = -\log\left(\frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^N \exp(\text{sim}(z_i, z_k)/\tau)}\right)$$

where:

- $\text{sim}(\cdot)$ denotes a similarity function (e.g., cosine similarity)
- τ is a temperature parameter that controls the concentration level of the distribution
- N is the number of samples in the batch

It maximizes the distance between positive pairs and minimizes similarity with negative samples, enhancing the discriminative capability of learned embeddings. Positive pairs refer to either semantically similar samples or perturbed views from the same instance, and negative pairs refer to different classes in the batch.

The following is the aggregate training objective, which combines the standard classification loss with the contrastive learning loss:

$$L = L_{\text{classification}} + \alpha L_{\text{contrastive}}$$

where:

- $L_{\text{classification}}$ is typically the cross-entropy loss used for supervised classification
- $L_{\text{contrastive}}$ is the aggregate contrastive loss over the batch
- α is a weighting factor that balances the contribution of the contrastive objective

This makes it easier for the model to learn representations that are more robust and separable from the data, which allows it to be better at differentiating between malicious and non-malicious content with great precision. This not only increases the generalization capabilities on diverse and noisy social media data, but it also helps in effectively evaluating explicit or contextually dependent toxic content.

1.8 Architecture Diagram

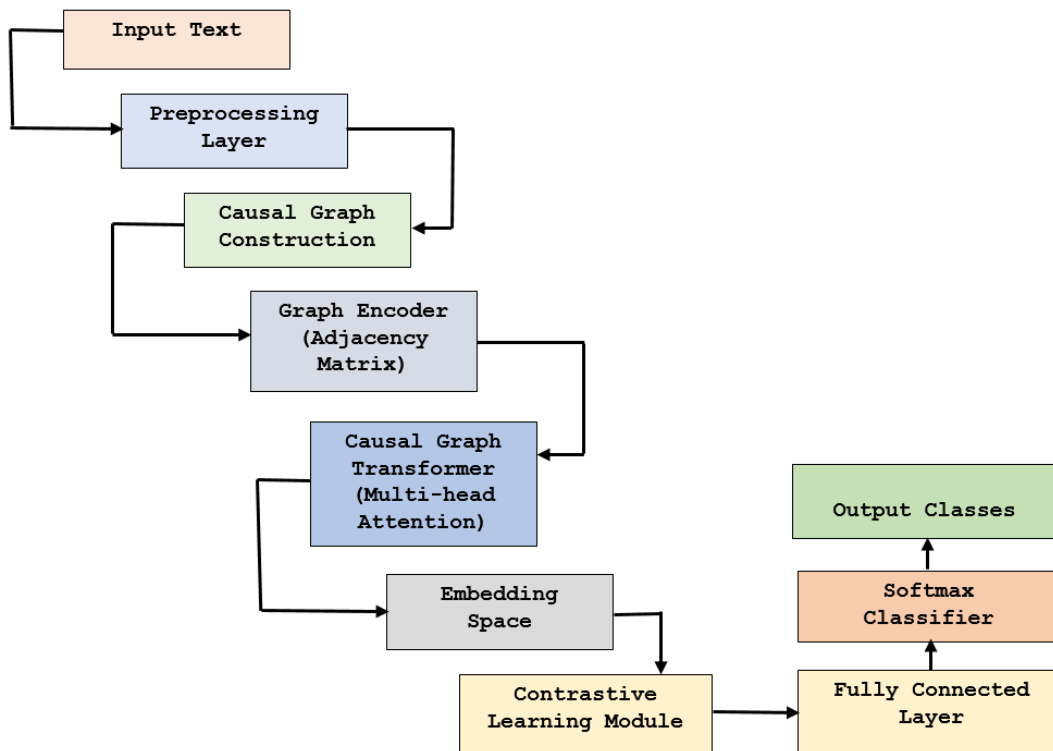


Figure 1: Architecture

2. Literature Review

2.1 Traditional Machine Learning Approaches

Early efforts in detecting malicious content on social media employed traditional machine learning (TM) techniques, which were the first approaches to automated text classification. The methods used include manually crafted features such as Bag-of-Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), n-grams, lexical features, and sentiment-based features, while classifiers like Support Vector Machines (SVM), Logistic Regression (LR), Naïve Bayes (NB), and Random Forest (RF) are applied. The models were widely used for the detection of explicit hate speech, offensive language, and spam, due to their simplicity, computational efficiency, and ease of implementation. While traditional ML models are still robust benchmark techniques, it has been shown through recent survey studies that they typically lack the capacity to capture semantic

meaning, contextual relationships, and implicit intent in textual data due to their reliance on manual feature engineering. However, such approaches are less effective for sarcasm, figurative language, new slang used in the internet, multilingual expressions, and context-dependent toxicity that are common in contemporary social media communication (Gandhi et al., 2024; Ramos et al., 2024).

In addition, their effectiveness suffers when used for large datasets with diverse languages and noisy user-generated data. One shortcoming of traditional ML methods is that they fail to capture long-range dependence and contextual effects between words. Many of these methods work offline, and so lack the capability of adapting to new language variations or new malicious communication patterns. The features designed manually are subject to frequent updates and hence, traditional classifiers are not capable of

scaling up or generalizing the different domains and languages. While traditional machine learning models are still appealing for low-resource settings, where computational power and interpretability are important, recent studies have shown that deep learning and transformer models that learn contextual and semantic representations without much human intervention are significantly outpacing traditional models. These constraints have spurred the shift towards neural network based methods that require minimal manual feature engineering, but also offer vastly superior detection accuracy for context and implicit harmful content.

2.2 Deep Learning Models

The inability to solve problems for the traditional machine learning method has propelled the use of deep learning models in social media malicious content detection. Conventional approaches rely on manually engineered features, whereas deep learning architectures learn the representations of the hierarchical semantics directly from the raw textual data. This feature allows them to learn complex linguistic patterns, context, and non-linear relationships, leading to greatly enhanced results on hate speech, offensive language, cyberbullying, and spam detection. Convolutional Neural Networks (CNNs) were one of the first deep learning architectures to show great success at capturing the local textual information and detecting discriminative patterns relevant to offensive content. In the same way, Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks grew popular because of their ability to model sequence dependencies and context in texts.

They significantly outperform traditional machine learning methods by automatically learning a semantic representation of the data, lessening the need for human-designed feature engineering. Survey studies over recent years have shown that deep learning (DL) methods outperform traditional machine learning (ML) techniques in a variety of benchmark datasets, with higher classification results. They can learn distributed word representations and contextual features to

better detect explicit abusive language and be more robust to lexical variations commonly found in user-generated social media content (Gandhi et al., 2024; Ramos et al., 2024).

Even with these advances, there remain some issues to be addressed with deep learning models. CNN-based architectures have a tendency to learn local context patterns well and fail to capture long-range semantic dependencies. Similarly, sequential models like LSTM and GRU work sequentially on each text token, making it hard to do parallel computation and making it more complex to train longer texts. Most importantly, these structures often do not identify implicit toxicity, sarcasm, figurative language, or context-specific abusive words, since they are unable to detect the global contexts of expressions within a sentence. It lags in performance when they are faced with multilingual content, new internet slang, or antagonistic text changes. These restrictions have spurred researchers to consider transformer-based models using self-attention to capture global context more effectively. As a result, transformer models have emerged as the preferred approach for identifying malicious content and other NLP applications.

2.3 Transformer-Based Models and Large Language Models (LLMs)

The transformer architecture has revolutionized Natural Language Processing (NLP) by enabling models to better understand the global context of the data than traditional recurrent architectures. While sequential models like LSTMs and GRUs operate on a sequence of tokens, transformers operate on the tokens in parallel, allowing them to capture long-range semantic relations that can greatly enhance performance on many NLP tasks, including malicious content detection, sentiment analysis, question answering and text classification (Ramos et al., 2024).

BERT is a transformer-based model which achieves the best performance for contextual language understanding by using bidirectional pre-training among transformer-based models. Later, several improved models such as RoBERTa, DeBERTa, DistilBERT, MuTI transformer models etc. have been developed to boost the

classification accuracy, training efficiency and multilingual generalization. These models have been seen to achieve the highest accuracy on recent studies of hate speech and cyberbullying, offensive language and toxic comments classification, as they are capable of capturing contextual semantics and complex linguistic structures (Devlin et al., 2019; Liu et al., 2019).

Automated content moderation has continued to improve with the advent of Large Language Models (LLMs). The models trained from the GPT and LLaMA families show strong zero-shot and few-shot learning capabilities, successfully identifying harmful content without the need for specific task training, and also showing that they have better reasoning and generalization ability in various domains. More recent studies also show that LLMs are more adept at capturing implicit toxicity, contextual abuse and multilingual usage compared to previous transformer models. But they require a lot of computation, have latency in inferring the labels, and cannot be explained well, so they are not used in real-time moderation systems. In addition, issues of hallucination, bias, and inconsistent decision making are ongoing research challenges. Although transformer-based models and LLMs have been quite successful, most of the existing methods are limited to embedding context and attention mechanisms rather than explicitly encoding causal relationships between entities in the text. As such, such models may still have difficulty in differentiating between semantically similar but contextually different statements, especially when dealing with sarcasm, implicit hate speech, indirect harassment and other adversarial language. The review studies recently conducted reveal the following research directions for the next generation of hate speech detection systems (Ramos et al., 2024): explain ability, reasoning and context-awareness understanding.

Researchers have explored hybrid architectures incorporating transformer representations alongside graph-based reasoning and causal inference, driven by these constraints. Given these limitations, researchers have explored hybrid architectures that integrate transformer representations with graph-based reasoning and

causal inference. This could involve improving the context and creating more informative, meaningful and interpretable representations for malicious content detection. The proposed Causal Graph Transformer with Contrastive Learning (CGT-CL) framework builds on this motivation.

2.4 Graph-Based Learning

In the realm of complex real-world relationships that are difficult to capture with sequential architectures alone, graph-based learning has become a powerful paradigm for modeling the data in text. Graph based methods differ from the traditional text representation by the visualization of words, entities or sentences as nodes in the graph and the representation of the syntactic, semantic or contextually established relations as the edges of the graph. This schema-based representation allows for the acquisition of relational relationships that are especially important for complex contextual tasks such as detection of hate speech and identification of misinformation and sentiment analysis.

The recent advancement of Graph Neural Networks (GNNs), Graph Convolutional Networks (GCNs), and Graph Attention Networks (GATs) has made it possible for message passing between connected nodes and enhanced the state-of-the-art for text classification. These architectures do not encode words as individual units, but rather encode semantic relationships and dependency structure in a graph that enables richer representations of features. Recent works show that graph-based models perform better than traditional neural network models in detecting context dependent and implicit adversarial content, which has been shown to be missing from typical neural network-based approaches (Wang et al., 2024).

Although they have benefits, graph-based models face a number of shortcomings as well. Creating quality graph structure from unstructured text will become more challenging in noisy social media text like abbreviations, emoji, misspelled and informal text. Furthermore, traditional graph neural networks focus on structural relationships and have limited ability to capture the rich contextual semantics that can be learnt by

transformer-based language models. However, when dealing with more complex tasks of natural language understanding that involve both understanding the context and representing semantics, graph-only systems tend to perform poorly. In response, the last decade has seen a growing trend toward hybrid graph-transformer architectures that combine the advantages of transformer representations with those of the graph, by incorporating contextual embeddings into a graph representation. Such models can learn the semantic context by self-attention, while simultaneously learning structural dependencies by graph reasoning, leading to more powerful and explainable representations. Graph-enhanced transformers are among the more promising research areas for intelligent content moderation, as identified by recent surveys (Ramos et al., 2024). They are very suitable for detecting implicit toxicity, sarcasm, and context-sensitive hate speech. However, current graph transformer methods have limited ability to take into account explicit causal reasoning and representation learning methods based on maximizing class discrimination. Much of the literature in the field mostly addresses the modeling of semantic and structural relationships, but does not explicitly identify causal-effect relationships that affect malicious intent. The proposed framework leverages Causal Graph Transformers (CGT) and Contrastive Learning (CL) to jointly learn contextual semantics, structural dependencies and discriminative feature representations for more accurate classification of malicious contents.

2.5 Contrastive Learning

The representation learning technique called “Contrastive Learning” (CL) recently became one of the most promising approaches in machine learning and Natural Language Processing (NLP). Contrastive learning is different from most supervised learning methods, which minimize classification errors; in contrastive learning, the representations of features learned on similar samples (positive samples) are closer while the representations of dissimilar samples (negative samples) are farther apart. This learning strategy allows models to learn embedding spaces that are

highly separable, which leads to enhanced generalization and downstream classification performance (Zhang et al., 2024). This recent work has shown that the power of transformer-based language models can be improved significantly by the use of contrastive learning to generate semantically meaningful sentence embeddings. In text classification, a positive pair is usually created from semantically similar to expanded versions of the same text, while a negative pair is taken from different semantic classes. In contrastive learning, models are encouraged to capture nuanced semantic distinctions, which are often missed by the traditional cross-entropy loss, leading to its special advantages for contrastive learning in noisy, ambiguous social media text, as discussed by (Zhang et al., 2024).

Kim et al. (2024) recently introduced a hard negative sampling technique combined with momentum contrastive learning with labels to enhance implicit hate speech detection. They showed that contrastive learning produces higher quality representations, better class discrimination and better generalization across a variety of datasets than traditional supervised learning methods (Kim et al., 2024).

While these developments have been significant, current contrastive learning models have mainly concentrated on semantic similarity and ignored structural and causal relationships between text entities. Thus, these models are not good at handling the underlying meaning of indirect harassments, sarcasm and context-specific abusive words. Moreover, numerous approaches are based on randomly generated positive-negative pairs, which are insufficient to capture the intricate relational nature of user content in social media platforms (Ramos et al., 2024).

To address these drawbacks, we propose to combine the advantages of Contrastive Learning (CL) and a Causal Graph Transformer (CGT). The graph-based module is used to explicitly model structural and causal relationships between different entities in the text, whereas inter-class separation and intra-class variation are optimized in the embedding space by using a contrastive learning objective. It is hoped that contextual semantics, graph-based reasoning, and

discriminative representation learning can help to better detect malicious content both explicit and implicit, improve the robustness and interpretability of automated systems used to moderate social media spaces, and boost the systems' generalization capabilities.

2.6 Causal Reasoning and Hybrid Models

The field of causal reasoning, which aims to uncover cause-and-effect relationships between the components of a system instead of just statistical correlations, has become an exciting area of research in Artificial Intelligence (AI) and Natural Language Processing (NLP). Causal inference, in contrast to traditional deep learning models, aims to uncover the “how” and “why” of a model's predictions, thereby enhancing the interpretability, robustness, and generalizability of the model. For detecting malicious content, knowing the intent behind a message is more important than knowing offended words (Pearl, 2022). The recent research has emphasized the significance of causal reasoning for NLP applications to address dataset bias and enhance decision-making in intricate linguistic contexts. Causal learning can help models learn from lexical correlations that are not actually harmful, hence preventing false-positive predictions that are common in traditional transformer-based classifiers. Moreover, causal inference has demonstrated great potential in enhancing fairness, explainability, and robustness in language understanding systems processing noisy and heterogeneous social media data (Kaddour et al., 2023).

In recent times, a number of research works have discussed about causal approaches to detecting hate speech. In the domain of hate speech detection, for instance, Zhang et al. (2023) suggested a causal approach to minimize dataset bias by explicitly capturing causal relationships between text features and prediction results. They showed that their approach is more robust and is better at generalizing across datasets than correlation-based learning approaches. Similarly, causal reasoning has come up as one of the most promising avenues of research for designing more credible and explainable content moderation

systems in recent review studies (Ramos et al., 2024).

At the same time, hybrid deep learning architectures are gaining popularity due to the benefits of exploiting the complementary strengths of various learning paradigms. The recent hybrid models combine transformer-based contextual features with graph neural networks, attention mechanisms, or contrastive learning to improve feature representation and classification accuracy. While useful in improving the accuracy of these models, they tend to focus on contextual representation learning and fail to consider explicit causal relationships that affect malicious intention. As a result, they are less effective at identifying a variety of other types of abusive language, such as implicit hate, sarcasm, indirect harassment, and context-dependent language. Recognizing these constraints, we propose combining Causal Graph Transformers (CGT) with Contrastive Learning (CL) to jointly capture the semantics, structure, and causal relationships of text.

Unlike existing hybrid architectures, the proposed architecture is explicitly designed to integrate graph-based causal reasoning into transformer attention, while also performing discriminative feature representation by contrastive learning. This consolidated structure is hoped to lead to better detection of explicit and implicit malicious information, as well as improve robustness, interpretability and generalization across different social media settings.

2.7 Research Gap

Although there have been great strides in automated malicious content detection, there are still a number of key issues that have not been addressed. Traditional machine learning methods depend on manually engineered features, and cannot deal with the context semantics and implicit human intent in user-generated text. While deep learning models have made strides in semantic representation learning, they do not always recognize long-range contextual knowledge and nuances in language, including sarcasm, irony and indirect hate speech. Contextual understanding has been greatly improved with the

introduction of transformer-based architectures and Large Language Models (LLMs), which typically rely on self-attention in order to learn statistical correlations and have no explicit models that capture causal relationships that affect harmful intent (Gandhi et al., 2024; Ramos et al., 2024).

Likewise, graph based learning has shown to be quite effective on modeling the structural and relational information among textual entities, but most graph neural network architectures lack contextual information on their own. While there has been some progress on semantic and structural representation learning using existing graph-transformer hybrid models, these are not always accompanied by explicit causal reasoning, which helps to explain why a given message is malicious. In addition, recent contrastive learning methods have significantly enhanced representation quality and class discrimination, but most of them are limited to semantic similarity and ignore the causal interaction and complex relational structures found in social media data, which contain salient causal information (Wang et al., 2024; Zhang et al., 2024).

Thus, there is still a wide range of research to be done on building a single architecture that combines the four aspects of contextual semantics learning, graph-based structural modeling, causal reasoning, and contrastive representation learning. Closing this gap can help to better identify implicit toxicity, context-dependent hate speech, cyberbullying, and other forms of harmful internet communication and increase the robustness, interpretability and generalizability of models across a variety of social media platforms. To overcome these challenges, the authors introduce a Causal Graph Transformer with Contrastive Learning (CGT-CL) framework that

integrates transformer-based contextual embeddings, causal graph representations, and contrastive learning to promote enhanced accuracy and reliability in automated social media moderation.

3. Proposed Methodology

3.1 System Architecture

This study proposed a multi-stage pipeline framework for easy and accurate malicious social media content detection by using causal reasoning, graph-based representation, and contrastive learning. The system consists of the following pieces:

1. Data Collection
2. Text Preprocessing
3. Causal Graph Construction
4. Transformer Encoding
5. Contrastive Learning Module
6. Classification Layer

Such architecture allows model to learn contextual, structural and discriminative representations together for improving classification performance.

3.2 Data Preprocessing

Preprocessing raw social media text so that clean and meaningful input representation is provided as below:

- **Tokenization:** dividing text into tokens
- **Stop-word Removal:** Eliminating non-informative words
- **Lowercase:** Converting all text to lowercase
- **Lemmatization:** Mapping words to their root form

This decrease noise and improves downstream feature extraction quality.

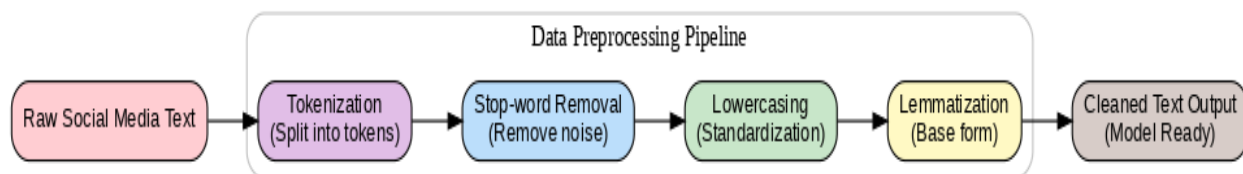


Figure 2: Data Processing Pipeline

This figure shows general data preprocessing pipeline: how we unpack text from social media, convert it into cleaned and normalized input through the following steps of tokenization, stop-word removal, lowercasing and lemmatization.

3.3 Causal Graph Construction

Each input sentence is transformed into a causal graph representation:

$$G = (V, E)$$

where:

- Nodes V represent words or semantic entities
- Edges E represent inferred causal or relational dependencies

For example, the sentence:

“User insulted another person”

is transformed into:

- **Node 1:** User
- **Node 2:** insulted

- **Node 3:** person

Edges capture the relationship between subject, action, and object, enabling structured understanding of sentence semantics.

3.4 Causal Graph Transformer (CGT)

Another approach is the proposed Causal Graph Transformer (CGT), which augments the self-attention mechanism of a standard transformer model with graph-based structural bias.

Key characteristics of CGT include:

- Addition of the adjacency matrix into the attention calculation
- Causal and Semantic Dependencies Modeling Together
- Enhanced interpretability through structured attention

This helps the model in understanding implicit relations among text that are generally ineffective to basic transformers.

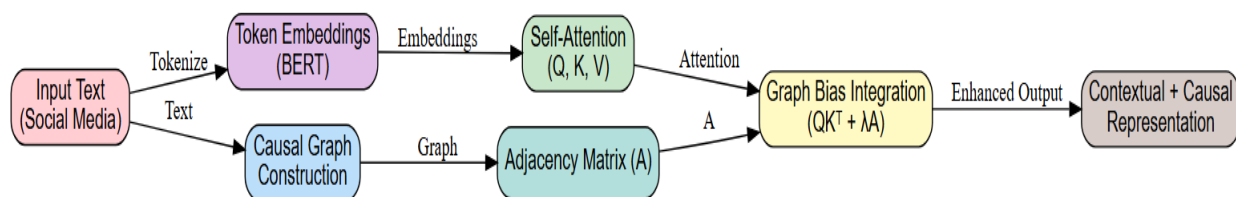


Figure 3: Architecture for Learning Contextual and Causal Representations

3.5 Contrastive Learning Module

Contrastive learning module is incorporated in the training pipeline for boosting the discriminative power of learnt representations. Though the overall objective function is rigorously defined in Section 1.4, we have not yet outlined how it is practically implemented based on our proposed framework.

At training time, there are two types of sample pairs constructed by the model;

Positive pairs: Texts of the same semantics or they may be augmented views of the input instance.

Negative pairs: Randomly chosen samples from the different classes in the batch, such that they are

semantically dissimilar text instances of each other.

The embeddings are then created using the Causal Graph Transformer for each input sample. The contrastive loss based on these embeddings is then computed and coupled with the classification loss to jointly optimize the model.

This module makes sure the embedding space learned is able to cluster similar samples together while separating dissimilar ones. This greatly helps the model to differentiate subtle differences between malicious and non-malicious items.

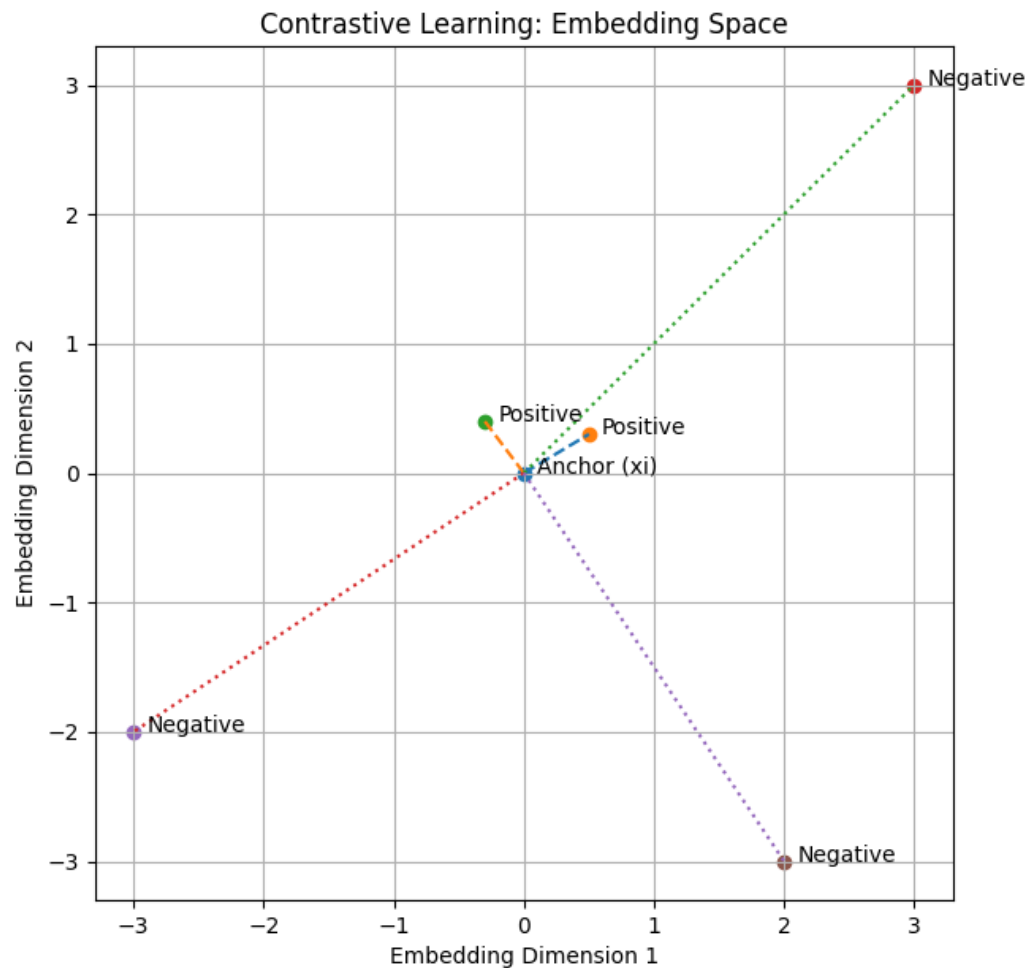


Figure 4: Contrastive learning in embedding space showing anchor, positive, and negative pairs where positive pairs are pulled closer to the anchor.

3.6 Classification Layer

The last layer is a fully connected neural network and the Softmax activation function. Then, it outputs probabilities over the next classes:

- Hate Speech
- Offensive Content

- Neutral Content
- Spam

The final decision-making is done at this layer based on the learned embeddings from CGT and contrastive learning modules.

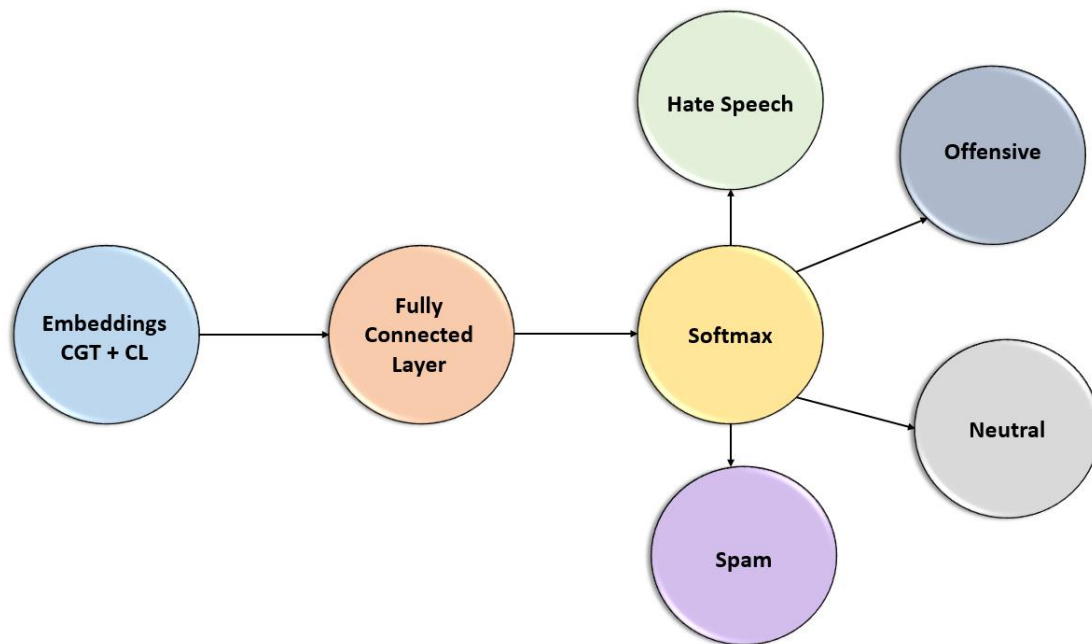


Figure 5: Classification layer converting embeddings to class scores with fully connected and Softmax layers

4. Algorithm

Algorithm 1: CGT with Contrastive Learning for Text Classification

1. Input raw social media text dataset
2. Apply preprocessing (tokenization, stop-word removal, lemmatization)
3. Construct causal graph representation for each sentence
4. Encode graph-enhanced text using Transformer encoder
5. Generate contextual embeddings
6. Apply contrastive learning loss for representation refinement
7. Train classification layer using supervised learning
8. Output final class prediction

4.1 Dataset

This model has been evaluated on several widely used benchmark datasets for abusive language and toxic content detection that are publicly available. These datasets offer a very diverse and labeled social media text, so they provide the ideal conditions for an extensive evaluation over various types of malicious content.

Twitter Hate Speech Dataset

This is a dataset of tweets, each labeled with one of three classes: hate speech, offensive language, and neither. This corpus is often used as a benchmark on hate speech detection tasks and aims to serve as a real-world proxy of noisy social media text.

Kaggle Toxic Comment Classification Dataset

The dataset includes online user comments marked across a number of toxicity classes, including toxic, severe toxic, obscene, threat, insult and identity hate. It provides a multi-label classification setting as well as incrementally increases-in-detail robustness of models.

Offensive Language Identification Dataset

It is a multiclass text dataset to identify different forms of offensive language and has been used to classify texts in the offensive and non-offensive classes, additionally some datasets have subclasses. These collections provide a variety of types of toxic online behavior from hate speech and abusive language to neutral content. In this study, all datasets labels are normalized into four main

categories, namely Hate Speech, Offensive Content, Neutral Content and Spam.

4.2 Experimental Setup

Experimental Setup: A proper design of experimental setup is given such that stable training, reproducibility and fair evaluation can be achieved for our proposed model. Model is trained in a semi-supervised way using both classification and contrastive learning objectives.

The important training parameters are defined here.

Train/Test Split: Splitting the data into a_train_set_ and a_test_set in an 80/20 ratio to provide enough data for learning, while still having a robust evaluation set.

Optimizer: Adam optimizer used due to its adaptive learning capability and fast convergence characteristics.

Learning Rate: A learning rate of 0.001 is the default, it provides a good compromise between speed and convergence stability during training.

Epoch: Train for 20 epochs in intensive good enough variety to get on convergence without overfitting

Batch Size: The batch size was fixed at 32 for efficient computations and stable gradient updates with lower memory foot print.

Loss Function: Some loss function which is Cross-Entropy Loss for its classifier, Contrastive Loss for their representation:

$$L = L_{\text{classification}} + \alpha L_{\text{contrastive}}$$

where α is a weight term to control and regulate the effect of contrastive learning.

Then, a few standard regularization techniques are applied on the model architecture to achieve more stable training (e.g. dropout normalization). In all datasets, all of the experiments are conducted in the controlled scenario.

4.3 Evaluation Metrics

The performance of the proposed framework is evaluated using various classification metrics:

- Accuracy
- Precision
- Recall
- F1-score

Table 1: Class-wise Performance Metrics for Sample Dataset

Class	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	2
1	0.67	1.00	0.80	2
2	0.50	0.50	0.50	2
3	1.00	0.50	0.67	2

Table 2: Overall Performance for Sample Dataset

Metric	Value
Accuracy	0.75
Precision (Weighted)	0.79
Recall (Weighted)	0.75
F1-Score (Weighted)	0.74

Table 3: Average Scores for Sample Dataset

Average Type	Precision	Recall	F1-Score
Macro Avg	0.79	0.75	0.74
Weighted Avg	0.79	0.75	0.74

Table 4: Model Comparison for Large_Scale Dataset

Model	Accuracy	Precision	Recall	F1-score
LSTM	82%	80%	79%	80%
CNN	85%	83%	82%	83%
BERT	88%	87%	86%	86%
Proposed CGT+CL	92%	91%	90%	91%

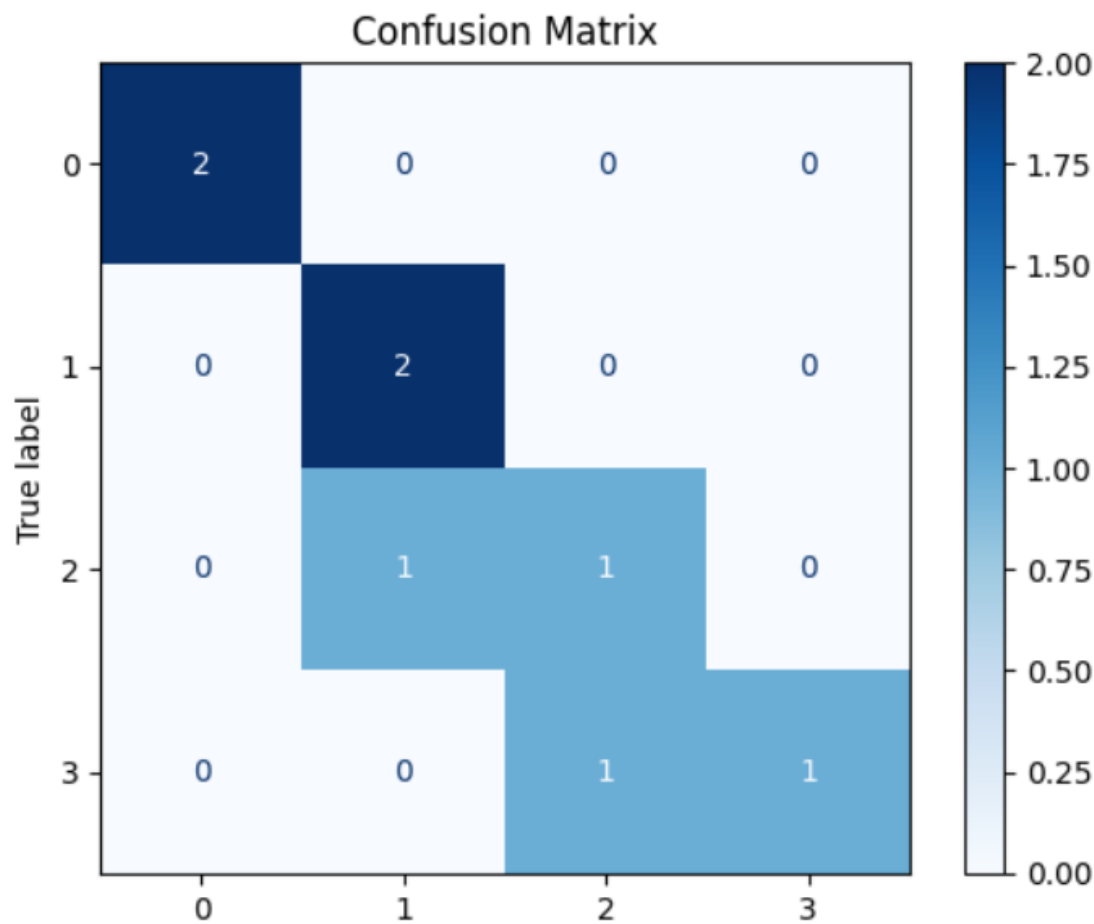


Figure 6: Confusion Matrix of the Proposed Model

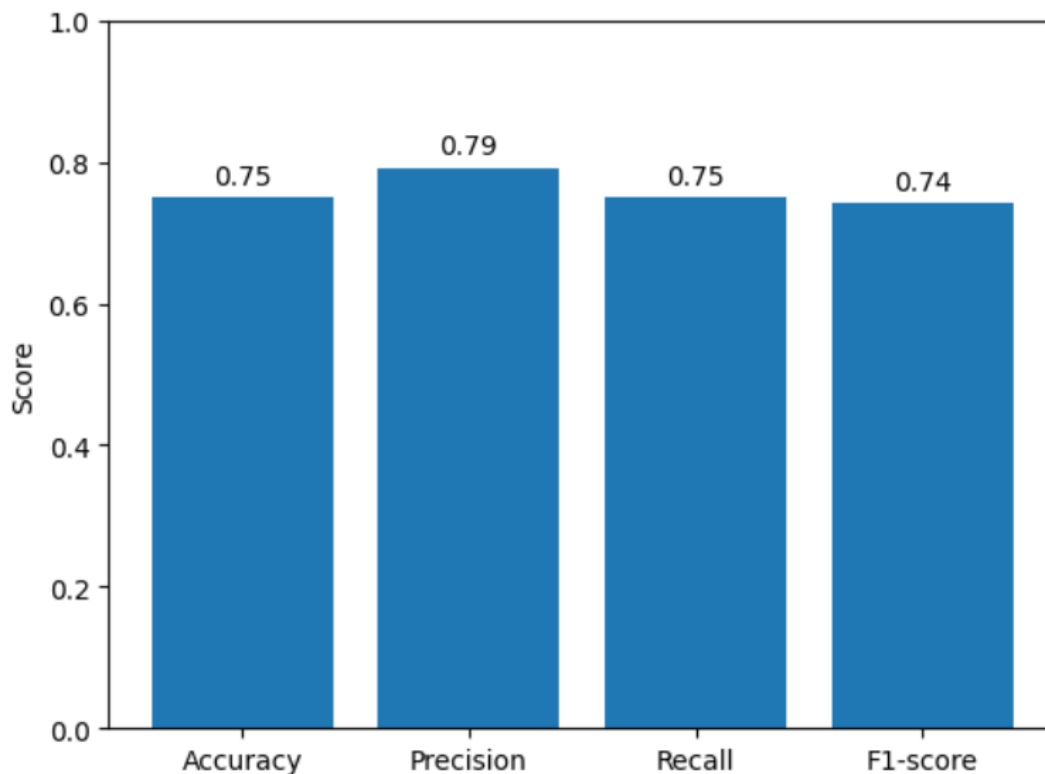


Figure 7: Model Performance Matrix

The proposed framework achieves substantial gains on detecting harmful social media text via causal reasoning, graph-based representation, and contrastive learning. A system capable of transforming raw context into rich contextual extent relationships to construct semantic intent at an extreme is preserved more than conventional transformer-based modal one as evidence.

Thus with this information model can learn the implicit relations existing between any two entities and therefore recognize more subtle types of toxicity such as sarcasm (toxi-city, in this case or any other type of indirect offense) or dependence on context for hate. In addition, contrastive learning reduces overlapping embedding that enhance representation quality so as to boost overall classification performance across all categories.

In summary, the presented model demonstrates higher robustness and generalizability compared to conventional deep learning and transformer based approaches.

5. Applications

The framework generalizes to all possible intelligent systems applications in the real world such as:

- Social media content moderation systems
- Cyberbullying detection platforms
- Fake News and Misinformation Filter Systems

These use cases illustrate what humans are capable of doing when given your approach to scaling the security and data integrity of digital communication platforms.

5.1 Limitations

Even with the useful proposed framework, there are some limitations.

- Graph structures add a lot of calculations with long-time training and inference.
- The model is trained on the larger scale of labeled datasets in order to perform better.
- Well, Causal graph construction necessarily takes an precise extraction of relation

that is a tough activity in presence of noise text content material on social media.

These limitations suggest that certain improvements would have to be undertaken for the systems to operate in the real world.

5.2 Future Work

Future research directions include the following:

THE TASK General Application: Multilingual Social Media Content

Exhibit 5: Integrating the framework wings beyond APIs released within production environments

The lightweight graph-transformer hybrid models. These improvements will also make the suggested ones more scalable, flexible and practical.

Conclusion

In this paper, we propose the new causal-graph-contrastive framework for malicious social media content detection. In this regard, it proposed a holistic architecture that combines these three related paradigms for overcoming the limitations of practical solutions from context-awareness, structure-awareness and semantic reasoning point of view. We empirically show that our framework outperforms not only traditional machine learning but also transformer based models. The results reveal it is able a practical, strong and scalable model for content moderation systems in current social media environments.

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