A Graph-Based Context-Aware Model to Understand Online Conversations

VIBHOR AGARWAL, University of Surrey, UK
ANTHONY P. YOUNG and SAGAR JOGLEKAR, King’s College London, UK
NISHANTH SASTRY, University of Surrey, UK

Online forums that allow for participatory engagement between users have been transformative for the public discussion of many important issues. However, such conversations can sometimes escalate into full-blown exchanges of hate and misinformation. Existing approaches in natural language processing (NLP), such as deep learning models for classification tasks, use as inputs only a single comment or a pair of comments depending upon whether the task concerns the inference of properties of the individual comments or the replies between pairs of comments, respectively. However, in online conversations, comments and replies may be based on external context beyond the immediately relevant information that is input to the model. Therefore, being aware of the conversations’ surrounding contexts should improve the model’s performance for the inference task at hand.

We propose **GraphNLI**, a novel graph-based deep learning architecture that uses graph walks to incorporate the wider context of a conversation in a principled manner. Specifically, a graph walk starts from a given comment and samples “nearby” comments in the same or parallel conversation threads, which results in additional embeddings that are aggregated together with the initial comment’s embedding. We then use these enriched embeddings for downstream NLP prediction tasks that are important for online conversations. We evaluate GraphNLI on two such tasks - **polarity prediction** and **misogynistic hate speech detection** - and find that our model consistently outperforms all relevant baselines for both tasks. Specifically, GraphNLI with a biased root-seeking random walk performs with a macro-$F_1$ score of 3 and 6 percentage points better than the best-performing BERT-based baselines for the polarity prediction and hate speech detection tasks, respectively. We also perform extensive ablative experiments and hyperparameter searches to understand the efficacy of GraphNLI. This demonstrates the potential of context-aware models to capture the global context along with the local context of online conversations for these two tasks.

CCS Concepts: • Computing methodologies → Natural language processing; Machine learning algorithms; Model development and analysis; Information extraction; • Information systems → World Wide Web;

Additional Key Words and Phrases: Online conversations, graph walks, polarity prediction, hate speech detection, Reddit, Kialo

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Authors’ addresses: V. Agarwal and N. Sastry, Department of Computer Science, University of Surrey, Guildford, Surrey, UK, GU2 7XH; e-mails: {v.agarwal, n.sastry}@surrey.ac.uk; A. P. Young and S. Joglekar, Department of Informatics, Bush House, Strand Campus, King’s College London, London, UK, WC2B 4BG; e-mails: {peter.young, sagar.joglekar}@kcl.ac.uk. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org. © 2023 Copyright held by the owner/author(s). Publication rights licensed to ACM.

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1 INTRODUCTION

The Internet has empowered people to take part in sharing their views and debating about many topics online, often as written comments or posts that argue for some claim. Such online debates can often become large and acrimonious, with some escalating into full-blown exchanges of hate and misinformation. As many of these debates concern topics of societal importance, such as health and politics, it is crucial to be able to model these debates accurately and at scale so that we can better understand and control for phenomena such as the spread of hate, fake news, how best to moderate political polarisation, and how to break echo chambers by connecting appropriate users who possess opposing views about the same issue.

An important task in modelling online debates is to be able to predict whether the reply of one comment to another is attacking (disagreeing) or supporting the comment it is replying to. This relation of agreement (support) or disagreement (attack) of a reply is known as its polarity, and we call the task of predicting this relation the polarity prediction task. The ability to accurately infer the polarity of replies in a large online debate can allow us to measure various properties of the debate, such as how “controversial” a discussion is, e.g., by counting the total number of supporting vs. attacking replies in the discussion, or model the “controversy” generated by each comment as the ratio of attacking to supporting replies to that comment. Perhaps more importantly, if the polarity is known, we can then use techniques from argumentation theory, a branch of artificial intelligence concerned with the formal representation and resolution of disagreements, to compute which arguments have been attacked and should be rebutted versus which ones stand unrebuted and thus should be believed.

Another important task in modelling online conversations is to infer whether the text of individual comments contain hate speech; we call this the hate speech detection task. Hate speech, informally defined, is public speech that incites negativity, hatred, and even violence against an individual or groups of people for reasons solely based on perceived group-level and stereotypical attributes such as sex, sexual orientation, race, nationality, religion, and political beliefs. Hate speech, if left unchallenged, can normalise unhealthy attitudes towards groups of people, divide societies, and cause real harm to individuals. Automatically and accurately identifying whether a piece of text contains hate speech at scale is highly non-trivial given the many ways hate speech can and should be operationalised in a precise way while maintaining an awareness to the relevant historical, conceptual, and ethical issues arising, in addition to the relative lack of good annotated data. If a model can be trained to accurately identify hate speech, then we can study effects such as how the proportion of comments posted to online debates that contain hate speech can change over time or whether moderation policies can be successful at encouraging and targeting the refutation of hate speech through subsequent comments submitted.

Polarity prediction and hate speech detection are examples of common tasks that are approached by applying natural language processing (NLP) techniques. NLP models typically make their predictions based on the natural language texts of single comments or, at most, pairs of comments such as a reply and the post it is replying to. However, by considering the input comment(s) in isolation from the rest of the discussion, such approaches risk losing crucial information. For example, in a large discussion thread with many comments, one comment can easily be taken out of context and misunderstood as “hate”. Similarly, if two correspondents have been replying...
to each other across multiple posts in a discussion (e.g., user B replies to A and A then replies back to B), it is conceivable that an incorrect polarity may be inferred if one looks at only a reply and the immediate post it is replying to in isolation from the existing context.

In this article, we call the input comment(s) the **local** context for the tasks and comments beyond those inputs, for example, those contained in the same or parallel discussion threads, the **global** context. We ask and answer the question: **Can we improve the performance on both the polarity prediction and hate speech detection tasks by incorporating additional global context beyond the most relevant comments in the local context?**

Typically, an online discussion can be seen as a directed tree, starting with an original post — the root of the tree — and each reply b creates a directed edge to the node a it is replying to. The tree structure derives from the often-true property that every non-root comment can only reply to one other comment. For the polarity prediction task, we hypothesise that nodes “near” a and b, e.g., their descendants, ancestors, and siblings in the discussion tree, contain additional context that may help understand whether b is attacking or supporting a. For example, if other siblings of b (i.e., children of a other than b) are also attacking a, then it may be more likely that b is also an attacking reply. Similarly, for the hate speech detection task, we hypothesise that understanding posts “near” a can better predict whether a contains hate speech or not compared with just knowing a itself. Our key idea is to use graph walk techniques to discover and utilise this neighbouring context in a principled fashion.

**The contributions of this article are as follows:**

1. We define random walks on the discussion trees that sample additional “nearby” nodes of the global context in online discussions. These additional nodes, along with the local context, appropriately featurised and aggregated, will serve as the input to our model.
2. We present **GraphNLI** — a novel graph-based deep learning architecture that is capable of accurately predicting reply polarity and accurately detecting misogynistic hate speech. We provide an open-source implementation of the model for the community.
3. We compare and contrast several NLP models, including Sentence-BERT [52], to establish relevant baselines for both the polarity prediction and the misogynistic hate speech detection tasks. For the polarity prediction task, we will use data from Kialo [6] that has been used in prior work [5, 15, 62]. For the misogynistic hate speech detection task, we will use data from Reddit [7] that has been labelled by experts [31]. Both datasets are in the form of discussion trees where the nodes are comments submitted to the discussion and the edges denote which comments reply to which other comments.
4. After training GraphNLI, we find that our model outperforms all of these baselines in both tasks. Specifically, GraphNLI with a weighted average, biased root-seeking random walk (see Section 3.2.1) classifies polarity with an accuracy of 82.95% and 78.96% macro-$F_1$ on the test set, while the best baseline, Sentence-BERT, has an accuracy of 79.86% and macro-$F_1$ of 75.81%. Further, GraphNLI with a weighted average, biased root-seeking random walk detects misogynistic hate speech with an accuracy of 93.18% and macro-$F_1$ of 74.79% on the test set, while the best baseline is BERT, which has an accuracy of 92.28% and macro-$F_1$ of

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2In the rest of this article, we will use the terms “comment”, “post”, “argument”, and “node” interchangeably. Further, we adopt the terminology that a “child” node points to (replies to) its “parent” node.

3We will briefly discuss non-tree debates in Section 7.

4“NLI” stands for “natural language inference” (see Section 2.1).

5The model code and the dataset is available at [https://netsys.surrey.ac.uk/datasets/graphnli/](https://netsys.surrey.ac.uk/datasets/graphnli/), last accessed 5 November 2022.

6See [https://www.kialo.com/](https://www.kialo.com/), last accessed 5 November 2022.

7See [https://www.reddit.com](https://www.reddit.com), last accessed 5 November 2022.
68.79%. These results suggest that knowing the context of online discussions does help with
the ability to classify whether a reply is supportive or attacking and whether the text of a
comment contains misogynistic hate speech.

(5) We also systematically investigate through ablation studies what features can be helpful in
capturing the wider context for both tasks and show that upstream text, the parent and other
ancestor nodes, help the model more than siblings and children replies. Moreover, we find
that in the best-performing versions of GraphNLI, the importance of neighbouring nodes
decreases as their distance from the given node increases. We also perform error analysis for
the hate speech detection task and show that GraphNLI gives less numbers of false positives
and false negatives due to the context-awareness of online conversations.

The rest of this article is structured as follows. Section 2 provides an overview of both the
polarity prediction and hate speech detection tasks. In Section 3, we will define and classify various
kinds of graph walks by the probability of the walk going “up” the tree towards the root and how
the contextual nodes captured are discounted. We will also define the architecture for GraphNLI.
In Section 4, we present an overview of the Kialo and Reddit datasets used to train and evaluate
GraphNLI. In Section 5, we explain how we train and evaluate different kinds of GraphNLI based on
their graph walks against various baselines for both tasks and show that GraphNLI outperforms
all baselines. We also discuss hyperparameter searches and conduct an ablation study to better
understand which features are important. In Section 6, we perform error analysis and give an
example from the Reddit dataset in which hateful speech, which has been misidentified as non-
hate by BERT, is correctly identified by GraphNLI given the latter’s awareness of the conversation
context. We also provide an example of non-hate that has been misidentified as hate by BERT that
is correctly identified as non-hate by GraphNLI. We conclude and outline possible future works in
Section 7.

2 BACKGROUND

2.1 Polarity Prediction

Suppose we have an online debate that has the structure of a directed tree, where the set of nodes
A denotes the arguments submitted to the debate and the directed edges \( E \subseteq A \times A \) denote which
arguments reply to which other arguments. The tree structure means that, apart from the very
first argument submitted in the debate, each argument replies to exactly one other argument. The
polarity prediction task asks: for the argument \( b \) that is replying to the argument \( a \), is this reply
in agreement (support) or disagreement (attack)? Note that both of these categories are defined
commonsensically and not rigorously, such that (e.g.) an attack does not have to contain some
logical contradiction.

Example 2.1. Let \( a \) be the argument or thesis that “All humans should be vegan”. Let \( b \) be the
argument, “Veganism is a restrictive diet and is not a healthy lifestyle for many people”. Further,
let \( b \) reply to \( a \).\(^8\) Most English-speaking people who understand the statements of \( a \) and \( b \) should
agree that argument \( b \) disagrees with argument \( a \). Can a machine-learning model replicate such
predictions accurately and at scale?

The polarity prediction task is one of many in the field of argument mining (e.g., [18, 43, 44]).
This is the application of NLP techniques to extract arguments and identify their relationships from
raw text. Other example tasks include identifying when tweets from Twitter are well-defined ar-
guments instead of insults, single URLs or pictures [14], identifying the claims, their reasons and

\(^8\)This example is taken from https://www.kialo.com/all-humans-should-be-vegan-2762, last accessed 5 November 2022.
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Fig. 1. The bipolar argumentation framework in Example 2.2 visualised. The broken (red) arrows denote attacks and the solid (green) arrows denote supports.

the relationships between these claims from clinical trials to inform medical decision making [48], or detecting fallacies from the transcripts of the United States Presidential Debates [56]. The polarity prediction task is important because once we have classified all replies in a debate as either supporting or attacking, we can apply ideas from argumentation theory to reason about which arguments should be justified given the information presented. Argumentation theory is a branch of AI that is concerned with the transparent and rational resolution of disagreements (e.g., [51]). Formally, online debates as described above can be represented as a bipolar argumentation framework (BAF) (e.g., [19]), which is a triple \( (A, R_{\text{att}}, R_{\text{sup}}) \) where \( A \) is the set of arguments submitted in the debate, \( R_{\text{att}} \subseteq A^2 \) is the set of edges that are attacking, and \( R_{\text{sup}} \subseteq A^2 \) is the set of edges that are supporting. It is required that \( R_{\text{sup}} \cap R_{\text{att}} = \emptyset \). Resolving the disagreements formally amounts to selecting a subset of arguments \( S \subseteq A \) that satisfy various normative criteria (e.g., [9, 28, 63]). For example, the property of conflict-freeness, \( (S \times S) \cap R_{\text{att}} = \emptyset \), formalises the idea of self-consistency because winning arguments should not attack each other.

Example 2.2. (Example 2.1 continued) Let argument \( c \) be, “It is often necessary for a vegan diet to include supplements, as it lacks specific essential nutrients”.

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Let argument \( d \) be, “Research results suggest that no significant vitamins or minerals deficiencies affect the vegan population compared to non vegans”.

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We have argument \( c \) supporting argument \( b \) (from Example 2.1), and argument \( d \) attacking argument \( c \). Suppose that these arguments are all there is of interest, then the corresponding BAF is \( A = \{a, b, c, d\}, R_{\text{sup}} = \{(c, b)\} \) and \( R_{\text{att}} = \{(b, a), (d, c)\} \). We can visualise this BAF in Figure 1.

Many other kinds of analyses can be performed once a debate has been represented as a BAF. For instance, based on the polarities of the edges, we may calculate which arguments should be justified and which arguments have been rebutted. This could potentially be used to present only the justified arguments as summary to a reader. Previous work has also looked at how the conclusions of idealised readers can change depending on which parts of a debate they read, thus underscoring the dangers of sampling only parts of a large online debate [60, 62, 63]. Other work has shown how the location of the justified arguments can be significantly influenced by whether the debate is acrimonious or supporting [15, 61]. BAFs are therefore useful as they allow for the application of both argument-theoretic and graph-theoretic ideas to gain insights about online discussions [61].

The polarity prediction task has been discussed in the argument mining literature. For example, [18] has reviewed the task in the context of persuasive essays or political debates. An early example of this work is [17], which applied textual entailment (e.g., [13, 25, 41, 47]) to predict the polarity of replies on the now-defunct Debatepedia dataset, with a test accuracy of 67%. Textual entailment is the task of identifying the relationship between an ordered pair of texts, specifically whether

9From https://www.kialo.com/it-is-often-necessary-for-a-vegan-diet-to-include-supplements-as-it-lacks-specific-essential-nutrients-2762.502?path=2762.0 2762.1 2762.11731_2762.502, last accessed 5 November 2022.

10From https://www.kialo.com/research-results-suggest-that-no-significant-vitamins-or-minerals-deficiencies-affect-the-vegan-population-compared-to-2762.1066?path=2762.0 2762.1 2762.11731_2762.502-2762.1066, last accessed 5 November 2022.

11This is archived in http://web.archive.org/web/20201008080532/http://www.debatepedia.org/en/index.php/Welcome_to_Debatepedia%21, last accessed 5 November 2022.
the first entails the second, contradicts the second, or is neutral, and is also called natural language inference. \footnote{See, e.g., https://nlp.stanford.edu/projects/snli/, last accessed 4 November 2022; our framework is named GraphNLI as it was first designed for polarity prediction, which is conceptually similar to textual entailment.} In \cite{liu2015}, long short-term memory networks were used to classify polarity, achieving 89\% accuracy. \footnote{Although this shows better results on the polarity prediction task than what we report in Section 5, neither their data nor their framework were available for benchmarking.} A more recent overview of the polarity prediction task \cite{reeves2018} has provided context-independent baselines of neural network models using a range of learning representations and architectures, finding an averaged performance of 51\% to 55\% of these different neural networks across such contexts. These contexts involve online debates on a range of controversial topics such as abortion and gun rights, persuasive essays, and presidential debates.

In all of the above-mentioned approaches, the inputs to the model are the texts of the replying argument and the argument being replied to, often represented by some appropriate word embedding. Arguably, this is the least amount of information one must input into the model to predict the polarity of the reply. What has not yet been considered is whether it is helpful to incorporate more information. Naively, one can input the entire conversation network into the model, although this is easily intractable when the sizes of such conversation networks are large. But suppose we were to add more context in an incremental fashion. For example, if argument \( c \) replies to argument \( b \), and \( b \) replies to argument \( a \), and we would like to predict the polarity of the reply from \( c \) to \( b \), then is it useful to design a model that accepts the inputs of \( c, b, \) and \( a \) to predict the polarity of the reply from \( c \) to \( b \)? How about if we randomly \footnote{“Randomly” in a well-defined sense; see Sections 3.2.1 and 3.2.2.} sample additional “nearby” comments to build up a context? To the best of our knowledge, these questions have not yet been addressed in the argument mining literature. We thus seek to investigate these questions by measuring whether models that incorporate additional context in online conversations outperform models that are not aware of this extra information on the polarity prediction task.

2.2 Hate Speech Detection

As mentioned in Section 1, Internet debates, especially those about controversial topics, can easily spread hate and misinformation. One reason is that many people, with a range of personalities and behavioural dispositions, can easily access the Internet and participate in various online forums or microblogging services. The relative anonymity the Internet offers can encourage some people to behave in ways that are unacceptable in the offline world, often resulting in the spread of hate speech \cite{doddridge2012,doddridge2016,goodwin2020,goodwin2015,kovacs2020}.

Hate speech is notoriously difficult to define. A sample of important attempted definitions (e.g., \cite[Section 2.1]{goodwin2015}) all agree that hate speech is public language that attacks individuals and groups of people because of protected characteristics, for example, their race, skin colour, religion, ancestry, nationality, gender, disability, sexuality, and so on. Hate speech, if left unchallenged, can promote and incite harmful societal consequences against individuals and groups such as (but not limited to) physical attacks, psychological intimidation, property damage, violence, and segregation. Therefore, it is important to at least be able to detect hate speech in online forums, accurately and at scale, such that appropriate action can be taken by the moderators, which can range from banning people who continuously send unambiguously hateful messages or encouraging more moderate users on how to publicly refute such arguments in a civil and transparent manner.

How can we detect hate speech in a scalable and accurate manner? If there exists an expertly annotated textual dataset that clearly denotes and explains which texts are examples of hate speech,
then we can use it to train various NLP models to classify and even explain whether a piece of text contains hate or not. However, this brings us back to our initial problem: how should hate speech be defined in a manner that is sensitive to the relevant historical, conceptual, and ethical issues that arise, and is untainted by ideology of the kind that seeks to silence opposing viewpoints by deliberately taking things out of context? Further, how should such a definition inform the labelling of data, especially data from online discussions?

Example 2.3. Consider the Reddit conversation in Figure 2. The rectangular text boxes represent posts submitted to this particular Reddit discussion, and the arrows denote which posts reply to which other posts. Suppose we wish to identify whether the text in the box with the thicker border (bottom left) contains hate speech. This text states, “Not if you are a woman it seems. Sad.” At first glance, this text appears to mention something about women and as such does not appear to be hate speech. Indeed, it could even seem like a post sympathetic to the difficulties or biases that women may encounter. However, considering the context of the surrounding comments in the thread, it is clear that the post is a derogatory statement about women, claiming that they are not as equally sentenced as men. Therefore, the post is an instance of misogyny. Most hate speech and misogyny models are currently unable to capture this nuance without any conversational context.

Examples like this demonstrate that although hate exists and should be dealt with accordingly, the accurate detection of hate speech is very important as speech misunderstood as hateful or not hateful can have real consequences in the offline world. Further, the real risk of people taking things out of context motivates the application of a similar technique to improving the polarity prediction task as discussed in Section 2.1: can hate speech models be improved by systematically incorporating the surrounding context in online conversations?

To begin to answer this question, we build on the recent work of Guest et al. [31], which is concerned with misogynistic speech in Reddit. Their contributions include a high-quality, expert-labelled dataset from various Reddit communities based on a clear taxonomy of misogynistic speech [31, Section 4]. Each of these labels have been checked by an average of three annotators. Further, three baseline classifiers were offered: logistic regression, unweighted BERT, and weighted BERT, with respective $F_1$ scores of 0.13, 0.42, and 0.43 [31, Section 7 and Appendix C] when classifying individual Reddit posts for misogyny on the basis of their text. This work therefore provides a clean dataset of misogynistic speech and several classifier baselines to improve upon. The work by Schmidt and Wiegand [53] provides a survey on various hate speech detection techniques using NLP. More recent work [7] proposes using the replies and title of the discussions as additional context for hate speech detection. However, this still does not include wider conversational context from up the discussion thread, which we find to be important. Other works [10] use
graph neural networks [34, 39, 55, 57] for hate speech detection in social media. The authors of [39] specifically use Graph Convolutional Networks (GCNs), which we use as one of the baselines. Like Kialo, Reddit discussions have an explicit reply tree structure. This allows us to incorporate context by incrementally and systematically including more “nearby” comments by aggregating their word embeddings with the embedding of the node to be classified as whether it contains misogynistic speech or not. We ask whether this incorporation of additional context helps misogynistic hate speech models better detect online hate speech.

3 METHODOLOGY

As stated in Sections 1 and 2, various deep learning models have been used in the literature to perform NLP classification tasks concerning online conversations. Depending on the task and model, most approaches usually consider either a single comment to be classified or take a pair of comments such as a reply and the post it is replying to. In this section, we propose a novel graph-based deep learning architecture that not only considers as input the single comment or the pair of comments but also systematically captures the context of nearby comments via graph walks.

3.1 Representing Online Discussions as Trees

For every online discussion \( D \), we construct a discussion tree, where a node represents a post / comment / argument and the edges are directed from a given node to the other unique node it is replying to. The discussion forms a tree structure because it starts with a root node (out-degree = 0), and every non-root node replies to exactly one other node (out-degree = 1), while all nodes can have zero or more replies to it (in-degree \( \in \mathbb{N} \)). Each such node has an associated label depending on the prediction task. For polarity prediction, the non-root nodes are labelled with support or attack, depending on whether the post is respectively for or against its parent post. For misogynistic hate speech, each node is labelled as either hate or non-hate. The root node of this discussion tree represents the opening comment or post of the discussion. Every non-root node replies to exactly one other node in the tree.

3.2 GraphNLI Architecture

In this subsection, we define different kinds of graph walks and explain how they (probabilistically) sample neighbouring nodes to feed in the global context into our classifier. Further, distant nodes can have their influences discounted by some appropriate discount factor (as a multiplicative factor to their word embeddings). We then provide the architecture of GraphNLI and explain how it makes inferences given the input discussion node (pairs) and their surrounding context as sampled from the graph walks.

3.2.1 Capturing Global Context through Graph Walks. GraphNLI captures the global context of online conversations through graph-based walks. A walk is defined as a finite sequence of nodes traversed from a given node in a tree such that each adjacent pair in the sequence is joined by an edge. In Section 3.1, we have stated that our trees are directed such that the edge directions denote which comments reply to which other comments. However, the walks we consider ignore the direction of the edges; traversal against the edge directions allows the capture of context such as the children or siblings (reachable by going up to the parent node and then back down again to the sibling) of the reply node. We define \( L \) to be the maximum number of distinct nodes sampled by a graph walk, including the starting node; then, the walk length is \((L – 1)\).

To sample the neighbouring nodes, we propose a biased root-seeking random walk. In a discussion tree, a biased root-seeking random walk starts from a given node and traverses other nodes probabilistically, but it is biased towards the root. This bias captures the intuition that the “best”
Fig. 3. The possible next node for a biased root-seeking random walk with $p = 0.75$, starting at $a_1$, from Example 3.1.

or most relevant context might be found in the sub-thread of replies leading from the root down to the node we are considering.

Recall that each non-root node replies to exactly one other node and each node has a non-negative number of nodes replying to it. Suppose we begin the walk on a non-root node $a_1$. Let $p \in [0, 1]$ be the probability that the next node traversed in the walk is the unique node that $a_1$ replies to. To bias the walk towards the root node, we choose $p \geq 0.5$. As we ignore the direction of edges in these walks, this allows the walk to traverse downwards as well as upwards in the tree. The remaining probability, $1 - p < 0.5$, is divided equally among all the children nodes replying to $a_1$. We illustrate this with Example 3.1.

Example 3.1. Suppose we have a section of a discussion tree with comments $a_0, a_1, a_2, a_3, a_4$ and edges $(a_1, a_0), (a_2, a_1), (a_3, a_1), (a_4, a_1)$ such that $(a_i, a_j)$ means $a_i$ replies to $a_j$. Let $p = 0.75$; then, $1 - p = 0.25$. A biased root-seeking random walk starting at $a_1$ will have probability 0.75 moving up to $a_0$ next. Similarly, starting from $a_1$, there is a probability $\frac{0.25}{3} = \frac{1}{12}$ of moving down (against the directions of the arrows) to any of $a_2, a_3, a_4$. This is shown in Figure 3.

Such biased root-seeking random walks therefore sample $L$ nodes in the discussion tree to be inputted into the GraphNLI model. However, as the walk is random and can go against the direction of reply, it is possible that the same node is visited more than once (this is consistent with the use of the term “walk” in graph theory, as opposed to “path” where vertices cannot repeat). If this happens, we ignore any duplicate nodes and continue the walk until either $L$ distinct nodes are traversed or the walk terminates when no more distinct nodes are available to be sampled. We illustrate this with Example 3.2.

Example 3.2. Suppose we have a section of a discussion tree with nodes $a_0, a_1, a_2, a_3, a_4$ and edges $(a_1, a_0), (a_2, a_1), (a_3, a_1), (a_4, a_2)$ such that $(a_i, a_j)$ denotes that $a_i$ replies to $a_j$. Let $p = 0.75$; then, $1 - p = 0.25$. A random walk, starting at $a_2$, can move to $a_1$ with probability 0.75 or to $a_4$ with probability 0.25. Suppose that the walk moves to $a_1$; then, there is a probability of 0.25 that the walk will move down and sample $a_2$ again. However, since $a_2$ has already been visited, it will be ignored and the walk continues. This is shown in Figure 4.

Notice that as $p \in [0, 1]$, it is possible to choose $p = 1$, which results in a deterministic walk towards the root node of the discussion. Agarwal et al. [4] calls this a root-seeking graph walk; it is
clearly a special case of biased root-seeking random walk. Intuitively, this walk captures only the prior context of the discussion leading up to the node of interest.

It is important to limit the walk length as online conversations can grow rapidly and capturing far away nodes through such random walks can lead to the over-smoothing problem [20], the phenomenon in which the resulting node embeddings of different pieces of text are almost indistinguishable and, consequently, the model loses its predictive power due to capturing too much context. The walk length $L - 1$ determines the maximum length of this random walk, where $L$ is the maximum number of distinct nodes to be visited from the starting node until the random walk terminates. By experimenting with walk length $L$ and evaluating how well GraphNLI performs, we found $L = 4$ to be the optimal walk length (see Section 5.6).

Example 3.3. (Example 3.2 continued) Consider a root-seeking graph walk starting at $a_2$, where by definition $p = 1$. Consider sampling $L = 4$ arguments. The result would be $(a_2, a_1, a_0)$ and then nothing else, as the walk can no longer move “up” after reaching the root, $a_0$. Therefore, $L$ is an upper bound on the number of nodes sampled.

The biased root-seeking random walk is thus a parametrised way of randomly sampling neighbouring nodes as a means of incorporating the global context for the prediction tasks. Note that there is no guarantee that the parent node will be visited in the random walk. By choosing the value of $p$, we can directly affect the probability of visiting the parent as discussed in Section 5.6.2. Even if the parent is not visited, there is likely to be information in the surrounding nodes that still helps in the prediction task. For example, if the majority of children nodes replying to the parent are attacking (perhaps because the parent post is controversial), knowing the sibling context may help in the prediction task.

3.2.2 Discounting the Influence of Distant Nodes. Once we have at most $L$ distinct nodes sampled using the biased root-seeking random walk, we can obtain each node’s text and thus each
text’s corresponding word embedding vector. We discount the contributions of each neighbouring node’s corresponding embedding vector by a weight of $\gamma^k$, where $\gamma \in [0, 1]$ is the discount parameter and $k$ is the distance along the graph walk from the starting or first node. This gives a weighted random walk, where the highest weight $\gamma^0$ is given to the starting node, the second-highest weight $\gamma^1$ is given to the immediate neighbour (either parent or a child node) of the starting node, then a further discounted weight of $\gamma^2$ to the third node in the random walk, and so on. This means that the closer the sampled node is to the starting node along the graph walk, the higher its weight will be and the more its embedding vector will contribute as an input towards a prediction task concerning the starting node.

Example 3.4. (Example 3.2 continued) Suppose that $L = 4$ and the resulting random walk starting at $a_2$ gives $(a_2, a_4, a_1, a_0)$. Suppose that $\gamma = 0.5$. Let $v_i$ be the embedding vector of the text of $a_i$ for $i \in \{0, 1, 2, 4\}$. The resulting weighted vectors are $\gamma^0 v_4$, $\gamma^2 v_1$, and $\gamma^3 v_0$. Notice that the powers of $\gamma$ refer to the position along the graph walk that a new node is encountered and not to the graph-theoretic distance between nodes. For example, node $a_1$ is one edge away from $a_2$, yet its discount factor is $\gamma^2$, not $\gamma^1$ since it is at the second position in the graph walk starting from $a_2$.

If $\gamma = 1$, then all the nodes sampled by the walk will have equal influence regardless of their distance from the starting node. Conversely, if $\gamma = 0$ and by adopting the convention that $\lim_{x \to 0^+} x^x = 1$,\(^{15}\) then all the nodes will have zero weight apart from the starting node. Intuitively, $\gamma$ is thus a measure of how much the model should care about the surrounding context.

At the end of a graph walk for each node, we obtain at most $L$ distinct comments, which include the starting comment and its ancestors, descendents, and siblings. We input these sets of comments into our GraphNLI model.

3.2.3 Model Overview. GraphNLI is a novel graph-based deep learning architecture which captures both the local and global contexts of online conversations through graph-based walks, as explained in the preceding two subsections. The architecture for GraphNLI is shown in Figure 5.

GraphNLI is inspired by S-BERT.\(^{52}\) Firstly, each of the arguments sampled by the graph walk, of which there is at most $L \in \mathbb{N}^+$ (Section 3.2.1), is input into the RoBERTa model to get their corresponding embeddings. Then, a mean-pooling operation, that is, calculating the mean of all the output vectors, is applied to derive a fixed-sized sentence embedding for each argument. The starting node in a graph walk is a point-of-interest (PoI) node. Let $u$ denote the sentence embedding corresponding to the PoI node. Let $v$ denote the aggregated embedding from its contextual nodes’ text embeddings (which may or may not include the parent) sampled by the graph walk starting from the PoI node. These $u$ and $v$ embeddings together are then used to predict the polarity of the reply from the PoI node to its parent or whether the PoI node’s text contains misogynistic hate speech. We have experimented with three aggregation strategies: summation (component-wise sum), average (component-wise arithmetic mean) and weighted average to compute the resultant embedding $v$. As stated in Section 3.2.2, the nodes sampled by a root-seeking random walk are weighted by powers of $\gamma$ in descending order from the PoI node up to the root. Given $u$ and $v$, we calculate an element-wise difference vector $|u - v|$. We then concatenate all three vectors $u$, $v$, and $|u - v|$ together to get the final embedding vector, which is then fed into a softmax classifier for the downstream prediction task.

In order to fine-tune BERT, we make the GraphNLI model end-to-end trainable to update weights during backpropagation such that the resulting sentence embeddings are semantically meaningful for the various downstream prediction tasks.

\(^{15}\)This limit can be informally verified by, e.g., plotting the graph of $y = x^x$ for $x \in \mathbb{R}^+$, and is a convention widely adopted in mathematics, e.g., in information theory when calculating entropy.
Fig. 5. The architecture for GraphNLI. Suppose we want to classify whether the argumentative text in node $a$ contains misogynistic hate speech or to classify whether the reply from $a$ to node $b$ is an attack or a support between arguments (assuming such a reply exists, but if it exists it is unique). We use a graph walk (see Section 3.2.1) to sample up to $L$ arguments for classifying a single node; we assume there are exactly $L$ such arguments sampled in the diagram for simplicity. Each argument is represented by its RoBERTa embedding, and then mean pooling is applied to obtain sentence embeddings. The arguments beyond the first are aggregated to an embedding vector $v$; we will compare the various aggregation methods in Section 5.6.2. The first argument is represented with a vector $u$. This is then concatenated into an embedding vector three times as long: $(u, v, |u - v|)$, where the last one denotes the element-wise difference of the embeddings of $u$ and $v$. This aggregated representation serves as the input to a softmax classifier for the downstream classification task.

4 PREDICTION TASKS AND DATASETS

4.1 The Polarity Prediction Task and the Kialo Dataset

As discussed in Section 2.1, polarity prediction aims to identify the argumentative relations of attack and support between natural language arguments. In our case, such arguments are comments submitted to online debates, and one text is replying to another text [4].

We use a dataset from Kialo to train GraphNLI. Kialo is an online debating platform that helps people “engage in thoughtful discussion, understand different points of view, and help with collaborative decision-making” [16]. In this study, we use data from discussions hosted on the Kialo debating platform as used by [4, 15, 61, 62]. In a Kialo debate, users submit claims supported by reasons; thus, each claim is an argument. Each claim submitted after the very first claim of a debate replies

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16 Quoted from https://www.kialo.com/about, last accessed 2 November 2022.
to exactly one other claim. The first claim submitted in a debate is its thesis, which does not reply to anything. This means that Kialo debates are trees and the thesis argument is the root of the tree. To start a discussion in Kialo, the user creates a thesis along with a tag that indexes the discussion by indicating the content of the discussion. A thesis can have many tags, which increases its visibility to the users. Users then comment on the discussions of their choice. The dataset contains 1,560 discussion threads dated until 28 January 2020. Each discussion thread has data about the tree structure, votes on each argument’s impact on the debate it has been submitted to, and the arguments’ texts. Further, each reply between arguments is clearly labelled as attacking (negative) or supporting (positive). Table 1 shows the number of examples per class. On each discussion tree, there is a reasonable amount of debate, with a mean of 204 and a median of 68 arguments (standard deviation 463). Kialo debates are typically balanced, with the vast majority of discussion trees having around 40% of its replies as supporting, with the rest being attacking (see Table 1).

Due to Kialo’s strict moderation policy, each piece of text submitted to a debate is a self-contained argument that has a clear claim backed by reasons. Thus, each post in Kialo can be taken as a node and directed edges can be drawn based on which post is replying to which other post. The polarity prediction task is to decide whether these edges are attacking or supporting.

### 4.2 The Misogynistic Hate Speech Detection Task and the Reddit Dataset

As discussed in Section 2.2, hate speech is prevalent in social media and it is important to at least be able to accurately identify its occurrence in a scalable manner such that appropriate action can be taken. The hate speech detection task aims to predict whether a comment is hate or non-hate in online conversations.

To evaluate how well GraphNLI classifies text as hate speech by being aware of the context of the discussion surrounding each piece of text, we use the dataset curated by Guest et al. [31]. This is an expert-annotated, hate speech dataset, sourced from Reddit. This dataset looks at the specific type of hate against women —misogyny. Therefore, the positive class is “misogynistic” and the negative class is “non-misogynistic”. Each instance is annotated by three annotators on average, following a clearly defined taxonomy that articulates various subtypes of misogynistic speech. However, for our purposes, we will only consider the most coarse-grained class —whether the speech is misogynistic or not. Table 1 shows the number of examples per class; we can see that misogynistic instances are in the minority.

We specifically choose this dataset for hate speech detection because it has information needed to construct discussion trees from Reddit conversations, from which we can sample the appropriate context using graph walks as discussed in Section 3.2.1. Specifically, every post has a parent ID, which allows us to infer the reply structure of the discussion tree. To the best of our knowledge, the baselines in [31] have not exploited the context.

### 5 EXPERIMENTS AND RESULTS

#### 5.1 Dataset Preprocessing

As described in Section 4.1, we use data from online debates conducted on Kialo for polarity prediction. All discussions from Kialo have a tree structure with a root node that represents the main
thesis and each other node is a reply to its parent, which either supports or attacks the parent. As discussed in Section 3.2.1, the graph walks treat Kialo debates as undirected discussion trees. Each edge is either a support or attack. We randomly sample 80% of the Kialo debates into a training set with the remainder serving as a test set. Overall, the training set contains 259,499 arguments (replies) in total, whereas the test set contains 64,874 arguments in Kialo debates.

For the hate speech detection task, we use the Guest dataset of misogynistic hate speech as described in Section 4.2. We represent Reddit conversations in the form of discussion trees; then, we randomly sample 80% of the conversations into the train set and the remaining 20% into the test set. The training set contains 5,335 posts, whereas the test set contains 1,516 posts in total.

5.2 Training Details

After preprocessing both datasets, we use the various graph walk techniques described in Section 3.2.1 to capture the neighbourhood and parent contexts for each of the nodes and feed them into our GraphNLI model. In the case of the biased root-seeking random walk, we perform a detailed hyperparameter search on $p$ and $\gamma$ values, which we will describe in Section 5.6.

We fine-tune the GraphNLI model with a softmax classifier objective function and cross-entropy loss for four epochs. We use a batch-size of 16, an Adam optimizer with a learning rate $2 \times 10^{-5}$, and a linear learning rate warm-up over 10% of the training data.

5.3 Baselines

We compare GraphNLI with the following relevant baselines. For the polarity prediction task, we concatenate the embeddings of parent and child comments for the model input as the model needs to predict whether the child comment attacks or supports the parent comment. In the case of the hate speech detection task, we directly input the comment embeddings into the machine learning model.

**Bag-of-Words with Logistic Regression:** The first baseline is a bag-of-words (BoW) model, which uses unigram features as input obtained from the comments in online conversations. For the polarity prediction task, the inputs are the concatenations of the parent and child BoW embeddings. For the hate speech detection task, the inputs are the single comment BoW embeddings. The inputs with their corresponding labels for each task are then fed into a logistic regression classifier with L2 regularization. The classifier is trained for 100 epochs.

**BERT:** Bidirectional encoder representations from Transformers (BERT) [27] is a Transformer network [54] pre-trained with a vast amount of raw text. It is one of the top performing models on various hate speech detection datasets [35]. As a baseline, it is fine-tuned on the Guest training set for 4 epochs with a batch-size of 16, Adam optimizer, and cross-entropy loss function.

**Sentence-BERT:** S-BERT [52] is a modification of a pre-trained BERT Transformer network to derive semantically meaningful sentence embeddings. We use the S-BERT architecture with a binary classification objective function and input the sentence pairs (parent and child arguments) into the model to get their sentence embeddings for the polarity prediction task. Later these embeddings are concatenated and fed into a softmax classifier. The S-BERT model is fine-tuned on the Kialo training dataset for 4 epochs with a batch-size of 16, the Adam optimizer, and binary cross-entropy loss function.

**Non-trainable BERT Embeddings with Graph Walks and Multi-layer Perceptron:** For each of the arguments (posts) in the two datasets, their embeddings are derived using a pre-trained BERT model and using CLS-token embeddings. Using the various graph walk techniques as described in Section 3.2.1, various neighborhood siblings and parent nodes are sampled for each node, and using their node embeddings, a resulting aggregated embedding is formed using an average aggregation function. These node embeddings are then fed into a multi-layer perceptron.
Table 2. Performance on Kialo Dataset for Polarity Prediction, Discussed in Section 5.5.1

| Model                                             | Accuracy | Macro-F<sub>1</sub> | Precision | Recall |
|---------------------------------------------------|----------|----------------------|-----------|--------|
| Bag-of-Words + Logistic Regression                | 67.00    | 62.00                | 62.00     | 62.00  |
| Sentence-BERT with classification layer          | 79.86    | 75.81                | 77.86     | 73.86  |
| BERT Embeddings: Root-seeking Graph Walk + MLP   | 70.27    | 52.32                | 44.87     | 64.12  |
| Graph Convolutional Networks                      | 57.94    | 57.82                | 67.74     | 50.44  |
| GraphNLI: Root-seeking Graph Walk + Sum           | 80.70    | 77.97                | 78.02     | 77.93  |
| GraphNLI: Root-seeking Graph Walk + Avg.          | 81.97    | 76.89                | 76.83     | 76.96  |
| GraphNLI: Biased Root-seeking Random Walk + Sum   | 79.95    | 76.32                | 76.29     | 76.35  |
| GraphNLI: Biased Root-seeking Random Walk + Avg.  | 80.44    | 76.62                | 76.68     | 76.56  |
| GraphNLI: Biased Root-seeking Random Walk + Weighted Avg. | 81.95    | 78.96                | 78.94     | 78.99  |

In case of root-seeking graph walk, $p = 1$ and $\gamma = 0.8$, whereas in root-seeking random walk, $p = 0.8$ and $\gamma = 0.8$.

(MLP) with two layers and a softmax objective function for prediction. The initial BERT embeddings are non-trainable. We train the MLP for 50 epochs or until the model converges on the Kialo training dataset with batch size of 16, using the Adam optimizer.

**Graph Convolutional Networks:** A GCN [39] is a variant of a Convolutional Neural Network which operates directly on graph-structured data. For both tasks, we use two-layered GCN for node classification on discussion trees, where each node represents a comment in an online conversation. We use S-BERT to obtain sentence embeddings for each node in a discussion tree.

### 5.4 Evaluation Metrics

Given the imbalanced nature of the Guest dataset, we use the following metrics to evaluate our model and other baselines. Although the Kialo dataset is balanced, we report all the metrics along with accuracy for consistency.

- **Accuracy:** Accuracy is the most intuitive performance measure and is a ratio of correctly predicted observations to the total observations.
- **Macro-F<sub>1</sub>:** Macro $F_1$ is the arithmetic mean of the $F_1$ scores per class.
- **Precision:** Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.
- **Recall:** Recall is the ratio of correctly predicted positive observations to all observations in the positive class.

Accuracy and macro-$F_1$ provide a high-level representation of the overall model performance. Precision and recall are used to evaluate the model’s ability to predict the minority class.

### 5.5 Model Evaluation

5.5.1 **Performance on the Kialo Dataset.** For the polarity prediction task, we evaluate the performance of GraphNLI on the test set of Kialo data. We use the various evaluation metrics as discussed in Section 5.4 to verify the model effectiveness. We train models with five different random seeds and report their average performances. Table 2 shows the performance of the various models on the polarity prediction task after being trained on the same Kialo training set.

The baseline model, Bag-of-Words embeddings with Logistic Regression, achieves an accuracy of 67% with 62% macro-$F_1$ score. The most relevant and state-of-the-art Sentence-BERT model trained on Kialo dataset achieves an accuracy of 79.86% and macro-$F_1$ of 75.81%. The initial MLP model with non-trainable BERT embeddings and root-seeking graph walk achieves an accuracy of 70.27% which is even worse than the Sentence-BERT. GCNs achieve an accuracy of 57.94% and macro-F1 score of 57.82%. GCNs have performed significantly poorer than GraphNLI and other
Table 3. Performance on Guest Dataset for Hate Speech Detection, Discussed in Section 5.5.2

| Model                                      | Accuracy | Macro-F₁ | Precision | Recall  |
|--------------------------------------------|----------|----------|-----------|---------|
| Bag-of-Words + Logistic Regression         | 92.08    | 61.45    | 56.98     | 71.49   |
| BERT with classification layer             | 92.28    | 68.79    | 74.96     | 65.47   |
| BERT Embeddings: Root-seeking Graph Walk + MLP | 92.14    | 66.56    | 61.89     | 71.65   |
| Graph Convolutional Networks               | 92.17    | 67.11    | 62.44     | 72.45   |
| GraphNLI: Root-seeking Graph Walk + Sum    | 92.63    | 72.74    | 78.34     | 69.33   |
| GraphNLI: Root-seeking Graph Walk + Avg.   | 92.95    | 72.91    | 78.46     | 69.92   |
| GraphNLI: Root-seeking Graph Walk + Weighted Avg. | 93.06    | 73.56    | 80.63     | 69.48   |
| GraphNLI: Biased Root-seeking Random Walk + Sum | 93.05    | 74.34    | 80.37     | 70.26   |
| GraphNLI: Biased Root-seeking Random Walk + Avg. | 93.16    | 74.56    | 80.24     | 70.81   |
| GraphNLI: Biased Root-seeking Random Walk + Weighted Avg. | **93.18** | **74.79** | **80.89** | **70.90** |

In case of root-seeking graph walk, $p = 1$ and $γ = 0.2$, whereas in root-seeking random walk, $p = 0.6$ and $γ = 0.2$.

baselines due to the incorporation of different kinds of conversational contexts. Specifically, GCNs incorporate all the nodes (broader context) within a given neighbourhood (1-hop and 2-hop in our case) of the node being classified, which is not as effective as capturing deeper context by GraphNLI. Furthermore, incorporating too much nearby context of a node may result in very noisy node embeddings, which weakens the model’s predictive ability.

Our model, GraphNLI, with the root-seeking graph walk (probability $p = 1$) and averaging node embeddings in the graph walk to get the aggregated node embeddings achieves an overall accuracy of 81.86%. Using weighted average node embeddings, the model achieves an even better accuracy of 81.97% with a macro-$F_1$ score of 76.89%. In the case of the biased root-seeking random walk and averaged node embeddings, GraphNLI achieves an accuracy of 80.44% with 76.62% macro-$F_1$. The best performing version of GraphNLI is with biased root-seeking random walk and weighted average aggregation, obtaining 81.95% accuracy and 78.96% macro-$F_1$. This implies a significant improvement of about 4 percentage points in macro-$F_1$ and 3 percentage points in the accuracy score. Clearly, all the variants of GraphNLI achieve better accuracy scores than all the baselines, including sentence-BERT. GraphNLI with a biased root-seeking random walk and weighted average node embeddings with probability $p = 0.8$ and gamma $γ = 0.8$ achieves the highest accuracy and macro-$F_1$ overall. We will discuss detailed hyperparameter search in Section 5.6. The results show that systematically incorporating the global context of the online debates or discussions along with the local context of the argument pairs does help in predicting the argumentative relations of support and attack. Also, weighted average aggregation gives higher weights to the arguments near to the given argument pair in the discussion tree whose polarity needs to be predicted and exponentially reduces the weights when the graph walk moves away from the given node.

5.5.2 Performance on the Guest Dataset. We evaluate the performance of the GraphNLI model on the Reddit dataset by Guest et al. [31] for the misogynistic hate speech detection task. Table 3 shows the performance of different models on the test set.

We have trained models with five different random seeds and report their average performances. The dataset is highly imbalanced, with the hate class in the minority. Hence, we use different evaluation metrics, such as macro-$F_1$, precision, and recall as described in Section 5.4. The baseline model, Bag-of-Words embeddings with Logistic Regression, achieves an overall accuracy of 92.08% with 61.45% macro-$F_1$ score. The state-of-the-art BERT model achieves an overall accuracy of 92.28%, 68.79% macro-$F_1$, 74.96% precision, and a poor recall of 65.47%. The initial MLP model with non-trainable BERT embeddings and root-seeking graph walk achieves an accuracy of 92.14% with 66.56% macro-$F_1$. GCNs achieve an accuracy of 92.17% and macro-$F_1$ score of 67.11%. Again, GCNs perform poorer due to the incorporation of broader context which leads very noisy node
embeddings. GraphNLI with a root-seeking graph walk (probability $p = 1$) performs the best with weighted average aggregation. It has an overall accuracy of 93.06% and macro-$F_1$ score of 73.56%. All of the different versions of GraphNLI outperform the baselines on all evaluation metrics with a significant improvement in macro-$F_1$. The best performing variant is GraphNLI with a biased root-seeking random walk and weighted average aggregation with probability $p = 0.6$ and gamma $\gamma = 0.2$. We will discuss the hyperparameter search in detail in Section 5.6.

The best performing model gives an overall accuracy of 93.18% and macro-$F_1$ of 74.79%. This implies a significant improvement in precision, recall, and macro-$F_1$, which is about 6 percentage points higher than the BERT baseline. Once again, this shows that systematically incorporating the global context of the conversations along with the local context improves the model performance in detecting hate speech online.

5.6 Hyperparameter Search and Ablative Experiments

5.6.1 Hyperparameter Search. In this section, we comment on the performance of GraphNLI on both tasks given the values of various hyperparameters and how such values were searched for.

Recall from Section 3.2.1 that in a biased root-seeking random walk, the probability $p$ is the probability of selecting the parent node (i.e., the node being replied to by the current PoI node in a discussion tree), whereas the remaining probability $1 - p$ is distributed equally among the children nodes of the PoI node. Recall from Section 3.2.2 that gamma ($\gamma$) is the discount parameter that exponentially decreases as the random walk moves away from the PoI node towards one of the parent or children nodes. For both the polarity prediction and the misogynistic hate speech detection tasks, we perform a detailed hyperparameter search on different pairs of values of $p$ and $\gamma$ ranging from 0 to 1 in increments of 0.2, and observe their macro-$F_1$ scores.

Figure 6 shows the heat map of the macro-$F_1$ scores for GraphNLI when trained on the Kialo dataset for different values of the discount factor $\gamma$ and probability $p$. If $p < 0.5$, then the children nodes of the PoI node will be selected via random walk more often than the parent and other...
Fig. 7. A heat map showing the macro-$F_1$ scores for different values of gamma ($\gamma$) and probability $p$ on the misogynistic hate speech detection task, where the GraphNLI model has been trained on the Reddit dataset by Guest et al. [31].

ancestor nodes. Conversely, if $p > 0.5$, then the parent and ancestor nodes of the PoI node will be selected more often. For a root-seeking random walk, the macro-$F_1$ score of 78.96% is the highest when $p = 0.8$ and $\gamma = 0.8$. A higher value of the probability ($p = 0.8$) shows that the importance of parent and other ancestor nodes is more than the children nodes for the polarity prediction task, whereas a higher value of gamma ($\gamma = 0.8$) indicates that immediate neighbors of a node (argument) matter more than the nodes that are farther away. For a root-seeking graph walk ($p = 1$), macro-$F_1$ is the highest when $\gamma = 1$ (all the nodes in a graph walk are weighted equally) but still lower than the root-seeking random walk. This demonstrates the importance of capturing and weighting the neighbouring context along with the local context for polarity prediction.

For the hate speech detection task, the analogous hyperparameter search results with the same ranges for $\gamma$ and $p$ are shown in the heat map in Figure 7.

For a root-seeking random walk, a macro-$F_1$ score of 74.79% for hate speech detection is the highest when $p = 0.6$ and $\gamma = 0.2$. As $p = 0.6 > 0.5$, ancestor nodes will be selected more often by such a random walk than the children nodes. A low value of $\gamma$, i.e., 0.2, means that context of nodes that are farther away matters a lot along with the immediate neighbours. For a specific random walk, a root-seeking graph walk ($p = 1$), the highest macro-$F_1$ score of 73.56% occurs when $\gamma = 0.2$. It is 1 percentage point lower than the highest macro-$F_1$ for a biased root-seeking random walk. This demonstrates the importance of capturing the context of children and other sibling nodes along with the ancestor nodes for hate speech detection. Both Figures 6 and 7 show that inputting neighbouring context is always better than no context.

Next, using Grid Search, we find the optimal value of the hyperparameter: walk length $L$. Recall from Section 3.2.1 that walk length $L$ is the maximum number of distinct nodes that can be visited during a random walk starting from a point-of-interest node. As shown in Table 4, $L = 4$ gives the best accuracy scores for both the Kialo and Guest datasets for polarity prediction and hate speech detection, respectively.

5.6.2 Ablative Experiments. We have demonstrated superior performance of GraphNLI with respect to the various baselines in Table 2 for polarity prediction and in Table 3 for hate speech.
A Graph-Based Context-Aware Model to Understand Online Conversations

Table 4. Accuracy (%) Scores of GraphNLI Model Trained on Kialo and Guest Datasets for Different Values of Walk Length $L$

| $L$ | Kialo | Guest |
|-----|-------|-------|
| 2   | 80.70 | 91.77 |
| 4   | 81.95 | 93.18 |
| 6   | 81.89 | 92.88 |

Table 5. Accuracy (%) Scores of GraphNLI Model Trained on the Kialo and Guest Datasets with Different Concatenation Techniques Using Weighted Average Aggregation, Discussed in Section 5.6.2

| Concatenation | Kialo | Guest |
|---------------|-------|-------|
| $(u, v)$      | 76.78 | 92.71 |
| $(u, v, u \ast v)$ | 82.05 | 93.06 |
| $(u, v, |u - v|)$ | 82.87 | 93.18 |
| $(u, v, |u - v|, u \ast v)$ | 82.38 | 92.48 |

The concatenations are denoted by tuples of the vectors concatenated in order, where $u \ast v$ denotes element-wise multiplication and $|u - v|$ denotes element-wise modulus of the differences.

detection. In this section, we perform ablative experiments and discuss different aspects of the GraphNLI model as well as the intuition behind the choices in order to gain a better understanding of the model.

First, we evaluate different graph walks by feeding the resultant embeddings obtained with the weighted average aggregation strategy into our model and compare their accuracy and $F_1$-scores. For both the tasks, as shown in Tables 2 and 3, all the graph walks with the GraphNLI architecture perform significantly better than the BERT-based model. S-BERT just considers the argument pairs (node and its parent embeddings) for polarity prediction and BERT just considers the node embedding for hate speech detection, whereas through graph walks, GraphNLI considers the global context of the discussion trees by exploring parents and neighborhoods of a node. Therefore, the global context along with the local context of the online discussions indeed helps in predicting the polarities of replies and the presence of misogynistic hate speech.

We further evaluate different aggregation strategies (summation, average and weighted average) to aggregate the node embeddings of the neighbouring nodes using the biased root-seeking random walk. As shown in Tables 2 and 3, the weighted average aggregation function performs better than the summation and average strategies. This shows that influence of the neighbouring comments decreases as the graph walk moves away from the given node. Hence, neighbouring nodes cannot be weighted equally but, instead, progressively in the decreasing order of their distance from the given node.
Table 6. Hate Precision, Recall, and $F_1$-scores for Models Trained on the Guest Dataset

| Model                | Hate Precision | Hate Recall | Hate $F_1$ |
|----------------------|----------------|-------------|------------|
| BERT                 | 0.53           | 0.39        | 0.45       |
| GraphNLI-small       | 0.52           | 0.42        | 0.47       |
| GraphNLI             | 0.65           | 0.44        | 0.52       |

We also evaluate different methods for concatenating a node’s embedding $u$ with the aggregated embedding of its neighbours $v$ obtained using the root-seeking random walk. The impact of the concatenation method on the model’s performance is significant. As depicted in Table 5, the concatenation of $(u, v, |u − v|)$ works the best for both tasks. As reported by the authors of [52], adding the element-wise multiplication $u \ast v$ decreased the performance. Element-wise absolute difference $|u − v|$, which measures the distance between the two node embeddings, is thus an important component.

Our initial non-end-to-end trainable model as discussed in Section 5.3, in which we keep the node embeddings obtained from the BERT model fixed, performs even worse than Sentence-BERT. This throws light on the importance of end-to-end training of the model for fine-tuning on specific tasks. After end-to-end training, the model outputs node embeddings that are rich in context suitable for downstream tasks such as polarity prediction and hate speech detection.

6 ERROR ANALYSIS ON HATE SPEECH DETECTION

In this section, we conduct an error analysis on hate speech detection and compare our GraphNLI model with the best performing baseline – BERT for hate speech detection. To check the effectiveness of conversational context, we also train GraphNLI for small conversations, which we define as conversations with no more than two comments. In other words, we only have the root post and its reply. In such conversations, the random walk exploration cannot gain any more context than a post (a leaf node) and the parent node it is replying to (i.e., the root node). Thus, we expect that this model, which we call GraphNLI-small, will perform no better than the baseline BERT model. Table 6 shows the precision, recall, and $F_1$-score for the hate class in the Guest dataset for BERT, GraphNLI-small, and GraphNLI. The best performing variant of GraphNLI with biased root-seeking random walk ($p = 0.6$ and $γ = 0.2$) is compared with the best performing baseline BERT on hate class. The BERT baseline gives an overall hate $F_1$-score of 45% with hate precision of 53% and a poor hate recall of 39%. GraphNLI gives a 7 percentage point higher hate $F_1$-score with an overall hate precision of 65% and hate recall of 44%. The improvement in hate precision is the highest at 12 percentage points and hate recall at 5 percentage points. Therefore, GraphNLI performs significantly better than BERT in detecting hate speech in online conversations. The performance drop in $F_1$-score for GraphNLI-small shows the effectiveness of incorporating conversational context in GraphNLI. Therefore, GraphNLI works better for larger conversations that have more comments for conversational context.

Next, we look at the confusion matrix in Table 7 for the baseline BERT model trained on the Guest dataset. Overall, 98 samples (7.96%) are misclassified. Out of these 98 samples, 36 (36.74%) are false positives and 62 (63.27%) are false negatives.

Table 8 shows the confusion matrix for GraphNLI model trained on Guest dataset. Overall, 82 samples (6.66%) are misclassified, which is less than the BERT baseline. Out of these 82 samples, 28 (34%) are false positives and 54 (66%) are false negatives.

Based on the above analysis, we conclude that GraphNLI’s ability to incorporate the global context of online conversations leads to fewer false positives and false negatives compared with the current-best
Table 7. Confusion Matrix of the BERT Model Trained on the Guest Dataset

| Prediction | Non-hate | Hate | Total |
|------------|----------|------|-------|
| Label      |          |      |       |
| Non-hate   | 1,093    | 36   | 1,129 |
| Hate       | 62       | 40   | 102   |
| Total      | 1,155    | 76   | 1,231 |

Table 8. Confusion Matrix of the GraphNLI Model Trained on the Guest Dataset

| Prediction | Non-hate | Hate | Total |
|------------|----------|------|-------|
| Label      |          |      |       |
| Non-hate   | 1,101    | 28   | 1,129 |
| Hate       | 54       | 48   | 102   |
| Total      | 1,155    | 76   | 1,231 |

Fig. 8. An example conversation from the Guest dataset containing a false-negative sample.

A graph-based context-aware model that does not incorporate context. Out of 62 false negatives for the BERT model, many cases are misclassified due to the lack of context of conversation threads. Thus, the BERT model, which does not explicitly take into account the conversation context, fails to recognise the misogyny in isolation.

Example 6.1. We now consider a false-negative example from the Guest dataset, as shown in Figure 8. This is the same conversation from Example 7, but we repeat it here for convenience. The nodes of this directed tree are Reddit posts, whose texts are:

1. **Bottom row:** “It’s funny to see the hamster that starts to act up in their little widdle tiny brains after saying that too”. This is labelled as misogynistic as the annotators agree that the text points out that women are intellectually inferior.
2. **Middle row, left:** “There aren’t many things that are more satisfying than telling a girl, ‘No’.”
3. **Middle row, right:** “A lot of women do this to their simp boyfriends and its sad, hope when I’m older (as in 14-16) I don’t fall into this trap.”
4. **Top row:** “Got a few girls sweet talking since the past few days hoping to get me to take them out for valentine’s day. Lmfao. A day designed to cuck more simps.”

The arrows between the nodes indicate which posts reply to which other posts.
We would like to automatically detect whether the post on the bottom row contains misogynistic hate speech. However, BERT cannot recognise that as it does not have enough context to understand that it refers to women. On the other hand, GraphNLI successfully recognises the bottom post as misogynistic since it has additional context from the surrounding comments, some of which are shown in Figure 2. In this manner, GraphNLI gives fewer false negatives than BERT.

We now look at a false-positive example.

**Example 6.2.** Consider a false-positive example from the Guest dataset, as shown in Figure 9. The nodes of this directed tree are Reddit posts, whose texts are:

1. **Bottom row, left:** “We are consistently told by the world that we only deserve love when were what the world wants us to be. Embrace yourself and know that nothing is required to earn someone love!”

2. **Bottom row, right:** “The most manly thing is to find your dream woman, marry her, and live happily ever after. The constant sex with women is so overrated anyways.” This is labelled as non-misogynistic by expert annotators. Although the text contains a few words that can overlap with misogynistic content, overall it suggests that things other than high levels of sexual activity should be prioritised, and therefore it is labelled as non-misogynistic.

3. **Middle row:** “Why is it so hard for guys to internalize this? It feels like no matter how many times I try to tell myself this, I still feel like less of a man for not getting laid on a regular basis.”

4. **Top row:** “Hey fellas, I’ve been a long time lurker on this sub. While there are a lot of things I don’t agree with people saying, I just wanted to remind you guys that your worth is NOT found in your body count or how many women you’ve been with. Learning to love yourself regardless of outside factors is the first step to finding long term joy. Keep a smile on!”

We would like to automatically detect whether the post on the bottom right row contains misogynistic hate speech. Although it is labelled as non-misogynistic, BERT recognises it as misogynistic as the post contains a few words often associated with misogynistic content. On the other hand, GraphNLI successfully recognises it as non-misogynistic since it has additional context from the surrounding comments, some of which are shown in Figure 9.

Overall, due to context awareness, GraphNLI gives fewer false positives compared with BERT.

### 7 CONCLUSIONS AND FUTURE WORK

In this article, we demonstrated a novel model, GraphNLI, which is capable of classifying the polarity of replies (attacking or supporting) in an online discussion, as well as whether the texts posted
in such discussions contain misogynistic hate speech. The classification component of GraphNLI is inspired by S-BERT, but it is novel in its application of graph walks to sample the “global” context surrounding the reply or post in an online discussion and then using this context to enrich its inputs. Empirically, we found that a biased root-seeking random walk with a weighted average aggregation of the neighbouring contexts is the best strategy in terms of classification accuracy. This strategy addresses the shortcomings of previous approaches that only capture the “local” context, such as the reply and the post it is replying to. We also showed through extensive ablative experiments that information from parent and other ancestor nodes generally provides more relevant contextual information than siblings and children of the reply node for both classification tasks. Furthermore, the importance of ancestor nodes should decrease as the distance from the reply node increases. The ability for GraphNLI to outperform the current state-of-the-art for two tasks shows the value of incorporating the context of online discussions.

Our work partly fixes the gap of inferring polarity and hate speech from the content and context of an online discourse. However, several questions remain to be answered to make it relevant for wider usage. For instance, we have demonstrated and evaluated our approach on Kialo, a tightly moderated online debating platform, as well as noisier, weakly moderated discourses, such as on Reddit. There are other forums, such as the BBC’s Have Your Say,\(^\text{17}\) that do not have an explicit threaded reply structure, requiring one to infer from the text of a reply which other post it is replying to prior to applying GraphNLI’s graph walk techniques. In such less restrictive user interfaces, posts may refer to multiple other posts. This, in turn, means that the reply graph is no longer a tree, although still a directed acyclic graph due to the time ordering of replies, i.e., that later posts can only reply to earlier posts. However, we note that discussions that are not trees should pose no limitations on our graph walk techniques (Section 3.2.1) because there would only be more context for the graph walk to sample; future work will make this claim precise. Currently, GraphNLI is trained on English datasets for both tasks. In future, we would like to apply the model to other languages, such as Hindi [26], Vietnamese [46, 50], and Chinese [36].

Further, GraphNLI can be applied to a range of problems in computational social science, for example:

- **Using reply polarity to enhance hate speech detection:** As stated in Section 2.2, hate speech on online forums is a common challenge [22], including in nationally important conversations between citizens and their elected representatives [1]. In other cases, some members of a discussion can be unfairly targeted, as in the case of misogyny on Reddit [31]. Knowledge about argument polarities can support the detection of hate speech; for example, many attacking comments towards female participants (if the gender of users is accurately known) can be a possible complementary indicator of potential misogyny.

- **Understanding conversation health:** As stated in Section 1, online discussion forums provide a great opportunity for socially positive interactions, such as peer support for long-term medical problems [37, 49]. On the other hand, many forums have unfortunately become a medium for rampant misinformation [42] and hate [29]. As such, identifying and promoting “healthy” conversations has been identified as an important priority by many (e.g., Twitter [33]). Intuitively, an online discussion is “healthier” if there is less hate speech than non-hate speech, and that there are less attacking replies than there are supporting replies, adjusted for how controversial the topic under discussion is. This can be used to develop conversation health “metrics” that can be tracked over time and guide appropriate action to be taken when necessary.

\(^{17}\text{See the comments of, e.g., https://www.bbc.co.uk/news/uk-politics-63484971#comments, last accessed 2 November 2022.}\)
• **Detecting filter bubbles:** Democratic conversations on news and social media sites can exhibit partisan tendencies \([2, 5, 11, 38]\). This can lead to filter bubbles, where two (or more) parallel conversations about the same topic exist, with each conversation consisting of posts largely agreeing with other posts in that conversation and yet having a large amount of disagreement with the other conversations happening in parallel. Predicting polarities could help detect filter bubbles by quantifying agreeability in conversations. For example, if we find that posts reachable from each other also agree with each other (i.e., are supporting), and yet if an imaginary edge is induced between posts in different parts of a conversation (or a different discussion thread), we find that the imaginary edge would be an attack edge, which could be indicative of a filter bubble. Further, one can extend the ability of detecting hate speech to identifying the target of such hatred, which can complement such efforts in identifying filter bubbles.

• **Eristic argumentation:** Formal models of argumentation (e.g., \([9, 19, 28, 59]\)) have focussed on logical and dialectical aspects of argumentation, which have made precise the central concepts of validity, justification, and explainability. However, such formal models have until recently paid less attention to **eristic argumentation** — where people argue for the sake of winning and causing conflict, rather than resolving conflict. such a style of argumentation is done without necessarily adhering to the norms of logic, facts, or civil debate. Perhaps unsurprisingly, online debates are highly eristic, and there have been attempts to model this using formal argumentation (e.g., \([12]\)). GraphNLI can contribute to this effort by relating how the presence of hate relates to when an online discussion that is initially civilised shifts to an eristic discussion, which would then suggest that more traditional models of argumentation may no longer apply.

We therefore hope to apply and adapt GraphNLI to some of the above problems in future work. We believe that GraphNLI will need to be fine-tuned on specific tasks at-hand and will need to perform hyperparameter tuning using grid search.

**REFERENCES**

[1] Pushkal Agarwal, Oliver Hawkins, Margarita Amaxonpoulou, Noel Dempsey, Nishanth Sastry, and Edward Wood. 2021. Hate speech in political discourse: A case study of UK MPs on Twitter. In *Proceedings of the 32nd ACM Conference on Hypertext and Social Media*(Virtual Event, USA) (HT ’21). Association for Computing Machinery, New York, NY, USA, 5–16. Last accessed 19 June 2022 from https://doi.org/10.1145/3465336.3475113

[2] Pushkal Agarwal, Sagar Joglekar, Panagiotis Papadopoulos, Nishanth Sastry, and Nicolas Kourtellis. 2020. Stop tracking me Bro! Differential tracking of user demographics on hyper-partisan websites. In *Proceedings of the Web Conference (WWW ’20)*. International World Wide Web Conferences Steering Committee, Taipei, Taiwan, 10 pages.

[3] Pushkal Agarwal, Nishanth Sastry, and Edward Wood. 2019. Tweeting MPs: Digital engagement between citizens and members of Parliament in the UK. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 13. 26–37.

[4] Vibhor Agarwal, Sagar Joglekar, Anthony P. Young, and Nishanth Sastry. 2022. GraphNLI: A graph-based natural language inference model for polarity prediction in online debates. In *Proceedings of the ACM Web Conference 2022*. 2729–2737.

[5] Vibhor Agarwal, Yash Vekaria, Pushkal Agarwal, Sangeeta Mahapatra, Shounak Set, Sakhthi Balan Muthiah, Nishanth Sastry, and Nicolas Kourtellis. 2021. Under the spotlight: Web tracking in Indian partisan news websites. In *Proceedings of the International AAAI Conference on Web and Social Media*, Vol. 15. 26–37.

[6] Hunt Allcott and Matthew Gentzkow. 2017. Social media and fake news in the 2016 election. *Journal of Economic Perspectives* 31, 2 (2017), 211–36.

[7] Noman Ashraf, Arkaitz Zubiaga, and Alexander Gelbukh. 2021. Abusive language detection in YouTube comments leveraging replies as conversational context. *Peer J Computer Science* 7 (2021), e742.

[8] Christopher A. Bail, Lisa P. Argyle, Taylor W. Brown, John P. Bumpus, Haohan Chen, M. B. Fallin Hunzaker, Jaemin Lee, Marcus Mann, Friedolin Merhout, and Alexander Volfovsky. 2018. Exposure to opposing views on social media can increase political polarization. *Proceedings of the National Academy of Sciences* 115, 37 (2018), 9216–9221.
[9] Pietro Baroni, Martin Caminada, and Massimiliano Giacomin. 2011. An introduction to argumentation semantics. The Knowledge Engineering Review 26, 4 (2011), 365–410.

[10] Matthew Beatty. 2020. Graph-based methods to detect hate speech diffusion on Twitter. In 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM ’20). IEEE, 502–506.

[11] Shweta Bhattacharjee, Sagar Joglekar, Shehar Bano, and Nishanth Sastry. 2018. Influencing an ecosystem of partisan websites. In Companion Proceedings of the Web Conference 2018 (Lyon, France) (WWW ’18). International World Wide Web Conferences Steering Committee, Republic and Canton of Geneva, Switzerland, 545–554. Last accessed 19 June 2022 from https://doi.org/10.1145/3184558.3188725

[12] Thomas Blount, David Millard, and Mark Weal. 2014. Towards modelling dialectic and eristic argumentation on the social web. (2014). Last accessed 19 June 2022 from https://eprints.soton.ac.uk/372090/1/argumentation.pdf

[13] Johan Bos and Katja Markert. 2006. When logical inference helps determining textual entailment (and when it doesn’t). In Proceedings of the 2nd PASCAL RTE Challenge. 26.

[14] Tom Bosc, Elena Cabrio, and Serena Villata. 2016. Tweeties squabbling: Positive and negative results in applying argument mining on social media. In 6th International Conference on Computational Models of Argument 2016 (2016), 21–32.

[15] Gioia Boschi, Anthony P. Young, Sagar Joglekar, Chiara Cammarota, and Nishanth Sastry. 2021. Who has the last word? Understanding how to sample online discussions. ACM Transactions on the Web (TWEB) 15, 3 (2021), 1–25.

[16] David A. Broniatowski, Amelia M. Jamison, SiHua Qi, Lulwah AlKulaibi, Tao Chen, Adrian Benton, Sandra C. Quinn, and Mark Dredze. 2018. Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. American Journal of Public Health 108, 10 (2018), 1378–1384.

[17] Elena Cabrio and Serena Villata. 2013. A natural language bipolar argumentation approach to support users in online debate interactions. Argument & Computation 4, 3 (2013), 209–230.

[18] Elena Cabrio and Serena Villata. 2015. Five years of argument mining: A data-driven analysis. In IJCAI, Vol. 18. 5427–5433.

[19] Claudette Cayrol and Marie-Christine Lagasquie-Schiex. 2005. On the acceptability of arguments in bipolar argumentation frameworks. In European Conference on Symbolic and Quantitative Approaches to Reasoning and Uncertainty. Springer, 378–389.

[20] Deli Chen, Yankai Lin, Wei Li, Peng Li, Jie Zhou, and Xu Sun. 2020. Measuring and relieving the over-smoothing problem for graph neural networks from the topological view. In Proceedings of the AAAI Conference on Artificial Intelligence, Vol. 34. 3438–3445.

[21] Naganna Chetty and Sreejith Alathur. 2018. Hate speech review in the context of online social networks. Aggression and Violent Behavior 40 (2018), 108–118.

[22] Matteo Cinelli, Andrea Pelicon, Igor Mozetič, Walter Quattrociocchi, Petra Kralj Novak, and Fabiana Zollo. 2021. Online hate: Behavioural dynamics and relationship with misinformation. arXiv preprint arXiv:2105.14005 (2021).

[23] Oana Cocarascu, Elena Cabrio, Serena Villata, and Francesca Toni. 2020. A dataset independent set of baselines for relation prediction in argument mining. arXiv preprint arXiv:2003.04970 (2020).

[24] Oana Cocarascu and Francesca Toni. 2017. Identifying attack and support argumentative relations using deep learning. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing. 1374–1379.

[25] Ido Dagan, Bill Dolan, Bernardo Magnini, and Dan Roth. 2009. Recognizing textual entailment: Rational, evaluation and approaches. Natural Language Engineering 15, 4 (2009), i–xvii. Last accessed 5 June 2022 from https://www.cambridge.org/core/services/aop-cambridge-core/content/view/A8332663248862777F4665C08BA33E9F/S1351326909990234a.pdf/recogznizing-textual-entailment-rational-evaluation-and-approaches-erratum.pdf

[26] Mithun Das, Punyajoy Saha, Binny Mathew, and Animesh Mukherjee. 2022. HateCheckHIn: Evaluating Hindi hate speech detection models. arXiv preprint arXiv:2205.00328 (2022).

[27] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional Transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers). 4171–4186.

[28] Phan Minh Dung. 1995. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. Artificial Intelligence 77, 2 (1995), 321–357.

[29] Ignacio Gagliardone, Danit Gal, Thiago Alves, and Gabriela Martinez. 2015. Countering Online Hate Speech. UNESCO Publishing.

[30] Kiran Garimella, Gianmarco De Francisci Morales, Aristides Gionis, and Michael Mathioudakis. 2017. Reducing conflation and violence in online discussions on social web. (2014). Last accessed 19 June 2022 from https://eprints.soton.ac.uk/372090/1/argumentation.pdf

[31] Ella Guest, Bertie Vidgen, Alexandros Mittos, Nishanth Sastry, Gareth Tyson, and Helen Margetts. 2021. An expert annotated dataset for the detection of online misogyny. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume. 1336–1350.
[32] Andreas Hanelowski, Avinesh Polisetty Venkata Sai, Benjamin Schiller, Felix Caspelherr, Debanjan Chaudhuri, Christian M. Meyer, and Iryna Gurevych. 2018. A retrospective analysis of the fake news challenge stance-detection task. In *Proceedings of the 27th International Conference on Computational Linguistics*. 1859–1874.

[33] Twitter Inc. 2022. Healthy Conversations. Last accessed 5 June 2022 from https://about.twitter.com/en/our-priorities/healthy-conversations

[34] Roshni G. Iyer, Wei Wang, and Yizhou Sun. 2021. Bi-level attention graph neural networks. In *2021 IEEE International Conference on Data Mining (ICDM ’21)*. IEEE, 1126–1131.

[35] Md Saroar Jahan and Mourad Oussalah. 2022. A systematic review of hate speech automatic detection using natural language processing. *arXiv preprint arXiv:2106.00742* (2021).

[36] Aiqi Jiang, Xiaohan Yang, Yang Liu, and Arkaitz Zubiaga. 2022. SWSR: A Chinese dataset and lexicon for online sexism detection. *Online Social Networks and Media* 27 (2022), 100182.

[37] Sagar Joglekar, Nishanth Sastry, Neil S. Coulson, Stephanie J. C. Taylor, Anita Patel, Robbie Duschinsky, Amrutha Anand, Matt Jameson Evans, Chris J. Griffiths, Aziz Sheikh, et al. 2018. How online communities of people with long-term conditions function and evolve: Network analysis of the structure and dynamics of the Asthma UK and British Lung Foundation online communities. *Journal of Medical Internet Research* 20, 7 (2018), e238.

[38] Dmytro Karamshuk, Tetiana Lokot, Oleksandr Pryymak, and Nishanth Sastry. 2016. Identifying partisan slant in news articles and Twitter during political crises. In *Social Informatics*, Emma Sprio and Yong-Yeol Ahn (Eds.). Springer International Publishing, Cham, 257–272.

[39] Thomas N. Kipf and Max Welling. 2016. Semi-supervised classification with graph convolutional networks. *arXiv preprint arXiv:1609.02907* (2016).

[40] Sebastian Köffer, Dennis M. Riehle, Steffen Höhenberger, and Jörg Becker. 2018. Discussing the value of automatic hate speech detection in online debates. *Multikonferenz Wirtschaftsinformatik (MKWI 2018): Data Driven X-Turning Data in Value, Leuphana* (2018).

[41] Milen Kouvylekov and Matteo Negri. 2010. An open-source package for recognizing textual entailment. In *Proceedings of the ACL 2010 System Demonstrations*. 42–47.

[42] Srijan Kumar, Robert West, and Jure Leskovec. 2016. Disinformation on the web: Impact, characteristics, and detection of Wikipedia hoaxes. In *Proceedings of the 25th International Conference on World Wide Web*. 591–602.

[43] John Lawrence and Chris Reed. 2020. Argument mining: A survey. *Computational Linguistics* 45, 4 (2020), 765–818.

[44] Marco Lippi and Paolo Torroni. 2016. *Argumentation mining: State of the art and emerging trends*. Springer.

[45] Yinhui Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. RoBERTa: A robustly optimized BERT pretraining approach. *arXiv preprint arXiv:1907.11692* (2019).

[46] Son T. Luu, Kiet Van Nguyen, and Ngan Luu-Thuy Nguyen. 2021. A large-scale dataset for hate speech detection on Vietnamese social media texts. In *Advances and Trends in Artificial Intelligence*. *Artificial Intelligence Practices: 34th International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems, IEA/AIE 2021, Kuala Lumpur, Malaysia, July 26–29, 2021, Proceedings, Part I*. 34. Springer, 415–426.

[47] Bill MacCartney and Christopher D. Manning. 2008. Modeling semantic containment and exclusion in natural language inference. In *Proceedings of the 22nd International Conference on Computational Linguistics (Coling ’08)*. 521–528.

[48] Tobias Mayer, Santiago Marro, Elena Cabrio, and Serena Villata. 2021. Enhancing evidence-based medicine with natural language argumentative analysis of clinical trials. *Artificial Intelligence in Medicine* (2021), 102098.

[49] Pietro Ponzarasa, Christopher J. Griffiths, Nishanth Sastry, and Anna De Simoni. 2020. Social medical capital: How patients and caregivers can benefit from online social interactions. *Journal of Medical Internet Research* 22, 7 (2020), e16337.
[56] Serena Villata. 2021. Towards Assessing Natural Language Argument Strength: Results and Open Challenges. Last accessed 5 June 2022 from http://argstrength2021.argumentationcompetition.org/programme.html

[57] Xiao Wang, Houye Ji, Chuan Shi, Bai Wang, Yanfang Ye, Peng Cui, and Philip S. Yu. 2019. Heterogeneous graph attention network. In The World Wide Web Conference. 2022–2032.

[58] Wenjie Yin, Vibhor Agarwal, Aiqi Jiang, Arkaitz Zubiaga, and Nishanth Sastry. 2023. AnnoANNO: Effectively representing multiple annotators’ label choices to improve hate speech detection. In Proceedings of the International AAAI Conference on Web and Social Media, Vol. 17. 902–913.

[59] Anthony P. Young. 2018. Notes on abstract argumentation theory. arXiv preprint arXiv:1806.07709 (2018).

[60] Anthony P. Young. 2021. Likes as argument strength for online debates. In The Third Workshop on Argument Strength. Last accessed 19 June 2022 from http://argstrength2021.argumentationcompetition.org/papers/ArgStrength2021_paper_8.pdf

[61] Anthony P. Young, Sagar Joglekar, Vibhor Agarwal, and Nishanth Sastry. 2022. Modelling online debates with argumentation theory. ACM SIGWEB Newsletter Spring (2022), 1–9.

[62] Anthony P. Young, Sagar Joglekar, Gioia Boschi, and Nishanth Sastry. 2021. Ranking comment sorting policies in online debates. Argument & Computation 12, 2 (2021), 265–285.

[63] Anthony P. Young, Sagar Joglekar, Kiran Garimella, and Nishanth Sastry. 2018. Approximations to truth in online comment networks. In The Workshop on Argumentation and Society at the 7th International Conference on Computational Models of Argument. Last accessed 22 January 2022 from https://nishrs.github.io/publication/young-2018-comma/

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